



Climate Debt Risk Index 2024

Equity and Justice Based Climate Finance for Vulnerable LDCs

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Climate Debt Risk Index 2024:

Equity and Justice Based Climate Finance for Vulnerable LDCs

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About Change Initiative

Change Initiative (CI) is a research-based think tank focused on solving critical global challenges. Founded in 2018, we specialize in crafting innovative, inclusive, and impactful solutions that address climate resilience, renewable energy, and social equity.

The name 'Change Initiative' (CI) represents the goal of embarking on the journey of devising an alternative research paradigm beyond the orthodox modalities.

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Lastly, we extend our heartfelt thanks to our families for their unwavering support and encouragement throughout this journey, and to the entire Change Initiative family for their collective dedication and commitment, making this work possible.

Abbreviation

| | |
|-----------------|---|
| ADP | Annual Development Program |
| AF | Adaptation Fund |
| BDT | Bangladeshi Taka |
| CAGR | Compound Annual Growth Rate |
| CCDR | Cumulative Climate Debt Risk |
| CDM | Clean Development Mechanism |
| CDRI | Climate Debt Risk Index |
| CF | Climate Finance |
| CFAF | Climate Finance Action Fund |
| CFU | Climate Funds Update |
| CI | Change Initiative |
| CO ₂ | Carbon Di-Oxide |
| COP | Conference of the Parties |
| CPI | Corruption Perceptions Index |
| CRI | Climate Risk Index |
| CSR | Corporate Social Responsibility |
| CTF | Clean Technology Fund |
| FY | Fiscal Year |
| GCF | Green Climate Fund |
| GDP | Gross Domestic Product |
| GEF | Global Environment Facility |
| GHG | Green House Gas |
| IEA | International Energy Agency |
| IIED | International Institute for Environment and Development |
| IMF | International Monetary Fund |
| KII | Key Informant Interview |
| LDC | Least Developed Country |
| LDCF | Least Developed Countries Fund |
| LMICs | Low- and Middle-Income Countries |
| LTSS | Long-term Climate Strategies |
| MDB | Multilateral Development Bank |
| MPI | Multidimensional Poverty Index |
| NAP | National Adaptation Plan |

| | |
|------------------|---|
| NGO | Non-Governmental Organizations |
| ODA | Official Development Assistance |
| OECD | Organisation for Economic Cooperation and Development |
| PCA | Principal Component Analysis |
| PDR | People's Democratic Republic |
| PPCR | Pilot Program for Climate Resilience |
| RE | Renewable Energy |
| RST | Resilience and Sustainability Trust |
| SA | South Asian |
| SCCF | Special Climate Change Fund |
| SEI | Stockholm Environment Institute |
| SIDS | Small Island Developing States |
| SOAS | School of Oriental and African Studies (University of London) |
| SREP | Scaling Up Renewable Energy Program |
| tCO ₂ | Tons of Carbon Di-Oxide |
| UN | United Nations |
| UNCTAD | United Nations Conference on Trade and Development |
| UNDP | United Nations Development Programme |
| UNEP | United Nations Environment Programme |
| UNFCCC | The United Nations Framework Convention on Climate Change |
| US | United States |
| USD | United States Dollars |
| WIM | Warsaw International Mechanism |

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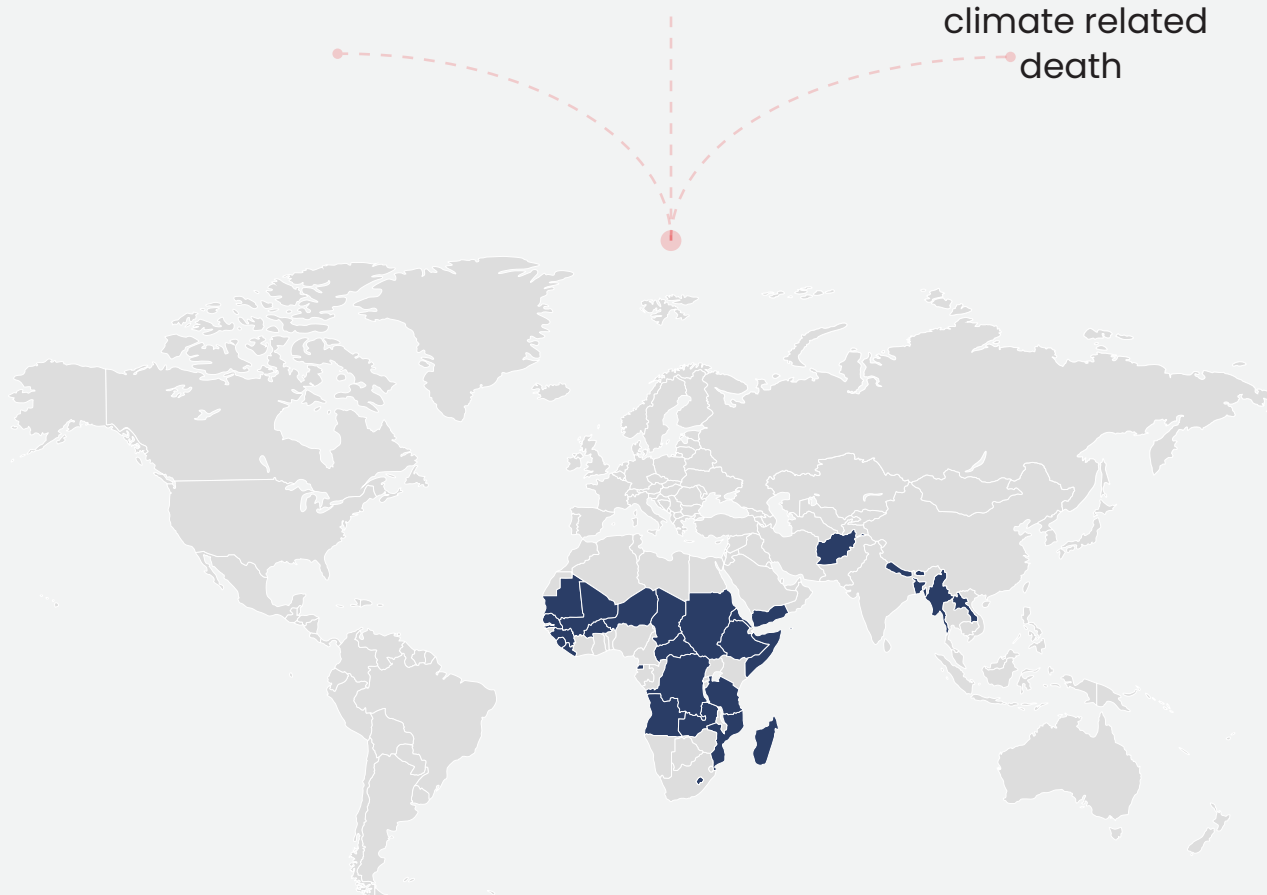
LDCs Country

1.1B

People's Home

69%

of World Wide
climate related
death



Executive Summary

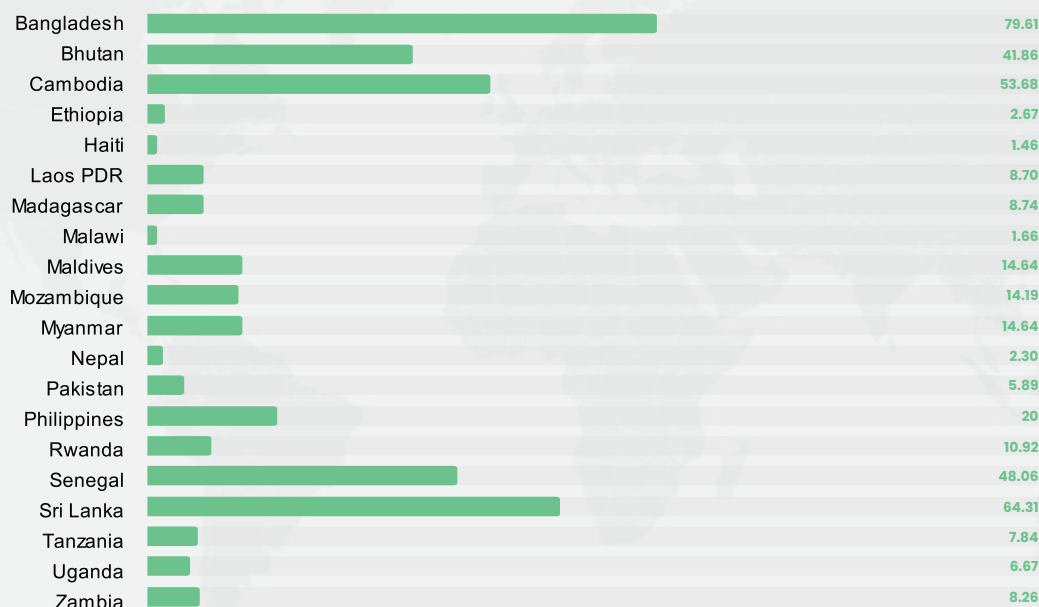
The world's 46 LDCs, home to about 1.1 billion people, have contributed only around 3.3% of global carbon emissions, however, over the last 50 years, 69% of worldwide deaths caused by climate-related disasters occurred in LDCs. LDCs disproportionately bear the burden of climate change impacts. However, LDCs' debt service tripled between 2011 and 2019, jumping from \$10 billion to \$33 billion; that is, from roughly 5% to 13% of LDC exports. COVID-19 has significantly worsened the situation, making debt burdens a significant obstacle to LDCs' recovery efforts and depleting resources for urgent humanitarian and sustainable development spending. LDCs' total external debt service reached \$31 billion in 2020, but for 2021 and 2022, this is expected to increase to \$50 billion and \$43 billion, respectively. That is an increase of more than \$20 billion compared to the pre-pandemic average.

In that context, the international community must consider their development needs and fully support them to ensure a just, balanced, and sustainable low-carbon transition (UNCTAD Secretary-General Rebeca Grynspan, 2022)¹. However, despite claims by industrialised countries of \$1.27 trillion in climate finance (FY 2021-22), less than 5% was provided as grants, and adaptation finance constituted a mere 5.43%, as the CPI report claimed. This falls significantly short of the approximately \$1 trillion in annual grant-based climate finance required from 2025 onwards to meet the increasing demands of LDCs. (UNCTAD, 2022)²

Climate finance lacks a universal definition, but the UNFCCC defines it as financial flows aimed at reducing emissions, enhancing carbon sinks, and building climate resilience. Sourced from the public and private sectors, these funds support both mitigation and adaptation efforts. Its complexity, diverse sources, and tracking challenges make measurement difficult. The Change Initiative (CI) report, “Equity and Justice in Climate Finance: Climate Debt Trap Risks for Bangladesh and Other LDCs,” investigates the alarming rise of loan-based climate finance and its potential to create a debt trap for top climate vulnerable Least Developed Countries (LDCs), including South Asian LDCs. Both qualitative and quantitative methods and analysis tools were used to reveal the findings. For this study, CI defines climate debt as financial obligations resulting from climate-related loans taken by vulnerable nations to support adaptation and mitigation.



Per Capita Overall Climate Burden of Vulnerable LDCs (2002–21)



Key Findings

The Copenhagen Accord mandates climate finance to be “new” and “additional” to ODA, with the Paris Agreement prioritising grants for LDCs. However, while Afghanistan and Malawi benefit solely from grants, Bangladesh’s high debt-to-grant ratio of 0.94 indicates a heavy reliance on loans, potentially hindering its climate resilience efforts.

As of 2023, Bangladesh’s cumulative per-capita climate debt from multilateral climate funding is \$2.04, lower than Rwanda (\$5.05), Senegal (\$4.47), Zambia (\$4.21), Sri Lanka (\$13.38), and Cambodia (\$3.67), yet Bangladesh faces greater challenges in managing its debt burden.

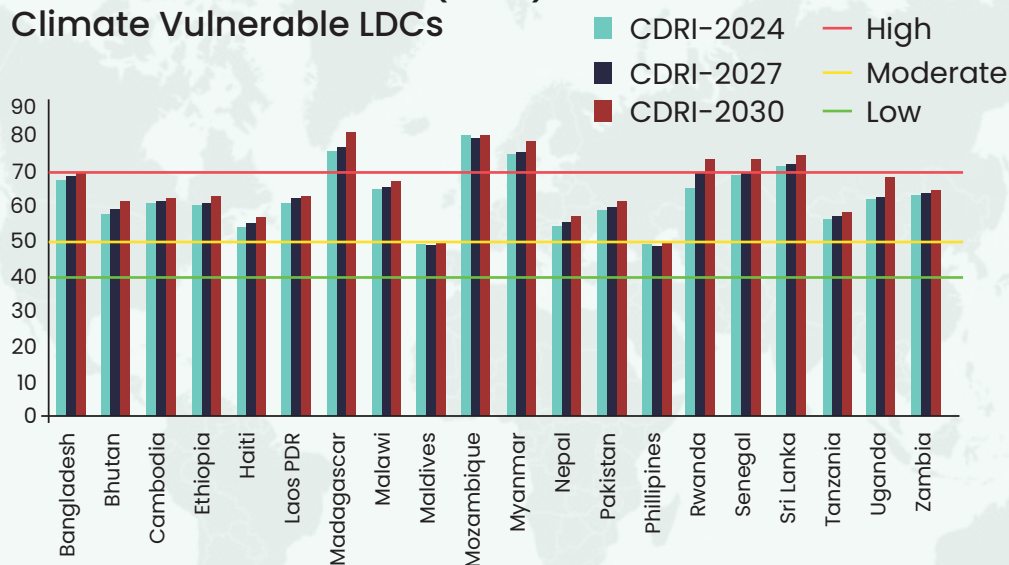
Overall cumulative per capita climate debt burden increased significantly, rising from \$0 in 2009 to \$79.61 in 2022. Sri Lanka (\$64.31) and Bhutan (\$53.68) also experience significant per capita burdens, underscoring the disproportionate climate impact on smaller economies and geographically vulnerable regions. In contrast, countries like Uganda (\$6.67), Zambia (\$8.26), and the Philippines (\$10.92) display comparatively lower per capita burdens, suggesting either differing adaptive capacities or less frequent exposure to extreme climate events.

Among climate-vulnerable LDCs, Bangladesh has one of the lowest disbursement-to-commitment ratio at 0.305 as of 2023, with only 30.5% of pledged funds disbursed, ranking it third lowest among 23 climate-vulnerable countries. From 2002 to 2021, Bangladesh received more for mitigation (\$8.83 billion) than adaptation (\$5.64 billion), resulting in a worsening adaptation-to-mitigation ratio of 0.90 for multilateral funds in 2023. This ratio further decreases to 0.69 when accounting for overall (multilateral + bilateral) funding, indicating a broader trend of underfunded adaptation in vulnerable countries like Senegal (ratio below 1).

A high per capita debt close to per capita income indicates heavy climate debt burdens, as identified in Sri Lanka, while Rwanda and Malawi show comparatively less strain. With a per capita debt-to-income ratio of 0.08, Bangladesh maintains a manageable debt level, indicating better fiscal health and economic stability compared to higher ratios in countries like Rwanda and Zambia. Bangladesh's low climate debt-to-GDP ratio of 0.0008 in 2023 reflects prudent borrowing but may indicate underfunding of critical climate adaptation and mitigation efforts. Bangladesh's favourable per capita income of \$2,529 suggests manageable debt for now, but increasing reliance on loans over grants could threaten financial stability in future. Moreover, Bangladesh's high per capita climate loan-to-carbon emission ratio of \$3.42/t CO₂ reflects a heavy climate debt burden relative to its low emissions, intensifying economic strain.

The analysis of per capita loans and credit ratings for twenty vulnerable LDCs shows that nations with high per capita loans and low credit ratings, like Rwanda, Senegal, and Zambia, face elevated climate debt risks. Bangladesh, with a moderate per capita loan of \$2.04 and a BB- rating, is less burdened than some but still vulnerable due to its weak credit profile, highlighting potential challenges for Bangladesh in balancing economic growth with climate financing needs and raising concerns about a future climate debt trap.

Climate Debt Risk Index (CDRI) for Climate Vulnerable LDCs



The Climate Debt Risk Index (CDRI) forecast illustrates a concerning trend for Least Developed Countries (LDCs) as the climate debt risk steadily increases from 2024 to 2030. The LDCs, including Bangladesh, Mozambique, and Zambia, show low Climate Risk Index (CRI) scores, high debt-to-GDP ratios, and low credit ratings, indicating significant long-term risks. The CDRI projections reveal a steady increase in climate debt risk for LDCs, with countries like Mozambique, Myanmar, and Madagascar reaching critical levels by 2030. Mozambique (80.05) and Madagascar (81.41) are projected to face Very High Climate Debt Risk by 2030, while most other countries, including Sri Lanka, Bangladesh, and Senegal, remain in the High-Risk category with CDRI scores between 50 and 70. This upward trend signals a growing financial burden on LDCs, emphasising the urgent need for more sustainable, grant-based climate finance solutions.

Notably, Mozambique, Myanmar, and Madagascar exhibit some of the highest projected risk levels, with Madagascar expected to reach a CDRI above 80 by 2030. Bangladesh's CDRI also climbs from 67.91 in 2024 to 70.47 in 2030, highlighting a growing financial strain. These projections underscore the urgent need for more grant-based climate finance; without it, LDCs may fall into debt traps that compromise their economic stability and resilience against climate impacts.



Photo: Art House Studio; pexels.com



Overall, decline of the revenue performance and shrinking natural resources have made the LDCs immensely vulnerable to climate-debt-risk trap. This investigation reinforces the urgent need to reform climate finance mechanism to ensure that they do not exacerbate the vulnerable communities of the countries they aim to support. The report resonates the relentless efforts of the international actors for scaling up international climate finance towards a paradigm shift to create a more equitable climate finance landscape, increasing grant-based support, and reforming multilateral financial institutions to offer more concessional financing terms to LDCs. These include defining clear climate finance metrics, prioritizing grants over loans, introducing innovative financing mechanisms like carbon taxes and debt-for-climate swaps, and enhancing transparency in climate finance disbursement.

This study justifies the climate equity and justice with the urgent shift toward significant debt-reliefs to LDCs, enhanced grant-based financing for resilience and addressing loss and damages aligning with the demand for NDCs. Moreover, specific actions for the UNFCCC, LDCs, and Bangladesh. Recommendations include debt relief, establishing a clear climate finance definition, prioritizing grants for adaptation, increasing transparency, and developing innovative financing mechanisms like climate resilience bonds. For LDCs e.g. Bangladesh, a focus should be provided to innovative sources of climate finance like carbon tax, sustainability bond, philanthropic includes donation, CSR and Zakat, a fixed charity of Muslims is essential. Without such reforms, climate finance risks pushing LDCs like Bangladesh further into a debt trap, jeopardizing both their fiscal health and their ability to build resilience against climate change. In the upcoming COP29 without significant economic system reforms potentially compromising fiscal stability and climate resilience efforts, LDCs may fall in the unprecedented debt-trap risks.

¹<https://unctad.org/news/unctad-sets-out-actions-support-least-developed-countries-global-low-carbon-transition#:~:text=%22LDCs%20disproportionately%20bear%20the%20burden,Secretary%2DGeneral%20Rebeca%20Grynspan%20said.>
²<https://unctad.org/topic/least-developed-countries/chart-march-2022>

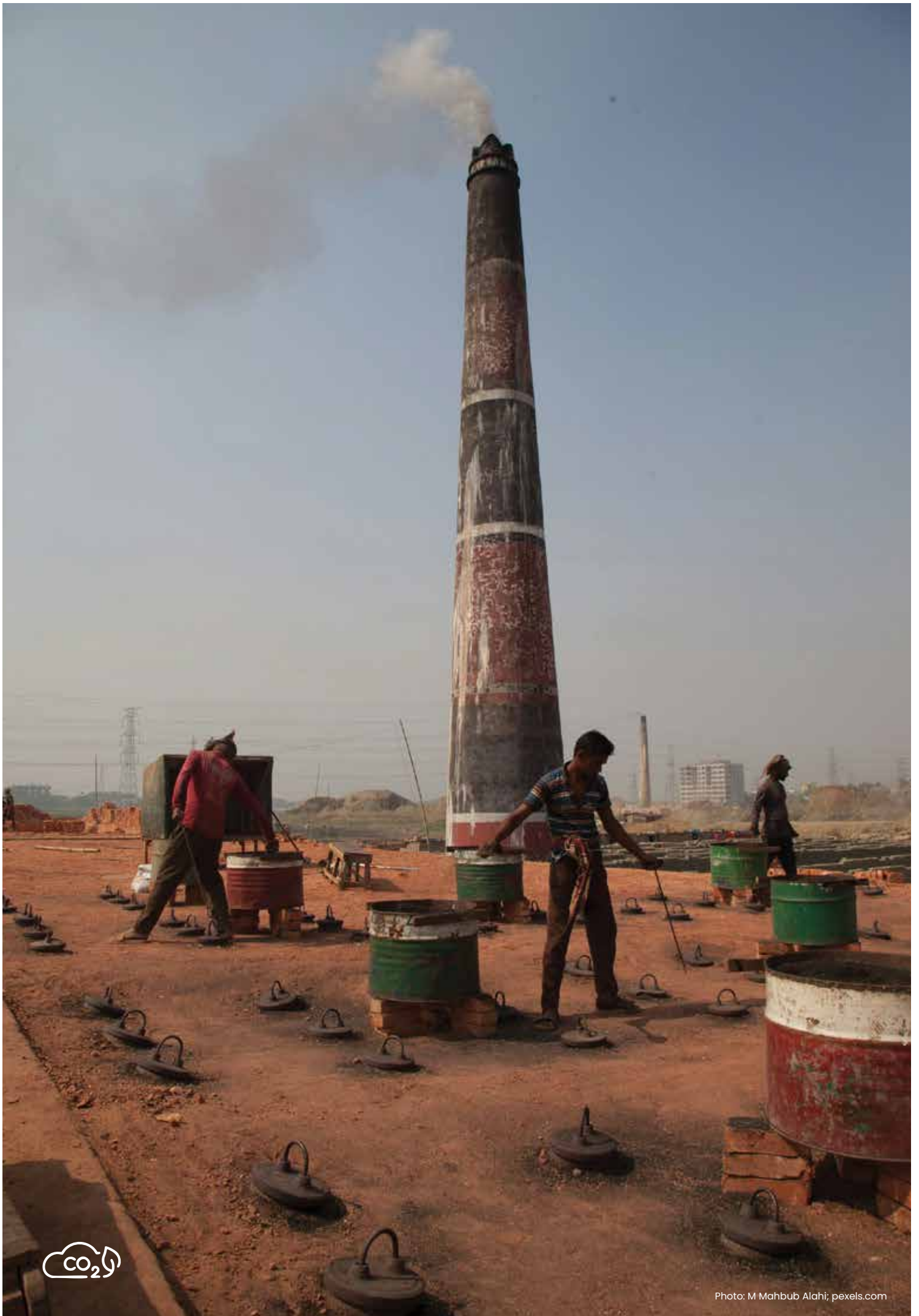




Photo: Masum Refat; pixabay.com

01

Introduction

Vulnerabilities caused by climate change are undoubtedly among the most devastating threats faced by nature and its elements in the current era. Developing countries, particularly Least Developed Countries (LDCs), are especially susceptible to these climate vulnerabilities. On the current trajectory, global average temperatures are likely to rise over 1.5°C above pre-industrial levels by mid-century and could exceed 3°C by the end of the century (Adapt now: a global call for leadership on climate resilience, 2019). However, the fact that from 2016 to 2022, 80 percent of global carbon dioxide emissions were produced by just 57 companies³, it is the developing nations, especially Least Developed Countries (LDCs), that suffer the most from climate vulnerabilities.

Climate change is projected to reduce global agricultural growth by up to 30% by 2050, affecting around 500 million marginalized farmers in developing countries. Hundreds of millions of people in coastal cities could be displaced due to rising sea levels and increased storm surges, potentially resulting in over \$1 trillion in annual costs for coastal urban areas by 2050. (Key Findings | United Nations, n.d.). The number of people lacking sufficient fresh water for at least one month annually is expected to rise from 3.6 billion in 2019 to over 5 billion by 2050 (sciencealert, 2021).

The world's 46 LDCs, home to about 1.1 billion people, have contributed only around 3.3% of global carbon emissions, however, over the last 50 years, 69% of worldwide deaths caused by climate-related disasters occurred in LDCs. LDCs disproportionately bear the burden of climate change impacts. Moreover, poverty rates in developing countries could soar, with over 100 million people projected to fall below the poverty line by 2030. (Revised Estimates of the Impact of Climate Change on Extreme Poverty by 2030, n.d.). The ongoing pace of climate change is deeply concerning for Least Developing Countries (LDCs) like Bangladesh.

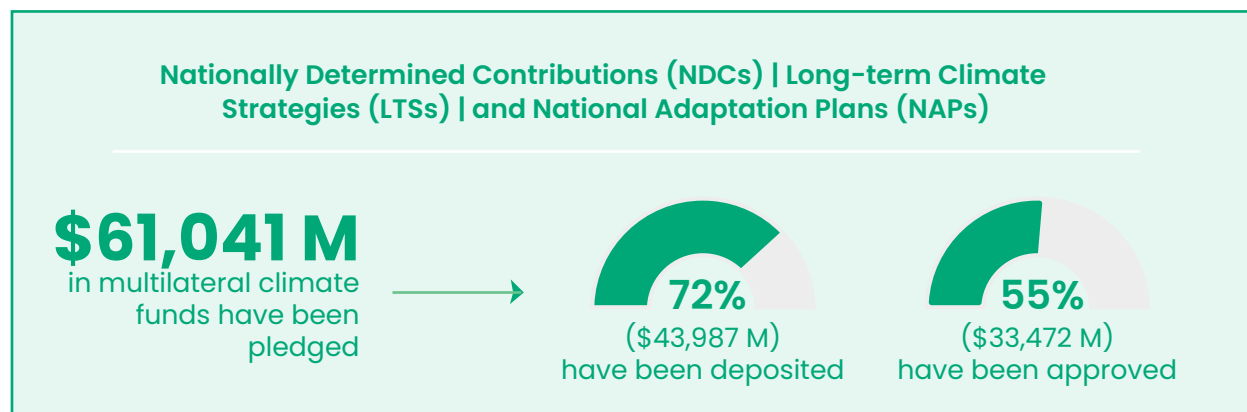
However, LDCs' debt service tripled between 2011 and 2019, jumping from \$10 billion to \$33 billion; that is from roughly 5% to 13% of LDC exports. The extent to which COVID-19 has exacerbated the situation, with debt burdens now looming large on LDCs' recovery efforts and subtracting resources from urgent humanitarian and sustainable development spending. LDCs' total external debt service reached \$31 billion in 2020, but for 2021 and 2022, this is expected to increase to \$50 billion and \$43 billion respectively. That is an increase of more than \$20 billion compared to the pre-pandemic average (United Nations Trade and Development (UNCTAD), n.d.)².

Regarding the climate finance it has been emphasized the adequate fundings for the LDCs, UNCTAD Secretary-General Rebeca Grynspan¹ on 2022 demanded that "The international community must consider their development needs and fully support them to ensure a just, balanced and sustainable low-carbon transition". However, according to Climate Policy Initiative⁴, despite claims by industrialized countries of \$1.27 trillion in climate finance (FY 2021-22), less than 5% was provided as grants, and adaptation finance constituted a mere 5.43% (Change Initiative analysis, 2024). This remains far short of around \$1 trillion in annual grant-based climate finance needed from 2025 onwards to meet the growing demands of LDCs (Reuters, 2024).

For effective tackling of climate vulnerabilities, largely driven by human actions such as greenhouse gas (GHG) emissions, deforestation, and ecosystem disruption, substantial climate finance is urgently needed. These countries lack the financial resources to adequately respond to the escalating threats posed by rising temperatures, extreme weather events, and environmental degradation. Climate finance is crucial for supporting adaptation strategies, such as building resilient infrastructure and safeguarding vulnerable communities from disasters, as well as mitigation efforts, including transitioning to low-carbon energy systems, advancing renewable energy, reforestation, and preserving

According to the United Nations Framework Convention on Climate Change (UNFCCC), Copenhagen Accord, and Paris Agreement, developed countries have historical obligation to provide financial resources to vulnerable developing nations to combat climate vulnerabilities in reflection of the polluters' pay principle, primarily priorities the grants. Article 9.1 of Paris Agreement states that,

“Developed country Parties shall provide financial resources to assist developing country Parties with respect to both mitigation and adaptation in continuation of their existing obligations under the Convention.”



At the 15th COP of the UNFCCC in Copenhagen in 2009, developed countries committed, through Nationally Determined Contributions (NDCs), Long-term Climate Strategies (LTSS), and National Adaptation Plans (NAPs), to raising \$100 billion annually by 2020 to fund climate action in lower income developing countries which was later reiterated and extended to 2025. (From Billions to Trillions: Setting a New Goal on Climate Finance | UNFCCC, n.d.) According to Climate Funds Update (CFU), as of December 2023, \$61,041 million in multilateral climate funds have been pledged, of which \$43,987 million have been deposited and around 55% (\$33,472 million) have been approved for the climate vulnerable countries. However, a key concern regarding these funds is whether they are being distributed justly, as pledged, in the form of grants rather than loans on the priority sectors.

LDCs claimed that the New Collective Goal on Climate Finance (NCQG) must be significantly higher than the current goal of \$100 billion per year, reflecting the actual needs for developing countries to address climate change, estimated at USD \$5.8 – \$5.9 trillion in the pre-2030 period (LDC-Climate, 2024).

However, debt-based climate finance is hindering LDCs' ability to address the growing climate risks. The Oxfam 2023 report (Zagema et al., 2023) and IIED's analysis of 2021 climate finance flows reveal a stark reality: most of the climate finance, even for adaptation, comes as loans. IIED found that of the US\$69.6 billion in climate finance received by developing countries in 2021, US\$53.2 billion was new debt. (Grants for Developing Nations to Address Climate

Change Outweighed Two to One by New Debt, n.d.) For LDCs, this translates to nearly half of their climate finance arriving as loans, with ten LDCs receiving more in loans than grants. This debt burden diverts critical resources from essential services like healthcare and education, undermining long-term resilience building. Post-disaster scenarios, like communities in Bangladesh rebuilding with high-interest loans after Cyclone Amphan, exemplify the debt cycle fueled by climate change.

This loan-driven approach is particularly harmful for adaptation and resilience. Resilience-building measures rarely generate direct financial returns, making them unattractive for private investors. Therefore, grant-based public finance is essential. Likewise, addressing loss and damage requires immediate support for recovery, not further indebtedness. With the LMICs already paying US\$232 million daily just to service debt, as reported by Project Drawdown, adding more loans for climate-related expenses is unsustainable. (Climate Aid Isn't Charity – It's Resilience for All of Us | Project Drawdown, n.d.)

A shift to grant-based financing for adaptation and loss and damage is crucial for enabling LDCs to effectively address climate risks without deepening their debt and jeopardizing their future.

This report investigates the hypothesis that loan-driven climate finance can lead LDCs into a debt trap by examining the mobilized climate related finances from both bi-lateral and multilateral sources) of the world's most climate-vulnerable countries, including Bangladesh. By analysing key indicators such as the loan-to-grant ratio, adaptation-mitigation funding balance, debt-to-GDP ratio, and per capita climate debt compared to income and emissions, and finally climate debt burden index the report assesses the current and potential future debt burdens by 2030, the endline of Paris Agreement.

The analysis specifically explores how loan-based climate finance impacts Bangladesh's fiscal health, its ability to invest in essential adaptation and mitigation measures, and the potential for escalating debt to hinder sustainable development. The methodology employed in this report, including the selection of indicators and data analysis techniques, is replicable and can be applied to other climate-vulnerable countries to assess their susceptibility to a climate debt trap, providing a framework for evaluating the long-term sustainability and equity of climate finance mechanisms on a global scale.



Photo: pexels.com





1.1 Analytical Framework and Methodology

1.1.1 Interplay of Climate Justice in Climate Finance

In climate finance, climate justice principles emphasize fairness, accountability, and inclusivity in addressing climate impacts. These principles are crucial in guiding how resources are allocated to support vulnerable communities, especially in developing countries and marginalized regions.



Figure 1: Interplay of Climate Justice in Climate Finance

Polluter Pays Principle:

Developed countries and corporations most responsible for GHGs should contribute the most to climate finance due to historic responsibilities, as major historic polluters, have an obligation to fund adaptation and mitigation in developing countries.

Equity and Fairness:

Climate finance should prioritize support for these communities of low-income and marginalized communities e.g. LDCs who bear the greatest impacts, addressing their disproportionate vulnerability.

Transparency and Accountability:

Climate finance mechanisms should be transparent in their allocation, tracking, and impact measurement. This helps ensure funds reach the intended beneficiaries and are used effectively for adaptation and resilience.

Community-led Access and Empowerment:

Those affected by climate change should have a voice in climate finance decisions, including direct access, how funds are allocated and used. Empowering communities ensure that finance is relevant, locally driven, and responsive to real needs.

Rights-Based Approach:

Climate finance should protect and uphold the human rights of affected populations, including the right to health, clean water, food security, and a sustainable environment. This approach ensures that climate actions do not exacerbate existing inequalities or infringe upon rights.

Intergenerational Responsibility:

Recognizing that future generations will inherit the impacts of today's actions, climate finance should focus on long-term solutions that foster resilience for the present and future.

Adaptation and Loss and Damage:

Climate justice in finance means acknowledging that adaptation alone is not enough. Finance mechanisms should also address losses and damage incurred from irreversible impacts, especially in countries with limited adaptive capacity.

Inclusive and Sustainability:

Climate finance should align with the broader goals of sustainable development, ensuring that financed projects promote social, economic, and environmental well-being without compromising the welfare of marginalized communities.

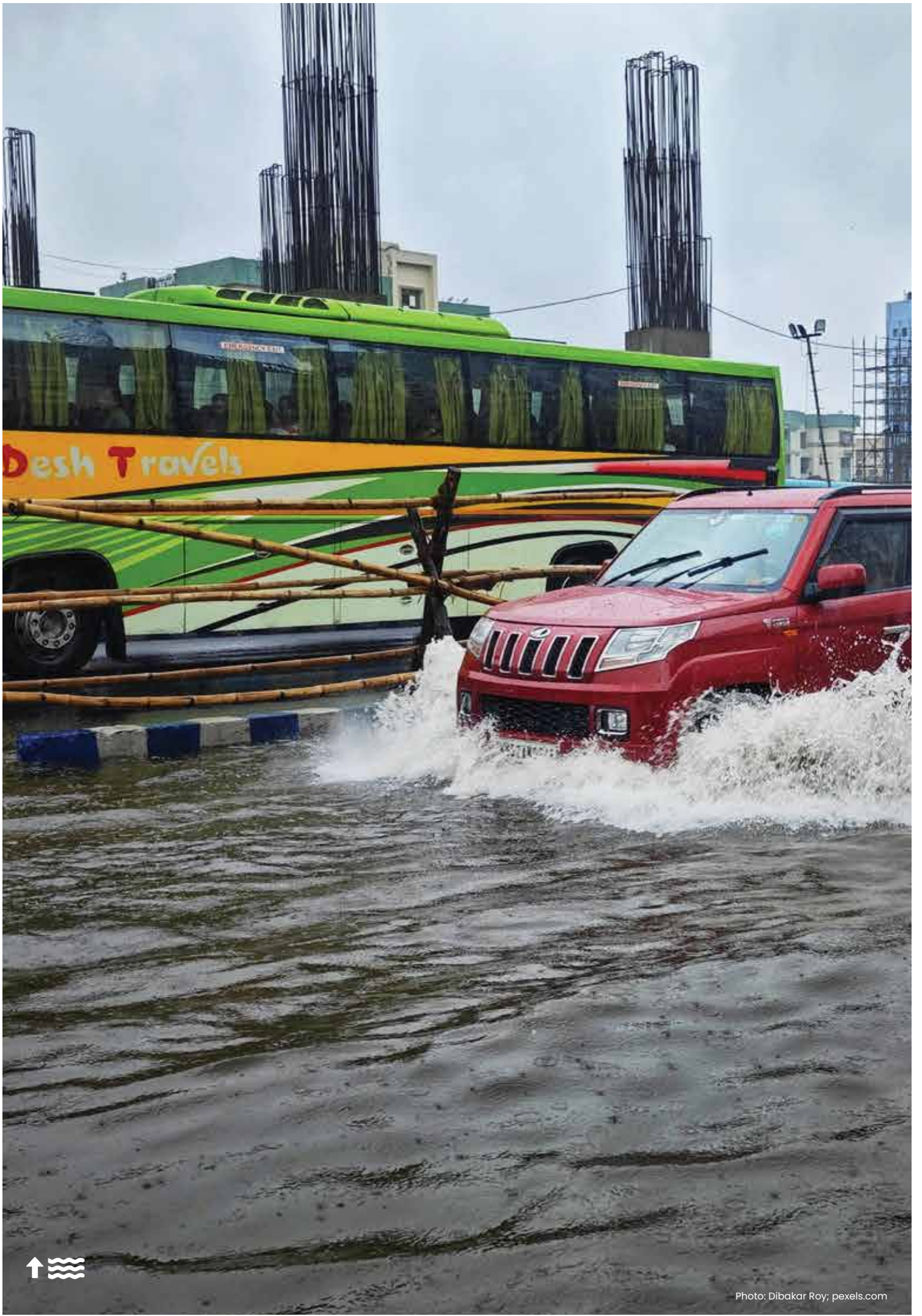
1.1.2 Method to Estimate and Forecasting the Climate Debt Risk Index (CDRI)

The Climate Debt Risk Index (CDRI) provides a comprehensive assessment of a country's vulnerability to financial risks driven by climate change. This methodology outlines the steps for calculating the CDRI, including climate debt indicators, governance variables, and economic resilience. CDRI not only represents the current state of climate debt risks for selected LDCs but also forecast for 2027 and 2030.

The CDRI is influenced by a combination of climate-related financial burdens and governance indicators. The following variables were included in the calculation:

Table 1: Variables with Measures, Units, Calculation Techniques, and Data Sources

| Variable Name | Measures/Unit | Description | Calculation Technique | Source of Data |
|--|--|---|--|---|
| CRI Score (Climate Risk Index) | Index Score | Measures climate vulnerability, with an inverse relationship to the Climate Debt Risk Index (CDRI). | Derived from climate impact assessments and vulnerability measures | Germanwatch (2021) ⁵ |
| Per Capita Overall Cumulative Climate Burden | Per Capita Overall Cumulative Climate Burden | Measures the financial cost of climate impacts per capita. | Calculated by dividing total climate-related financial burdens by population size for each year and adding them cumulatively | Authors' Estimation from SEI-AID ATLAS database |
| Government Debt to GDP Ratio | Percentage (%) | Represents the percentage of a country's government debt relative to its GDP. | Ratio of total government debt to national GDP | World Bank, IMF |
| Per Capita Development-Related External Debt Burden | USD per capita | Captures the external development debt burden in relation to the population size. | Divides total external development debt by population size | Authors' Estimation from SEI-AID ATLAS database |
| Per Capita GDP | USD per capita | Indicates a country's economic wealth, with an inverse relationship to the CDRI. | Calculated from total GDP divided by population size | World Bank |
| Population in Multidimensional Poverty | Percentage of population (%) | Shows the proportion of the population in poverty, indicating increased climate vulnerability. | Ratio of population in poverty to total population | Macrotrends, World Bank |
| Credit Rating (Moody's) | Rating score (e.g., Aaa, Baa) | Reflects a country's financial stability and capacity to manage debt. | Based on Moody's financial stability and creditworthiness assessment | Moody's and Trading Economics |



Data Normalization

Each variable was normalized on a scale of 0 to 10 to ensure comparability, with higher values representing a higher debt risk. For variables such as the CRI Score and Per Capita GDP (which inversely affect CDRI), the following normalization formula was applied:

$$\text{Normalized Score} = 10 \times \frac{\text{Max Value} - \text{Min Value}}{\text{Max Value} - \text{Variable}} \dots (1.1)$$

For variables like climate burden and poverty (which positively affect CDRI), the following normalization formula was used:

$$\text{Normalized Score} = 10 \times \frac{\text{Max Value} - \text{Min Value}}{\text{Value} - \text{Max Variable}} \dots (1.2)$$

Weighted Averaging

The CDRI for each country was calculated as a weighted average of the normalized variables. The weights were assigned based on the relative importance of each variable in assessing climate debt risk. The Climate Debt Risk Index (CDRI) weights were assigned to balance the influence of each variable on climate-related financial risk, grounded in empirical findings.

Table 2: Weight Factor of the variables

| Variable Name | Weight (%) | Explanation | Sources |
|--|------------|---|---|
| CRI Score (Climate Risk Index) | 15% | Reflects climate exposure without overshadowing socioeconomic factors crucial for resilience. | (Eckstein, 2018) |
| Per Capita Climate Burden | 25% | Indicates long-term individual financial strain from cumulative climate exposure, especially relevant in highly vulnerable regions. | – |
| Debt-GDP Ratio | 5% | Captures the overall debt burden of a country's government but is secondary to immediate climate and poverty burdens. | (IMF, 2019) |
| Per Capita Development-Related External Debt Burden | 5% | Measures external debt burden relative to population size, acknowledging its impact as secondary. | (IMF, 2019) |
| Per Capita GDP | 10% | Represents economic wealth, reflecting resilience benefits without overvaluing wealth as a single measure. | (Mendelsohn, 2006) |
| Population in Multidimensional Poverty | 15% | Higher ratio indicates increased vulnerability; reflects the significance of poverty in resilience. | Ratio of population in poverty to total population |
| Credit Rating (Moody's) | 25% | Indicates financial stability and capacity for managing debt; reflects high importance in adaptive capacity and financial access. | (Buhr, 2018), Notre Dame Global Adaptation Initiative, 2021) ⁶ |

The formula to calculate CDRI⁷ (2024) is:

LDCs Specific CDRI 2024

$$\begin{aligned}
 &= 10 \\
 &\times \{ (0.15 \times \text{CRI Score}) \\
 &+ (0.25 \times \text{Per Capita Overall Cumulative Climate Burden Percentile Score}) \\
 &+ (0.05 \times \text{Normalized Debt to GDP Score} + 0.05 \times \text{Normalized Per Capita Development Related External Debt Burden Score}) \\
 &+ (0.15 \times \text{Normalized Inverted Per Capita GDP Score}) \\
 &+ (0.15 \times \text{Normalized Population in Multidimensional Poverty Score}) \\
 &+ 0.25 \times \text{Indexed Credit Rating} \} \dots (1.3)
 \end{aligned}$$

Incorporating Governance Factors for Forecasting

For forecasting the country specific CDRI in 2027 and 2030, scores of the relevant governance and corruption related indicators were included, as they influence a country's ability to manage financial risks related to climate change. For the estimate The governance related indicators were adopted from Transparency International's Corruption Perceptions Index (CPI)⁸, World Bank Governance Indicators⁹ e.g. Control of Corruption and Rule of Law. These governance indicators were combined into a single Governance Score using the following equation:

$$\begin{aligned}
 \text{Governance Score} = & (\text{CPI} \times 0.02) + (\text{Control of Corruption} \times 0.015) \\
 & + (\text{Rule of Law} \times 0.015) \dots (1.4)
 \end{aligned}$$

The weight for CPI (0.02) reflects its central role in assessing governance by capturing broad public sector corruption. Control of Corruption (0.015) is weighted to highlight its importance in curbing misuse of power, directly impacting governance stability (World Bank, 2021)¹⁰. Rule of Law (0.015) supports governance quality by enforcing legal integrity, ensuring fairness and accountability (Daniel Kaufmann, 2010).

Forecasting the CDRI

- 1. Growth Rate Calculation for Per Capita Climate Debt:** The Per Capita Climate Debt for each country was forecasted for 2027 and 2030 based on historical growth trends. The compound annual growth rate (CAGR), as detailed by Investopedia¹¹, for Per Capita Climate Debt was calculated as follows:

$$\text{Growth Rate} = \left(\frac{\text{Per Capita Climate Debt 2021}}{\text{Per Capita Climate Debt 2015}} \right)^{\frac{1}{\text{Year}}} - 1 \dots (1.6)$$

- 2. Forecasting Climate Debt Risks for LDCs:** To assess heteroscedasticity in the Climate Debt Risk Index (CDRI) variables, we conducted statistical and visual tests to examine the variance consistency of residuals. To refine the Climate Debt Risk Index (CDRI) and identify the most influential factors in climate-related financial risk, we conducted three analytical approaches that include Multiple Linear Regression, Principal Component Analysis (PCA), and Weight Optimization using python codes. For the codes, please see Annex-3.

1

Multiple Linear Regression: Using Multiple Linear Regression, we modelled the CDRI with climate, socioeconomic, and financial factors as independent variables, obtaining residuals for further analysis. This analysis quantified the influence of each variable on the CDRI by calculating standardized beta coefficients. By setting the CDRI as the dependent variable and the contributing factors (e.g., CCDR Percentile Score, CRI Risk Score, Poverty Ratio, Credit Rating, and others) as independent variables, we assessed the relative strength of each factor in predicting climate debt risk. Variables with high beta coefficients were deemed primary contributors to climate vulnerability, supporting weight adjustments based on empirical importance. For fixing the heteroscedastic impacts we have applied the standard tests. This combination of tests and diagnostics allowed for a comprehensive examination of variance stability in the CDRI model¹².

2

Principal Component Analysis (PCA): PCA was applied to reduce dimensionality and reveal which variables explained the most variance in the dataset, identifying those with the greatest impact on differentiating climate debt risk across countries. The explained variance for each component guided the reassessment of weight assignments, with a focus on variables contributing the most to overall data variance. Variables with high contributions to the first principal component were prioritized in the CDRI calculation, aligning the index more closely with empirically derived factors.

3

Weight Optimization: Following regression and PCA findings, an optimization technique was applied to adjust weights to minimize the error between actual and predicted CDRI values. The goal was to enhance the index's predictive accuracy by fine-tuning the variable weights based on statistical significance. The optimization confirmed the need for higher weights for key climate and socioeconomic variables, while minimizing the role of secondary factors like debt indicators.

Using the growth rate calculated in Equation 1.6, the Per Capita Climate Debt for 2027 and 2030 was forecasted using the following equations:

$$\text{Per Capita Climate Debt 2027} = \text{Per Capita Climate Debt 2021} (1 + \text{Growth Rate})^6 \dots (1.7)$$

$$\text{Per Capita Climate Debt 2030} = \text{Per Capita Climate Debt 2021} (1 + \text{Growth Rate})^9 \dots (1.8)$$

Then putting the updated value in equation for CDRI-2024 we get the values of CDRI for 2027 and 2030. For details, please see Annex-2.



1.2 Data

Primary data was collected from Key Informant Interviews (KIIs) with policymakers, climate finance experts, and civil society organizations, while secondary data was sourced from official reports and global climate finance databases.

For quantitative analysis, the most climate-vulnerable LDCs, based on the Climate Risk Index, were selected to evaluate the impacts of climate finance. We divided our dataset into two categories:

- Multilateral Funds Data of selected 20+ countries based on their economic status, population, climate vulnerability since 2009
- Overall (Multilateral + Bilateral) Climate Financing Data since 2002 of selected 20 plus countries based on their economic status, population, climate vulnerability

We selected the top 10+ countries (sovereign states)¹³ with the highest average Climate Risk Index (CRI) score from 2000 to 2019 as reported by Germanwatch⁵ to capture the most climate-vulnerable nations (GLOBAL CLIMATE RISK INDEX 2021, N.D.). Additionally, for comparative analysis we included other LDCs with similar per capita GDP levels of Bangladesh. Moreover, despite not all are in top vulnerable lists but for considering the integrated ecosystems e.g. river system all South Asian LDCs were chosen so that evidence forge for enhanced regional collaborations. By analysing key indicators such as the loan-to-grant ratio, adaptation-mitigation funding balance, debt-to-GDP ratio, and per capita climate debt compared to income and emissions, and finally climate debt risk index the report assesses the current and potential future debt burdens risks associated with climate finance. For detailed formulas of the indicators, please see Annex-1.

Table 3: Data Types and Sources

| Data Type | Source |
|--|--|
| Bilateral Climate Finance, Bilateral Development Finance | Aid Atlas ¹⁴ |
| Multilateral Climate Finance | Climate Funds Update ¹⁵ |
| Per Capita Emissions | International Energy Agency (IEA) ¹⁶ |
| Population Data | Macrotrends ¹⁷ |
| Governance Data | Transparency International ¹⁸ , IMF ¹⁸ |
| Per Capita GDP / Per Capita Income | World Bank Database ⁹ |
| Poverty Related Data | World Bank Database ⁹ |
| Credit Ratings | Trading Economics ²⁰ |

Data Sorting and Management: From the development finance data collected from Aid Atlas, we isolated projects with a value of '2' in the 'climate_change' column. Using the SUMIF function, we aggregated the total amounts for ODA loans, ODA grants, MDB loans, and MDB grants based on the 'grant_type' column. We then calculated the total loan and total grant amounts, summing these to obtain the total climate finance. To determine the loan-to-grant ratio, we divided the total loan amount by the total grants.

Next, we used the SUMIF function on the 'climate_adaptation' column to sum the amounts for projects with a value of '2', thereby calculating total adaptation funding. Similarly, from the 'climate_mitigation' column, we derived the total mitigation funding. Finally, we calculated the adaptation-to-mitigation ratio by dividing total adaptation funding by total mitigation funding.

1.3 Limitations and Ethics

This study, while comprehensive, faces limitations primarily due to constraints in accessing in-depth data and methodology to calculate the climate finance properly that lacks the clear definition. First, the reliance on historical and publicly available climate finance data means the analysis may not fully capture all nuanced financial flows, particularly informal or undocumented channels of climate funding. Additionally, the Climate Debt Risk Index (CDRI) is a composite measure subject to the limitations of the chosen variables and weighting methods; adjustments to these could influence the outcomes, and the lack of universally standardized data may impact the precision of cross-country comparisons. Furthermore, the use of forecast models introduces inherent uncertainty, especially given the rapidly evolving nature of climate finance policies.

Ethical considerations were integral to this research. The study adheres to transparency and rigor, ensuring that all data sources and intellectual outputs are cited properly, and interpretations are presented without bias. The respect for vulnerable populations affected by climate finance structures, emphasizing equitable climate finance as a fundamental human right was maintained. Any recommendations prioritize minimizing the financial burden on climate-impacted communities, particularly in Least Developed Countries (LDCs), ensuring that findings contribute to policies that support justice and sustainability rather than exacerbating existing vulnerabilities.

³ <https://www.smithsonianmag.com/smart-news/since-2016-80-percent-of-global-co2-emissions-come-from-just-57-companies-report-shows-180984118/>

⁴ <https://www.climatepolicyinitiative.org/publication/global-landscape-of-climate-finance-2023/>

⁵ <https://www.smithsonianmag.com/smart-news/since-2016-80-percent-of-global-co2-emissions-come-from-just-57-companies-report-shows-180984118/>

⁶ <https://www.climatepolicyinitiative.org/publication/global-landscape-of-climate-finance-2023/>

⁷ <https://www.germanwatch.org/en/19777>

⁸ <https://gain.nd.edu/our-work/country-index/>

⁹ We did the normalization in 0-10 scale, but our final CDRI Index is in 0-100 scale. The scaling methodology in our report aligns closely with established approaches used in the Worldwide Governance Indicators (WGI) and Human Development Index (HDI), reinforcing the robustness of our analytical framework. Like WGI, which standardizes diverse indicators to a common scale and applies weighted aggregation, our use of PCA for weighting captures the relative importance of each parameter, followed by normalization on a 0-10 scale. The HDI's methodology further parallels ours, as it normalizes indicators and then resizes them for interpretability (0-1 scale, often presented as 0-100), a step mirrored in our final 0-100 scaling. These consistent practices validate our approach as a statistically sound and widely recognized scaling methodology.

¹⁰ <https://www.transparency.org/en/cpi/2023>

¹¹ <https://www.worldbank.org/en/publication/worldwide-governance-indicators>

¹² <https://databank.worldbank.org/source/worldwide-governance-indicators>

¹³ [https://www.investopedia.com/terms/c/cagr.asp#:~:text=How%20to%20Calculate%20Compound%20Annual%20Growth%20Rate%20\(CAGR\)&text=To%20calculate%20the%20CAGR%20of,the%20answer%20into%20a%20percentage](https://www.investopedia.com/terms/c/cagr.asp#:~:text=How%20to%20Calculate%20Compound%20Annual%20Growth%20Rate%20(CAGR)&text=To%20calculate%20the%20CAGR%20of,the%20answer%20into%20a%20percentage)

¹⁴ For heteroscedasticity Test we followed this with White's test to detect whether the non-linear heteroscedasticity exists, providing a robust confirmation of variance patterns. The Breusch-Pagan test was then applied to test if residual variance depended on independent variables, with a p-value below 0.05 indicating heteroscedasticity (If the p-value is below 0.05, this suggests heteroscedasticity is present. If the p-value is above 0.05, this suggests the residuals are homoscedastic (no heteroscedasticity). Finally, we plotted residuals against fitted values to visually inspect variance patterns, where random scatter suggests homoscedasticity, while systematic patterns indicate heteroscedasticity. If the residuals are randomly scattered with no visible pattern, heteroscedasticity is unlikely. If there is a pattern (e.g., funnel shape), heteroscedasticity is likely present.

¹⁵ Puerto Rico is no 1 on CRI list by Germanwatch, but Puerto Rico is Organized and Unincorporated U.S. territory, therefore it is not considered.

¹⁶ <https://aid-atlas.org/>

¹⁷ <https://climatefundsupdate.org/data-dashboard/>

¹⁸ <https://www.iea.org/countries/bangladesh/emissions>

¹⁹ <https://www.macrotrands.net/>

²⁰ <https://www.imf.org/external/datamapper/NGDPDPC@WEO/OEMDC/ADVEC/WEOWORLD>



Photo: Sohan Rahat, pexels.com

02

Climate Finance Paradigm

2.1 Legacy and Global Efforts

Climate finance lacks a universally accepted definition due to its multifaceted nature, but the UNFCCC Standing Committee describes it as financial flows aimed at reducing greenhouse gas emissions, enhancing carbon sinks, and increasing resilience to climate impacts. These funds, sourced from public and private sectors at regional and international levels, support both mitigation and adaptation projects. The complexity of climate finance, its diverse funding sources, and tracking challenges make it difficult to measure. Key areas requiring significant funding include energy transition, adaptation, loss and damage, and emissions reduction.

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As part of the 1992 Rio Earth Summit, organized by the UNFCCC, the Polluters' Pay Principle was adopted to ensure that the industrialized countries that are responsible for GHG emission bear the costs of managing the damage they cause.

The developed country Parties and other developed Parties included in Annex II shall provide new and additional financial resources to meet the agreed full costs incurred by 14 developing country Parties in complying with their obligations under Article 12, paragraph 1. They shall also provide such financial resources, including for the transfer of technology, needed by the developing country Parties to meet the agreed full incremental costs of implementing measures that are covered by paragraph 1 of this Article and that are agreed between a developing country Party and the international entity or entities referred to in Article 11, in accordance with that Article. The implementation of these commitments shall take into account the need for adequacy and predictability in the flow of funds and the importance of appropriate burden sharing among the developed country Parties (Article 4.2).

Rooted in the idea of accountability, the principle holds that entities producing harmful or potentially harmful substances should be financially responsible for mitigating their impacts. Since its adoption, the principle has been integrated into various international agreements, and many governments have implemented policies like carbon taxes or emissions trading systems to enforce it, ensuring polluters fund the cleanup and restoration of the environment. Launched in 1994 amidst growing environmental concerns, the Global Environment Facility (GEF) pioneered multilateral environmental financing. Established through collaboration between institutions like the World Bank, UNDP, and UNEP, the GEF piloted new financing methods for projects addressing both national development and global environmental needs. In 2001 the Special Climate Change Fund (SCCF) and Least Developed Countries Fund (LDCF) were established to further support climate action in vulnerable nations, particularly adaptation. SCCF, one of the first multilateral adaptation finance instruments, operates under the GEF. GEF's current (2022–2026) adaptation strategy prioritizes SIDS and promotes technology transfer, innovation, and private sector engagement.

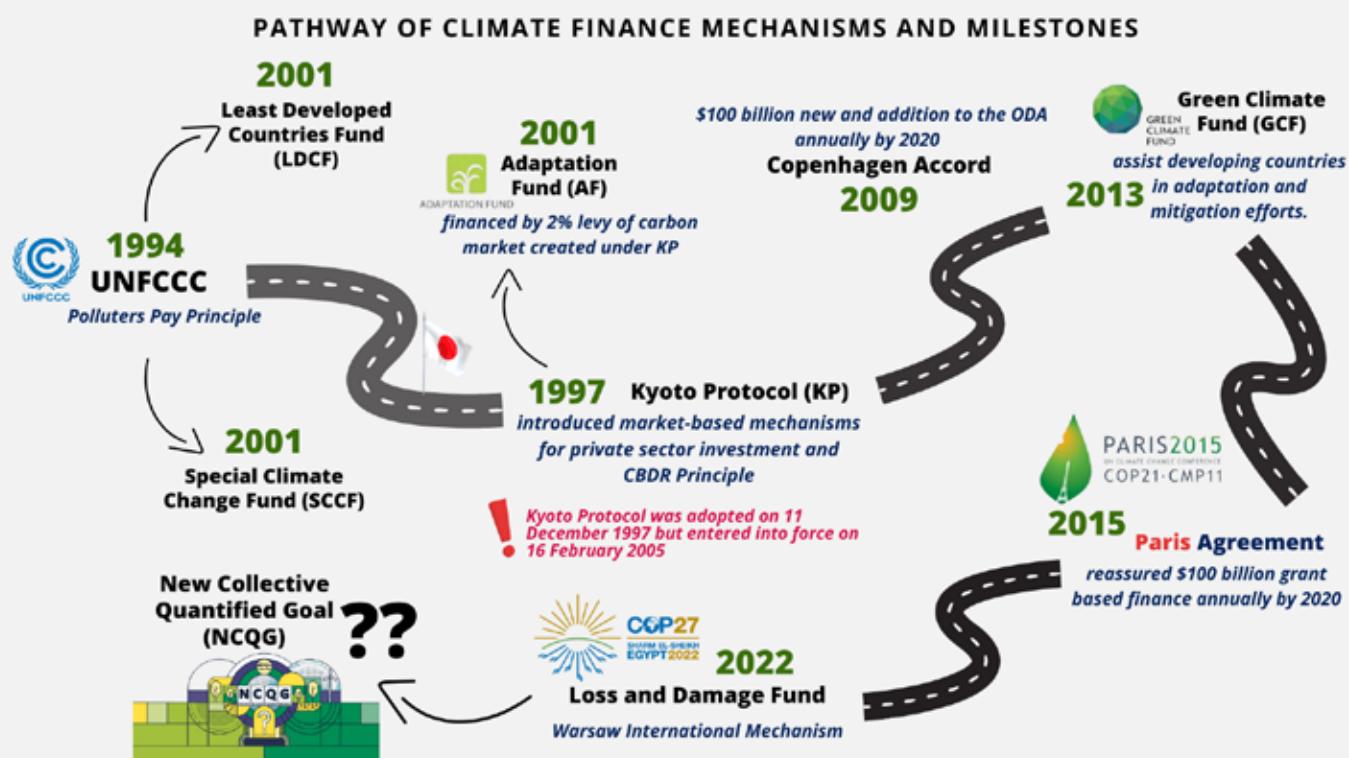


Figure 2: Pathway of Climate Finance Mechanism and Key Milestones

Adopted in 1997 and entering into force in 2005, the Kyoto Protocol committed industrialized countries to GHG emission reductions based on individual targets. Underpinning the protocol was the principle of "common but differentiated responsibility," recognizing developed nations' larger contribution to GHG levels. The 2012 Doha Amendment extended commitments to 2020 with an 18% reduction target. The protocol also introduced market mechanisms like emissions trading and the Clean Development Mechanism (CDM), enabling flexible target achievement. Crucially, the Adaptation Fund (AF) was established under the Kyoto Protocol to support developing countries' adaptation efforts.

The Green Climate Fund (GCF), established in 2011 at COP16, further expanded the climate finance roadmap. As an operating entity of the Convention's Financial Mechanism, the GCF, governed by its Board and the COP, serves both the Convention and the Paris Agreement (Article 9, paragraph 8). The COP ensured alignment by stipulating that prior Financial Mechanism guidance applies to the GCF as relevant to the Paris Agreement.

2.2 Paris Agreement: A Roadmap for Justice-Based Climate Finance

The Paris Agreement, adopted in 2015 by 196 State Parties, is a treaty was adopted to limit global warming to well below 2°C, striving for 1.5°C, above pre-industrial levels. The Agreement Acknowledging that climate change is a common concern of humankind, Parties should, when taking action to address climate change, respect, promote and consider their respective obligations on human rights, the right to health, the rights of indigenous peoples, local communities, migrants, children, persons with disabilities and people in vulnerable situations and the right to development, as well as gender equality, empowerment of women and intergenerational equity²¹. Moreover, the Agreement highlights the importance of ensuring the integrity of all ecosystems, including oceans, and the protection of biodiversity, recognized by some cultures as Mother Earth, and noting the importance for some of the concept of "climate justice", in climate actions.

Article 9 of the Paris Agreement particularly focused on developed countries' financial support to developing nations to address climate actions. The Global Stocktake, a five-yearly assessment of collective progress, informs updates and enhancements to climate actions and support. Through a five-year cycle of increasingly ambitious national climate action plans, known as Nationally Determined Contributions (NDCs), the Agreement "ratchets up" global efforts. The first Global Stocktake concluded at 28th Conference of Parties (COP28) in Dubai, assessing mitigation, adaptation, and finance, to guide future climate action and increase ambition. COP26 reaffirmed the \$100 billion climate finance goal, but with developed countries missing the 2020 target, the deadline shifted to 2023. After having the Warsaw International Mechanism (WIM) on loss and damages the COP27 established the Loss and Damage Fund, the most desire step towards addressing irreversible climate impacts, though funding mechanisms remain under discussion.

It is expected that at COP28, the Global Stocktake concluded, and discussions on a new collective quantified goal (NCQG) for climate finance post-2025 will began, while the operationalization of the Loss and Damage Fund saw some initial pledges.

Change Initiative has championed redirecting fossil fuel subsidies towards climate finance²². Just before kick of the CoP29 with the establishment of the Climate Finance Action Fund (CFAF)²³ will be capitalised with contributions from fossil fuel producing countries and companies across oil, gas and coal, and Azerbaijan will be a founding contributor; members will commit to transfer annual contributions as a fixed-sum or based on volume of production. It is expected that Fund to target climate projects in developing countries that need support, meeting next generation of NDCs to keep 1.5°C within reach, and will catalyse public and private sectors across mitigation, adaptation, and research and development, and will contain additional special facilities. Initial fundraising aiming for \$1 billion, as COP29 President-Designate calls for contributors to come forward with climate finance. However, in terms of the loss and dagames the proposed amount is peanuts and COP29 and beyond will continue to grapple with grant-based climate finance as a central issue, focusing on delivering timely and equitable support to the most vulnerable nations.

2.3 Modalities of Climate Finance

Climate finance for developing nations primarily flows through Official Development Assistance (ODA), introduced by the OECD in 1969 to support economic and technical assistance. By FY22, 32.9% of ODA (about \$50 billion) was targeted climate objectives, with increasing funds directed toward both mitigation and adaptation projects (Official Development Assistance for Climate in 2022: A Snapshot, n.d.). These funds are provided as grants, concessional loans from Multilateral Development Banks (MDBs), and commercial loans. Additionally, private finance was mobilized, raising \$7.4 billion in 2022.

Sovereign bonds, carbon trading, and carbon taxes also serve as key mechanisms for financing climate action. Countries further contribute via Nationally Determined Contributions (NDCs) under the Paris Agreement, which drive short- and medium-term mitigation and adaptation targets. Besides ODA, climate funds like the Global Environment Facility (GEF) and Green Climate Fund (GCF) provide additional support for climate projects. However, ODA remains a critical avenue for developing countries to secure necessary resources, especially for long-term resilience and low carbon transitions.

For this study, we used Climate Funds Update (CFU) to obtain data on multilateral climate funds and Aid Atlas to gather data on overall climate funds, including both multilateral and bilateral sources.





Photo: Artem Makarov; pexels.com

2.4 Climate Debt and Climate Justice

In this paper, climate debt has been defined as the financial obligations incurred by vulnerable countries through climate financing in the form of loans provided by bilateral or multilateral funds. This view emphasizes the increasing burden these nations face when financing climate adaptation and mitigation efforts. To some other group of climate activists, climate debt is understood as the cumulative cost of emission-related damages imposed on the global community without compensation, but here, we focus on the immediate financial strain resulting from loan-based climate support mechanisms.

Article 9 of the Bali Principle of Climate Justice affirming the principle of Ecological debt, it recognizes that climate justice protects the rights of victims of climate change and associated injustices to receive full compensation, restoration, and reparation for loss of land, livelihood and other

¹⁹ <https://view.officeapps.live.com/op/view.aspx?src=https%3A%2F%2Ffophi.org.uk%2Fsites%2Fdefault%2Ffiles%2F2024-10%2FTable%25201%2520National%2520Results%2520MPI%25202024.xlsx&wdOrigin=BROWSELINK>

²⁰ <https://tradingeconomics.com/country-list/rating>

²¹ <https://unfccc.int/most-requested/key-aspects-of-the-paris-agreement>

²² https://www.changei.org/uploads/3/3/4/2/334264/draft_call_to_action_2407091829.pdf?fbclid=IwZXh0bgNhZW0CMTAAR36JLdhPEyJiVhVwEzNxWcHPKb5ZQb1toY1-swSpuRd7vNJM2h-m2TUz2Q_aem_UjBFY3Tq9XFfFS641hH18g

²³ https://cop29.az/en/media-hub/news/azerbaijan-launches-climate-finance-action-fund-in-package-of-initiatives-for-cop29?fbclid=IwY2xjawGcTUVleHRuA2FibQlXMAABHRIFXfW0JrurNy_e_jnl4i47LldFuPLT2ver2QQM6vHs_8fMcxP3e2xEsw_aem_AZAPrpyXXwZQRma8_beOcQ



Photo: pixabay.com

03

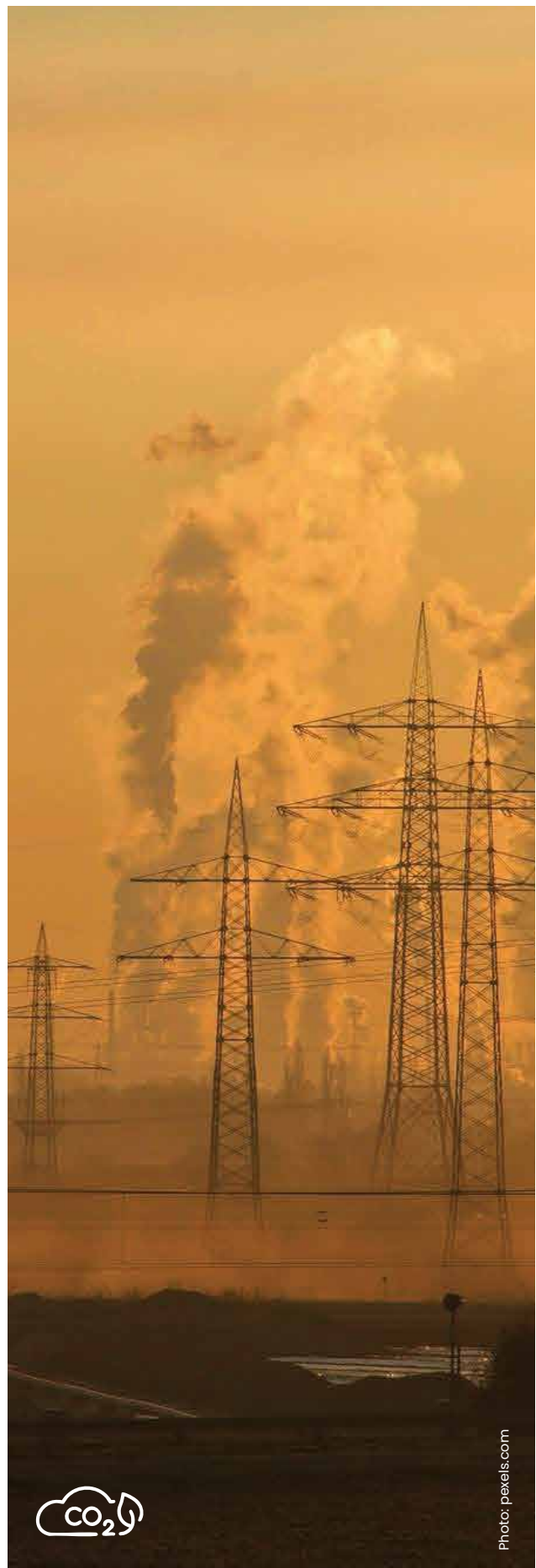
Trend in Climate Financing in Vulnerable LDCs

This study revealed the current state of the climate finance status and debt burdens for the vulnerable LDCs in terms of equity and justice. The key indicators include the Loan-to-Grant Ratio (with sub-indicators for Adaptation-Mitigation and Disbursement-to-Commitment), Debt-to-GDP Ratio (including Debt-to-Tax, Debt-to-Per Capita Income, and an adjustment for exaggerated GDP), Per Capita Debt vs. Per Capita Income, and

the Carbon Emission to Climate Debt Ratio. The Loan-to-Grant Ratio is critical for understanding the financial burden, distinguishing between concessional loans and grants, while the Adaptation-Mitigation and Disbursement-to-Commitment sub-indicators measure the balance between different types of climate financing and the efficiency of fund disbursement.

Between **2009 and 2022**, Bangladesh received just **\$14.47 billion** international climate financing—**barely 9.7% (\$149.5 billion)** of the staggering it urgently needed

Debt-to-GDP, alongside Debt-to-Tax and Debt-to-Per Capita Income, examines the debt load in relation to national economic capacity, providing insight into how manageable the climate debt is for different countries. Per Capita Loan vs. Per Capita Income explores the individual financial strain caused by climate loans, highlighting the potential for increased financial vulnerability. Lastly, the Carbon Emission to Climate Debt Ratio reflects the cost of climate debt relative to a country's emissions, which is crucial for analysing the equity of debt allocation based on historical and current contributions to global emissions. These indicators were chosen to provide a holistic understanding of the intersection between climate finance, debt sustainability, and equity in vulnerable economies.



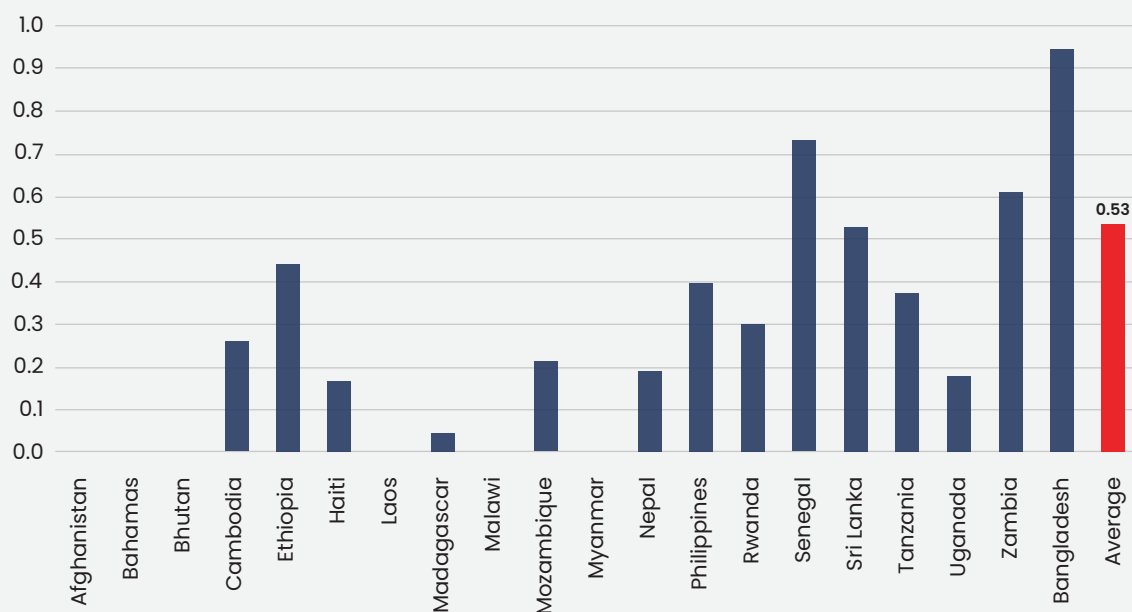


Figure 3: Debt-to-Grant Ratio of Multilateral Climate Fundings for LDCs

3.1 Climate Debt and Climate Justice

The Climate Loan-to-Grant Ratio highlights the proportion of climate finance provided as loans versus grants, a critical indicator for vulnerable economies. As per the Copenhagen Accord, the climate finance should be “New” and “Additional” to ODA and Paris Agreement has emphasized the grant-based finance for the LDCs.

The Loan-Grant Ratio among the observed Least Developed Countries (LDCs) as depicted in Figure-03 reveals a range of financing approaches. The average Loan-Grant Ratio across these LDCs is 0.53, highlighting a blend of financing methods, but with an increased loan reliance for some nations, which raises potential concerns for debt sustainability and climate resilience in the region. Specifically, Bangladesh has the highest Loan-Grant Ratio at 0.94, indicating a considerable dependence on loans alongside grants, which could contribute to a significant debt burden given its high vulnerability to climate impacts.

However, Sri Lanka and Senegal show ratios of 0.72, similarly reflecting a growing reliance on loan-based climate finance, which may challenge their financial stability if this trend continues. In contrast, several countries, including Afghanistan, Bahamas, and Malawi, have a ratio of 0, relying solely on grants. This grant-focused approach may offer these countries a more sustainable financing path for climate adaptation and mitigation without adding to their debt load.

3.1.1 Climate Debt and Climate Justice

The Disbursement-to-Commitment Ratio for the selected Least Developed Countries (LDCs) and climate-vulnerable nations highlights varying degrees of access to climate finance commitments. The weighted average ratio shown of 0.444 (Figure-04) suggests that, on average, less than half of committed funds are disbursed, indicating a significant gap between pledged and actual funding.

However, among the LDCs Mozambique and Cambodia have higher disbursement ratios at 0.633 and 0.628, respectively, showing relatively better access to committed funds, which can facilitate timely climate adaptation and mitigation projects. In contrast, Tanzania, the Bahamas and Bangladesh exhibit lower ratios of 0.219, 0.263 and 0.305 respectively, indicating substantial delays or challenges in accessing committed funds. This disparity in disbursement ratios points to an uneven climate finance landscape, where lower disbursement ratios may hinder countries with pressing climate vulnerabilities from effectively implementing adaptation and resilience projects.

A significant discrepancy between the demand and supply of climate funds is evident. As a case story we examined the scenario for Bangladesh and identified that until October 2024, Bangladesh has been promised \$719.59 million of climate funds, consisting of \$369.95 million in grants and \$349.64 million (49%) as concessional loans. Of the committed funds, only \$219.77 million or 30% in the form of concessional loans, have been disbursed. Source: Climate Funds Update (CFU)

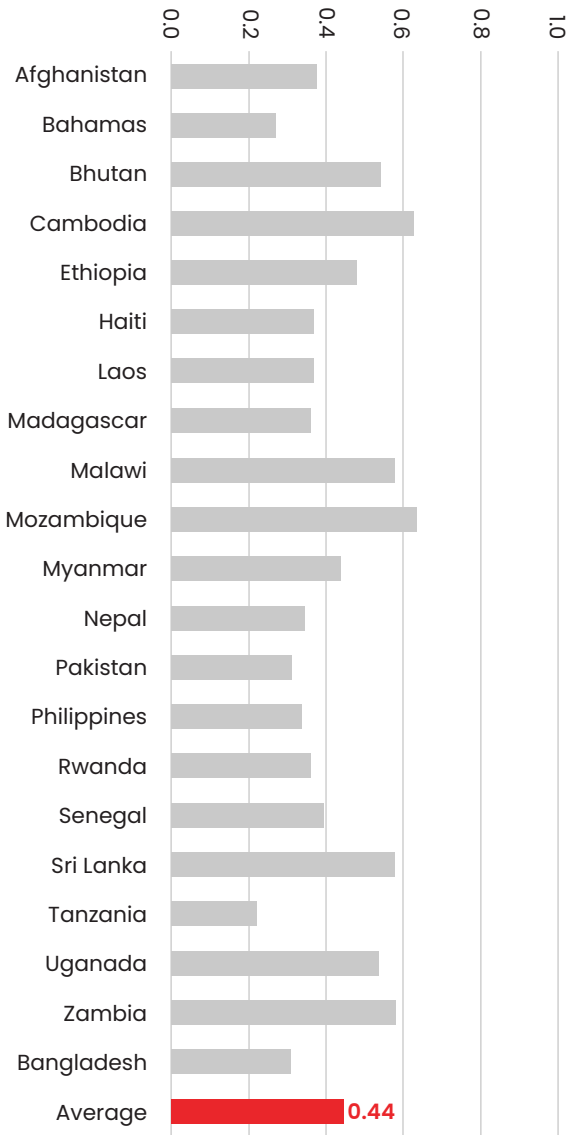


Figure 4: Disbursement to Commitment Ratio of LDCs (Multilateral Climate Funding)

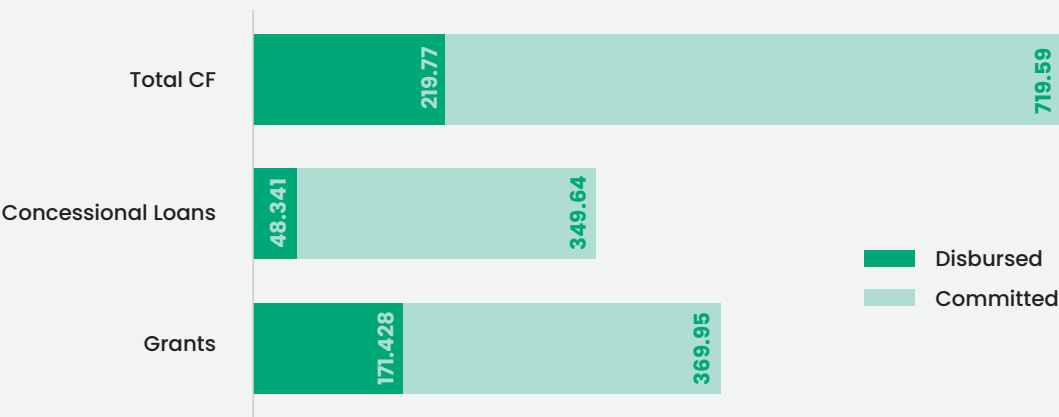
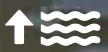


Figure 5: Total Commitments and Disbursements of Multilateral Climate Funds for Bangladesh



3.1.2 Adaptation–Mitigation Ratio

The Adaptation–Mitigation Ratio reveals a pronounced focus on adaptation in certain Least Developed Countries (LDCs), with a weighted average of 0.738, suggesting a bias toward mitigation funding across the vulnerable LDCs. Across the LDCs Mozambique stands out with the highest adaptation-mitigation ratio at 54.449, reflecting a strong emphasis on adaptation efforts, Bhutan and Malawi also have high ratios of 18.937 and 8.304, respectively, underscoring their prioritization of adaptation over mitigation, which is often critical for highly climate-vulnerable regions.

In contrast, Bangladesh and Senegal have ratios of 0.904 and 0.865, close to an even split but leaning slightly toward mitigation. The Philippines has a notably low ratio of 0.261, indicating a predominant focus on mitigation over adaptation. This variation in ratios

highlights how climate finance allocations vary significantly, with some countries focusing more on immediate resilience (adaptation) while others, especially those with higher emissions, are more mitigation focused. For many LDCs, higher adaptation funding is essential for enhancing resilience to immediate climate impacts, yet the data suggests that adaptation needs may still be underfunded relative to mitigation.

The global trend favoring mitigation over adaptation leaves vulnerable countries like Bangladesh underprepared for imminent climate impacts, jeopardizing their ability to build resilience and manage climate-induced disasters effectively.

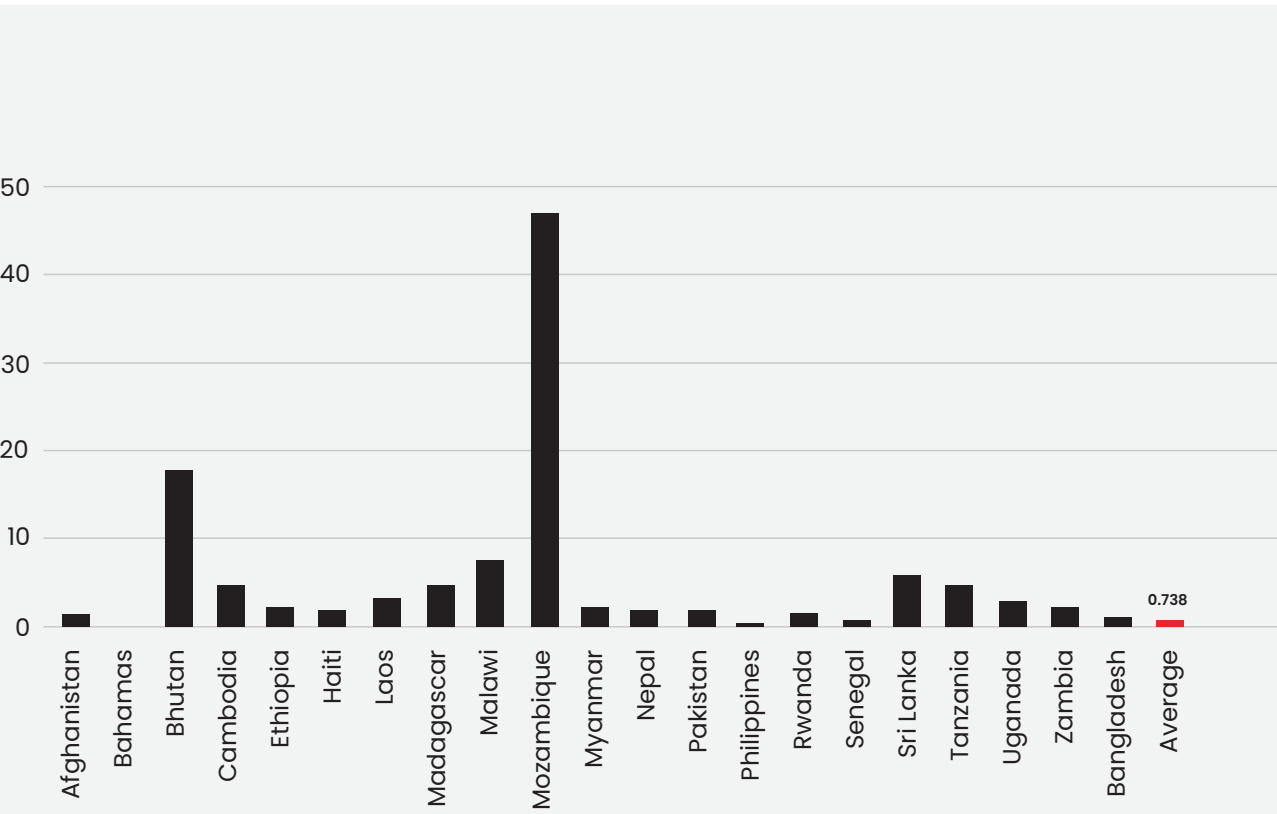


Figure 6: Adaptation to Mitigation Ratio of Multilateral Climate Funds of SA and LDCs

Reduced Grants and Enhanced Mitigation Financing for Bangladesh

Vulnerabilities caused by climate change are undoubtedly among the most devastating threats faced by nature and its elements in the current era. Developing countries, particularly Least Developed Countries (LDCs), are especially susceptible to these climate vulnerabilities. On the current trajectory, global average temperatures are likely to rise over 1.5°C above pre-industrial levels by mid-century and could exceed 3°C by the end of the century (Adapt now: a global call for leadership on climate resilience, 2019). However, the fact that from 2016 to 2022, 80 percent of global carbon dioxide emissions were produced by just 57 companies, it is the developing nations, especially Least Developed Countries (LDCs), that suffer the most from climate vulnerabilities.

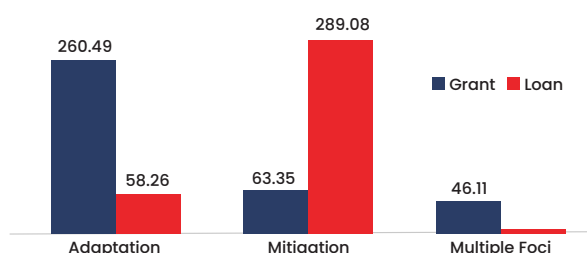


Figure 7: Grant-Loan Ratio of Bangladesh (Multilateral Climate Fundings)

Bangladesh's climate finance has been disproportionately skewed towards mitigation, with an adaptation-to-mitigation ratio of 0.90, indicating underfunding of critical adaptation measures. While mitigation projects, such as large-scale solar power installations and energy-efficient solutions supported by programs like the Scaling Up Renewable Energy Program (SREP) and the Clean Technology Fund (CTF), have made significant strides in reducing emissions and promoting sustainable urban development, adaptation finance is crucial given Bangladesh's vulnerability to climate impacts like flooding and cyclones.

Adaptation projects, funded by initiatives such as the Least Developed Countries Fund (LDCF) and the Pilot Program for Climate Resilience (PPCR), focus on enhancing agricultural sustainability, improving water resource management, and strengthening infrastructure in vulnerable areas. However, the current imbalance in funding prioritizes long-term mitigation over immediate adaptation needs, potentially exacerbating the socio-economic vulnerabilities of communities that urgently require resilience-building measures. For a climate-vulnerable nation like Bangladesh, a more adaptation-focused financial strategy is essential to safeguard against imminent climate threats.

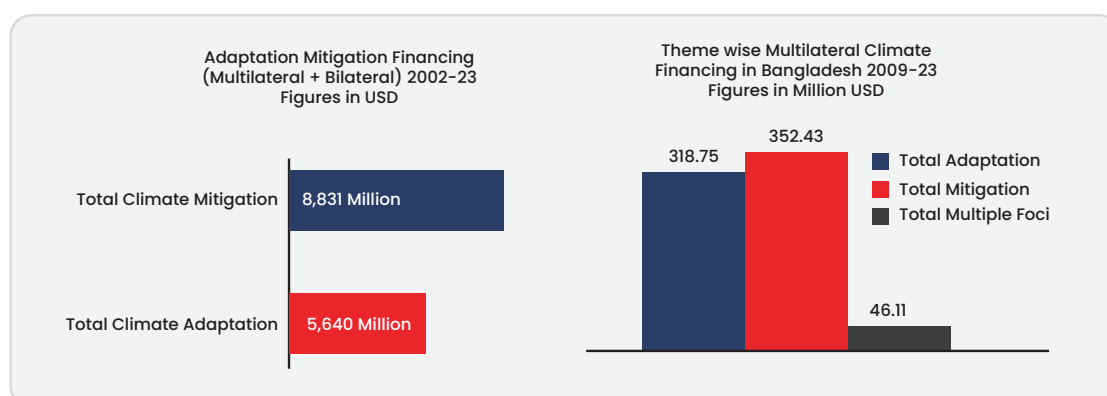


Figure 18: Adaptation-Mitigation Financing in Bangladesh





3.2 Climate Debt-to-GDP Ratio

The Debt-to-GDP Ratio across the selected Least Developed Countries (LDCs) shows a generally low debt burden relative to their GDP, with a weighted average ratio of 0.0002977. This suggests a minimal climate debt load in proportion to their economic output for most LDCs. Sri Lanka has the highest ratio at 0.0208, indicating a comparatively higher debt burden relative to its GDP, which could pose risks to its financial stability and resilience against climate impacts. In contrast, several countries, including Afghanistan, Bahamas, and Malawi, report a ratio of 0, indicating an absence of climate-related debt, which supports their economic sustainability in terms of climate finance obligations.

Bangladesh's low 2023 Climate Debt-to-GDP ratio (0.0008) indicates cautious borrowing yet suggests potential underfunding of critical adaptation and mitigation efforts needed to address its severe climate risks, such as floods and cyclones. The relatively low ratios across the majority of LDCs imply limited exposure to climate debt in their GDP; however, for countries with higher ratios, even small climate-related debt can compound financial strain, especially in regions with limited economic resilience.

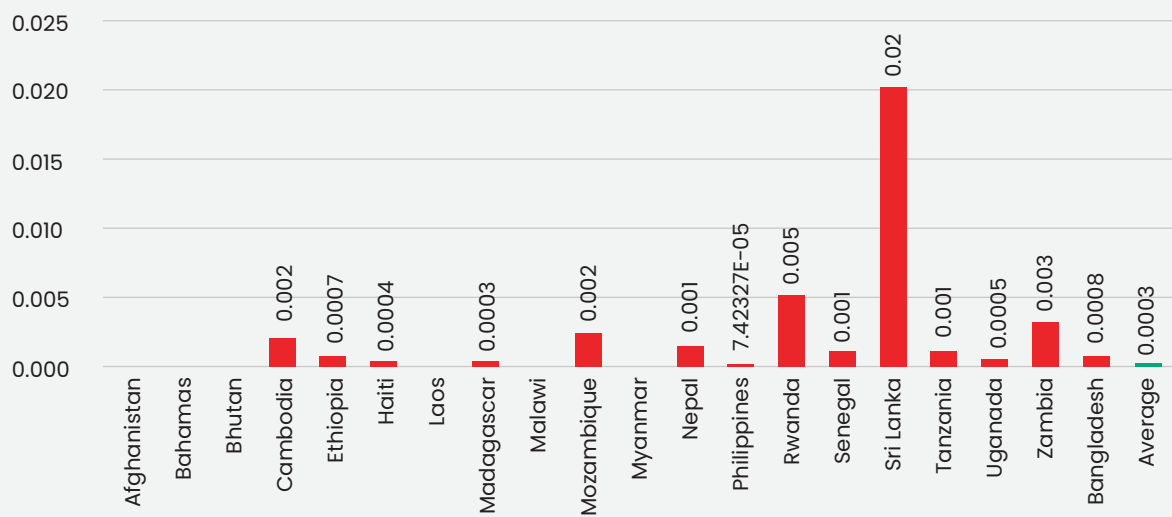


Figure 8: Climate Debt-to-GDP Ratio of LDCs (Multilateral Climate Fundings)



3.3 Per Capita Climate Debt-to-Per Capita Income

The Per Capita Debt to Per Capita Income Ratio across the selected Least Developed Countries (LDCs) shows a diverse range in debt burden relative to individual income levels. Rwanda has the highest ratio at 0.49, suggesting that nearly half of an average individual’s income could be impacted by debt-related obligations, which may strain personal economic resilience.

Moreover, Zambia and Mozambique also exhibit higher ratios of 0.31 and 0.27, respectively, indicating significant debt burdens relative to income and potentially limited economic flexibility for individuals in these countries. In contrast, countries like Bangladesh (0.08) and Sri Lanka (0.03) show relatively low ratios, suggesting a smaller impact of per capita debt on personal income levels. However, the average ratio across these LDCs highlights that, while some countries maintain manageable levels, others face notable per capita debt impacts, which could challenge individual economic stability and resilience in the face of climate and development pressures.

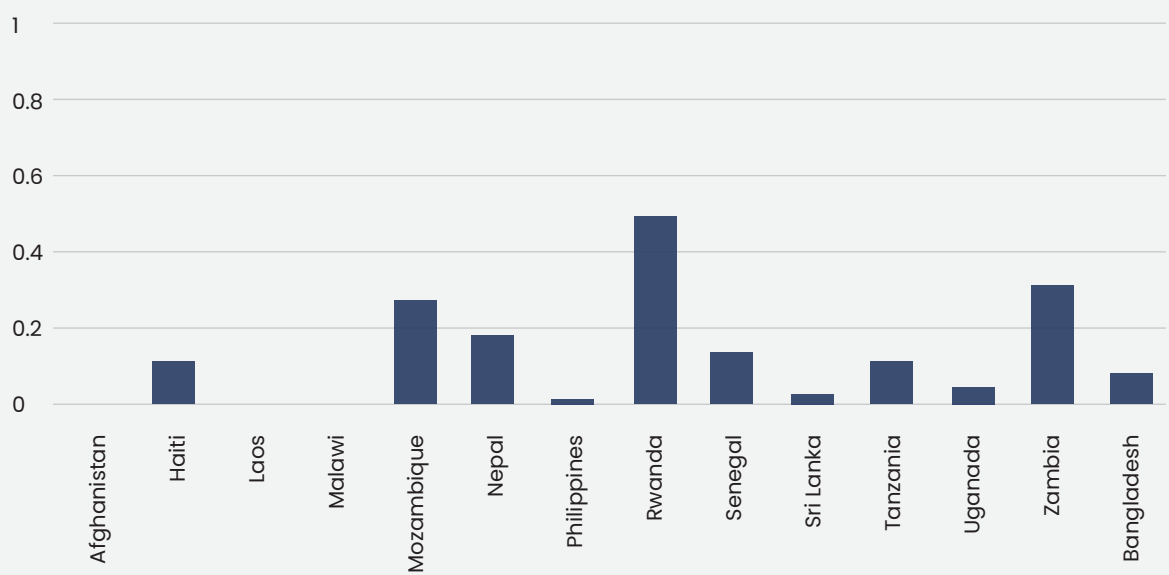


Figure 9: Ratio of Per Capita Debt-to-Per Capita Income of LDCs (Multilateral Climate Funds)



Photo: pixabay.com

3.4 Debt-to-Tax Ratio of Bangladesh

The Debt-to-Tax ratio sheds light on how Bangladesh's climate debt interacts with its ability to generate revenue through taxes. A high Debt-to-Tax ratio indicates that the government is heavily dependent on borrowing to meet its expenditures, raising concerns about fiscal sustainability. In contrast, a lower ratio suggests healthier debt management, where the country can service its debt obligations with tax revenue.

Bangladesh's Debt-to-Tax ratio peaked at 0.09 in 2014, reflecting a period when climate-related debt was higher in relation to tax revenues. However, in recent years, this ratio has begun to decline, signalling either improved tax collection or reduced reliance on debt. This downward trend highlights better fiscal management, but it also underscores the tension between managing climate debt and ensuring sufficient funding for environmental needs.

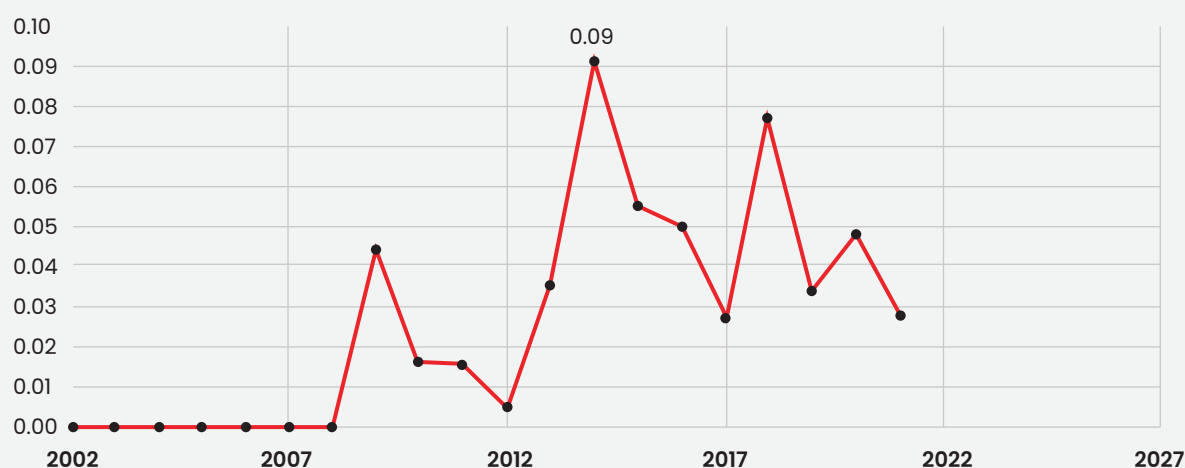


Figure 10: Multilateral Climate Debt to Tax Ratio of Bangladesh

Case 1: Climate Debt to GDP considering exaggerated GDP

Modern autocrats tend to depend on their so-called economic accomplishments to legitimise their hold on power. Many statistics like GDP growth, inflation rate, population, per capita income, agricultural production and consumption, export earnings, foreign exchange reserves, etc. were falsified at various times during the last 15-plus years. The credibility of the GDP growth calculation shown every year was questioned by many economists and local and international organisations. (The Daily Star, 2024)

Figure 11 shows Bangladesh's Total External Debt-to-GDP Ratio from 2002 to 2023, highlighting potential GDP inflation by the previous government. The ratio, which starts at 0.30 in 2002 and decreases to 0.12 by 2017 before rising to 0.15 in 2023, indicates that higher inflation rates lead to inflated debt ratios. If GDP is overestimated, the true debt burden may be significantly higher than reported, suggesting that Bangladesh's financial vulnerability could be understated. This underscores the risks associated with debt mismanagement and reliance on inflated GDP figures.

The accompanying graph illustrates Bangladesh's Total Climate Debt-to-GDP Ratio from 2002 to 2023, factoring in various inflation assumptions (5% to 25%). The cyan line shows the ratio without inflation, remaining low until peaking in 2012, followed by fluctuations and another increase between 2017 and 2020. Higher inflation rates correlate with increased debt ratios, particularly during peak periods. If GDP is inflated by 25%, the actual climate debt burden could be significantly underestimated, indicating a more severe financial reality than official figures suggest.

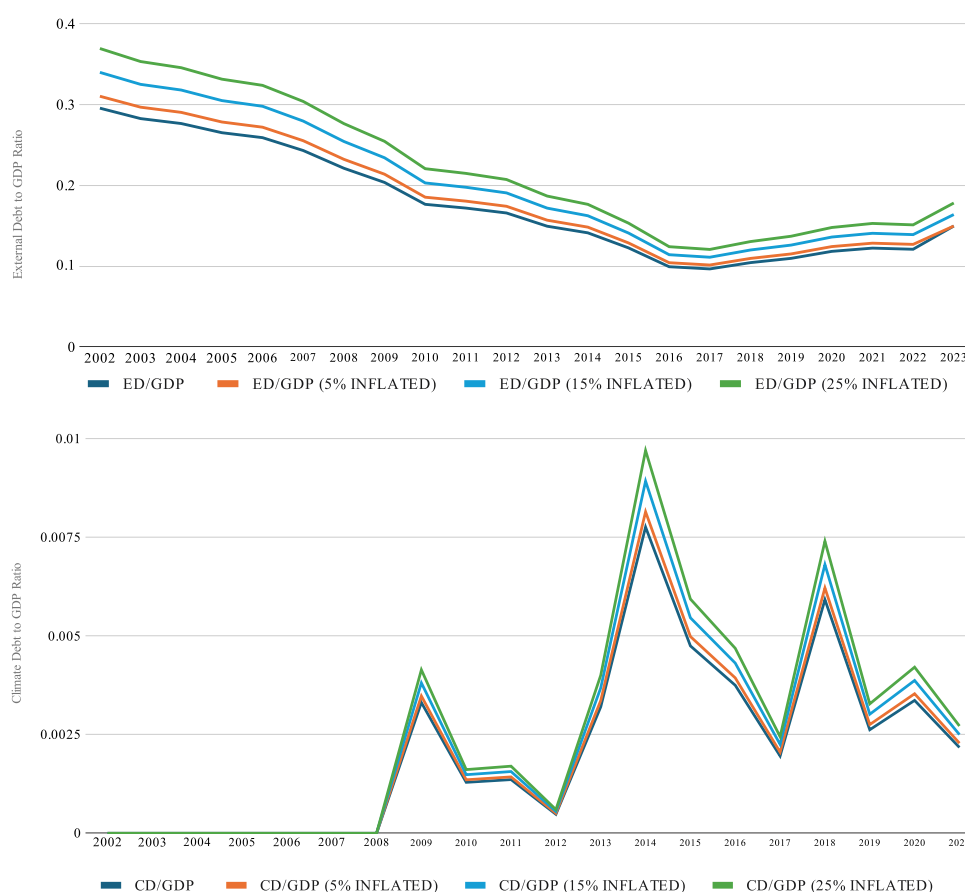


Figure 11: External Debt and Climate Debt-to-GDP Ratio Assuming GDP Exaggeration

3.5 Per-Capita Overall Climate Debt Burden

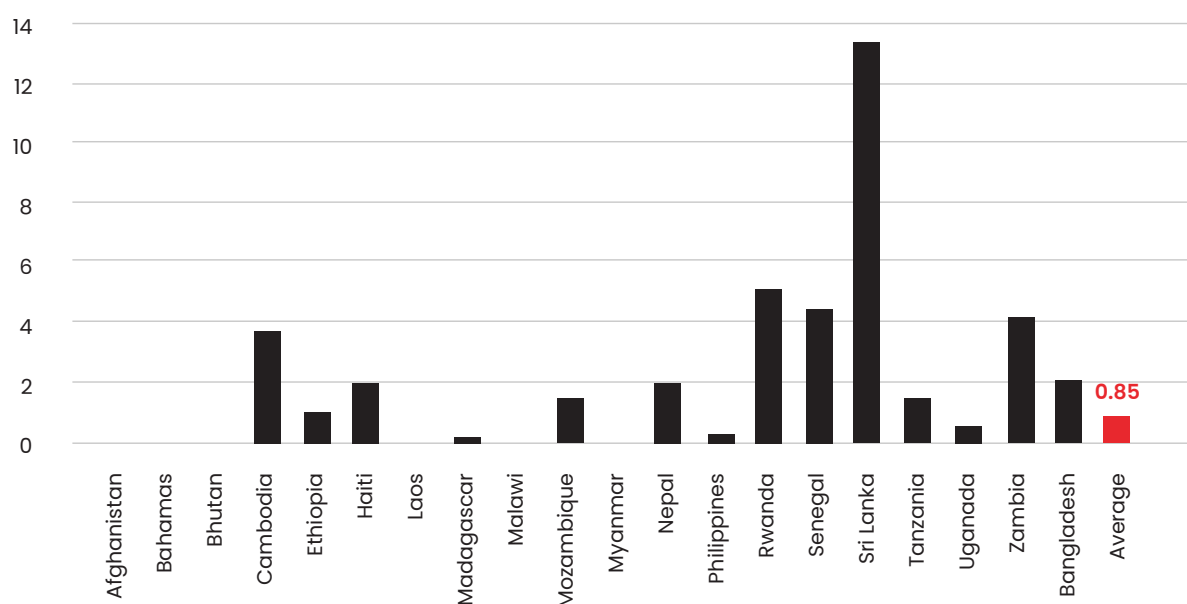


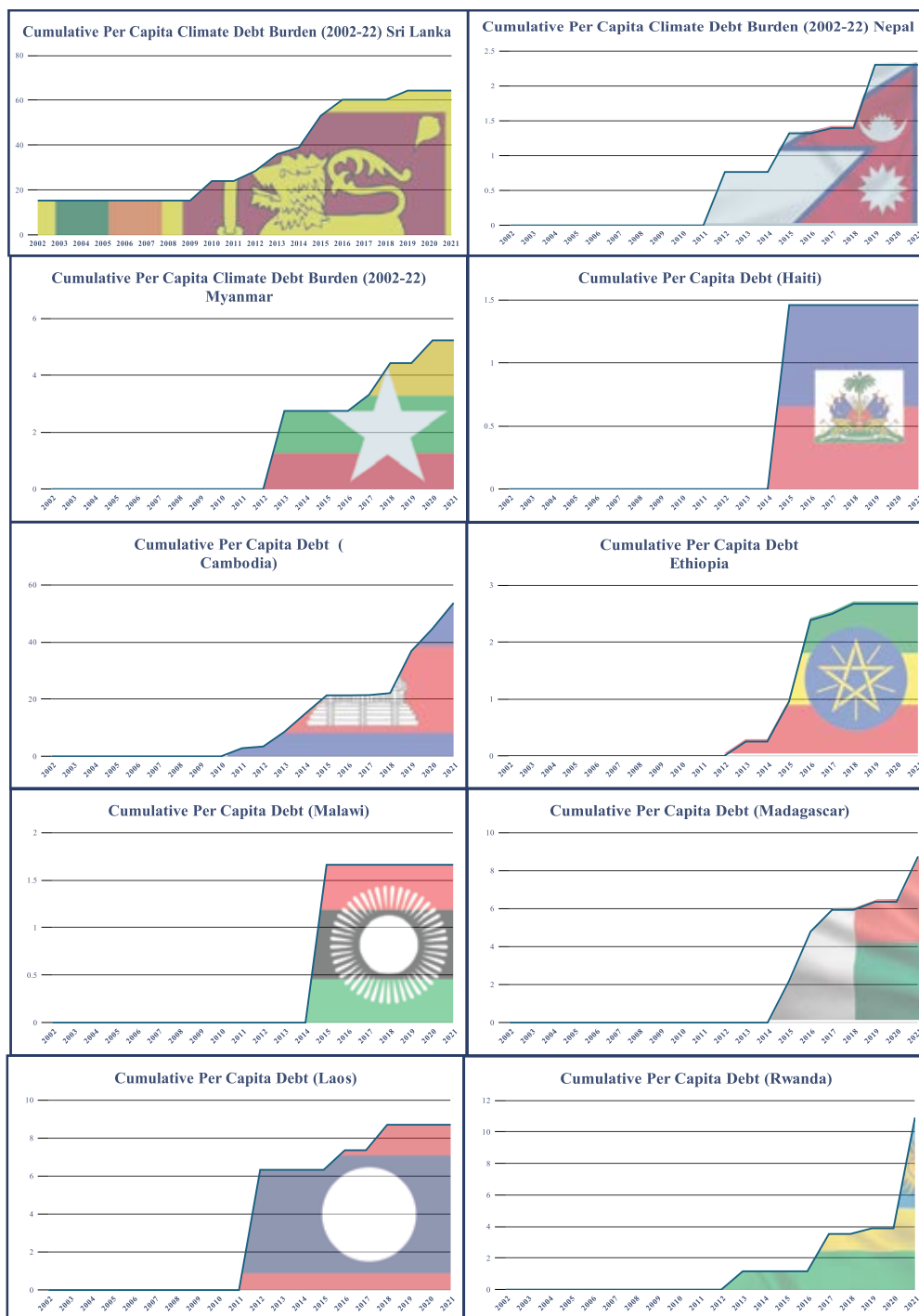
Figure 12: Per-Capita Climate Loan of LDCs (Multilateral Climate Funds)

Figure 12 illustrates the per-capita overall climate loan amounts received from multilateral funds by some of the most climate vulnerable nations, showcasing the relative economic burdens for the studies LDCs. The Per Capita Climate Debt distribution among the selected Least Developed Countries (LDCs) and other climate-vulnerable nations highlights significant variation in individual debt burdens. Overall, the weighted average per capita loan of \$0.85 across selected vulnerable LDCs that are maintaining low individual debt levels, others face significantly higher per capita burdens, which may affect their economic resilience and capacity to address climate challenges without additional financial stress.

Country specific findings shows that Sri Lanka leads with a per capita loan of \$13.38, indicating a substantial individual debt load that could strain economic resilience at the personal level, especially in times of climate crisis. Moreover, Rwanda and Senegal also show higher per capita loans at \$5.05 and \$4.47, respectively, suggesting considerable debt impacts on individuals in these countries. In contrast, countries such as Madagascar (\$0.19) and Philippines (\$0.28) maintain much lower per capita loan burdens, indicating relatively minimal impact on individuals. However, Bangladesh has a moderate per capita loan of \$2.04, reflecting a balanced but noticeable debt obligation per citizen.

As one of the most climate vulnerable countries Bangladesh's overall per capita climate debt burden has risen sharply from zero dollar in 2009 to reaching \$79.61 by 2022. This surge, illustrated in the accompanying graph, reflects the previous government's increasing reliance on concessional loans for climate finance, often misallocated to projects with limited climate relevance, such as the Matarbari coal-fired power plant of Bangladesh, and to sectors like industry and transport, rather than addressing climate vulnerabilities. Consequently, marginalized communities, especially in disaster-prone coastal regions, received inadequate support for rebuilding after events like Cyclone Amphan and the 2022 floods, exacerbating their vulnerability and highlighting the misdirection of loan funds away from crucial resilience-building efforts. While per capita debt remained relatively stable from 2002 to 2008, a sharp increase from 2009 onwards demonstrates the growing financial strain on individuals due to the escalating reliance on concessional loans.

The Per Capita Overall Climate Burden (2002–2021) across these countries shows substantial variability, (Figure-13). The weighted average cumulative burden of \$18.34 per capita suggests that while some countries face considerable individual costs related to climate finance, others maintain relatively minimal burdens, likely influenced by their climate financing structure and investment capacity. More specifically, Bangladesh is bearing the highest cumulative burden at \$79.61 per capita, indicating a significant individual cost for climate-related expenses, which could strain economic resilience and elevate debt risks. Among the LDCs Sri Lanka and Cambodia follow with high per capita burdens of \$64.31 and \$53.68, respectively, further highlighting the increased climate cost on individuals in these nations. In contrast, countries like Ethiopia (\$2.67) and Haiti (\$1.46) exhibit much lower per capita burdens, suggesting less financial pressure on individuals, albeit potentially reflecting lower climate financing or climate investment capacity.



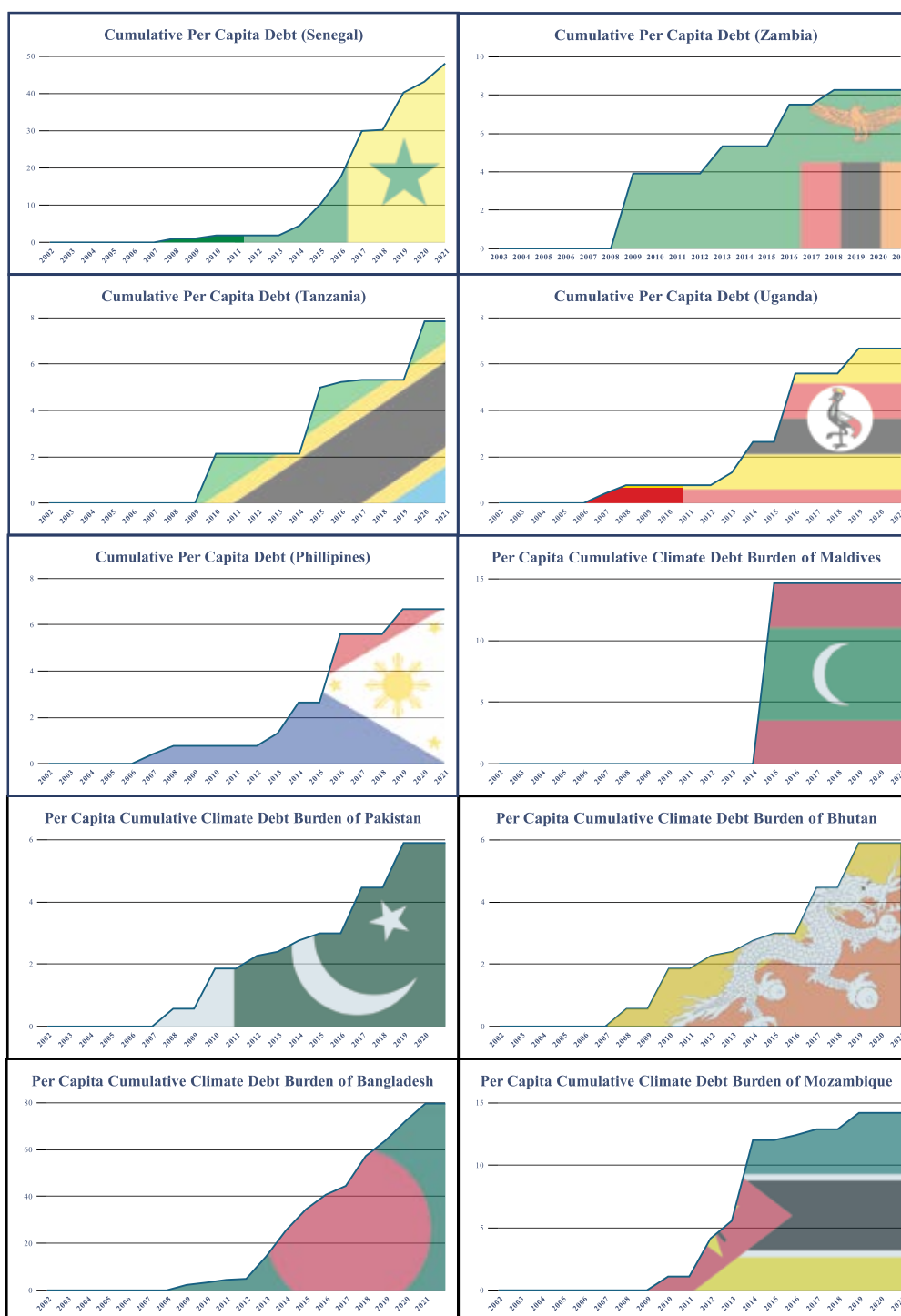


Figure 13: Per capita cumulative climate debt burden of Climate vulnerable LDCs

3.6 Per Capita Debt vs Per Capita Income

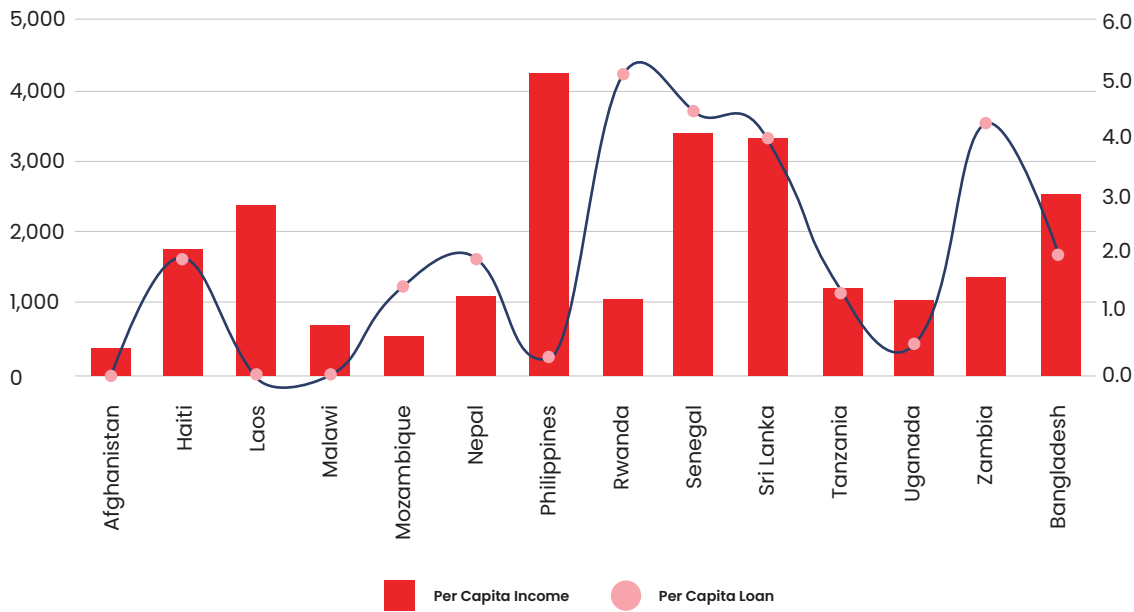


Figure 14: Per Capita Loan vs Per Capita Income (Multilateral Climate Funds) of LDCs (2009-2023)

In figure 14, a higher per capita loan value close to the per capita income is a negative indicator, signifying that a large portion of a country's income is likely to be directed towards repaying climate-related debts. The comparison between Per Capita Income and Per Capita Loan across these Least Developed Countries (LDCs) and climate-vulnerable nations reveals varying levels of debt burden in relation to individual earnings.

Rwanda and Senegal have high per capita loans of \$5.05 and \$4.47 against per capita incomes of \$1,038.64 and \$3,393.50, respectively, indicating a considerable debt burden relative to individual income. Zambia also shows a high per capita loan of \$4.21 compared to an income of \$1,369, suggesting a significant portion of individual income is directed toward debt repayment, which may limit financial resilience. In contrast, countries such as Haiti and Mozambique show lower per capita loans of \$1.94 and \$1.44 relative to their incomes, suggesting a somewhat manageable debt burden per individual. Bangladesh reflects a moderate scenario, with a per capita income of \$2,529 and a per capita loan of \$2.04, indicating a balanced yet notable debt load. These differences underscore how certain countries, especially those with high per capita loans relative to income, may face heightened financial strain and vulnerability to climate debt burdens, impacting their ability to allocate resources effectively for adaptation and resilience efforts.

3.7 Per Capita Climate Loan-to-Per Capita Carbon Emission Ratio

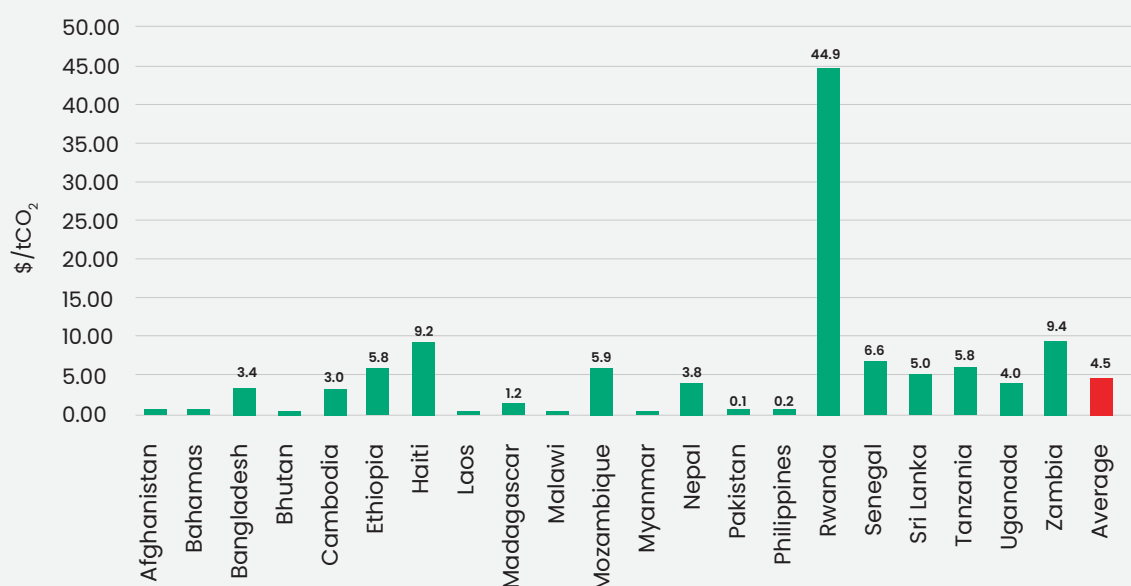


Figure 15: Per Capita Climate Loan to Per Capita Carbon Emission in 2022 (\$/t CO₂)

Figure 15 delineates Per Capita Climate Loan-to-Per Capita Carbon Emission, explicating how much climate loan a country incurs for each unit of carbon emissions (measured in \$ per ton of CO₂). A higher ratio indicates that the country faces a disproportionate climate debt burden for its emissions. Countries with elevated ratios bear a heavier financial responsibility per ton of CO₂ emitted. The weighted average is \$4.58/tCO₂ suggests that, while some countries face manageable levels, others are disproportionately burdened with climate debt relative to their emissions, potentially impacting their economic stability and resilience to climate change.

Among the LDCs Rwanda has the highest ratio at \$44.92 per ton of CO₂, indicating a significant debt cost per emission unit, which may strain its financial resources and capacity for climate action. Zambia and Haiti also exhibit high ratios of \$9.44 and \$9.20 per ton of CO₂, suggesting these countries bear a disproportionately high loan burden in relation to their emissions, potentially reflecting an inequitable climate finance structure. In contrast, Pakistan and Philippines show relatively low ratios of \$0.18 and \$0.21 per ton of CO₂, respectively, indicating a smaller loan burden per unit of emission. Bangladesh sits moderately high at \$3.42, pointing to a significant but manageable climate loan burden relative to its emissions.

3.8 Country Credit Rating vs Per Capita Climate Debt

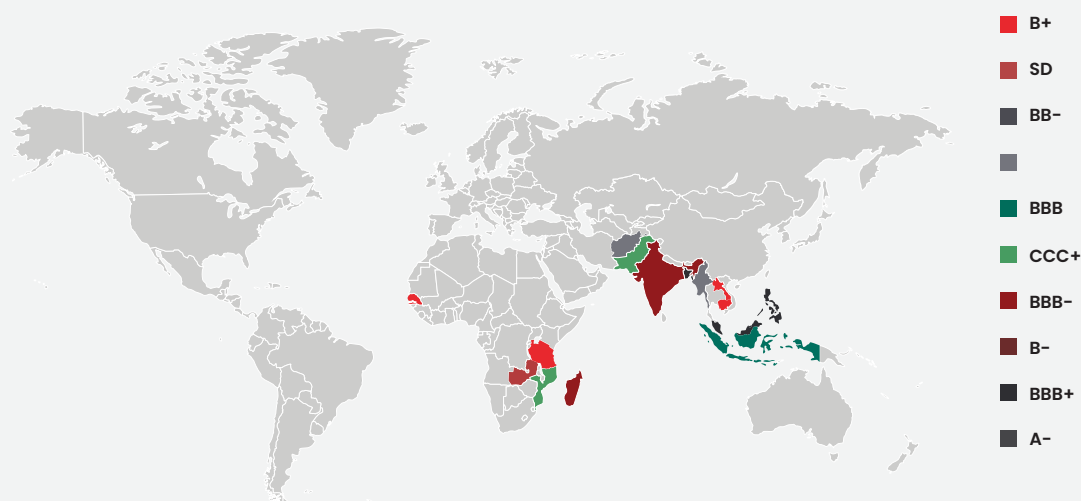


Figure 16: Credit Rating vs Per Capita Climate Loan of Selected Countries

The Credit Rating vs. Per Capita Climate Loan indicator is essential in evaluating a country's ability to repay climate-related debt while maintaining fiscal responsibility. Credit ratings reflect a nation's financial credibility, and when paired with the per capita climate loan, they provide insight into whether a country is taking on unsustainable climate debt relative to its repayment capacity. Analyzing this helps identify potential risks of a climate debt trap, particularly in nations with lower credit ratings and higher per capita loan burdens, such as Bangladesh, which faces growing fiscal pressure.

The data shows the per capita loan and S&P credit rating for 21 countries, indicating varying levels of financial vulnerability. Countries like Rwanda (\$5.047), Senegal (\$4.466), and Zambia (\$4.205) exhibit high per capita loans despite lower credit ratings (B+ and SD), signifying a higher risk of debt dependency. This trend suggests that countries with higher per capita loans, but weaker credit profiles are more prone to falling into a climate debt trap, where increasing borrowing to tackle climate change exacerbates financial instability.

Lower-credit-rated countries like Pakistan (CCC+, \$0.154) and Mozambique (CCC+, \$1.441) are also at risk, highlighting the importance of sound debt management. The data reveals that Bangladesh holds a per capita loan of \$2.039 with a credit rating of BB-, placing it among countries with moderate debt but higher financial risks. Compared to nations like Rwanda and Senegal, Bangladesh's loan burden is lower, but its weak credit rating indicates potential vulnerability in managing future climate-related debt. This suggests that Bangladesh may face increasing difficulty balancing economic growth and climate adaptation financing, raising concerns about its capacity to avoid falling into a climate debt trap if borrowing increases.

3.8 Overall Climate Debt Scenarios for LDCs

An analysis of collected data from Aid Atlas provides a comprehensive overview of the overall climate finance situation, encompassing both multilateral and bilateral sources. The table below landscapes the distribution of climate finance, detailing each country's loan and grant allocations, loan-to-grant ratios, and the emphasis on adaptation versus mitigation funding. This analysis allows for a deeper understanding of the financial structures supporting climate action across various developing and least-developed countries.

Table 4: Overall Climate Finance Landscape of various countries (Figures in billion USD)

| Country | Total Loan | Total Grant | Loan-Grant Ratio | Total Climate Adaptation Finance | Total Climate Mitigation Finance | Adaptation and Mitigation Ratio | Total CF (in billion \$) |
|-------------|------------|-------------|------------------|----------------------------------|----------------------------------|---------------------------------|--------------------------|
| Afghanistan | 0.00 | 0.42 | 0.00 | 0.21 | 0.30 | 0.72 | 0.42 |
| Bangladesh | 12.78 | 1.53 | 8.34 | 5.64 | 8.83 | 0.69 | 14.31 |
| Bhutan | 0.03 | 0.16 | 0.19 | 0.12 | 0.08 | 1.56 | 0.19 |
| Cambodia | 0.85 | 0.49 | 1.74 | 0.99 | 0.48 | 2.07 | 1.35 |
| Ethiopia | 0.28 | 1.53 | 0.18 | 1.16 | 0.90 | 1.29 | 1.86 |
| Haiti | 0.02 | 0.56 | 0.03 | 0.42 | 0.22 | 1.89 | 0.59 |
| Laos PDR | 0.06 | 0.29 | 0.20 | 0.18 | 0.19 | 0.91 | 0.35 |
| Madagascar | 0.23 | 0.35 | 0.66 | 0.34 | 0.31 | 1.12 | 0.59 |
| Malawi | 0.03 | 0.88 | 0.03 | 0.44 | 0.56 | 0.79 | 0.92 |
| Maldives | 0.01 | 0.09 | 0.07 | 0.04 | 0.07 | 0.56 | 0.10 |
| Mozambique | 0.37 | 1.07 | 0.34 | 0.60 | 0.98 | 0.62 | 1.45 |
| Myanmar | 0.27 | 0.22 | 1.21 | 0.22 | 0.31 | 0.69 | 0.50 |
| Nepal | 0.06 | 0.63 | 0.10 | 0.32 | 0.48 | 0.68 | 0.71 |
| Pakistan | 1.23 | 0.58 | 2.10 | 0.42 | 1.45 | 0.29 | 1.84 |
| Philippines | 2.04 | 0.70 | 2.92 | 1.57 | 1.28 | 1.23 | 2.79 |
| Rwanda | 0.14 | 0.40 | 0.36 | 0.33 | 0.25 | 1.31 | 0.56 |
| Senegal | 0.73 | 0.68 | 1.07 | 0.76 | 0.69 | 1.10 | 1.42 |
| Sri Lanka | 1.33 | 0.11 | 12.13 | 0.36 | 1.15 | 0.31 | 1.44 |
| Tanzania | 0.42 | 0.66 | 0.64 | 0.38 | 0.79 | 0.48 | 1.11 |
| Uganda | 0.25 | 0.83 | 0.30 | 0.60 | 0.98 | 0.61 | 1.37 |
| Zambia | 0.12 | 0.60 | 0.21 | 0.26 | 0.51 | 0.51 | 0.72 |

Table 4 provides a situational analysis of climate finance allocations across multiple developing and least-developed countries, highlighting a predominant reliance on loans over grants in many cases. Bangladesh, for instance, exhibits a high Debt-to-Grant Ratio of 8.34, indicating significant loan-based financing in its total climate finance (CF) of \$14.31 billion, where adaptation and mitigation funding are also imbalanced with an Adaptation-Mitigation Ratio of 0.69. Conversely, countries like Ethiopia and Haiti show lower Loan-to-Grant Ratios (0.18 and 0.03, respectively), indicating a greater reliance on grants, which may alleviate long-term debt risks. Countries such as Sri Lanka (12.13) and Pakistan (2.10) reveal high Loan-to-Grant Ratios, suggesting substantial debt vulnerability as a large portion of their climate finance comes from loans rather than grants.

In terms of adaptation versus mitigation funding, Cambodia and Senegal have relatively balanced Adaptation-Mitigation Ratios of 2.07 and 1.10, suggesting a focus on both immediate resilience and emission reductions. However, other countries such as Pakistan (0.29) and Tanzania (0.48) demonstrate a strong skew toward mitigation, potentially leaving adaptation needs underfunded. Smaller island nations like Maldives and Malawi have lower total climate finance amounts, with modest Loan-to-Grant Ratios, emphasizing their reliance on limited grant-based assistance. This analysis highlights a clear disparity in climate finance distribution, where countries with high debt dependence may face sustainability challenges, while those with a more balanced grant-to-loan approach may experience less long-term financial strain in addressing climate adaptation and mitigation.



Growing Demand-Supply Gaps of Climate Finance in Bangladesh: Jeopardized External Debt Trap

Like most of the climate vulnerable countries, Bangladesh faces a substantial climate finance gap, with an annual demand of \$22.55 billion to address its growing climate vulnerabilities. Key areas of demand include \$8.5 billion annually for climate adaptation measures outlined in the National Adaptation Plan (NAP), \$3.26 billion for mitigation and renewable energy, \$7.7 billion in private spending for disaster preparedness, and \$3.1 billion for climate-related government expenses. The adaptation needs include high-priority interventions, requiring a total of \$230 billion by 2050, while mitigation efforts target a 40% renewable energy transition by 2041. On the supply side, Bangladesh's national climate funding, primarily through the Annual Development Program (ADP) and the Bangladesh Climate Change Trust Fund, provides \$4.3 billion per year. International climate finance sources, such as the Green Climate Fund, Pilot Program for Climate Resilience, and other multilateral funds, contribute only around \$0.1 billion annually, leaving a significant gap of approximately \$18.15 billion per year between the available supply and the required climate finance. This funding shortfall highlights the urgent need for increased international climate finance to help Bangladesh meet its climate goals and build resilience against rising climate risks.

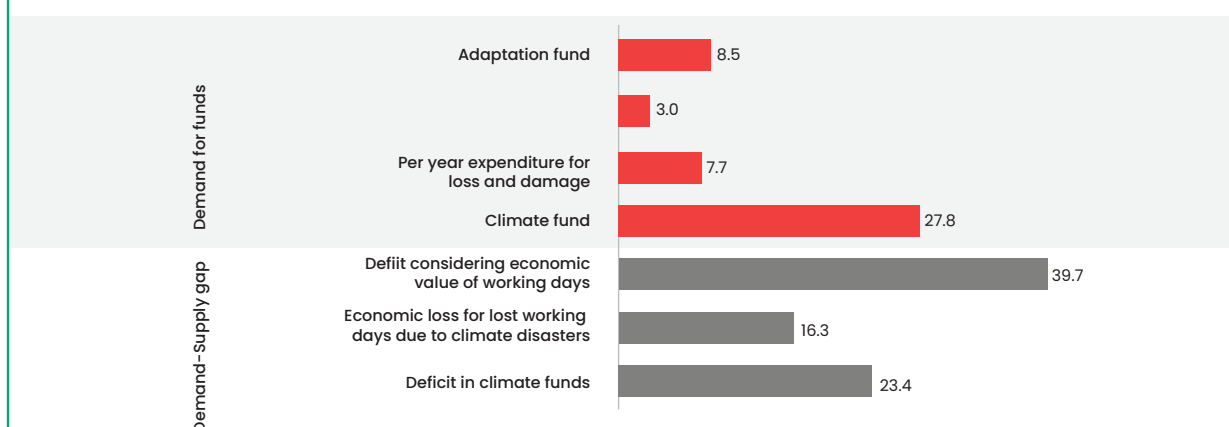


Figure 18: Effective Demand-Supply Trend of Climate Finance in Bangladesh

In figure 17, we observe that through financial demand for climate finance of Bangladesh is \$11.5 billion annually but in terms of economic demand real deficit of climate finance is around \$40 billion considering the opportunity cost in terms of workdays lost \$8.79 billion and household private expenses to cope with climate induced disasters, mostly out-of-pocket spending of the most vulnerable and poverty-stricken people of Bangladesh.

²⁴ <https://www.thedailystar.net/opinion/views/news/statistics-given-hasina-regime-need-urgent-correction-3691981>

²⁵ Overall per capita climate burden = multilateral + bilateral per capita climate debt burden



04

Climate Debt Risk Index (CDRI)

The Climate Debt Risk Index (CDRI) is a comprehensive tool designed to assess a country's financial vulnerability to climate-related risks. As climate change intensifies, countries face increasing exposure to economic challenges stemming from climate impacts, including infrastructure damage, agricultural losses, and increased healthcare costs. The CDRI combines multiple factors—including climate vulnerability, socioeconomic conditions, debt burdens, and financial stability—to capture a nuanced picture of how prepared a country is to manage and adapt to these risks. By

incorporating variables such as the Climate Risk Index (CRI), cumulative climate burden, poverty ratios, and credit ratings, the CDRI identifies countries most at risk of falling into "climate debt traps," where the economic cost of climate impacts exceeds their financial capacity to respond effectively. This index supports evidence-based decision-making, guiding policymakers, international organizations, and financial institutions in prioritizing climate resilience investments for the countries' most vulnerable to climate-induced financial strain.

By observing the Disbursement-to-Commitment Ratio, we understand its role as a variable in the Climate Debt Risk Index (CDRI) impacting the Population in Multidimensional Poverty. A low ratio signifies delays in climate finance reaching vulnerable communities, exacerbating poverty levels as these groups lack resources to build resilience against climate impacts. Similarly, the Adaptation-Mitigation Ratio influences both the CRI Score and Population in Multidimensional Poverty Ratio. Imbalances here can leave climate-vulnerable nations with insufficient adaptation funds, raising their CRI scores and increasing poverty due to inadequate protection against climate threats.

The Climate Debt-to-GDP Ratio directly informs the Government Debt-to-GDP Ratio and Credit Rating. High climate debt relative to GDP places financial strain on a country, which can lead to unfavorable borrowing terms and intensified debt vulnerability over time. Climate Debt-to-Per Capita Income Ratio further impacts Per Capita GDP and Government Debt-to-GDP Ratio, highlighting individual income stress due to climate debt. Observing this indicator reveals that a high debt-to-income ratio burdens the economy by limiting individual and national financial resilience.

The Per-Capita Burden of Climate Loan provides insight into the Per Capita Overall Cumulative Climate Burden and Per Capita Development-Related External Debt Burden, reflecting the combined impact of climate and development-related debt on individual citizens. High burdens suggest compounded economic stress on national resources. Per Capita Climate Loan-to-Per Capita Carbon Emission Ratio links to the CRI Score and Multidimensional Poverty Ratio. Countries with low emissions but high climate debt face an inequitable debt-to-emission burden, impacting their CRI scores and increasing poverty by diverting funds from poverty alleviation. Finally, Credit Rating vs Per Capita Climate Loan affects Credit Rating and Development-Related Debt Burden, as low credit ratings with high per capita loans elevate borrowing costs, straining economies and increasing climate debt risks.

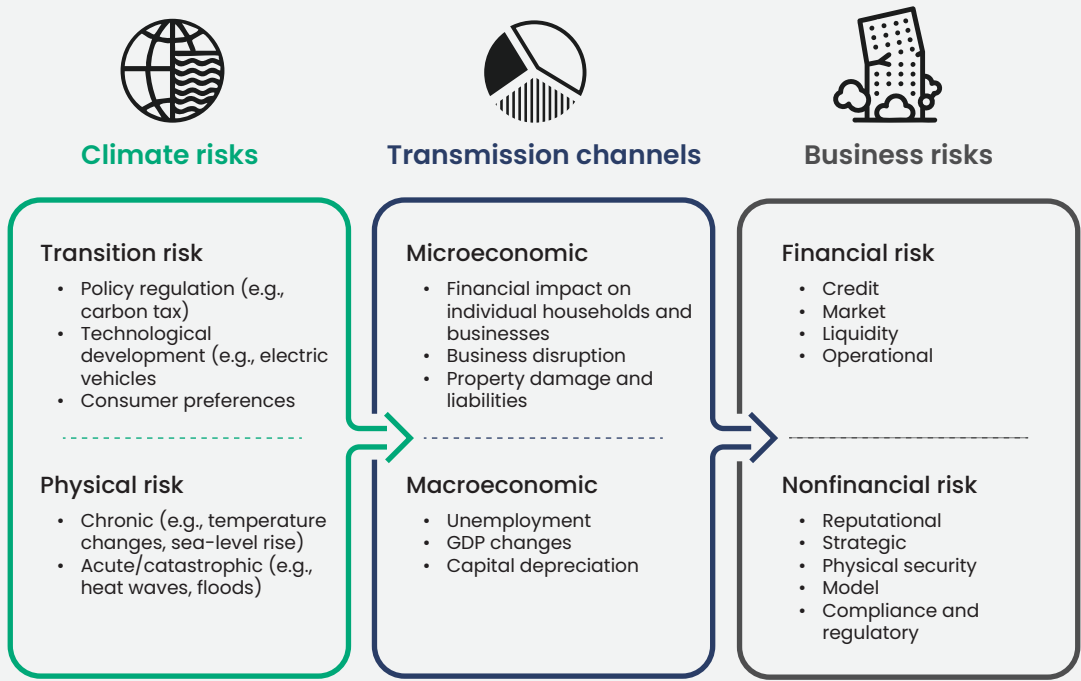


Table 5: Indicators for Climate Debt Risk Index Analysis

| Country | CRI Score (2000–20) | Per Capita Overall Cumulative Climate Burden 2002–21 | Government debt to GDP Ratio (%) | Per Capita Development Related External Debt Burden | Per Capita GDP | Population in multidimensional poverty (Headcount ratio) | Credit Rating (Moody's) |
|-------------|---------------------|--|----------------------------------|---|----------------|--|-------------------------|
| Laos PDR | 55.17 | 8.70 | 128.51 | 483.20 | 2054.43 | 23.07 | Caa3 |
| Bhutan | 118.00 | 41.86 | 124.79 | 1281.43 | 3704.02 | 9.79 | – |
| Sri Lanka | 41.83 | 64.31 | 117.66 | 695.47 | 3342.72 | 2.92 | Ca |
| Maldives | 97.33 | 14.64 | 114.94 | 2868.99 | 11780.82 | 47.91 | Caa2 |
| Zambia | 63.33 | 8.26 | 110.79 | 373.15 | 1456.90 | 23.07 | Caa3 |
| Mozambique | 25.83 | 14.19 | 104.52 | 337.17 | 558.30 | 60.67 | Caa2 |
| Pakistan | 29.00 | 5.89 | 75.75 | 221.76 | 1589.26 | 38.33 | Caa2 |
| Senegal | 55.17 | 48.06 | 74.97 | 734.75 | 1594.99 | 50.83 | B1 |
| Malawi | 15.17 | 1.66 | 70.14 | 225.75 | 643.43 | 49.88 | – |
| Rwanda | 53.33 | 10.92 | 64.43 | 499.39 | 966.57 | 48.82 | B2 |
| Myanmar | 10.00 | 14.64 | 63.90 | 340.26 | 1149.02 | 38.32 | – |
| Philippines | 26.67 | 20.00 | 57.52 | 167.42 | 3499.11 | 3.89 | Baa2 |
| Madagascar | 40.33 | 8.74 | 56.99 | 275.76 | 516.77 | 68.42 | – |
| Uganda | 42.17 | 6.67 | 50.83 | 343.12 | 964.35 | 57.17 | B3 |
| Ethiopia | 69.33 | 2.67 | 46.37 | 232.96 | 1027.50 | 68.74 | Caa3 |
| Nepal | 31.33 | 2.30 | 43.83 | 421.72 | 1348.16 | 20.07 | – |
| Tanzania | 66.50 | 7.84 | 41.62 | 1410.38 | 1193.36 | 47.22 | B1 |
| Bangladesh | 28.33 | 79.61 | 39.09 | 391.35 | 2687.90 | 24.64 | B1 |
| Cambodia | 75.83 | 53.68 | 36.53 | 616.56 | 1759.61 | 16.64 | B2 |
| Haiti | 13.67 | 1.46 | 25.01 | 186.84 | 1748.26 | 41.27 | – |

Table 5 provides a detailed analysis of several key indicators that assess the risk of falling into a climate debt trap, particularly for climate-vulnerable countries. One crucial aspect to note is that the lower the Climate Risk Index (CRI) score, the more vulnerable a country is to climate change impacts. This means that countries with lower CRI scores, such as Myanmar (CRI 10.00), Mozambique (CRI 25.83), and Ethiopia (CRI 69.33), are among the most vulnerable to climate change. In contrast, countries like Bhutan (CRI 118.00) and Senegal (CRI 67.50) are comparatively less vulnerable.

Interplay of Climate Debt Trap Risk Related Indicators

Debt-Trap Risk: The debt-trap risk categorization combines multiple factors, including CRI score, government debt-to-GDP ratio, and per capita climate and development-related debt burden. Countries like Mozambique, Laos PDR, and Maldives, which have very high climate vulnerability, significant debt-to-GDP ratios, and weak economic indicators, are flagged as being at "Very High" risk of falling into a debt trap. The combination of high vulnerability (low CRI score), high debt, and low economic resilience makes these countries especially susceptible.

Per Capita Overall Cumulative Climate Burden (2002–2021): This indicator highlights how much climate-related debt has accumulated per citizen over the given period. For instance, Bangladesh, with a per capita climate burden of \$79.61, stands out as having a relatively high debt burden for a country with significant climate vulnerability (CRI 28.33). This indicates a growing strain on Bangladesh's economic resources as it tackles climate adaptation. In contrast, countries like Haiti and Malawi have much lower per capita climate debt burdens, but their overall economic situation remains dire due to other factors such as high poverty rates.

Government Debt-to-GDP Ratio (%): High government debt-to-GDP ratios, as seen in Laos PDR (128.51%), Bhutan (124.79%), and Mozambique (104.52%), suggest that these countries are heavily indebted relative to the size of their economies. When combined with low credit ratings and high climate vulnerability, this increases the likelihood of falling into a debt trap. Even countries with moderate government debt-to-GDP ratios, such as Bangladesh (39.09%) and Senegal (74.97%), face risks if their climate finance continues to rely on loans rather than grants.

Per Capita Development-Related External Debt Burden: This metric measures the financial burden per person due to development-related external debt. Countries like Maldives (\$2,868.99) and Tanzania (\$1,410.38) have significantly higher per capita development-related debt burdens, making them more susceptible to financial instability. Conversely, countries like Ethiopia (\$232.96) and Uganda (\$343.12) have lower external debt burdens, but their high poverty rates make it difficult to absorb further debt without compromising economic stability.

Per Capita GDP: Higher per capita GDP reflects greater economic resilience to external shocks. Maldives (\$11,780.82) and Sri Lanka (\$3,342.72) have relatively high per capita GDPs, which suggests they might better withstand debt-related challenges. However, countries like Mozambique (\$558.30) and Madagascar (\$516.77) have extremely low per capita GDP, meaning their economies are less capable of handling additional debt burdens, particularly related to climate finance.

Population in Multidimensional Poverty: Countries with high poverty rates, such as Mozambique (60.67%), Madagascar (68.42%), and Ethiopia (68.74%), are at a higher risk of falling into a debt trap because a larger portion of their populations lacks the means to contribute to national economic resilience. This poverty exacerbates the impact of climate finance loans, as the country has fewer resources to pay off debts and build necessary infrastructure.

Credit Rating (Moody's): Credit ratings play a crucial role in determining how expensive it is for countries to borrow money. Countries like Laos PDR (Caa3), Sri Lanka (Ca), and Mozambique (Caa2), with poor credit ratings, face higher borrowing costs, which worsens their debt sustainability. Lower credit ratings increase the likelihood of falling into a debt trap, as these countries will find it harder to manage repayments and may face increasing interest rates on their loans.

The Debt Trap Risk Index is primarily driven by the interplay of climate vulnerability (CRI score), debt burden, and creditworthiness. Countries with low CRI scores (indicating high climate vulnerability), high debt-to-GDP ratios, and low credit ratings – such as Mozambique, Laos PDR, and Zambia—are at a heightened risk of falling into a climate debt trap. Despite a somewhat lower debt burden, countries like Bangladesh, with a CRI score of 28.33 and a high per capita climate burden, are also vulnerable as they continue to rely on loan-based finance for climate adaptation. The table highlights the urgent need for more grant-based financing to prevent economically vulnerable nations from falling deeper into unsustainable debt cycles while managing the impacts of climate change.

Table 6: CDRI for LDCs (2024, 2027 and 2030)

| Vulnerable LDCs | Region | CDRI-2024 | | CDRI-2027 | | CDRI-2030 | |
|-----------------|-----------------|-----------|------------------------|-----------|------------------------|-----------|------------------------|
| | | Score | Climate debt trap risk | Score | Climate debt trap risk | Score | Climate debt trap risk |
| Philippines | South-East Asia | 49.20 | Moderate | 49.75 | Moderate | 49.35 | Moderate |
| Maldives | South Asia | 49.37 | Moderate | 48.62 | Moderate | 49.64 | Moderate |
| Nepal | South Asia | 54.12 | High | 54.68 | High | 56.92 | High |
| Haiti | Caribbean | 54.61 | High | 55.09 | High | 57.00 | High |
| Tanzania | East Africa | 56.40 | High | 56.98 | High | 58.01 | High |
| Bhutan | South Asia | 58.15 | High | 58.86 | High | 61.68 | High |
| Pakistan | South Asia | 58.97 | High | 59.50 | High | 61.63 | High |
| Ethiopia | East Africa | 60.38 | High | 60.95 | High | 63.22 | High |
| Cambodia | South-East Asia | 61.20 | High | 61.70 | High | 62.41 | High |
| Laos PDR | South-East Asia | 61.39 | High | 61.91 | High | 62.70 | High |
| Uganda | East Africa | 61.83 | High | 62.35 | High | 68.38 | High |
| Zambia | Africa | 63.08 | High | 63.65 | High | 64.59 | High |
| Malawi | East Africa | 64.57 | High | 65.12 | High | 67.35 | High |
| Rwanda | East Africa | 65.23 | High | 69.82 | High | 73.68 | Very high |
| Bangladesh | South Asia | 67.91 | High | 68.42 | High | 70.47 | Very high |
| Senegal | West Africa | 69.11 | High | 69.71 | High | 73.39 | Very high |
| Sri Lanka | South Asia | 71.38 | Very high | 71.94 | Very high | 74.17 | Very high |
| Myanmar | South-East Asia | 75.09 | Very high | 75.58 | Very high | 78.87 | Very high |
| Madagascar | East Africa | 76.21 | Very high | 76.73 | Very high | 81.41 | Very high |
| Mozambique | East Africa | 80.10 | Very high | 79.32 | Very high | 80.05 | Very high |

Source: Authors' Estimation

* Very High Risk: Final Index ≥ 70 ; High Risk: $50 \leq \text{Final Index} < 70$; Moderate Risk: $40 \leq \text{Final Index} < 50$; and Low Risk: Final Index < 40 .

The results of the Climate Debt Risk Index (CDRI) for 2024, 2027, and 2030 reveal important insights into the evolving climate-related financial risks across countries. Countries like Mozambique (with a CDRI of 80.1 in 2024, slightly decreasing but remaining high in 2027 and 2030) and Madagascar (76.2 in 2024, increasing to 81.4 by 2030) are among the most vulnerable, reflecting the significant climate burden and financial risks they face.

Countries like Sri Lanka (71.4 in 2024, rising to 74.2 by 2030) and Myanmar (75.1 in 2024, increasing to 78.9 by 2030) also show high and growing climate debt risks, indicating a sustained vulnerability over time. On the other hand, countries like Maldives (with a relatively low CDRI of 49.4 in 2024, maintaining stability through 2030) and Philippines (49.2 in 2024, with minimal fluctuations) demonstrate stronger resilience to climate debt risk. Bangladesh exhibits a moderately high Climate Debt Risk Index (67.9 in 2024), which gradually increases to 70.5 by 2030, indicating rising vulnerability to climate-related financial risks over time.

Notably, countries like Rwanda and Senegal exhibit moderate CDRI scores but are on a rising trajectory, suggesting increasing vulnerability over time. This comprehensive analysis shows that, while some countries may maintain stability or experience modest increases in climate debt risk, others, particularly those with high CDRI values in 2024, will continue to face significant challenges in managing climate-related financial risks in the coming years.





Photo: Jody Dell Davis: pixabay.com

05

Is the Debt-Trap Risks for LDCs Intensifying?

A loss and damage (L&D) fund have been established to support particularly vulnerable developing countries. It has estimated that for the year 2025, total L&D funding needs are estimated to be US \$395 [128–937] billion (Tavoni, 2024). To address the climate hazards around \$480 billion per annum in additional concessional (external public) finance is required to address climate actions by 2030. That means more than quadrupling the currently committed \$100 billion ‘new’ and ‘additional’ to ODA per annum or tripling ODA to just over 1 percent of OECD countries’ 2022 gross national income, up from currently 0.36 percent. Total debt service on external debt stands at around US\$43 billion (Figure 19). It seems that from 2011 to 2022 development and pandemic related debt burdens for LDCs have almost tripled. The rate of recovery is also declining

Ethiopia, Rwanda and Bangladesh have the highest Climate-Debt burden in the world in terms of per-capita carbon emission

Source: UNCTAD

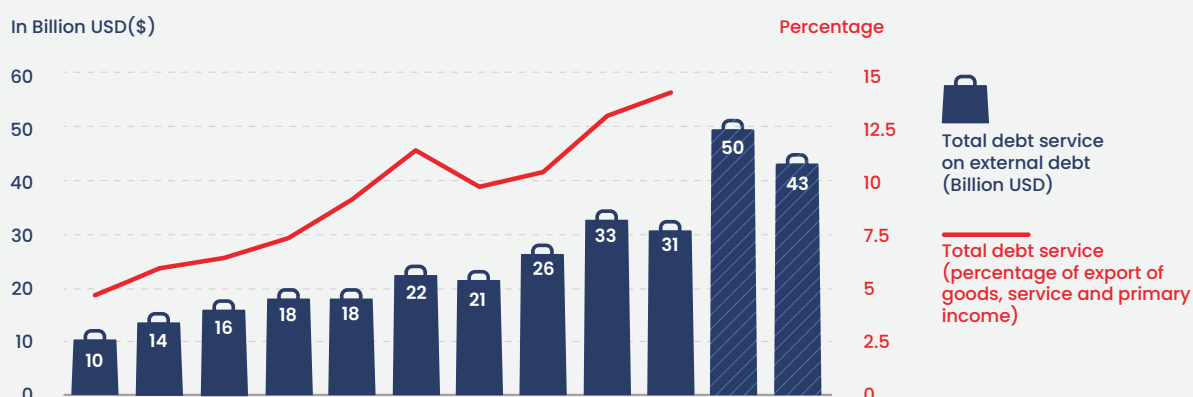


Figure 19: Soaring debt burden jeopardizes recovery of least developed countries

Since the disasters are growing the countries with higher degrees of climate vulnerability or impacts tend to have higher sovereign borrowing costs. And for every US\$10 paid in interest by developing countries, an additional dollar will be spent due to climate vulnerability. This financial burden exacerbates the present-day economic challenges of poorer countries. The magnitude of this burden will at least double over the next decade . Moreover, the additional interest payments attributable to climate vulnerability to increase to between USD146–168 billion over the next decade. (UNEP, Imperial College Business School and SOAS of University of London).

It is claimed that between 2011 and 2022, debt liabilities exceeded 60% of GDP, almost tripled, from 22 to 59 and 53% of low-income countries, 23 of which are among the 50 most climate-vulnerable nations globally—are in or at high risk of debt distress. The Jubilee Debt Campaign claimed that the 46 low-income countries that applied for help have had \$10.3billion (£7.5bn) of debts suspended. Three Sub-Saharan countries of Africa Chad, Ethiopia and Zambia applied for debt cancellation under the Common Framework, but without success due to not agreement of all creditors to agree to the same deal. Thus far, the private sector has refused to do so and there is not a lot the G20, the World Bank or the IMF can do about it. Moreover, the climate debt burdens of the LDCs have been intensifying the debt-trap risks in LDCs, and UNCTAD study warned that soaring debt burden jeopardizes recovery of least developed countries. Change Initiative study on debt risk has revealed that after the Copenhagen Accord on climate fiannce the overall climate related debt burden for selected LDCs has been increased by 24 times higher (from US\$0.9 billion in 2009 to US\$22 billion in 2022).

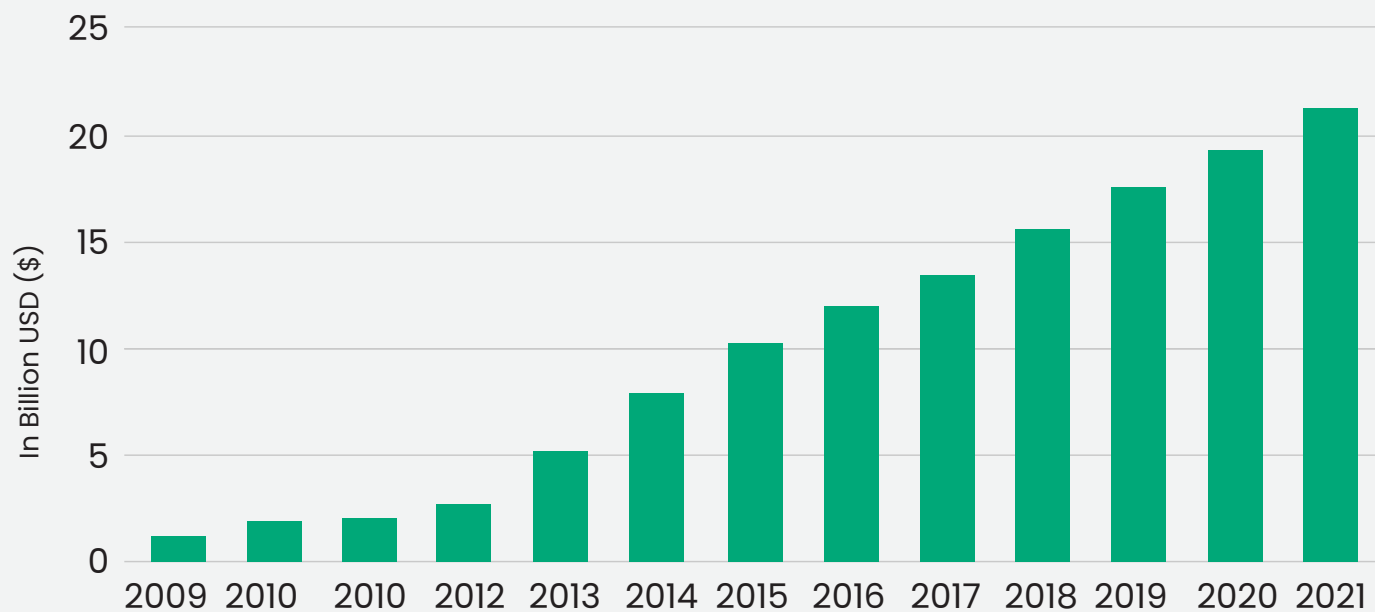


Figure 20: Total Cumulative Climate Debt Burden for Selected LDCs (From 2009 to 2022)



The two graphs in Figure-19 and Figure-20 illustrate the growing financial pressures on selected Least Developed Countries (LDCs) due to external debt obligations, including climate-related debt. The first graph highlights the increasing total debt service on external debt (in billion US\$) for the years 2011-2022, alongside the debt service as a percentage of exports of goods, services, and primary income.

The steady increase in both metrics demonstrates an escalating burden, peaking in 2021 with total debt service costs reaching \$50 billion, a value that slightly decreased in 2022 but remains high. This rising debt service directly affects the fiscal space available for LDCs to address development priorities, including climate resilience. The second graph shows the total climate debt for selected LDCs from 2009 to 2021, peaking at 2.73 billion US\$ in 2014 before fluctuating but remaining significant in recent years. The overall climate debt burden has risen 24-fold, from 0.88 billion USD in 2009 to 21.25 billion USD in 2022.

Developing countries' net interest payments on public debt reached US\$ 847 billion in 2023, a 26% increase compared to 2021. In the same vein, in 2023 a record 54 developing countries, equivalent to 38% of the total, allocated 10% or more of government revenues to interest payments. Together, while LDCs face mounting climate-related financial obligations, they are concurrently challenged by the substantial costs of servicing external debt. This dynamic underscores the need for international support mechanisms, such as debt relief or climate financing, to alleviate the compounded financial strains and promote sustainable development in vulnerable economies.



The Climate Debt Risk Index (CDRI) projections for 2024, 2027, and 2030, as shown in the table, provide a critical insight into the growing financial vulnerabilities associated with climate-related debt across multiple nations.

In 2024, the CDRI score reveals that acute climate-related debt pressures for countries such as Mozambique, Madagascar, and Myanmar are at "Very High" risk category, with significant reliance on loan-based climate finance creating a debt-trap risk that could destabilize these economies. Moreover, Sri Lanka and Senegal are classified as "High" risk, indicating early warning signs of potential difficulties in managing climate debt sustainably.

Moreover, by 2027 Mozambique, Madagascar continues persistent vulnerabilities, will be at the brink of debt trap if immediate efforts will not be adopted for full debt relief. "High" risk countries show. However, Myanmar and Sri Lanka continue to experience severe risk levels, reinforcing concerns over the sustainability of their climate debt repayment capacity. Among "High" risk countries, Bangladesh and Malawi exhibit rising CDRI scores, pointing to a worsening climate debt burden that may threaten financial stability. However, Maldives (48.62) and Philippines (49.75) continue with "Moderate" risk scores, indicating sustained relative stability in climate debt management.





Photo: Mrs Brown, pixabay.com

Overall, the most alarming consequence of this skewed climate finance landscape is the looming threat of a debt trap. The Oxfam report's findings on the dominance of loan-based finance, even in adaptation, echo these concerns. The implications are profound: as climate impacts intensify, requiring increased investments in adaptation, the mounting debt burden will divert scarce resources from essential services, crippling Bangladesh's ability to respond effectively and jeopardizing its long-term development. This is not merely a financial concern; it's a matter of climate justice, as marginalized communities, already bearing the brunt of climate change, are disproportionately impacted by the debt burden created by loans intended for their adaptation.

The pursuit of climate finance, while crucial for addressing the existential threat of climate change, presents a complex and often contradictory landscape for vulnerable nations like Bangladesh. Our analysis, combined with insights from key informant interviews (KIIs) and secondary literature, reveals a concerning mismatch between the rhetoric of climate action and the realities of finance flows, raising serious questions about debt sustainability and the efficacy of current mechanisms. A central point of contention revolves around the very definition of climate finance. The absence of a universally accepted definition creates a breeding ground for ambiguity and manipulation. This lack of clarity allows developed countries to creatively inflate reported figures, as documented in the Oxfam report, by including export credits, private finance, and repurposed development aid, thereby obscuring the true grant element and potentially overstating their contributions. This ambiguity also hinders accurate tracking and accountability, making it difficult to assess the actual additionality of climate finance, and further blurring the lines between climate action and development finance, as pointed out by one of our key informants.



This definitional ambiguity exacerbates the already concerning trend of prioritizing mitigation over adaptation. While our analysis reveals a growing imbalance in Bangladesh, with the adaptation-to-mitigation ratio falling to a concerning 0.90 in 2023, the KIIs offer further context. One observation was that even in LDCs over 50% of climate finance goes to mitigation exposes a systemic injustice, forcing vulnerable nations to prioritize emission reductions over building resilience to the very impacts they are already facing. This is further compounded by the fact that much of what is labeled "adaptation finance" in LDCs including Bangladesh is essentially disaster risk reduction, lacking integration with climate change projections (Expert from I-NGO, March 2024).

Change Initiative analysis shows a concerning rise in Bangladesh's per capita climate debt, reaching \$79.61 by 2022, largely driven by concessional loans. This trend, corroborated by the KIIs, paints a bleak picture of debt sustainability. Before the deceased of the autocratic government of Bangladesh the experts claimed that "Bangladesh is already at debt trap risks," and highlighted the severity of the alarming alleviation of debt burdens. The dire need for adaptation funding, highlighted by the \$8.5 billion annual requirement of Bangladesh's National Adaptation Plan compared to the limited funds received, underscores the urgency of rectifying this imbalance.

²⁷ Equivalent to more than double the total (not only climate-related) 2022 disbursements of the top five DFIs or the total ODA received from OECD countries in 2022.

²⁸ Climate Change and the Cost of Capital in Developing Countries

²⁹ <https://unctad.org/publication/world-of-debt>

³⁰ The next global economic emergency? Deepening debt in the developing world | Larry Elliott | The Guardian

³¹ <https://www.theguardian.com/business/worldbank>

5.1 Equity and Justice Principles Missing in Climate Finance

| Principle | Status |
|---|---|
| Polluter Pays Principle | <ul style="list-style-type: none"> · Insufficient grant-based climate finance; in the fiscal year 2021-22 only around 4.9% of the grant was allocated for climate adaptation in LDCs. · Interest against the debt (2.4% of GDP) outweighs climate investments (2.1% of GDP) in emerging and developing countries, excl. China. |
| Equity and Fairness | <ul style="list-style-type: none"> · The ten countries most affected by climate change between 2000 and 2019 received just less than 2% (USD 23 billion) of total climate finance (CPI, 2023). · The Climate Debt Risk Index (CDRI) forecast illustrates a concerning trend for Least Developed Countries (LDCs) as the climate debt risk steadily increases from 2024 to 2030. At least or more than 50% CDRI score for 20 LDCs clearly shows the most vulnerable countries are approaching climate debt trap risk. With high per capita loans and low credit ratings, countries like Rwanda, Senegal, and Zambia face elevated climate debt risks. · High Debt-to-Grant Ratio for Bangladesh (0.94). · Worsening adaptation-to-mitigation ratio (0.69). · High Per Capita Climate Loan-to-Carbon Emission Ratio (\$3.42/t CO₂). · Low Climate Debt-to-GDP ratio (0.0008). · More than half of developing countries allocate at least 8% of government revenues to interest payments, a figure that has doubled over the past decade. The increasing pressure of interest payments is significant across various regions, especially in the vulnerable zones of Africa, Latin America and the Caribbean. |
| Adaptation and Loss and Damage | More funding for mitigation (\$8.83B) than adaptation (\$5.64B). |
| Transparency and Accountability | <ul style="list-style-type: none"> · Fugitive climate related bi-lateral fundings has been revealed e.g. project related to ultra super technology for coal plant was shown as climate fund. · Less than 3% of the global total (USD 30 billion) went to or within least developed countries (LDCs), while 15% went to or within EMDEs, excluding China. (CPI, 2023). · Low Disbursement-to-Commitment Ratio for LDC (only 44%). · Delays and uncertainties increase the cost of resolving debt crises. Debt restructurings since 2020 are taking longer to finalise compared to episodes in previous decades, underscoring the need for improved debt crisis resolution mechanisms. |
| Intergenerational Responsibility | The Rising Climate Debt Risk Index (CDRI) highlights future climate debt risks for Least Developed Countries (LDCs) such as Myanmar, Sri Lanka, Mozambique, and Madagascar. Additionally, Malawi, Rwanda, Bangladesh, and Senegal are also approaching a significant level of |

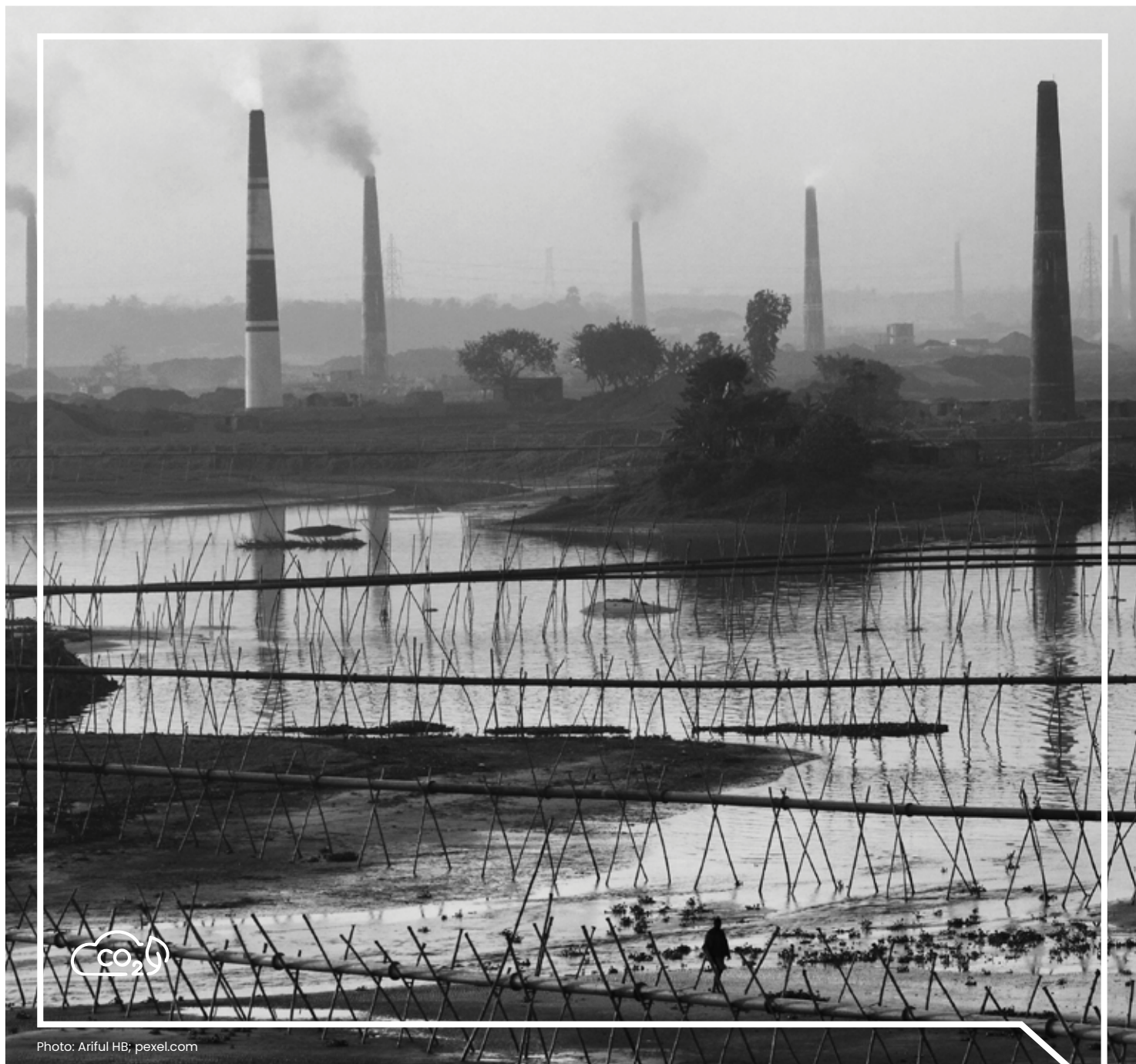


Photo: Ariful HB; pexels.com

06

Pathway to Equitable and Justified Climate Finance

To effectively address the climate crisis and avert a debt trap for vulnerable nations, a paradigm shift in the climate finance landscape is crucial. These recommendations offer a pragmatic approach, focusing on actionable steps and building existing structures:

i. Action for International Actors (Developed Countries and Multilateral Institutions):

01

Adopt a Universal Definition of Climate Finance in CoP29

Adopt a universally accepted definition of climate finance that explicitly excludes export credits, private finance mobilized through non-concessional instruments, and repurposed ODA. This definition should be based on grant equivalence and clearly delineate between adaptation, mitigation, and loss and damage finance. Bangladesh should emphasize to define the climate finance aligning with the UNFCCC and Article 9.3 of Paris Agreement

03

Framework of the Climate Resilient Debt Clauses

Consideration of debt-for-climate swaps; and sustainability linked bonds. Voluntary IMF Special Drawing Rights (SDRs) should be rechannelled, subject to national legal frameworks, including through the Resilience and Sustainability Trust (RST) funds of the IMF.

02

Debt Relief and Reforms of MDBs Towards Grant Based Climate Finance

Bangladesh along with the LDCs should raise the issue for full implementation of the “Common Framework for Debt Treatments Beyond the Debt Service Suspension Initiative”. Recognizing the Report of the G20 Independent Expert Group on Strengthening MDBs, the MDBs need to enhance operating models, improve responsiveness and accessibility, and increase financial capacity and need to work as a system, including through common country platforms, and collaborating with the multilateral funds to streamline access to finance, including local currency financing and making a difference in public adaptation finance.

04

Scaling Up Climate Finance and New Quantified Goal

Scaling up climate finance and setting a new quantified goal is crucial for addressing the increasing costs of climate adaptation and mitigation, especially for vulnerable nations. It ensures that developing countries receive adequate and timely financial resources to build resilience against climate impacts. Without this, the gap between the resources needed and available will widen, hampering global efforts to combat climate change effectively.

The pathway can be following:



Figure 21: Recommended Modalities of Climate Financing

³ In 2022, the public subsidy for fossil fuels of OECD and partner countries almost doubled to reach more than USD 1.4 trillion.

05

Prioritize Grant-Based Finance for Adaptation and Addressing Loss and Damages:

Commit to providing at least 70% of adaptation and 100% of loss and damage finance as grants, recognizing the limited capacity of LDCs to repay loans for non-revenue-generating resilience-building activities. Establish a grant window for community-led adaptation and resilience initiatives. Utilize innovative financing tools like

- Pilot a "Grant Equivalence Top-Up" Mechanism: Pilot a program where concessional loans for adaptation are accompanied by a "top-up" grant that effectively neutralizes the repayment burden, achieving near grant equivalence. This pilot should focus on a specific sector (e.g., agriculture, water) within a select group of LDCs to assess feasibility and scalability.

Develop Climate Resilience Bonds with First Loss Guarantees: Introduce a new class of bonds specifically designed

- for adaptation finance. Attract private sector investment by offering first-loss guarantees to mitigate the perceived risks associated with adaptation projects.

06

Climate Finance Transparency Dashboard:

Create a user-friendly, open-access online dashboard to track climate finance flows in real-time. This dashboard should utilize standardized reporting metrics, grant equivalence calculations, and gradually incorporate granular projects.



ii. Action for the Government of Bangladesh

1 Carbon Taxing

Commit to providing at least 70% of adaptation and 100% of loss and damage finance as grants, recognizing the limited capacity of LDCs to repay loans for non-revenue-generating resilience-building activities. Establish a grant window for community-led adaptation and resilience initiatives. Utilize innovative financing tools like

2 Reform Public Financial Management System to Use Philanthropic Finance

Bangladesh should reform the current public financing system so that philanthropic finance such as CSR, Zakat can be used for the community adaptation and resilience under the public-private-partnership model.

3 Integrate Climate Resilience into National Infrastructure Planning

Systematically incorporate climate change projections and resilience criteria into all national infrastructure planning and budgeting processes. This mainstreaming approach ensures that adaptation considerations are factored into all infrastructure investments.

4 Create a "Citizen's Climate Budget Tracker

Develop a user-friendly online tracker to provide the public with accessible information on climate-related budget allocations and expenditures. Focus on key metrics and outcomes to facilitate citizen understanding and budget monitoring.

4 Strengthen Negotiation Capacity on Climate Finance

Invest in building the capacity of Bangladeshi negotiators engaged in international climate finance discussions. This includes training on grant negotiation strategies, debt sustainability analysis, and advocacy for improved terms on climate loans.



07

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Annex-1: Formulas for Various Indicators

1. *Debt to Grant Ratio* = $\frac{\text{Total Debt}}{\text{Total Grant}}$
2. *Disbursement to Commitment Ratio* = $\frac{\text{Total Climate Finance Disbursed}}{\text{Total Climate Finance Committed}}$
3. *Adaptation to Mitigation Ratio* = $\frac{\text{Total Climate Finance Committed in Adaptation Projects}}{\text{Total Climate Finance Committed in Mitigation Projects}}$
4. *Loan to Grant Ratio* = $\frac{\text{Total Climate Finance Committed in form of Loan}}{\text{Total Climate Finance Committed in form of Grant}}$
5. *Debt to GDP Ratio* = $\frac{\text{Total Climate Finance Committed in form of Loan upto 2021}}{\text{GDP of FY 2021–22 of the country}}$
6. *Per capita Debt to Per Capita Income* = $\frac{\frac{\text{Total Climate Finance Committed in form of Loan upto 2021}}{\text{Population of 2021 of the country}}}{\text{Per Capita Income of FY 2021–22 of the country}}$
7. *Per Capita Climate Debt Burden* = $\sum_{\text{Year}=2002}^{2021} \frac{\text{Total Climate Finance taken as loan in the year}}{\text{Population of the year}}$
8. *Per Capita Climate Loan to Per Capita Carbon Emission Ratio* = $\frac{\text{Per Capita Climate Loan}}{\text{Per Capita Carbon Emission}}$

Annex-2: Method of calculating *Climate Debt Risk Index (CDRI)*

Procedure step by step:

Selecting independent variables.

Providing data for each variable.

Scoring the variables based on a scale from 0 to 10 reflecting their contribution to the overall risk index.

Assigning a weighting factor to each variable to reflect its importance in the final Climate Debt Risk Index once the variables are scored.

Independent Variables:

- CRI Score (2000–2020)– negative relationship
- Per Capita Overall Cumulative Climate Burden (2002–2021)–positive relationship
- Debt-to-GDP Ratio
- Per Capita Development Related External Debt Burden–positive relationship
- Per Capita GDP–negative relationship
- Population in Multidimensional Poverty (Headcount ratio)–positive relationship
- Credit Rating (Moody’s)–negative relationship

CRI Score

There is an inverse relationship between the CRI score and the Climate Debt Risk Index, interpreting a higher CRI score (which means less climate vulnerability) leads to a lower contribution to the Climate Debt Risk Index (CDRI).

Normalization to a 0–10 Scale:

CRI score ranges from 10 (minimum) and 118 (maximum) in the given data.

Lower CRI scores (more climate vulnerable) get higher risk scores (closer to 10), while higher CRI scores (less climate vulnerable) should get lower risk scores (closer to 0).

Normalization Formula:

Min-Max normalization is used to convert the CRI scores into a 0–10 scale.

$$\text{Normalized Score} = 10 \times \frac{(\text{Max CRI} - \text{CRI Score})}{(\text{Max CRI} - \text{Min CRI})}$$

Where:

- Max CRI = Highest CRI score in the dataset.
- Min CRI = Lowest CRI score in the dataset.
- CRI Score = Actual CRI score of the country.

Explanation:

Countries with the lowest CRI score (most climate vulnerable) will get the highest possible risk score (10), and countries with the highest CRI score (least vulnerable) will get the lowest possible risk score (0).

Per Capita Overall Cumulative Climate Burden (2002–21)

Per Capita Overall Cumulative Climate Burden has no ceiling, and the values vary widely. To normalize and score the values for the Climate Debt Risk Index (CDRI), Percentile Rank Scoring approach has been used. Percentile ranking scales the values between 0 and 1 based on their distribution, and therefore can be converted to 0–10 scale.

Explanation:

Countries with the highest burden will get a score close to 10. Countries with the lowest burden will get a score closer to 0.

Government Debt to GDP Ratio (%)

For the variable Government Debt to GDP Ratio (%), a higher value typically indicates a higher financial burden on the country, which could lead to a higher climate debt risk. Hence, it can be assumed that higher debt ratios should correspond to higher scores on the Climate Debt Risk Index.

Z-score normalization (also called standardization) has been used to calculate the discrepancy between the Debt-to-GDP ratio of each country and means, relative to the standard deviation of the dataset.

Formula for Z-Score:

$$Z = \frac{R - \mu}{\sigma}$$

Where:

- **R** is the debt-to-GDP ratio for the country.
- **μ** (mu) is the mean (average) of the debt-to-GDP ratios for all countries.

- σ (sigma) is the standard deviation of the debt-to-GDP ratios.

Normalization Formula:

$$Score = 5 + (Z \times \frac{5}{Max(Z)})$$

Explanation:

A higher Z-score indicates a higher debt burden, and therefore a higher risk score.

Per Capita Development Related External Debt Burden

Since the values are relatively large and vary widely, and there's no upper ceiling for this variable, a logarithmic transformation has been applied to the variable. Logarithmic transformation reduces the impact of large outliers, scales proportionately and handles a wide range of values. Therefore, the logarithmic transformed values have been normalized to 0-10 scale.

Explanation:

Countries with higher debt burdens (like Maldives) will get a higher log-transformed value, but the transformation will compress the extreme values, so they don't dominate the scoring. Countries with lower debt burdens will retain relatively lower scores, but their values will be more distinguishable after the log transformation.

Per Capita GDP

Similar approach alike the previous variable **Per Capita Development Related External Debt Burden**

has been applied to this variable, just in an inverted manner.

Formula for Logarithmic Transformation:

$$Log\ Score = \log \log (GDP)$$

$$Inverse\ Log\ Score = Max\ Log - \log(GDP)$$

Normalization Formula:

$$Normalized\ Score = 10 \times \frac{Inverse\ Log\ Score - Min\ Inverse\ Log}{Max\ Inverse\ Score - Min\ Inverse\ Score}$$

Population in Multidimensional Poverty (Headcount ratio)

In the context of multidimensional poverty measurement, the *population* refers to the total number of people within a defined region or demographic group (e.g., a

country, community, or household sample) who are assessed for poverty status. This population is then evaluated against various indicators across multiple dimensions of deprivation, such as health, education, and living standards.

For the *headcount ratio* specifically, this population is categorized based on those individuals considered "multidimensionally poor"- those deprived in at least a certain proportion of the indicators considered relevant in the multidimensional poverty index (MPI) framework. The headcount ratio (H) is calculated as:

$$H = \frac{q}{N}$$

where:

- **q** is the number of people identified as multidimensionally poor within the population,
- **N** is the total population.

The headcount ratio expresses the proportion of the population living in multidimensional poverty.

For the variable Population in Multidimensional Poverty (Headcount ratio), a higher poverty rate which means a higher percentage of the population living in multidimensional poverty indicates greater vulnerability, contributing to increase in the climate debt risk. Since the values are percentages, they naturally range between 0 and 100, so a linear transformation could work well here.

Normalization Formula:

Min-Max normalization is used to convert the poverty rate scores into a 0-10 scale.

$$Normalized\ Score = 10 \times \frac{(Poverty\ Rate - Min\ Value)}{(Max\ Value - Min\ Value)}$$

Explanation:

Countries with high poverty rates (e.g., Mozambique and Ethiopia) will receive higher scores closer to 10, indicating higher risk. Countries with lower poverty rates (e.g., Maldives) will receive lower scores, indicating lower risk.

Credit Rating (Moody's)

Moody's credit ratings typically range from Aaa (highest rating) to C (lowest rating), indicating a country's ability to meet its financial obligations. A lower credit rating

(closer to C) indicates higher financial risk, while a higher credit rating (closer to Aaa) signals lower financial risk. Given that lower ratings imply higher climate debt risk, this variable is inversely related to the Climate Debt Risk Index. Countries with better credit ratings (closer to Aaa) have a lower risk score, while those with poorer credit ratings (closer to C) have a higher risk score.

To handle credit ratings in a way that fits a 0-10 scale, numeric values are assigned to the different credit rating categories. Higher credit ratings (like Aaa) get lower scores, and lower credit ratings (like C) get higher scores, reflecting the inverse relationship between creditworthiness and debt risk. For the countries with missing data, a default score of 9 is assigned, reflecting higher risk due to missing data.

Conversion Table:

| Moody's Rating | Numeric Score |
|----------------|---------------|
| Aaa | 0 |
| Aa1 | 0.5 |
| Aa2 | 1 |
| Aa3 | 1.5 |
| A1 | 2 |
| A2 | 2.5 |
| A3 | 3 |
| Baa1 | 3.5 |
| Baa2 | 4 |
| Baa3 | 4.5 |
| Ba1 | 5 |
| Ba2 | 5.5 |
| Ba3 | 6 |
| B1 | 6.5 |
| B2 | 7 |
| B3 | 7.5 |
| Caa1 | 8 |
| Caa2 | 8.5 |
| Caa3 | 9 |
| Ca | 9.5 |
| C | 10 |

Explanation:

Countries with lower credit ratings (C) get the maximum risk score of 10, indicating the highest risk. Countries with the best credit ratings (Aaa) get a score of 0, indicating the least risk.

Methodology for Calculating and Forecasting the Climate Debt Risk Index (CDRI)

1. Calculating final Climate Debt Trap Risk Index (CDRI) using a weighted average for 2024

Objective:

The goal of the CDRI is to evaluate a country's vulnerability to climate debt risk, which is influenced by a combination of climate-related factors, economic conditions, and poverty levels. Countries with high climate debt risk will face greater financial stress when addressing climate change impacts, especially in the context of their existing economic vulnerabilities.

Step 1: Variables Used

The CDRI is influenced by a combination of climate-related financial burdens and governance indicators. Six key variables have been used to calculate CDRI:

CRI Score (2000–2020):

- Reflects the climate vulnerability of a country, with higher scores indicating less vulnerability.
- Inversely related to climate debt risk (higher CRI, lower risk).

Per Capita Overall Cumulative Climate Burden (2002–2021):

- Measures the cumulative impact of climate-related financial and social burdens over time.
- Directly related to climate debt risk (higher burden, higher risk).

Debt-to-GDP Ratio:

- Indicates a higher financial burden on the country
- A higher debt-to-GDP ratio refers to higher risk.

Per Capita Development Related External Debt Burden:

- Captures the burden of external financial obligations a country faces.
- A higher debt burden signals a higher risk of financial instability, increasing debt risk.

Per Capita GDP:

- Represents the economic wealth of a country. Higher GDP generally reduces debt risk.

- Inversely related to debt risk (higher GDP, lower risk).

Population in Multidimensional Poverty (Headcount Ratio):

- Measures the percentage of the population living in multidimensional poverty.
- Higher poverty levels increase vulnerability to climate impacts and economic shocks, raising debt risk.

Credit Rating (Moody's):

- Reflects the country's creditworthiness, with lower ratings indicating higher financial risk.
- Directly related to debt risk (lower rating, higher risk).

Step 2: Data Normalization

Each variable was normalized on a scale of 0 to 10 to ensure comparability, with higher values representing a higher debt risk. For variables such as the CRI Score and Per Capita GDP (which inversely affect CDRI), the following normalization formula was applied:

$$\text{Normalized Score} = 10 \times \frac{\text{Max Value} - \text{Variable}}{\text{Max Value} - \text{Min Value}}$$

For variables like climate burden and poverty (which positively affect CDRI), the following normalization formula was used:

$$\text{Normalized Score} = 10 \times \frac{\text{Variable} - \text{Min Value}}{\text{Max Value} - \text{Min Value}}$$

Step 3: Calculate the Weighted Average

The CDRI for each country was calculated as a weighted average of the normalized variables. The weights were assigned based on the relative importance of each variable in assessing climate debt risk:

Formula for Weighted Average:

$$\text{CDRI Score} = 10 \times \{ (\text{CRI Score} \times \text{WeightCRI}) + (\text{Climate Burden} \times \text{WeightClimate}) + \dots + (\text{Credit Rating} \times \text{WeightCredit}) \}$$

Step 4: Assign Risk Categories

Once the weighted average is calculated, each country is assigned to a risk category based on their CDRI score **out of 100**. For example:

- Very High Risk: Final Index ≥ 70
- High Risk: $50 \leq \text{Final Index} < 70$
- Moderate Risk: $40 \leq \text{Final Index} < 50$

- Low Risk: Final Index < 40

2. Incorporating Governance Factors for Forecasting

For forecasting the CDRI in 2027 and 2030, governance indicators were included, as they influence a country's ability to manage financial risks related to climate change. The governance indicators used were:

- Corruption Perceptions Index (CPI),
- Control of Corruption,
- Rule of Law.

These governance indicators were combined into a single Governance Score using the following equation:

$$\text{Governance Score} = (\text{CPI} \times 0.02) + (\text{Control of Corruption} \times 0.015) + (\text{Rule of Law} \times 0.015)$$

Normalization of Governance Score:

The governance score was normalized on a 0-10 scale using the formula:

$$\text{Governance Score (Normalized)} = 10 \times \frac{\text{Governance Score} - \text{Min Value}}{\text{Max Value} - \text{Min Value}}$$

3. Forecasting the CDRI for 2027 and 2030

Growth Rate Calculation for Per Capita Climate Debt:

The Per Capita Climate Debt for each country was forecasted for 2027 and 2030 based on historical growth trends. The annual compound growth rate (CAGR) for Per Capita Climate Debt was calculated as follows:

$$\text{Growth Rate} = \left(\frac{\text{Per Capita Climate Debt}_{2021}}{\text{Per Capita Climate Debt}_{2015}} \right)^{\frac{1}{6}} - 1$$

Where:

- Per Capita Climate Debt₂₀₂₁ and Per Capita Climate Debt₂₀₁₅ are the per capita debt values for the years 2021 and 2015, respectively.
- 06 represents the number of years between 2015 and 2021.

Forecasting Per Capita Climate Debt for 2027 and 2030:

Using the growth rate calculated, the Per Capita Climate Debt for 2027 and 2030 was forecasted using the following equations:

$$\text{Per Capita Climate Debt}_{2027} = \text{Per Capita Climate Debt}_{2021} \times (1 + \text{Growth Rate})^6$$

$$\text{Per Capita Climate Debt}_{2030} = \text{Per Capita Climate Debt}_{2021} \times (1 + \text{Growth Rate})^9$$

4. Final CDRI Calculation for 2027 and 2030

Formula:

Related External Debt Burden Score) + (0.15 × Normalized Inverted Per Capita GDP Score) + (0.15 × Normalized Population in Multidimensional Poverty Score) + (0.25 × Indexed Credit Rating) + (0.0125 × Normalized Governance Score)]

- $\text{CDRI (2030)} = 10 \times [(0.15 \times \text{CRI Score}) + (0.25 \times \text{Per Capita Overall Cumulative Climate Burden Percentile Score}) + (0.05 \times \text{Normalized Debt to GDP Score}) + (0.05 \times \text{Normalized Per Capita Development Related External Debt Burden Score}) + (0.15 \times \text{Normalized Inverted Per Capita GDP Score}) + (0.15 \times \text{Normalized Population in Multidimensional Poverty Score}) + (0.25 \times \text{Indexed Credit Rating}) + (0.125 \times \text{Normalized Governance Score})]$

| Country | Normalized CRI Risk Score | CCDR Percentile Score | Normalized Debt-GDP Score | Normalized Score (0-10) development debt burden | Normalized Inverted Score (0-10) per capita GDP | Normalized Score (poverty ratio) | Indexing Credit Rating | Climate Debt Risk Index | Debt-Trap Risk |
|-------------|---------------------------|-----------------------|---------------------------|---|---|----------------------------------|------------------------|-------------------------|----------------|
| Laos PDR | 5.7 | 4.2 | 10.0 | 3.7 | 5.6 | 3.1 | 9.0 | 62.701 | High |
| Bhutan | 0.0 | 7.9 | 9.7 | 7.2 | 3.7 | 1.3 | 9.0 | 61.684 | High |
| Sri Lanka | 6.9 | 9.5 | 9.0 | 5.0 | 4.0 | 0.4 | 9.5 | 74.169 | Very High |
| Maldives | 1.9 | 6.3 | 8.8 | 10.0 | 0.0 | 0.1 | 8.5 | 49.636 | Moderate |
| Zambia | 4.9 | 3.7 | 8.4 | 2.8 | 6.7 | 6.4 | 8.5 | 64.592 | High |
| Mozambique | 8.3 | 5.8 | 7.9 | 2.5 | 9.8 | 8.1 | 8.5 | 80.051 | Very High |
| Pakistan | 8.0 | 2.1 | 5.3 | 1.0 | 6.4 | 5.1 | 8.5 | 61.630 | High |
| Senegal | 4.6 | 8.4 | 5.2 | 5.2 | 6.4 | 6.8 | 6.5 | 73.385 | High |
| Malawi | 9.3 | 0.5 | 4.8 | 1.1 | 9.3 | 6.7 | 9.0 | 67.345 | High |
| Rwanda | 5.8 | 5.3 | 4.3 | 3.8 | 8.0 | 6.5 | 7.0 | 73.679 | High |
| Myanmar | 9.7 | 6.3 | 4.2 | 2.5 | 7.4 | 5.1 | 9.0 | 78.874 | Very High |
| Philippines | 8.2 | 7.4 | 3.7 | 0.0 | 3.9 | 0.5 | 4.0 | 49.349 | Moderate |
| Madagascar | 7.0 | 4.7 | 3.6 | 1.8 | 10.0 | 9.1 | 9.0 | 81.411 | Very High |
| Uganda | 6.8 | 2.6 | 3.1 | 2.5 | 8.0 | 7.6 | 7.5 | 68.383 | High |
| Ethiopia | 4.4 | 1.6 | 2.7 | 1.2 | 7.8 | 9.2 | 9.0 | 63.222 | High |

| | | | | | | | | | |
|----------------|-----|------|-----|-----|-----|-----|-----|--------|------|
| Nepal | 7.8 | 1.1 | 2.5 | 3.3 | 6.9 | 2.7 | 9.0 | 56.918 | High |
| Tanzania | 4.6 | 3.2 | 2.3 | 7.5 | 7.3 | 6.3 | 6.5 | 58.007 | High |
| Banglade sh | 8.1 | 10.0 | 2.0 | 3.0 | 4.7 | 3.3 | 6.5 | 70.470 | High |
| Cambodi a | 3.8 | 8.9 | 1.8 | 4.6 | 6.1 | 2.2 | 7.0 | 62.412 | High |
| Haiti | 9.4 | 0.0 | 0.8 | 0.4 | 6.1 | 5.5 | 9.0 | 57.001 | High |

Table: CDRI-2024 Calculation Table

Annex-3: Codes for Weight Refining Models

Python Code for Multiple Linear Regression Analysis and Principal Component Analysis (PCA)

```
import pandas as pd
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import numpy as np

# Load the provided dataset into a pandas DataFrame
data = {
    'Country': ['Laos PDR', 'Bhutan', 'Sri Lanka', 'Maldives', 'Zambia', 'Mozambique',
                'Pakistan', 'Senegal',
                'Malawi', 'Rwanda', 'Myanmar', 'Philippines', 'Madagascar', 'Uganda', 'Ethiopia',
                'Nepal',
                'Tanzania', 'Bangladesh', 'Cambodia', 'Haiti'],
    'Normalized CRI Risk Score': [5.7, 0.0, 6.9, 1.9, 4.9, 8.3, 8.0, 4.6, 9.3, 5.8, 9.7, 8.2, 7.0, 6.8,
                                   4.4, 7.8, 4.6, 8.1, 3.8, 9.4],
    'CCDR Percentile Score': [4.2, 7.9, 9.5, 6.3, 3.7, 5.8, 2.1, 8.4, 0.5, 5.3, 6.3, 7.4, 4.7, 2.6, 1.6, 1.1,
                              3.2, 10.0, 8.9, 0.0],
    'Normalized Debt-GDP Score': [10.0, 9.7, 9.0, 8.8, 8.4, 7.9, 5.3, 5.2, 4.8, 4.3, 4.2, 3.7, 3.6, 3.1,
                                   2.7, 2.5, 2.3, 2.0, 1.8, 0.8],
    'Normalized Score (0-10) development debt burden': [3.7, 7.2, 5.0, 10.0, 2.8, 2.5, 1.0,
                                                           5.2, 1.1, 3.8, 2.5, 0.0, 1.8, 2.5, 1.2, 3.3, 7.5, 3.0, 4.6, 0.4],
    'Normalized Inverted Score (0-10) per capita gdp': [5.6, 3.7, 4.0, 0.0, 6.7, 9.8, 6.4, 6.4,
                                                         9.3, 8.0, 7.4, 3.9, 10.0, 8.0, 7.8, 6.9, 7.3, 4.7, 6.1, 6.1],
    'Normalized Score (poverty ratio)': [3.1, 1.3, 0.4, 0.1, 6.4, 8.1, 5.1, 6.8, 6.7, 6.5, 5.1, 0.5, 9.1,
                                           7.6, 9.2, 2.7, 6.3, 3.3, 2.2, 5.5],
    'Indexing Credit Rating': [9.0, 9.0, 9.5, 8.5, 8.5, 8.5, 8.5, 6.5, 9.0, 7.0, 9.0, 4.0, 9.0, 7.5, 9.0,
                               9.0, 6.5, 6.5, 7.0, 9.0],
    'Climate Debt Trap Index': [6.1, 5.8, 7.1, 4.9, 6.3, 8.0, 5.9, 6.9, 6.5, 6.5, 7.5, 4.9, 7.6, 6.2, 6.0,
                                5.4, 5.6, 6.8, 6.1, 5.5]
}

df = pd.DataFrame(data)
```

```

# Separate the independent variables (X) and the dependent variable (y)
X = df.drop(columns=['Country', 'Climate Debt Trap Index'])
y = df['Climate Debt Trap Index']

# Standardize the independent variables for regression
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Perform multiple linear regression
regression_model = LinearRegression()
regression_model.fit(X_scaled, y)

# Get the regression coefficients (beta values)
regression_coefficients = regression_model.coef_

# Now performing PCA on the standardized independent variables
pca = PCA()
pca.fit(X_scaled)

# Explained variance for each component
explained_variance = pca.explained_variance_ratio_

# Combine results for display
results = pd.DataFrame({
    'Variable': X.columns,
    'Regression Coefficient (Beta)': regression_coefficients,
    'Explained Variance (PCA)': explained_variance
})

# Print the results
print(results)

```

Python Code to Optimize the Weights

```

import numpy as np
from scipy.optimize import minimize
import pandas as pd
from sklearn.preprocessing import StandardScaler

```

```

# Load the provided dataset into a pandas DataFrame
data = {
    'Country': ['Laos PDR', 'Bhutan', 'Sri Lanka', 'Maldives', 'Zambia', 'Mozambique',
                'Pakistan', 'Senegal',
                'Malawi', 'Rwanda', 'Myanmar', 'Phillipines', 'Madagascar', 'Uganda', 'Ethiopia',
                'Nepal',
                'Tanzania', 'Bangladesh', 'Cambodia', 'Haiti'],
    'Normalized CRI Risk Score': [5.7, 0.0, 6.9, 1.9, 4.9, 8.3, 8.0, 4.6, 9.3, 5.8, 9.7, 8.2, 7.0, 6.8,
                                   4.4, 7.8, 4.6, 8.1, 3.8, 9.4],
    'CCDR Percentile Score': [4.2, 7.9, 9.5, 6.3, 3.7, 5.8, 2.1, 8.4, 0.5, 5.3, 6.3, 7.4, 4.7, 2.6, 1.6, 1.1,
                              3.2, 10.0, 8.9, 0.0],
    'Normalized Debt-GDP Score': [10.0, 9.7, 9.0, 8.8, 8.4, 7.9, 5.3, 5.2, 4.8, 4.3, 4.2, 3.7, 3.6, 3.1,
                                   2.7, 2.5, 2.3, 2.0, 1.8, 0.8],
    'Normalized Score (0-10) development debt burden': [3.7, 7.2, 5.0, 10.0, 2.8, 2.5, 1.0,
                                                           5.2, 1.1, 3.8, 2.5, 0.0, 1.8, 2.5, 1.2, 3.3, 7.5, 3.0, 4.6, 0.4],
    'Normalized Inverted Score (0-10) per capita gdp': [5.6, 3.7, 4.0, 0.0, 6.7, 9.8, 6.4, 6.4,
                                                         9.3, 8.0, 7.4, 3.9, 10.0, 8.0, 7.8, 6.9, 7.3, 4.7, 6.1, 6.1],
    'Normalized Score (poverty ratio)': [3.1, 1.3, 0.4, 0.1, 6.4, 8.1, 5.1, 6.8, 6.7, 6.5, 5.1, 0.5, 9.1,
                                           7.6, 9.2, 2.7, 6.3, 3.3, 2.2, 5.5],
    'Indexing Credit Rating': [9.0, 9.0, 9.5, 8.5, 8.5, 8.5, 8.5, 6.5, 9.0, 7.0, 9.0, 4.0, 9.0, 7.5, 9.0,
                               9.0, 6.5, 6.5, 7.0, 9.0],
    'Climate Debt Trap Index': [6.1, 5.8, 7.1, 4.9, 6.3, 8.0, 5.9, 6.9, 6.5, 6.5, 7.5, 4.9, 7.6, 6.2, 6.0,
                                5.4, 5.6, 6.8, 6.1, 5.5]
}

df = pd.DataFrame(data)

# Standardize the independent variables for regression
X = df.drop(columns=['Country', 'Climate Debt Trap Index'])
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Define the actual CDRI values (dependent variable)
actual_cdri = df['Climate Debt Trap Index'].values

# Initial weights based on current assignment (total sum of weights should be 1)
initial_weights = [0.15, 0.25, 0.05, 0.05, 0.10, 0.15, 0.25] # Corresponding to the
variables

```

```

# Define the function that calculates the predicted CDRI using the current weights
def calculate_predicted_cdri(weights, X_data):
    weights = np.array(weights)
    weights = weights / np.sum(weights)
    predicted_cdri = np.dot(X_data, weights)
    return predicted_cdri

# Define the objective function to minimize (least squares error between actual and
predicted CDRI)
def objective_function(weights, X_data, actual_cdri):
    predicted_cdri = calculate_predicted_cdri(weights, X_data)
    return np.sum((predicted_cdri - actual_cdri) ** 2)

# Perform the optimization
optimized_result = minimize(objective_function, initial_weights, args=(X_scaled,
actual_cdri), bounds=[(0, 1)]*7)

# Get the optimized weights
optimized_weights = optimized_result.x / np.sum(optimized_result.x)

# Display the optimized weights
print("Optimized Weights:")
for variable, weight in zip(X.columns, optimized_weights):
    print(f"{variable}: {weight:.4f}")

```

Python Code For Heteroscedasticity Test

```

import statsmodels.api as sm

from statsmodels.stats.diagnostic import het_breuschpagan, het_white

import matplotlib.pyplot as plt

import pandas as pd

# Sample data
data = {
    'Country': ['Laos PDR', 'Bhutan', 'Sri Lanka', 'Maldives', 'Zambia', 'Mozambique',
'Pakistan', 'Senegal',

```

'Malawi', 'Rwanda', 'Myanmar', 'Philippines', 'Madagascar', 'Uganda', 'Ethiopia',
'Nepal',

'Tanzania', 'Bangladesh', 'Cambodia', 'Haiti'],

'Normalized CRI Risk Score': [5.7, 0.0, 6.9, 1.9, 4.9, 8.3, 8.0, 4.6, 9.3, 5.8, 9.7, 8.2, 7.0, 6.8,
4.4, 7.8, 4.6, 8.1, 3.8, 9.4],

'CCDR Percentile Score': [4.2, 7.9, 9.5, 6.3, 3.7, 5.8, 2.1, 8.4, 0.5, 5.3, 6.3, 7.4, 4.7, 2.6, 1.6, 1.1,
3.2, 10.0, 8.9, 0.0],

'Normalized Debt-GDP Score': [10.0, 9.7, 9.0, 8.8, 8.4, 7.9, 5.3, 5.2, 4.8, 4.3, 4.2, 3.7, 3.6, 3.1,
2.7, 2.5, 2.3, 2.0, 1.8, 0.8],

'Normalized Score (0-10) development debt burden': [3.7, 7.2, 5.0, 10.0, 2.8, 2.5, 1.0,
5.2, 1.1, 3.8, 2.5, 0.0, 1.8, 2.5, 1.2, 3.3, 7.5, 3.0, 4.6, 0.4],

'Normalized Inverted Score (0-10) per capita gdp': [5.6, 3.7, 4.0, 0.0, 6.7, 9.8, 6.4, 6.4,
9.3, 8.0, 7.4, 3.9, 10.0, 8.0, 7.8, 6.9, 7.3, 4.7, 6.1, 6.1],

'Normalized Score (poverty ratio)': [3.1, 1.3, 0.4, 0.1, 6.4, 8.1, 5.1, 6.8, 6.7, 6.5, 5.1, 0.5, 9.1,
7.6, 9.2, 2.7, 6.3, 3.3, 2.2, 5.5],

'Indexing Credit Rating': [9.0, 9.0, 9.5, 8.5, 8.5, 8.5, 8.5, 6.5, 9.0, 7.0, 9.0, 4.0, 9.0, 7.5, 9.0,
9.0, 6.5, 6.5, 7.0, 9.0],

'Climate Debt Trap Index': [6.1, 5.8, 7.1, 4.9, 6.3, 8.0, 5.9, 6.9, 6.5, 6.5, 7.5, 4.9, 7.6, 6.2, 6.0,
5.4, 5.6, 6.8, 6.1, 5.5]

}

Create DataFrame

df = pd.DataFrame(data)

Separate dependent and independent variables

X = df.drop(columns=['Country', 'Climate Debt Trap Index'])

y = df['Climate Debt Trap Index']

Add constant to the model (intercept)

X = sm.add_constant(X)

Fit the regression model

model = sm.OLS(y, X).fit()

```

residuals = model.resid # Get residuals

# Perform Breusch-Pagan test

bp_test = het_breuschpagan(residuals, model.model.exog)

bp_test_results = dict(zip(["Lagrange Multiplier Statistic", "p-value", "f-value", "f
p-value"], bp_test))

# Perform White's test for heteroscedasticity

white_test = het_white(residuals, model.model.exog)

white_test_results = dict(zip(["Lagrange Multiplier Statistic", "p-value", "f-value", "f
p-value"], white_test))

# Visualize residuals

plt.scatter(model.fittedvalues, residuals)

plt.axhline(0, color='red', linestyle='--', linewidth=1)

plt.xlabel("Fitted Values")

plt.ylabel("Residuals")

plt.title("Residual Plot for Heteroscedasticity Check")

plt.grid(True)

plt.show()

bp_test_results, white_test_results

```

Annex-4: Refining the Climate Debt Trap Index (CDRI) Weighting for Enhanced Accuracy

Multiple Linear Regression was performed to examine the relationship between the **Climate Debt Trap Index (CDRI)** and the selected independent variables: **CRI Score**, **CCDR Percentile Score**, **Debt-GDP Ratio**, **Development Debt Burden**, **Per Capita GDP**, **Poverty Ratio**, and **Credit Rating**. The regression analysis provided **standardized beta coefficients**, which represent the relative importance of each variable in predicting the CDRI. These coefficients were then compared with the weights we

assigned to each variable (e.g., 15% for CRI Score, 25% for Climate Burden, etc.). The beta values indicate the degree of influence each variable has on the CDRI.

Table 7: Result of Multiple Linear Regression

| Variable | Assigned Weight (%) | Beta Co-efficient (Standardized) |
|---|----------------------------|---|
| CRI Score | 15 | 0.384274 |
| CCDR Percentile Score | 25 | 0.754243 |
| Debt-GDP Ratio | 5 | 0.134802 |
| Development Debt Burden | 5 | 0.120390 |
| Per Capita GDP | 10 | 0.338783 |
| Population in Multidimensional Poverty | 15 | 0.430672 |
| Credit Rating | 25 | 0.340571 |

The **regression coefficients (beta values)** show the relative contribution of each independent variable to predicting the **Climate Debt Risk Index (CDRI)**. The higher the coefficient, the greater the impact of that variable on the CDRI.

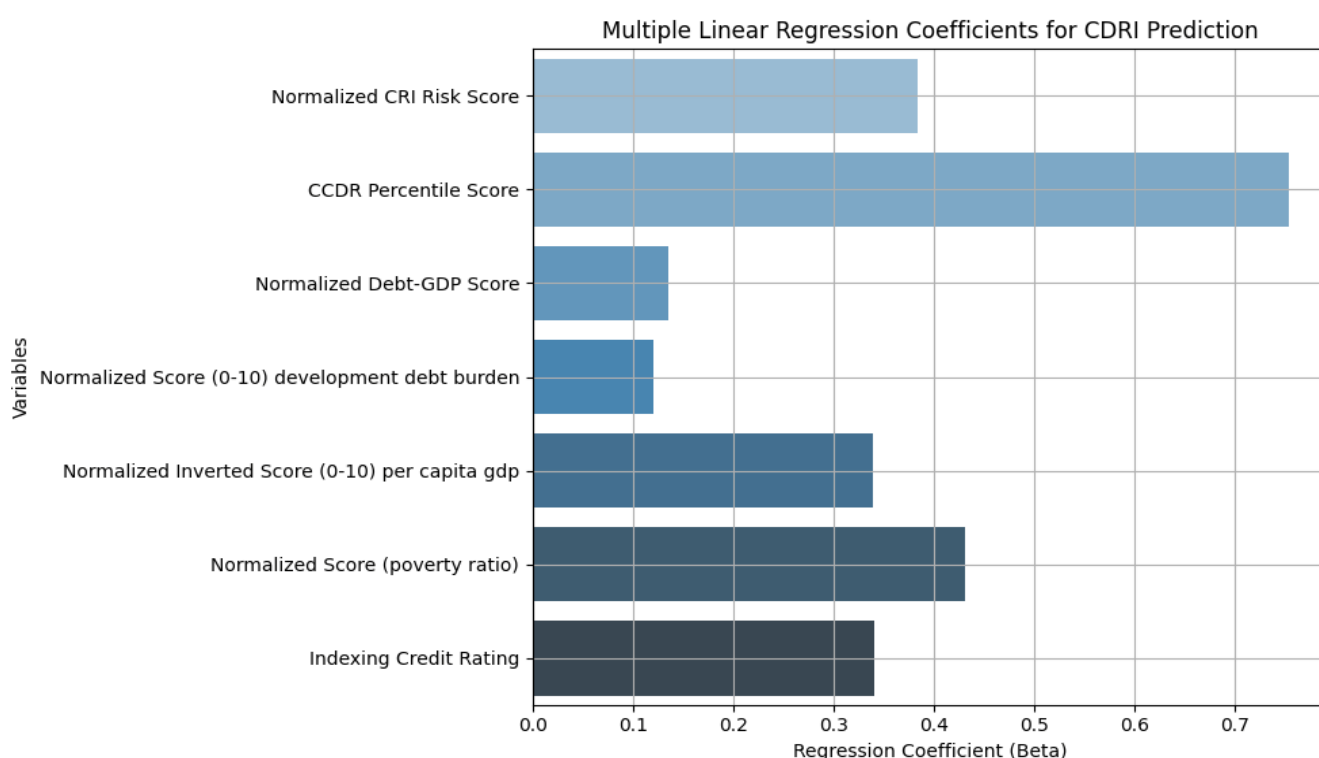


Figure 22: Multiple Linear Regression Coefficients for CDRI Prediction

Key Insights from Regression Coefficients:

- **CCDR Percentile Score** has the highest beta value (0.754), indicating that it has the strongest influence on the CDRI. This suggests that the percentile score based on cumulative climate burden should have significant weight in your index.
- **Poverty Ratio** (0.431) and **CRI Risk Score** (0.384) also have high beta values, indicating that climate risk and poverty are important factors in determining climate debt risk.
- **Credit Rating** (0.341) and **Per Capita GDP** (0.339) also contribute, though with somewhat less impact than CCDR and Poverty.
- **Development Debt Burden** (0.120) and **Debt-GDP Ratio** (0.135) have the smallest beta values, indicating that their contribution to the CDRI is weaker compared to other variables.

To further assess the relative importance of each variable in determining the **Climate Debt Risk Index (CDRI)**, a **Principal Component Analysis (PCA)** was

conducted. PCA helps identify the variance each variable explains within the dataset. By evaluating the **explained variance ratios**, we can confirm whether the chosen weights for each variable reflect the true influence on the CDRI.

Table 8: Principal Component Analysis Results

| Variable | Explained Variance (%) |
|--|------------------------|
| CRI Score | 0.471959 |
| CCDR Percentile Score | 0.212186 |
| Debt-GDP Ratio | 0.128604 |
| Development Debt Burden | 0.093081 |
| Per Capita GDP | 0.049553 |
| Population in Multidimensional Poverty | 0.029372 |
| Credit Rating | 0.015245 |

The **explained variance** shows how much of the total variability in the dataset is captured by each variable. The higher the variance explained by a variable, the more important it is in explaining the variation in the data.

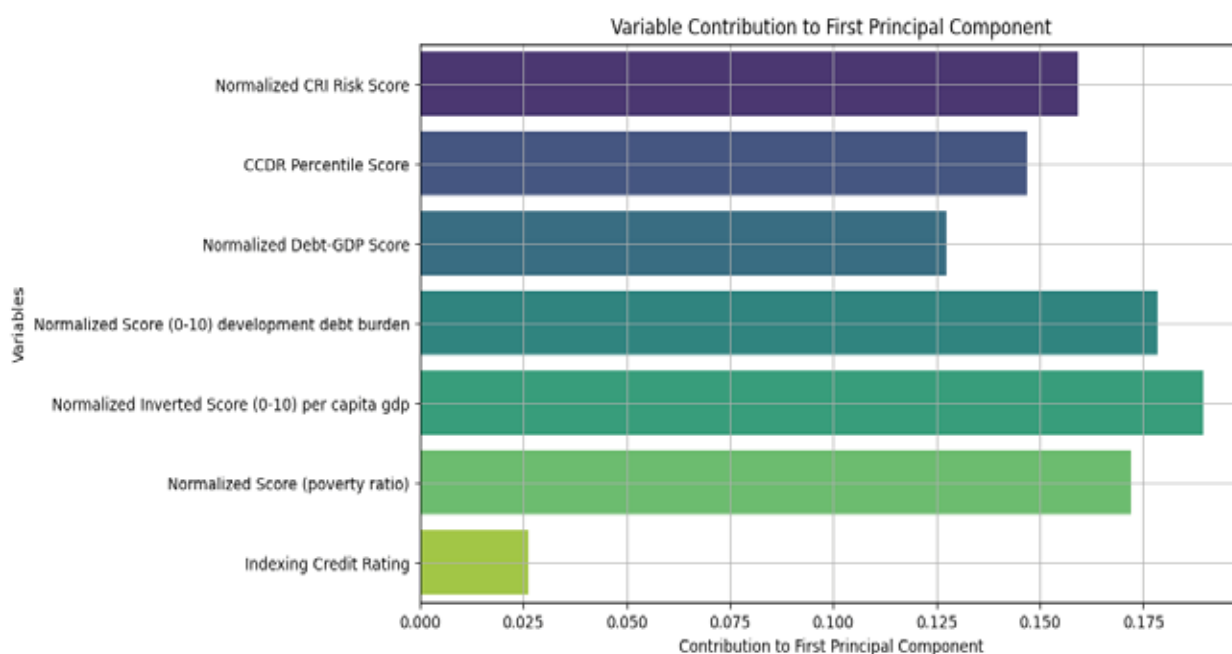


Figure 23: Variable Contribution to First Principal Component

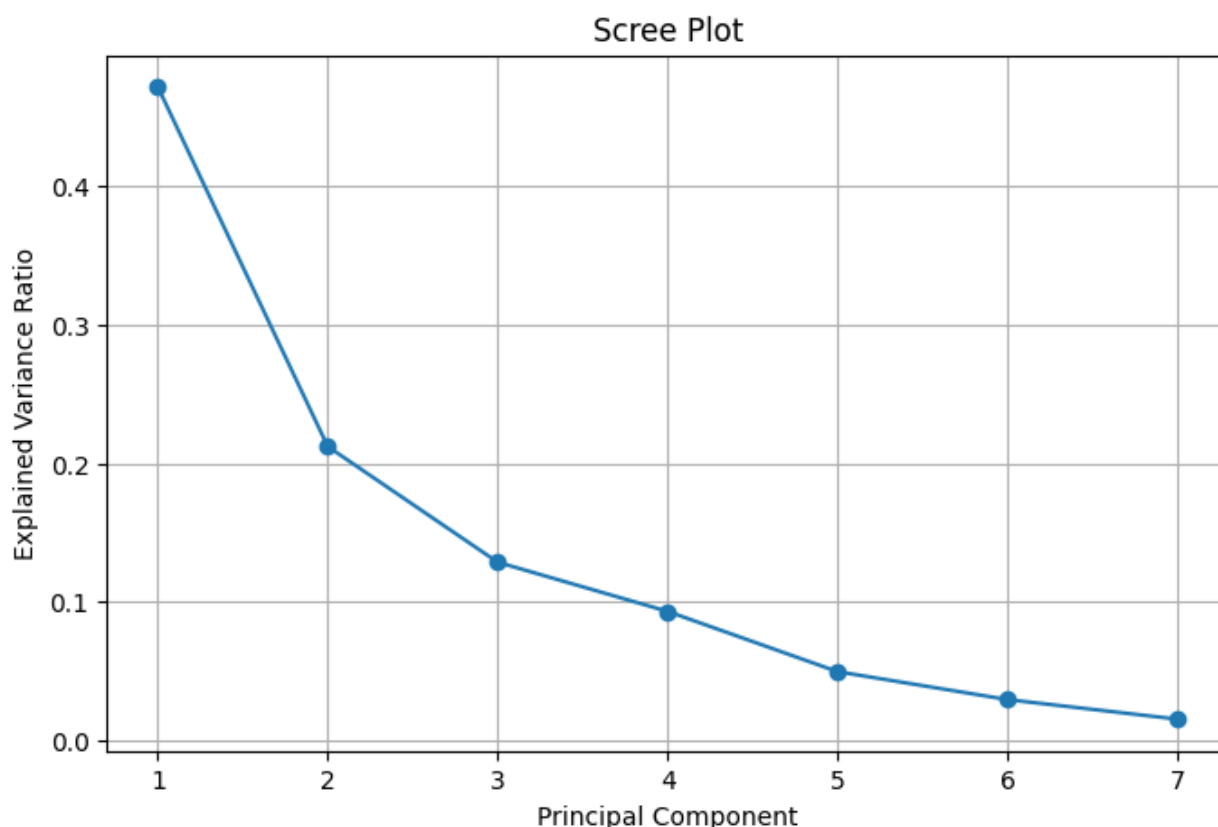


Figure 24: Explained Variance Ratio vs Principal Component

Key Insights from PCA:

- **CRI Risk Score** explains the largest share of the variance (47.2%), making it the most important variable in the dataset in terms of explaining differences in CDRI scores.
- **CDDR Percentile Score** explains 21.2% of the variance, confirming its strong role in the data.
- The remaining variables (Debt-GDP, Development Debt Burden, Per Capita GDP, Poverty, and Credit Rating) explain smaller portions of the variance, with Credit Rating contributing only 1.5%.

The **Multiple Linear Regression** analysis identified the **CDDR Percentile Score** as the most significant predictor of the **Climate Debt Risk Index** with a beta coefficient of 0.754, followed by the **Poverty Ratio** (0.431) and the **CRI Risk Score** (0.384). This suggests that these variables have the largest impact on climate debt risk, aligning with the decision to assign higher weights to these factors in our CDRI formula. Other

variables, such as **Credit Rating** and **Development Debt Burden**, had smaller contributions, indicating that their influence on climate debt risk may be more moderate than initially expected.

The **Principal Component Analysis (PCA)** supports these findings, with the **CRI Risk Score** explaining the largest share of variance (47.2%), followed by the **CCDR Percentile Score** (21.2%). These results suggest that these two variables capture the majority of the variance in the CDRI data, further justifying the higher weights assigned to them. In contrast, variables like **Credit Rating** and **Poverty Ratio**, while important, explain smaller portions of the variance and may not require as much weight in the final CDRI model.

Optimizing the **Climate Debt Risk Index (CDRI) weights** requires a robust methodology to ensure the index accurately reflects the underlying phenomenon. We employ a **least-squares minimization** approach to refine the variable weights, enhancing the CDRI's explanatory power. This optimization process begins with the current CDRI weights as a starting point. Subsequently, an iterative optimization algorithm adjusts these weights, minimizing the discrepancy between the calculated CDRI values (derived from the weighted sum of the constituent variables) and the empirically observed or theoretically expected CDRI values. This iterative process seeks to identify the optimal weight configuration that best captures the complex interplay of factors contributing to the CDRI.

The result is as follows:

| | |
|----------------------|---|
| Optimized Weights | Normalized CRI Risk Score: 0.0248 |
| | CCDR Percentile Score: 0.3583 |
| | Normalized Debt-GDP Score: 0.0000 |
| | Normalized Score (0-10) development debt burden: 0.0000 |
| | Normalized Inverted Score (0-10) per capita gdp: 0.4433 |
| | Normalized Score (poverty ratio): 0.0283 |
| | Indexing Credit Rating: 0.1453 |

Figure 25: Result of Weight Optimization

The analysis of the **Climate Debt Risk Index (CDRI)** using **Multiple Linear Regression** and **Principal Component Analysis (PCA)** provided critical insights into variable influence, leading to empirically driven adjustments to the weighting scheme. These

refinements enhance the index's effectiveness in measuring climate-related financial risk, with findings organized as follows:

1. **Multiple Linear Regression Insights:**

- The regression analysis identified the **CCDR Percentile Score** and **CRI Risk Score** as primary contributors to climate debt risk, supporting increased weights for these variables. The **Poverty Ratio** also emerged as a key factor, emphasizing the importance of socioeconomic vulnerability in the index. Economic indicators like **Credit Rating** and **Per Capita GDP** had moderate influence, suggesting they should maintain balanced but secondary weights. The **Development Debt Burden** and **Debt-GDP Ratio** had minimal impact, indicating they are less critical in assessing climate vulnerability.

2. **Principal Component Analysis (PCA) Insights:**

- PCA results reinforced the importance of the **CRI Risk Score** and **CCDR Percentile Score**, as these explained a significant portion of the variance. **Poverty Ratio** and **Per Capita GDP** also accounted for a notable share, highlighting the role of economic resilience in climate risk. Lower variance for **Credit Rating** and debt indicators supports the need for reduced emphasis on these factors in the CDRI.

3. **Implications for CDRI Weighting and Policy Recommendations:**

- Based on regression and **PCA** findings, adjustments to the **CDRI** weightings increase the emphasis on climate burden and socioeconomic vulnerability while reducing the role of debt indicators. This makes the **CDRI** more responsive to real-world drivers of climate debt risk, capturing vulnerabilities more accurately across countries. From a policy perspective, the optimized **CDRI** serves as a tool to prioritize climate adaptation and support efforts in countries with high climate burdens and socioeconomic vulnerability, where resources are most urgently needed.

We conducted heteroscedasticity **tests** to assess the reliability of the regression model used in calculating the **Climate Debt Risk Index (CDRI)**. Heteroscedasticity, or inconsistent variance of residuals, can indicate model instability and affect the accuracy of results. By performing the **Breusch-Pagan** and **White's tests**, we aimed

to confirm that the variance of residuals remained constant across all levels of independent variables, ensuring the robustness of the CDRI model.

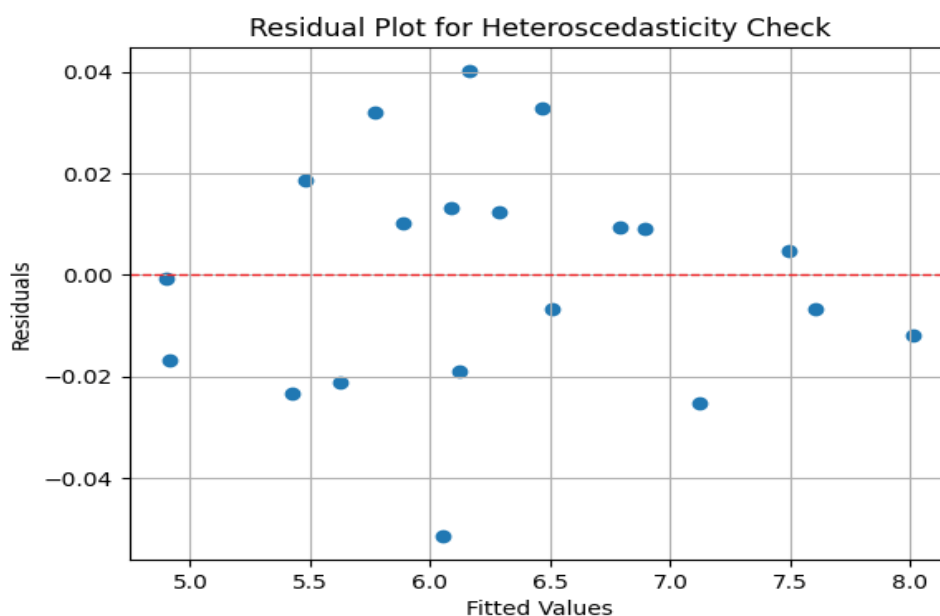


Figure 26: Residual Plot for Heteroscedasticity Check

Here's a table summarizing the Breusch-Pagan and White's Test results for heteroscedasticity in the Climate Debt Risk Index model:

Table 9: Result of Heteroscedasticity Tests

| Test | Lagrange Multiplier Statistic | p-value | f-value | f p-value |
|-------------------------------|----------------------------------|---------|---------|--------------|
| Breusch-Pagan Test | 8.037 | 0.3293 | 1.1518 | 0.3953 |
| White's Test | 20.0 | 0.3946 | N/A | N/A |

The results from the **Breusch-Pagan** and **White's tests** indicate that **heteroscedasticity is likely not present** in the model's residuals:

1. **Breusch-Pagan Test:**

- o The **p-value** of **0.329** is well above the typical significance level of 0.05, suggesting that we do not have sufficient evidence to reject the null hypothesis of homoscedasticity. This means that the residuals' variance does not appear to be dependent on the independent variables.

2. **White's Test:**

- o Similarly, the **p-value** of **0.395** suggests that we cannot reject the null hypothesis of homoscedasticity. This indicates that there is no strong evidence of non-linear heteroscedasticity either.

Overall, these results imply that the residuals in the model are likely homoscedastic, meaning they have a consistent variance across all levels of the independent variables. This consistency supports the reliability of the regression model and indicates that additional adjustments for heteroscedasticity may not be necessary.



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