Global Climate Change Adaptation and Resilience Finance (GCARF) Database

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Table of Contents

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I. Introduction

Funding for developing and vulnerable countries and communities to adapt to climate change is severely inadequate. According to a study led by Professor Garschagen at the Ludwig Maximilian University of Munich, half of the nations at greatest risk from climate change impacts did not receive any or sufficient funds for adaptation projects from the UN's Green Climate Fund (the largest fund for climate change adaptation). Some of the reasons mentioned by the study for the inadequate funding support include a lack of human resources, data, and infrastructure to get access to funding, as well as the broad scarcity of international funding for adaptation. As the effects of climate change increase in frequency, intensity, and magnitude, helping developing countries and vulnerable communities to adapt is equally as important as climate change mitigation. Moreover, adaptation initiatives, especially through the use of nature-based climate solutions, can help mitigate climate change too. Yet, little attention has been given to assessing the geographical areas, communities, and countries' relative risk to climate change impacts (hereafter referred to as 'climate risk') and the amount of adaptation funding provided (or needed). Thus, this project was conceived to address the following questions:

(1) How does the vulnerability to disasters related to climate change (such as droughts and floods) vary across space?
(2) How is the adaptation funding provided by UNFCCC-affiliated programs proportional or disproportional to the vulnerability and degree of climate risk of countries?
(3) What is the effect of adaptation funding on vulnerability and climate risk?
(4) What is the state of nation-level empirical data on climate risk?

II. Methods

II-1. Verifying Data

(1) EM-DAT

The EM-DAT International Disaster Database is a comprehensive database consisting of global data and information of disasters that occurred from the year 1900. Managed by the Center for research on the Epidemiology of Disasters (CRED), the database is active and well-known for disaster damage assessment.[3]

Each row represents a single disaster and includes information on the disaster (i.e. group, type, subtype, name), damage (i.e. number of people affected, reconstruction costs), geographical information (i.e. country, region, location), and temporal information (i.e. start date, end date).

As observation and record techniques have improved over the years, the data on the disasters that happened in the early years have a lot of missing values. Therefore, we decided to consider disasters occurred after 1980. For the three main metrics that we are interested in—total number of deaths, total number of affected people, and total economic damages (USD)—79.12%, 68.92%, and 21.36% of the disasters had values, respectively. When examining the economic damages metric, users must take this into account for their analyses.

(2) Finance

The finance dataset is obtained from the United Nations Framework Convention on Climate Change Climate Finance portal. Datasets for adaptation-related programs/finance mechanisms were chosen if they supported adaptation initiatives in countries. From these datasets, we extracted the amount of financial support (in USD or converted to USD), the year of the initiation of the adaptation program/allocation of funds for the program, and the recipient country or countries.

II-2. Tidying Data

We used the R programming language R version 4.2.1 to conduct data cleaning and visualization. Additional packages used include: shinythemes_1.2.0; hrbrthemes_0.8.0; magrittr_2.0.3; plotly_4.10.0; tidyverse_1.3.2; and shiny_1.7.2.

(1) EM-DAT Data

We filtered the raw dataset based on the temporal range and type of disasters we are interested in. Disasters that happened after the year 1980 are considered. On top of that, out of the different types of

[3] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8552254/

disasters, the ones that are related to climate change are considered. They are droughts, mass movements, storms, floods, epidemics, landslides, wildfires, extreme temperatures, and insect infestations.

For the disasters that happened throughout multiple years, we made the disasters represent multiple rows, where one row represented a single year. For the metrics, we assumed that the casualties happened evenly across the time period. Therefore, we divided the metric values by the number of years and assigned them evenly. Also, we kept the decimals when dividing casualties, even for human related metrics.

Also, as the data include disasters occurred from the year 1980, some of them happened in countries that disappeared. For these cases, we have interpreted and combined the data with the modern context. For example, we included disasters that happened in East and West Germany to Germany.

For the lives lost and humans affected metrics, we divided the values into 100,000 and assigned it to the lives lost per 100,000 people metric and humans affected per 100,000 people metric. We used the population data from the World Bank. For the total damages metric, we adjusted the values using the base year and 2022's consumer price index. The consumer price index was included in the raw EM-DAT database.

After filtering and tidying the raw dataframe, we exported the dataframe as emdat_final.csv. Our app is based on this dataframe.

(2) UNFCCC ClimateFinance Data

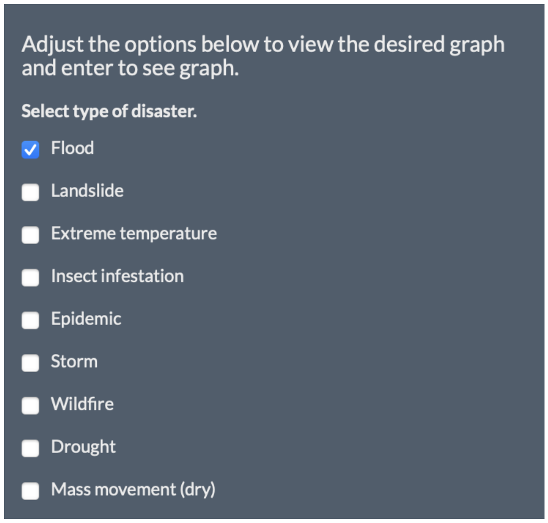
Several subsidies were provided to multiple countries. For these cases, we assumed that the subsidies were divided evenly across countries. Therefore, we divided the total subsidy with the number of countries and assigned it evenly. After the division, we exported the dataframe as finance_tot.csv. Our app is based on this dataframe.

III. Shiny App

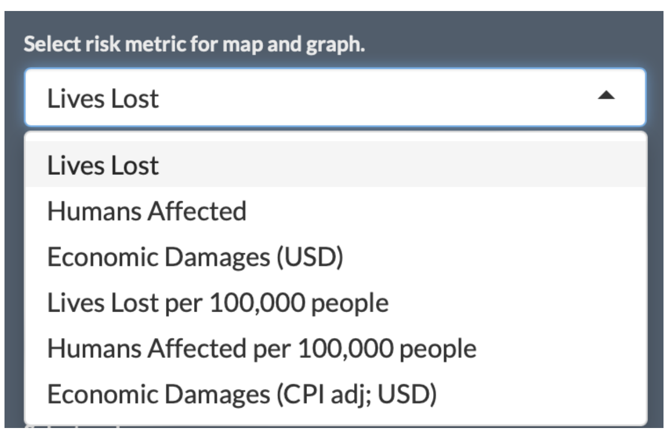
Access application **here**.

(1) Side Panel

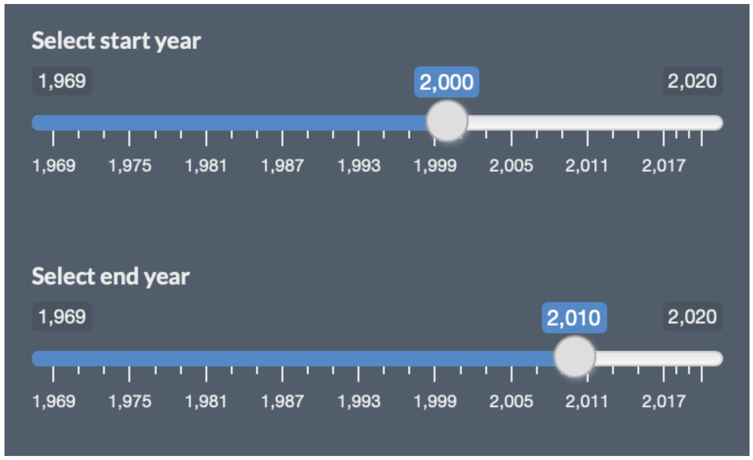
The side panel allows users to input variables that they are interested in.



The first part allows users to select the type of disaster. Users can select multiple disasters, and the output will be aggregated.



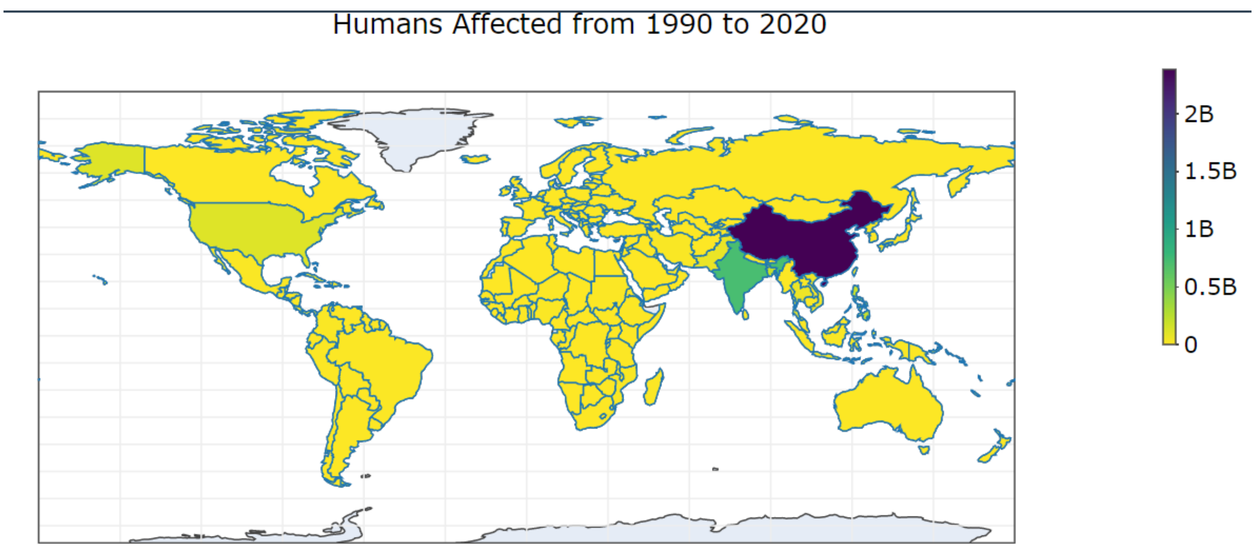
The second part allows users to select the impact metric. There are 6 available metrics, which are: lives lost, humans affected, economic damages (USD), lives lost per 100,000 people, humans affected per 100,000 people, and CPI adjusted economic damages (USD). Only one metric can be selected per action.



The last part consists of two sliders that allow users to select the year range. The top and bottom slider each defines the start and end year. After choosing the variables, users should press the enter button to generate plots. Users can easily change the type of disaster(s), impact metric, and temporal range through the side panel, and the graph will be updated after clicking the enter button.

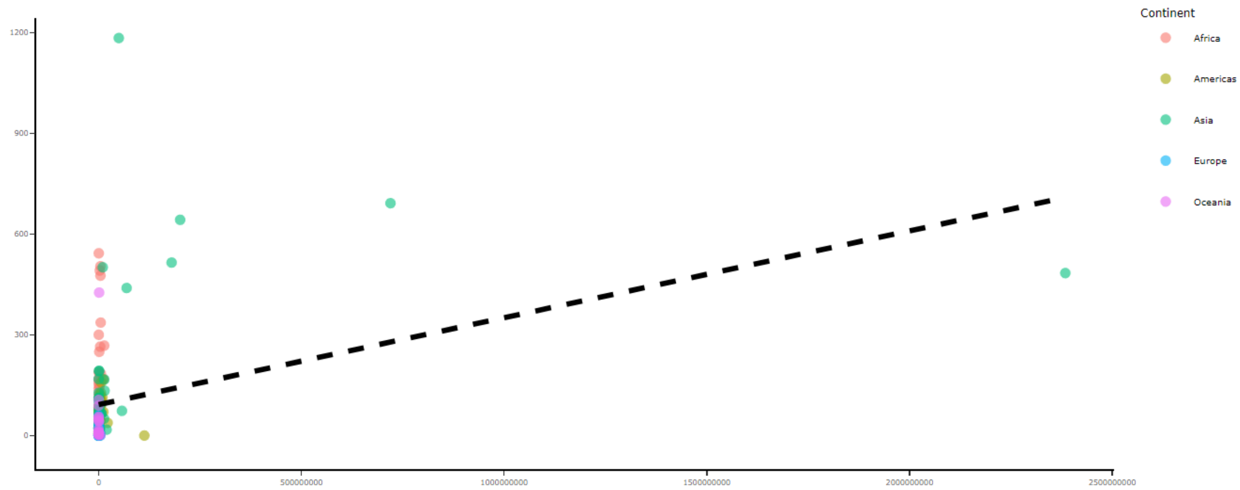
(2) Choropleth

The first graph that is shown is an interactive global-level choropleth. This choropleth successfully shows the value of the chosen metric (number of humans affected by flood, landslide, and storms) in a certain period of time (1990 - 2020) using viridis colors, with darker colors signifying larger numbers. Users can hover on top of the map and view the ISO-3 code of the country and the value for the metric.



(3) Risk:Finance Scatterplot

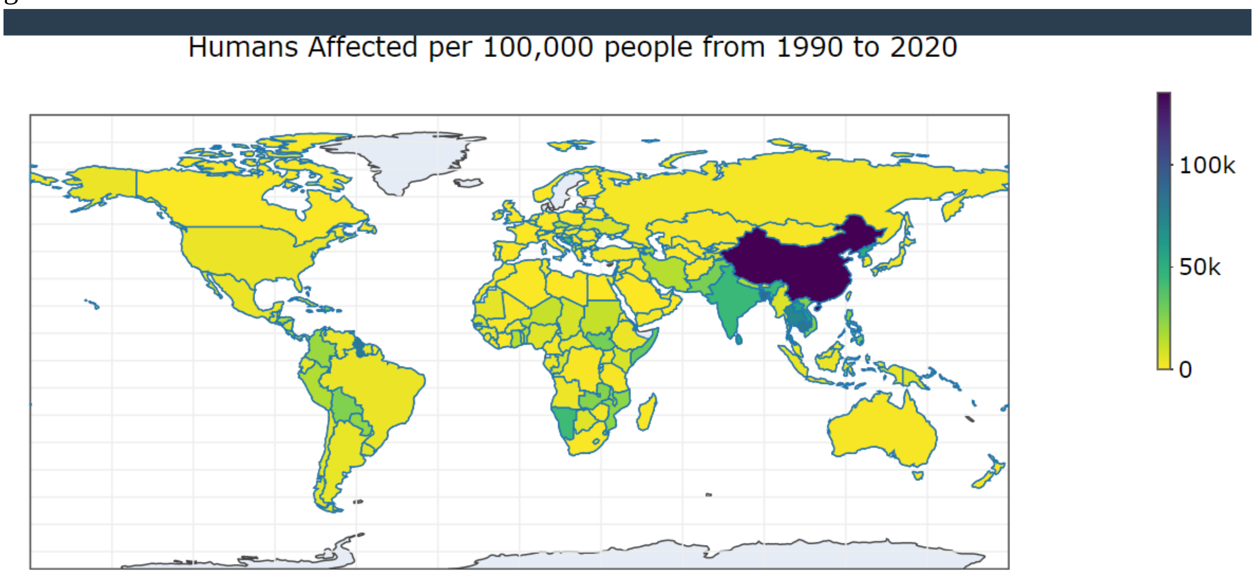
The graph below illustrates the relationship between the degree of climate risk and the adaptation funding provided. The horizontal axis is the metric chosen based on disaster type and range of years. The vertical axis is the funding (USD, millions) provided to the countries in the range of years. The countries are colored based on their continents. A dashed regression line is fitted.



IV. Analysis

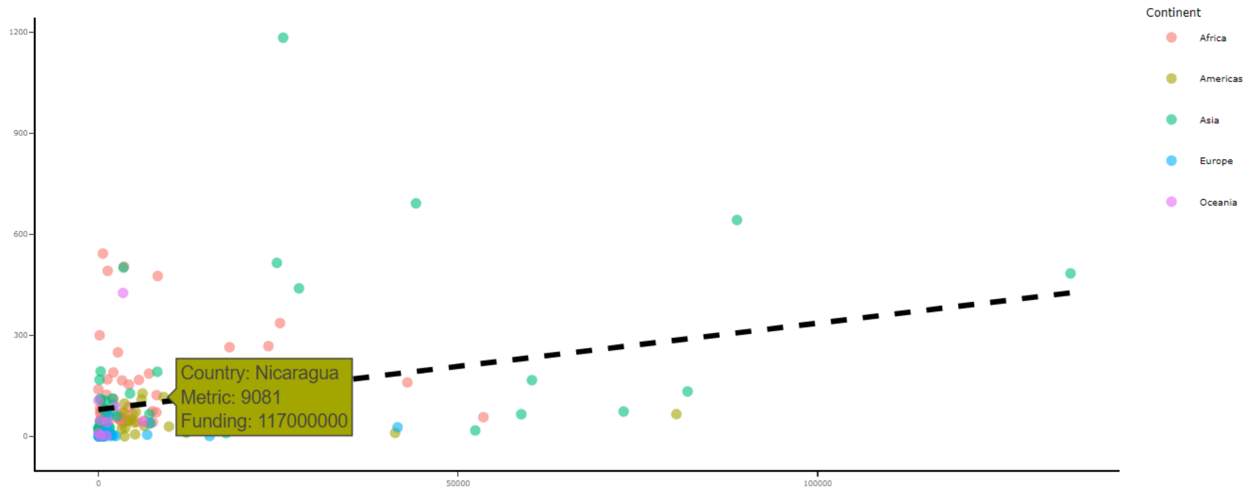
IV-1. Choropleth Map

The choropleth is effective in illustrating the spatial and temporal variations in the degree of climate risk and vulnerability across space, based on the different types of climate change-related disaster and chosen metric. The choropleth below depicts the number of humans per 100, 000 affected by floods from 1990 to 2020. As seen, China has 135,000 individuals affected in this span of 30 years (greater than 100,000 likely due to their large population). Other South Asian and Southeast Asian countries are at relatively greater risk from floods.



IV-2. Risk:Finance Scatterplot

The risk:finance scatterplot is a very useful tool to assess how proportional/disproportional the adaptation funding provided to a country is with regards to the degree of climate risk. In illustrating the data with a regression line, users can compare the climate risk and adaptation funding between countries. **In general,** countries near the top right corner receive more funds but are at greater risk; countries near the top left corner receive more funds but are at a smaller risk; countries near the bottom left corner receive fewer funds and are at a smaller risk (or have less data); and countries near the bottom right corner receive fewer funds but are at a greater risk. The scatterplot below illustrates the number of humans per 100, 000 affected by floods from 1990 to 2020.

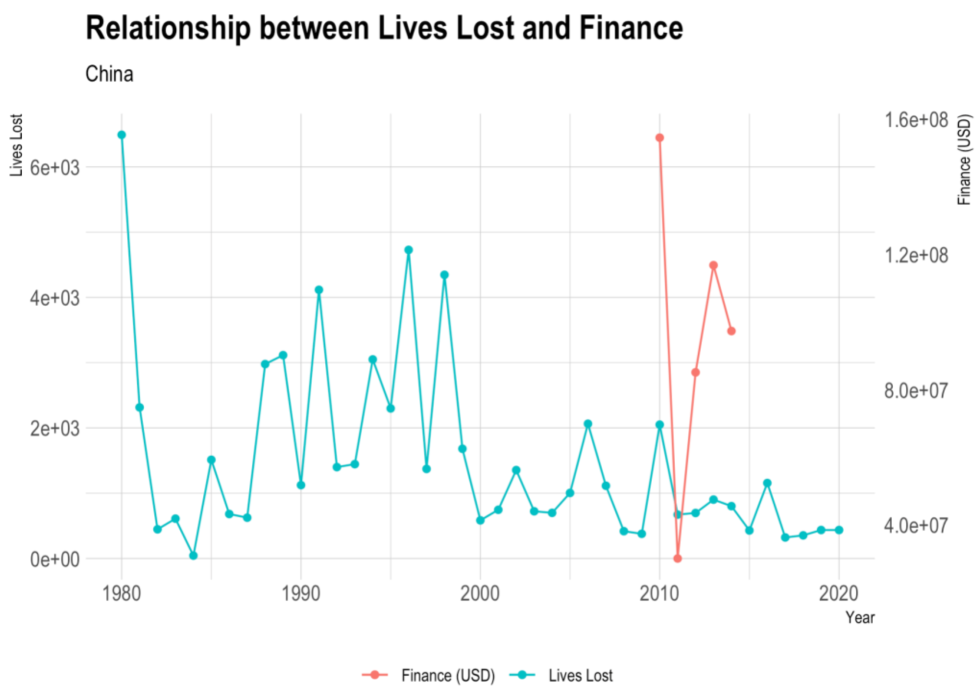


IV-3. Impacts of Financing over Time

Now, we are interested in how different metrics differ over time, and what the impacts of financing are. Using the Graph3.R script, we can generate graphs that show both the trend of a certain metric and the amount of funding provided in a certain country.

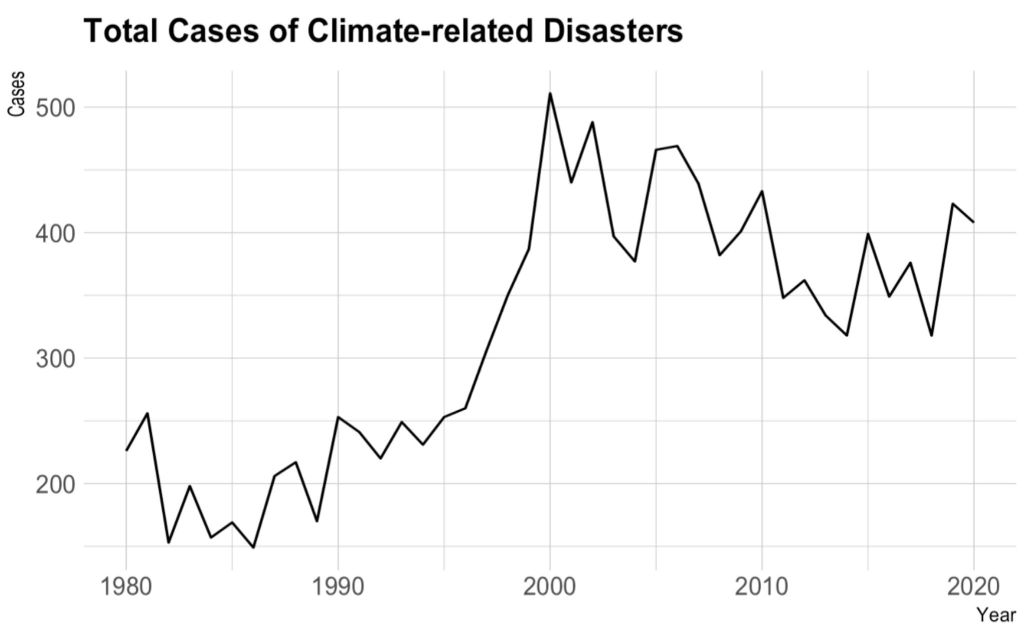
```
#input metric (character value)
metric <- "Lives Lost"

#input country (character vector)
country <- Global

#input disaster (character vector)
disaster <- c("Drought", "Flood", "Storm")
```

The code consists of three inputs—*metric* as a character value, and *country* and *disaster* as a character vector. For the *metric* input, users can input one out of the six impact metrics as a character value. For the *country* input, users can input as many iso values as they want to. If a user is interested in looking at a certain region, users can input either one of LAC, SA, SSA, ECA, MENA, EAP, NorthA, and Global, each representing Latin America & Caribbean, South Asia, Sub-Saharan Africa, Europe & Central Asia, Middle East & North Africa, East Asia & Pacific, North America, and global countries. Lastly, users can input as many types of disasters as a character value to *disaster*. After inputting values, running the whole R script will result in a graph that looks like the following.

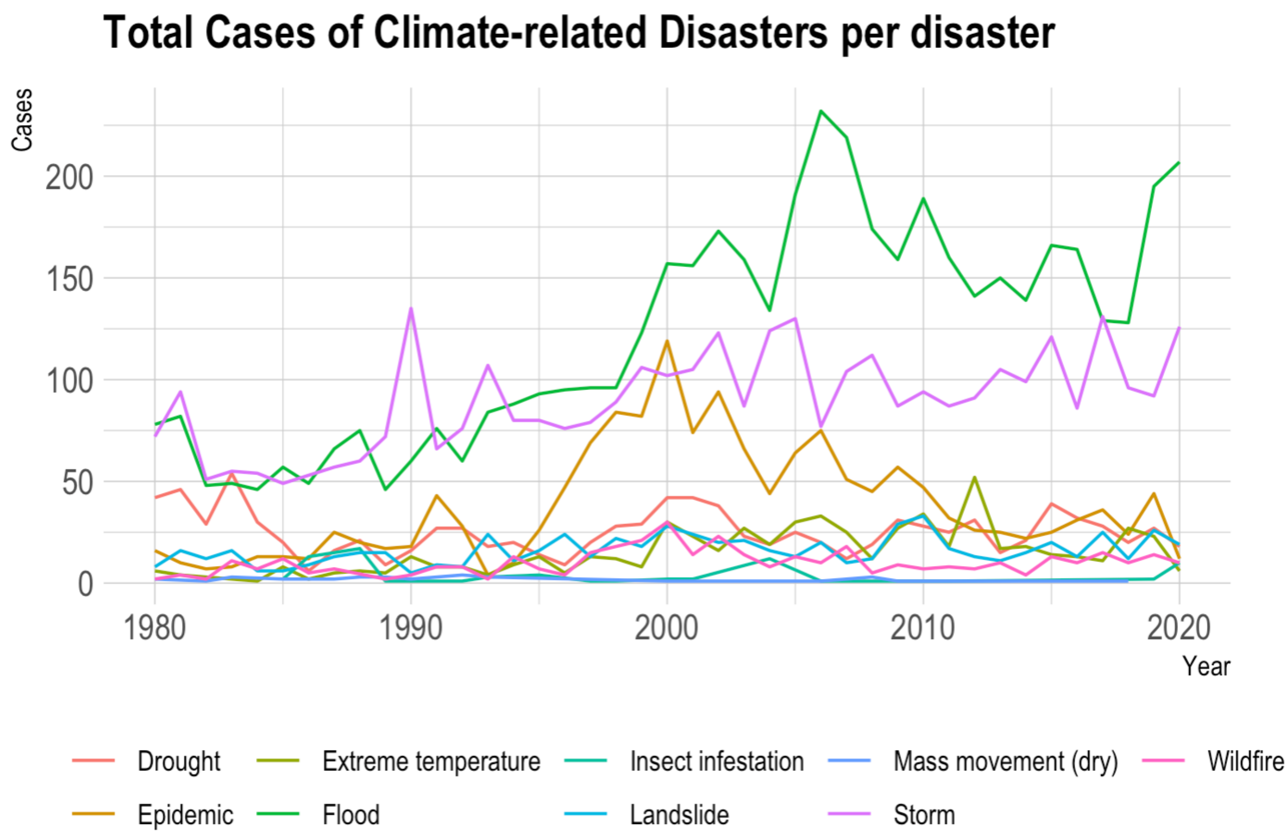


(1) Total Number of Cases

First, we decided to investigate the total cases of disasters that happened from 1980 to 2022. As the total number of cases is not one of the six impact metrics, we used a different R script to generate these graphs. We looked at the number of total cases of climate related disasters throughout the years on a global scale.



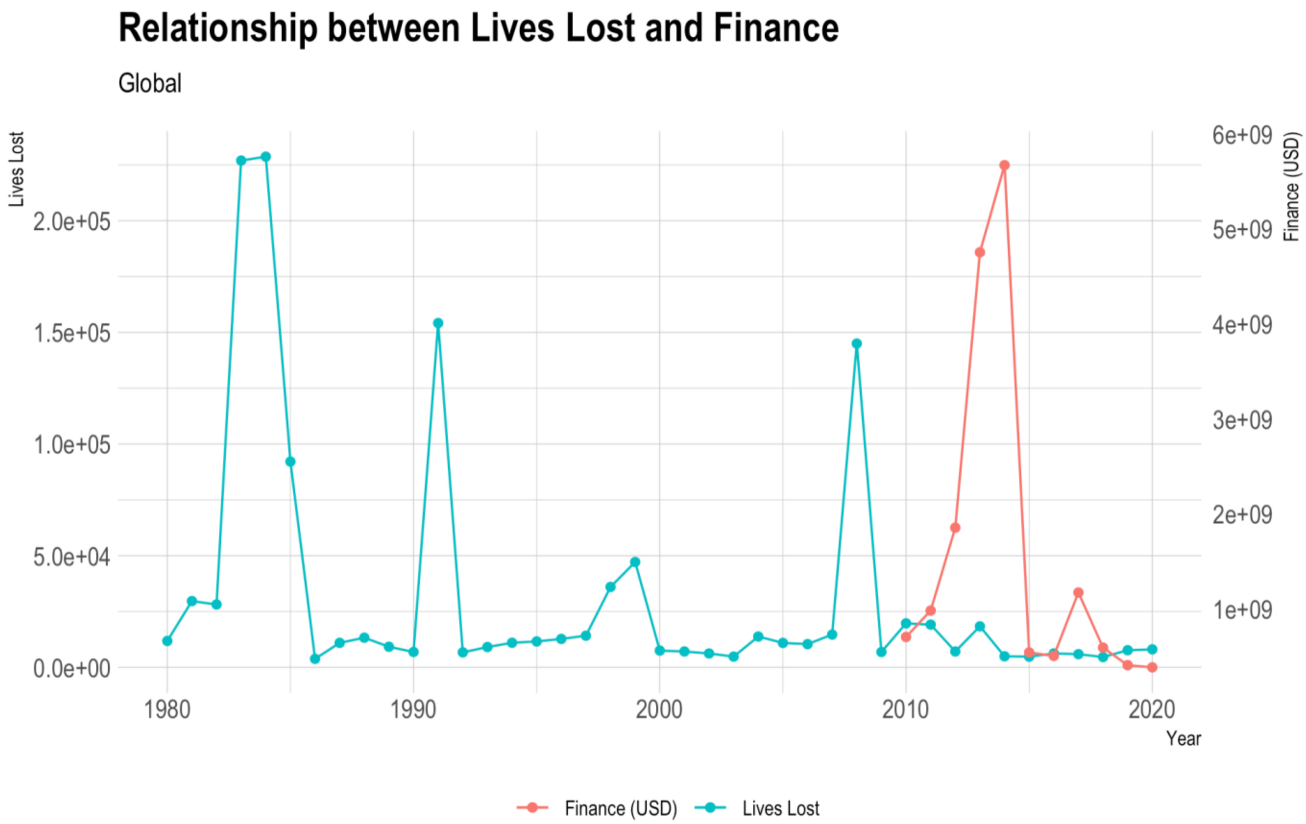
From this graph, we can see that the total number of climate related disasters that happened in the world increased from the year 1980 to 2000, then gradually decreased from 2000 to 2020. Regarding the increase from 1980 to 2000, a factor we should consider aside from climate change is the development of data collection techniques. Also, we can conclude that the global resilience against climate change increased after the year 2000.



We have investigated the total cases of climate related disasters but per type of disaster through the graph above. It is seen that the trend is quite different per different types of disasters—while the number of epidemics have drastically decreased from the year 2000, floods and wildfires kept on increasing even until now.

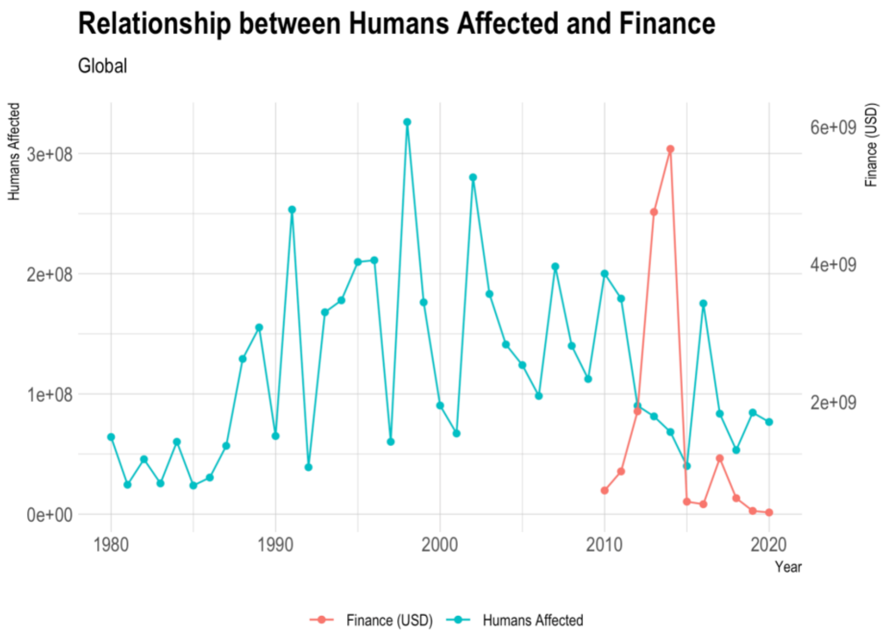
(2) Lives Lost

We are interested in how the lives lost metric changes over time, and by overlapping finance data, we will be able to infer the relationship of finance subsidies with the trend.



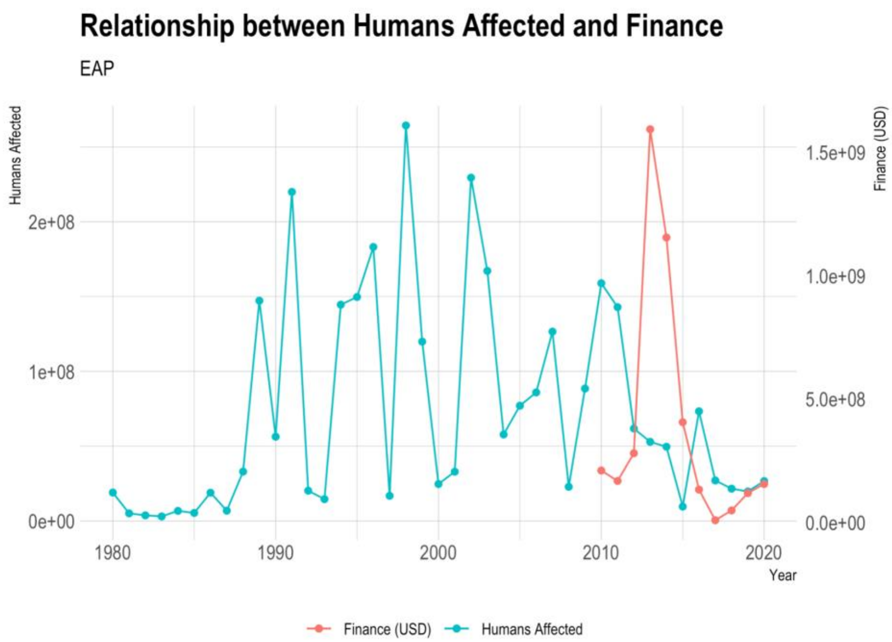
As seen from the graph above, we can see that the lives lost metric has been decreasing over time. A lot of funding projects have been implemented between 2010 and 2015, and we can conclude these financing projects have affected the decreasing trend of lives lost.

(3) Humans Affected



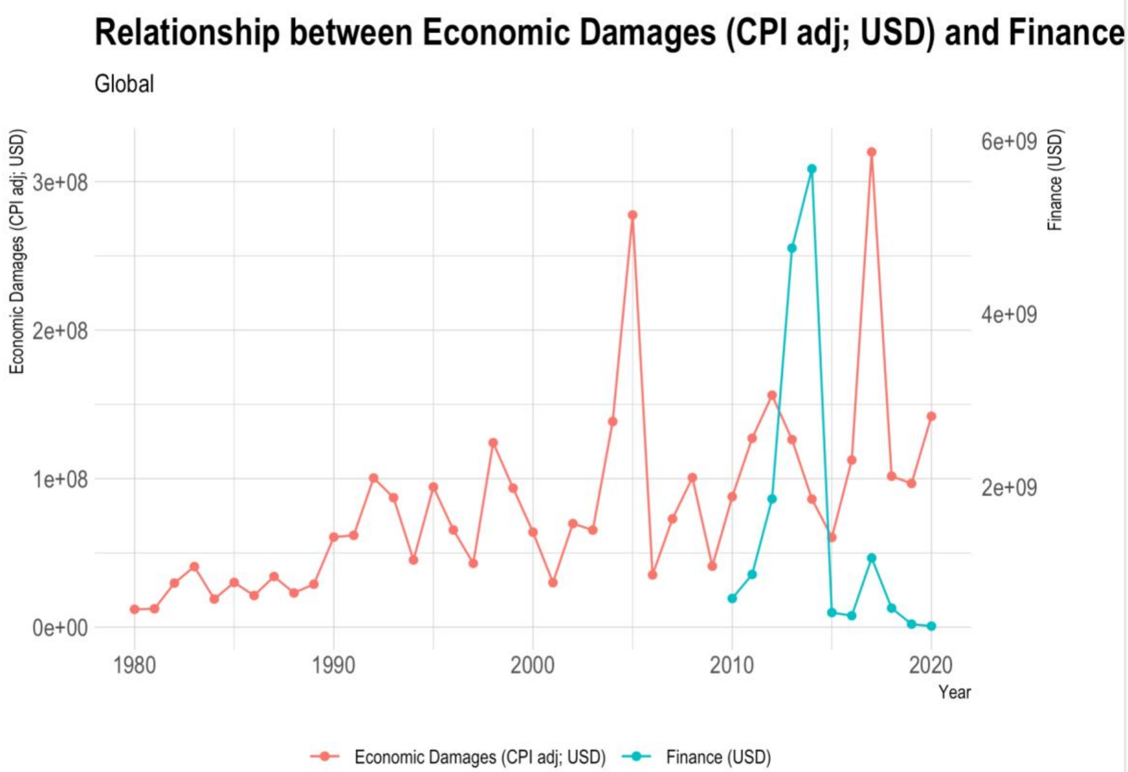
In a similar vein, we can see that the number of humans affected starts decreasing between 2000 and 2005. We can also conclude that financing projects have affected the decreasing trend.

Next, we are interested in specific disasters—floods and storms— happening in the East Asia and Pacific regions.



We can lead to a similar conclusion on this graph as well. Generally, we see a trend where the metric starts to decrease between 2000 and 2005, and it is inferable that the financing projects are relevant to this trend.

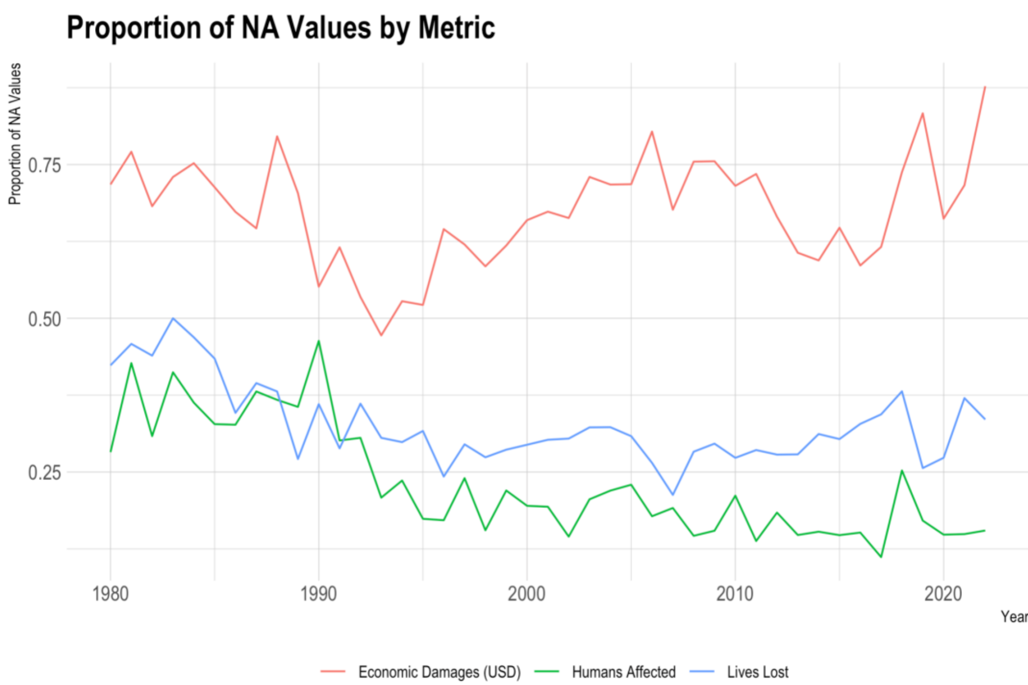
(4) Economic Damages (CPI Adjusted; USD)



For CPI adjusted economic damages, the results show a different trend. First of all, different from other metrics, the damage keeps on increasing over time, even after financial projects come in. Further investigation is required to find out the reason for this trend. We should also consider that more than 70% of the disasters do not have economic damage data, which we will examine in the following section.

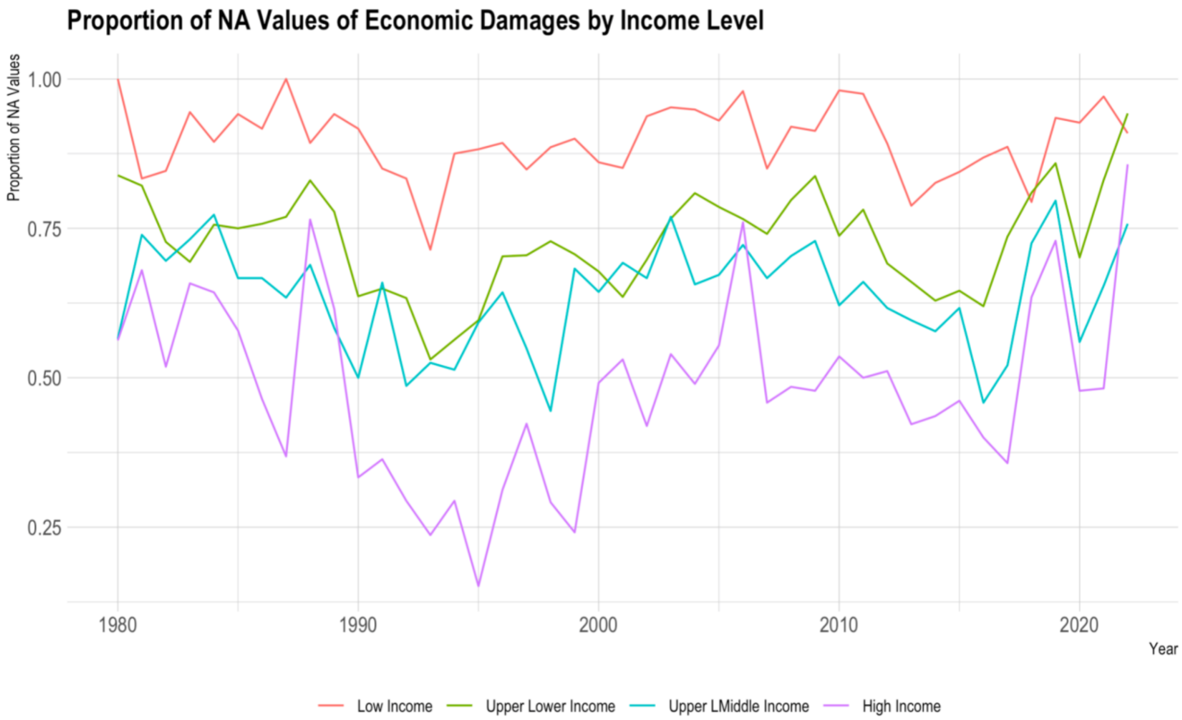
IV-4. NA Values

As briefly mentioned in III-1-(1), for total number of deaths, total number of affected people, and total economic damages (USD), 79.12%, 68.92%, and 21.36% of the disasters had values, respectively. As NA values itself implies how countries are doing with data collection of the disasters that happened, we examined the data closely.

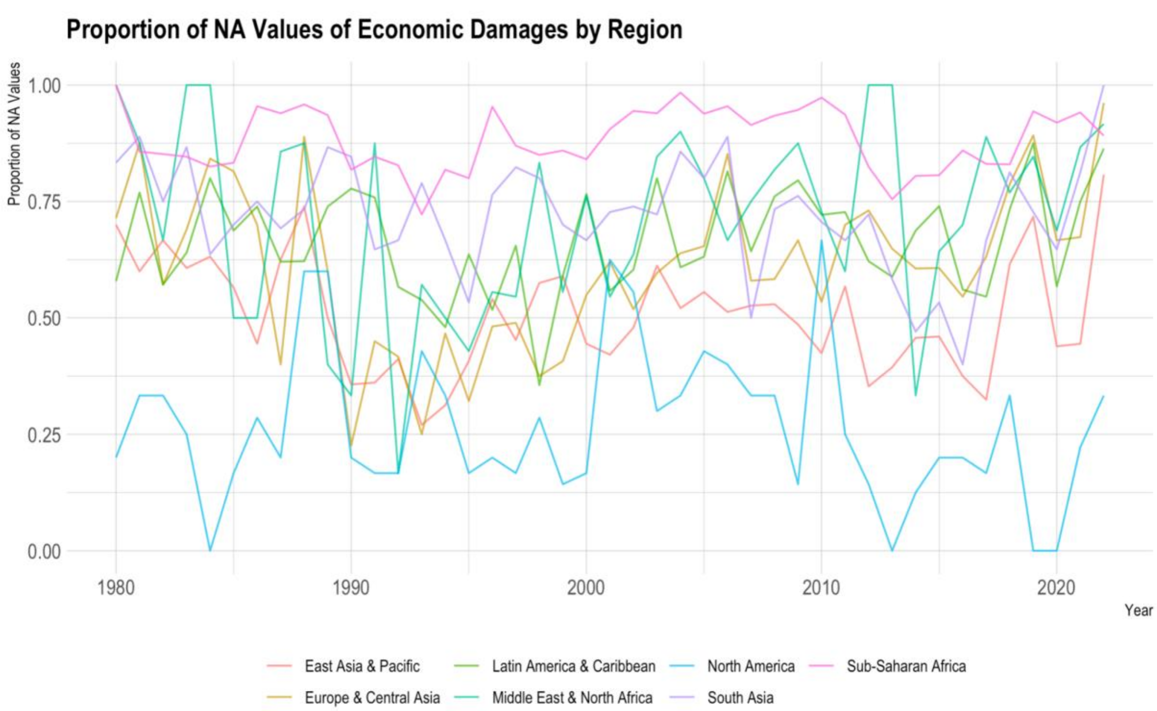


As seen from the graph above, for the humans affected and lives lost metrics, we can see that the proportion of NA values decrease over time. This aligns with our assumption that the proportion of NA values will decrease as data collection technology develops and the need for accurate data collection increases. However, compared to the other two metrics, economic damages were not tallied properly throughout the years, resulting in a high proportion of NA values.

We decided to take a look into the difference in proportion of NA values of economic damages per income level of countries. We used the income level metric provided by the World Bank, which consists of 4 levels—high income countries, upper middle income countries, upper lower income countries, and low income countries.



From the graph above, it is clearly shown that as the level of income is higher, the proportion of NA values of economic damages decreases. It is inferred that countries with lower income lack the ability to track data of economic damages caused by disasters, which is the very first step to increase climate resilience.



This time, we investigated how the proportion of NA values of economic damages differ by region. We used the region classification provided by the World Bank—East Asia & PAcific, Latin America & Caribbean, North America, Sub-Saharan Africa, Europe & Central Asia, Middle East & North Africa, and South Asia. Though there is not a distinct difference shown between regions, it is comparatively apparent that North American and European & Central Asian countries are doing well with data collection.