Impact Distribution of Consecutive Events – A Global Hotspot Analysis

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MSc Econometrics and Operational Research - Climate Econometrics

August 2022

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Acknowledgements

In this year of becoming, this Master Thesis exceeded both my expectations regarding my limits, as well as my perceptions of how difficult it is to do research. I would firstly like to show my utmost appreciation to my girlfriend, Dumitrache Anca, whose love and care could end droughts and calm the storms, if only they could listen to her. I would also like to thank my supervisors, Dr. Marleen de Ruiter and Dr. Marina Friedrich, for the guidance, expertise and, most importantly, for their patience. This was a lovely, challenging and rewarding endeavour.

Abstract

This study proposes a global perspective of consecutive disasters, as defined by specific definitions of climate disasters and disaster chains. The dataset for the analysis is constructed by taking observations from the EM-DAT dataset and enriching them with demographic information. The analysis interprets the global impact of each combination of hazards in a disaster chain, as well as how each international region was affected by them. Three case studies are discussed in detail: Western Europe, South-Eastern Asia and Southern America. Results indicate that most damages occur in consecutive disasters that have a short frame of time in between them. Findings also confirm existing research that secondary disasters have a significantly higher financial impact and consecutive disasters are more damaging than the sum of the component disasters. Regression results show that disasters tend to increase in impact over time and large, developed countries tend to have the highest financial loss.

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1 Introduction

Throughout history, climate hazards had an enormous impact on society, from city placement to avoid such events to the deification of various natural elements in the hope of disaster minimisation. Even if society has evolved, our capacity to decrease the impact of hazards is still limited, as one is still terrified and awed by the Mount Vesuvius eruption in 79 AD, as well as by the Fukushima earthquake in 2011. However, data from the modern period shows that climate change exacerbates the impacts of disasters, and this is becoming ever more evident as time passes by and more data is gathered.

The study of hazards is complex and the difficulty in finding predictors and correlations increases in line with the effects felt from climate change. Observing hazards as single events misses out on a wide array of factors derived from contextualising them into sequences of disasters, especially with regards to the expected impact such disasters tend to have. In particular, hazards that interact have been shown to have a significantly higher impact than the sum of the hazards by themselves [Terzi et al., 2019]. This shows that events must be analysed by also taking in consideration what has happened prior, as well as posterior to that specific hazard, in a holistic multi-hazard approach.

There are numerous reasons for which such a conceptual multi-hazard perspective is beneficial. Firstly, more accurate forecasts can be done, which will better predict the financial impact of different series of events. These forecasts could allow for better cost-benefit analysis and point out the most damaging pairs. Regarding abatement, synergies between preventive measures could target the same group of hazards or could be applicable as effective measures against the most damaging pairs. For example, a better control of water resources could alleviate the effects of both droughts and floods [Kalantari et al., 2018]; stronger foundations for houses are helpful against both floods and earthquakes [Buchanan et al., 2011]. Furthermore, a good understanding of hazard interaction is important in viewing which primary hazards decrease the probability or intensity of secondary hazards, as well as how preventive measures have potential negative consequences for some types of hazard.

The main purpose of this study is to use quantitative techniques to form distributions of the disaster chains, segmented by region. This allows for a perspective on the hierarchy between the most damaging pairs and the regions which are most affected, information needed to forecast impacts and enact effective prevention measures. In order to address these concerns, this study proposes a global quantitative analysis on the impact of consecutive hazards. By analysing the EM-DAT dataset, enriched with information from World Development Indicators, several perspectives are proposed and the respective questions are answered. Section 3 describes the database in detail and introduces the main methodologies of analysis used throughout the study as well as the statistical techniques. Section 4.1 zooms in on three regions with different demographics and climates (Western Europe, South America and South-Eastern Asia), after which Section 4.2 presents a global analysis of some of the more complex interactions of disasters. Afterwards, Section 4.3 compares different hazards and the way the expected impact differs depending on the order of hazards and them being part of a disaster chain. Finally, Section 4.4 introduces a regression analysis to determine the relevance and effect of demographic factors in forecasting financial impacts.

1.1 Terminology

Several terms, concepts and notations are being introduced, most of which are main concepts from hazard studies and some are particular to this research [Kelman, 2018]. UNDRR defines disaster risk as "the potential loss of life, injury, or destroyed or damaged assets which could occur to a system, society, or a community in a specific period of time, determined probabilistically as a function of hazard, exposure, vulnerability, and capacity." Hazard is defined as "a process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption or environmental degradation." Exposure refers to "the situation of people, infrastructure, housing, production capacities and other tangible human assets located in hazard-prone areas." Vulnerability is defined as "the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards." Lastly, capacity is "the combination of all the strengths, attributes and resources available within an organization, community or society to manage and reduce disaster risk and strengthen resilience" [Aronsson-Storrier, 2019] [Noy and Yonson, 2018] [UNDRR, 2016]. Thus, the four components of a disaster risk are the hazard, exposure, vulnerability and capacity, elements which are dynamic, depending on numerous other variables, and they shift in response to previous disasters that happened in the same geo-temporal context [Peduzzi, 2019]. The formula for risk could be interpreted as $risk = hazard * exposure * vulnerability/capacity$. Understanding consecutive disasters is part of a multihazard approach, defined by the United Nations Office for Disaster Risk Reduction to mean "the selection of multiple major hazards that the country faces, and the specific contexts where hazardous events may occur simultaneously, cascadingly or cumulatively over time, and taking into account the potential interrelated effects" [UNDRR, 2016].

Throughout this study the term consecutive disasters shall be used to mean two or more disasters that occur in succession, and whose direct impacts overlap spatially before recovery from a previous event is considered to be completed [de Ruiter et al., 2020]. This includes compound events (defined as the combination of multiple drivers and/or hazards that contribute to societal or environmental risk [Zscheischler et al., 2018]) and cascading events (defined as extreme events in which cascading effects increase in progression over time and generate unexpected secondary events of strong impact [Pescaroli and Alexander, 2015]). In particular, throughout this paper, the terms chain and disaster chain will be used exclusively for a series of two consecutive disasters, with primary denoting the first one and secondary being the second one chronologically.

2 Literature Review

2.1 Compound Impact

Several studies have approached the subject of multi-hazard impact, given its increasing importance and relevance, as underlined by the UNDRR. Gill and Malamud (2014) analyse the interactions between hazard types, observing how they affect the impact of subsequent events and the probability of occurrence, by either triggering or increasing the probability [Gill and Malamud, 2014]. The paper defines four types of hazard interaction: interactions where a hazard is triggered, interactions where the probability of a hazard is increased, interactions where the probability of a hazard is decreased, events involving the spatial and temporal coincidence of natural hazards. Another interaction distinction made in the literature is that of unidirectional versus bidirectional, where the former is defined as a primary hazard followed by a secondary hazard, and the latter includes feedback mechanisms from the secondary hazard influencing the primary hazard. The type of interaction between hazards further determines the intensity of their impacts, usually leading to an increase in the impact. The main tendency is for initial hazards to either trigger or increase the possibility of a secondary hazard, which has the potential to lead to cascades of disasters. For example, Gill and Malamud underline how an initial storm event may trigger flooding, which then triggers landslides. In turn, these landslides may trigger or increase the probability of further flooding through the blocking of a river or the increase of sediment within the fluvial system. In particular, storms, earthquakes and volcanic eruptions are prone to trigger a secondary event. On the other hand, landslides, volcanic eruptions and floods tend to be the secondary hazard most often caused by primary incidents. Findings also include the observation that a larger spatial overlap between hazards increases the chance of interaction, thus increasing the probability of the secondary disaster being triggered, as well as the intensity of the hazards. Moreover, after accounting for the spatial overlap, disaster interaction is also dependent on the temporal overlap. For example, in the case of storms triggering landslides, there is a high spatial overlap, as landslides occur in most places storms also occur, and high temporal overlap, as the presence of storms increases the water level, thus creating conditions for landslides.

Building on these findings and classifications, De Ruiter et al. further expand the understanding of consecutive disasters [de Ruiter et al., 2020]. Findings conclude that hazards have a global tendency to increase in terms of both frequency and impact. This is particularly damaging due to the fact that there is a strong trend for people to have more exposure, in terms of asset value, and are more vulnerable to disasters [Di Baldassarre et al., 2018]. The regions that are most at risk are the major agricultural sources and the ones comprised of low income countries [Mann et al., 2018]. It is, then, exceptionally important that the additional risks of consecutive disasters are taken into account. Besides the type of disaster sequence, the duration of time between each disaster is a significant factor in the impact, as well as in the capacity to adapt and decrease the vulnerability. The specific type of the impacted entity is also important when defining the spatial consequences of consecutive disasters, just as much as the interval between events matters for the timeline observations. Events can happen within the same country, but may not have overlapping direct effects. For example, storms in South-Eastern Asia are frequent and nationally the Philippines is hit by an average of 20 cyclones per year, but it is unlikely that the same village will be directly impacted by consecutive storms [Santos, 2021]. On the other hand, the area of impact from a single earthquake can coincide with several areas of impact from other events with a smaller spatial effect, such as storms, so it is not uncommon to see chains made of storms and earthquakes. Moreover, the impacted entity need not be spatially identical to the one in which the hazard has happened, as the regional supply of goods and services can be severely disrupted by various disasters [de Ruiter et al., 2020]. This is decidedly relevant for critical requirements, such as food, where severe impacts within a country can cascade to neighbours that depend on such goods.

2.2 Response to Disaster

The response each country has to disasters fluctuates non-linearly and non-intuitively. Research has shown that an increasing number of disasters does not lead to better policies regarding disaster risk reduction (DRR), and neither does disaster impact [Nohrstedt et al., 2021]. Nohrstedt et al. analysed the link between policy changes and several variables in turn, such as fatalities, affected people, economic losses and the number of events. The countries were segmented into low income, lower middle income, upper middle income and high income. The observations included a tendency to disregard disasters, in general. One reason for which countries that are repeatedly hit by intense disasters do not invest in DRR measures is the fact that they have to use capital and resources for recovery after the impacts. Therefore, it means that these countries have fewer capabilities to invest in proactive DRR measures, which is particularly relevant in the case where countries are either low income or lower middle income. The immediate requirements outweigh the importance of sustainable investment and this adds up with each disaster, leading to a continuously lower capacity to cope, recover and adapt. In particular, consecutive disasters may have a tendency to affect unprepared countries the worst. If there is a sequence of similar disasters, the latter ones might happen before the reconstruction is finalised, thus interrupting the flow of events. On the other hand, if the disasters are of a different nature, countries will be hit by different immediate requirements, which will cause additional strain on their budget [Tilloy et al., 2019]. On a similar note, the time interval between the events is relevant, as they can be concurrent or somewhat spread apart, and the interpretation might be different with regards to the type of disaster and the type and speed of recovery. The drivers of risk also vary with development and density, as urban areas have a higher exposure, whereas rural areas have higher vulnerabilities [Kc et al., 2021].

3 Methods

3.1 Data

Throughout this study, the standard will be to consider the national spatial scale in which disasters can be considered consecutive. The analysis, however, will focus on supra-national geographical regions, simply called regions from here onwards. The segmentation of regions and the component countries can be found in Table 13 of the Appendix. Furthermore, unless otherwise stated, a blanket approach is taken where two disasters are considered consecutive if the second one starts fewer than 100 days after the first one ended.

The data is obtained from two main sources, namely EM-DAT and World Development Indicators, each providing specific input. The main information is obtained from EM-DAT, a database which contains a selection of climate catastrophes and extremes that have happened worldwide since 1900, as well as their classification and their impact [D. Guha-Sapir, 2022]. The timeline of analysis is selected as 01.01.1960 - 31.12.2021. Based on the EM-DAT database specificities, several definitions and limitations were put in place. A disaster is defined as having at least the following: ten or more people reported killed, a hundred or more people reported affected, the declaration of a state of emergency and a call for international assistance [D. Guha-Sapir, 2022]. The data was further subsetted to contain only natural disasters, thus excluding the technological ones. Moreover, several disasters with a low count were excluded (animal accident, glacial lake outburst, impact and fog). As such, the disasters to be analysed are grouped in the following way, each with its disasters types: biological (epidemics and insect infestations), climatological (droughts and wildfires), geophysical (earthquakes, dry mass movements, and volcanic activities), hydrological (floods and landslides) and meteorological (extreme temperatures and storms).

Each event contains information regarding the starting time and ending time, segmented into year, month and day. Multiple disasters missed entries for the starting day, which was selected to be the first day of the month, and ending day, which was selected to be the last day of the month. A few observations, mainly droughts and epidemics, missed the starting month, which was assumed to be January, or the ending month, which was synthetically added as December. In the particular case of drought it is usually difficult to set a specific week or even a month from which the droughts emerge, as they are events that require a prolonged absence of water and last for a long period of time. All types of drought (meteorological, hydrological and agricultural) are grouped in a single bucket. Lastly, the initial data pool was cleaned for observations that did not include the financial impact of the disaster and the CPI value (Consumer Price Index).

In order to make the database for analysis, each disaster was checked to see if it is part of a chain. As such, there are disasters that appear several times as part of different chains, particularly storms, and each appearance of an event within a chain was considered independent of other chains. The conditions for being in a consecutive chain are: the countries of both disasters have to be the same, the second disaster has to start after the first one and it has to start at most 100 days later than the first one ends. Based on this procedure, two databases were created: one for the chains of consecutive disasters and one for events that are not part of any chain. Each database was enriched with information from the World Development Indicators regarding country data: GDP (PPP adjusted), population, urbanisation and surface area. The choice of start for 1960 was guided by the availability of this data. Considering that some countries have changed their structure since 1960 and the country information is guided by the ISO, a few adjustments were made: USSR data is merged into current Russia, East and West Germany are merged into current Germany data, Yugoslavia data was excluded due to the difficulty of mapping each incident to the modern country, Guadeloupe and Anguilla were excluded due to country and region conflicts. Finally, the impacts are adjusted to PPP and CPI, the frequencies and impact sums of each disaster and chain are calculated both per country and per region. Whereas the chains are structured at country level, the analysis in Section 4.1 and Section 4.2 focuses on the supra-national regional level. The region segmentation can be found in Table 13 of the Appendix.

Regarding notation, for ease of reading, the chains are referred to in the structure First_Second, with First denoting the primary event and Second being the secondary event. For example, the chain Storm_Flood is a shorter way to meaning storms followed by floods, in the same way that a Drought_Wildfire chain refers to an event where the wildfire occurred after a drought.

3.2 Methods

In order to assess if the means of two distributions are different, two statistical tests are being used in section 4.3. The first one is the T-test, a family of parametric tests that compare the means of two distributions under specific requirements and assumptions. For our purposes, we will assume that the samples are independent, variances of the distributions are unequal and the sample sizes are also unequal. This prompts the use of the Welch's t-test. The following information is extracted from the data:

$$
\begin{gathered}
n_1 = \text{number of observations in the first group },\\
n_2 = \text{number of observations in the second group },\\
\overline{X_1} = \text{mean of the first group },\\
\overline{X_2} = \text{mean of the second group},\\
s_1^2 = \text{unbiased estimator of the variance of the first group },\\
s_2^2 = \text{unbiased estimator of the variance of the second group }.
\end{gathered}
$$

As such, the test statistic is calculated as :

$$t = \frac{\overline{X_1} - \overline{X_2}}{s_{\overline{\Delta}}}$$

for

$$s_{\overline{\Delta}} = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}$$

with the degrees of freedom calculated as

$$df = \frac{(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2})^2}{\frac{(s_1^2/n_1)^2}{n_1-1} + \frac{(s_2^2/n_2)^2}{n_2-1}}.$$

Thus, the test statistic follows an approximate Student's t-distribution with the above degrees of freedom, on the basis of which hypotheses can be formed and the respective p-values calculated.

To balance the strengths and weaknesses of the T-test, the non-parametric Wilcoxon signed-rank test is also used for hypotheses testing. Similar hypotheses as for the T-test can be mapped to the Wilcoxon test, such as checks for the probability that the mean of a sample is greater than a different one. For two data sets with samples X and Y, it analyses the difference between X_i and Y_i for each i of the sample set. In our context, the hypotheses are formed around

$$p = P(1/2(X_i - Y_i + X_j - Y_j)),$$

and the null hypothesis is formed around the value of p.

To complement the findings regarding mean hierarchy, the main demographic drivers are observed and analysed in Section 4.4 through regression methods. The main algorithm of analysis is the linear regression. Generally, regression models can be represented as

$$y = X\beta + \epsilon,$$

where y is the predicted variable, X is the design matrix which contains all observations for all dependent variables, β is the vector of coefficients and ϵ stands for the error. In an OLS model, β is estimated by minimising

$$(y - X\beta)^2.$$

LASSO and RIDGE introduce a regularisation element λ, with the purpose of reducing multicollinearity. An L1 parameter is introduced for LASSO and and L2 parameter is introduced for RIDGE. A generalisation of these algorithms, called an Elastic Net, aims to combine both L1 and L2 regularisation. Thus,

$$\hat{\beta}_{LASSO} = argmin(y - X\beta)^2 + \lambda|\beta|$$

$$\hat{\beta}_{RIDGE} = argmin(y - X\beta)^2 + \lambda\beta^2$$

$$\hat{\beta}_{ElasticNet} = argmin(y - X\beta)^2 + \lambda(\frac{1-\alpha}{2}\beta^2 + \alpha|\beta|).$$

In case of the Elastic Net, $\alpha = 0$ leads to a RIDGE regression and $\alpha = 1$ leads to a LASSO regression. The main purpose of such extensions to the OLS regression is the focus on having a parsimonious model and avoid multicollinearity. In order to compare the models, the value of the model R^2 is calculated and compared, with the highest being preferable. To further analyse this information, the comparison will involve two loss functions: MSE (Mean Squared Error) and MAE(Mean Absolute Error). These measures are similar, but MSE penalises outliers more by squaring the difference, with the mean being the optimal prediction, whereas the optimal prediction for MAE would be the median of the distribution. These metrics of accuracy are used mainly for forecasting error, a lower value being preferred. For n being the number of observations in the dataset, $\hat{y}$ being predicted values and y observed values, the loss function described above are obtained as :

$$MSE = \frac{1}{n}(\sum(\hat{y}_i - y_i)^2$$

$$MAE = \frac{1}{n}(\sum|\hat{y}_i - y_i|$$

3.3 Analysis Structure

Section 4 contains the analysis of the topic at hand. Section 4.1 details the impact disaster chains have on each region, focusing on graphical descriptions of the most damaging combinations. Three case studies are included, observing regions with distinct climate context and demographic dimensions: South America, South-Eastern Asia and Western Europe.

Section 4.2 focuses on the global perspective and provides graphical descriptions of the most damaging chains worldwide. The definition of chain is also recalculated, in order to see what the difference would be if the timeline was restricted to 30 days or extended to 365. Case studies of Flood_Storm and Drought_Flood are analysed in particular.

In Section 4.3 the means of disasters are analysed and a hierarchy between different disaster context is attempted thorough the means of T-test and Wilcoxon test. Section 4.3.1 compares secondary events of chains with individual events, with the a-priori hypothesis that secondary events have a higher impact. Section 4.3.2 compares the impact of chains with the sum of individual events, with the a-priori hypothesis that chains have a higher impact. Section 4.3.3 observes if the order of events in a chain has any relevance, without any specific hypothesis regarding the hierarchies of chain orders.

Section 4.4 observes if there are specific demographic indicators for an increase in impact, the scale of their effect and their interaction. This is done though regression methods, by comparing OLS with LASSO, RIDGE and Elastic Net.

Throughout the Section 4.1 and Section 4.2 of the analysis, the main point of focus are going to be graphical descriptions of data. They are going to show the impact of disaster chains or single events under specific conditions or grouping. They are structured as barplots in decreasing order of magnitude, from right to left, and the frequency of the events is written on top of the respective barplot. They are mostly presented in groups of two figures, with the top one presenting hierarchies of total impacts and the bottom figure presenting the average impact.

4 Analysis

4.1 Region Analysis

Within this section, the analysis shall focus on three regions (South America, South-Eastern Asia and Western Europe) and their specific impacts, their similarities and differences, as well as what measures have the potential to be beneficial for them. Figure 1 shows the total damage done by the most impactful series of disasters for the three regions. Furthermore, Figure 2 complements the information and shows the mean impact of the disaster chains. In all the figures, the impact is quantified in billion USD and the total frequency of the event is shown on top of the respective bar.

Floods, storms and droughts, in various combinations, comprise many of the top positions. Storm_Storm is the most damaging combination, by total sum, for both South-Eastern Asia and Western Europe. The figures in Figure 1 and Figure 2 are presented again in Section 9 of the Appendix, structured per each region, for a clearer perspective on the risk segmentation of each region

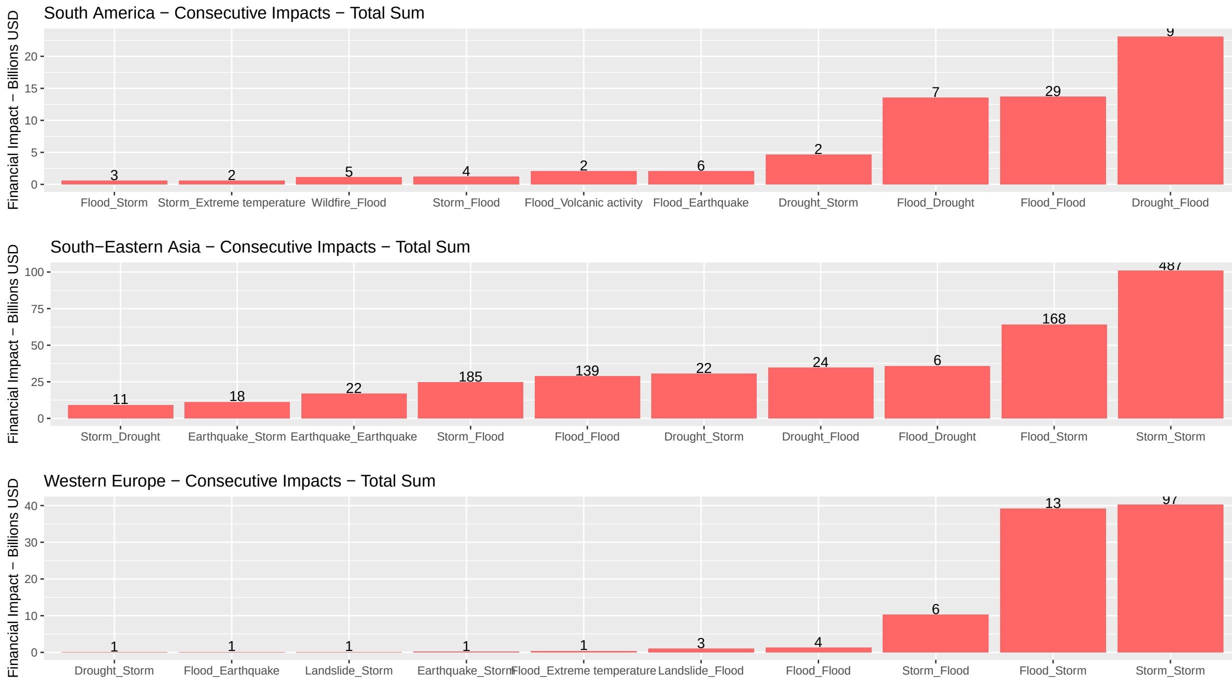

Figure 1: Global disaster distribution segmented by regions, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

Figure 2: Global disaster distribution segmented by regions, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

4.1.1 South America

The countries in South America with entries in the database for consecutive disasters are: Argentina, Bolivia, Brazil, Chile, Colombia, Ecuador, Peru and Venezuela. The predominating climate is temperate and tropical. Figure 3 presents the sum and average impact of each individual impact, as well as their frequency. Figure 4 presents the same information, but limited to the secondary disasters from chains.

An important event was the Haiti earthquake of January 2010, which has strengthened the focus on climate issues when discussing regional policy. This is particularly relevant for South America, as it can be seen from Figure 3 that earthquakes are the disaster that produces the highest damages by aggregate, more than 32 billion USD, as well as by individual event, averaging 0.63 billion USD per event.

The region has suffered intensely from droughts, in particular from the one that started in 2014 in Brazil and lasted for more than two years, having an estimated impact of 4.7 billion USD. In South America, climate phenomena were responsible for 88% of the disasters in the region in the period 2010 - 2016 [Yamamoto et al., 2017]. This region was particularly affected in the past decades by hazards and extreme weather events. Moreover, the socioeconomic characteristics of the population and the geographic features have contributed to the strengthening of the vulnerability of human systems to natural hazards. With regards to secondary events, floods are the most frequent event (57 observations), but droughts are the most impactful in terms of total damage (12.5 billion USD) and single impact (1.25 billion USD). As such, the preventive measure that are most efficient involve control of water. Building on analysis done for the concomitant control of floods and droughts in the valley of the Yangtze River, measures could involve capital investment in agricultural water conservancy construction and subsidies for the construction of small-scale water conservancy projects in village collective farmland [Liu et al., 2019].

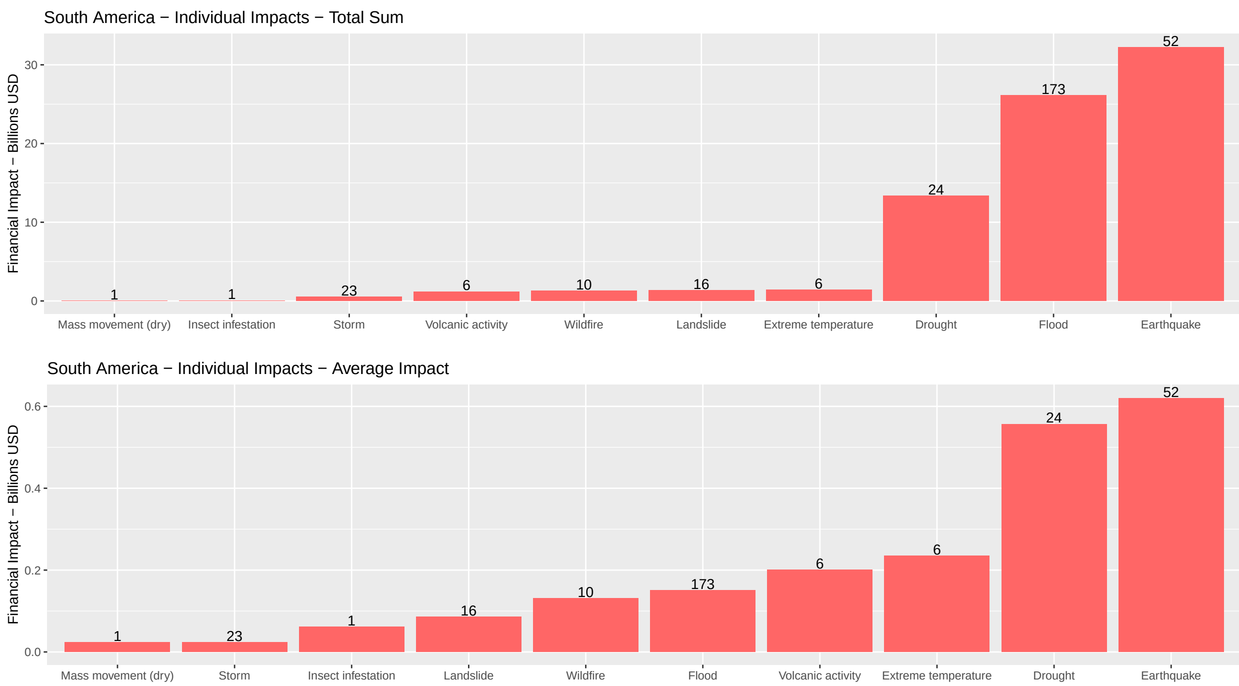

Figure 3: Most impactful disasters in South America, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

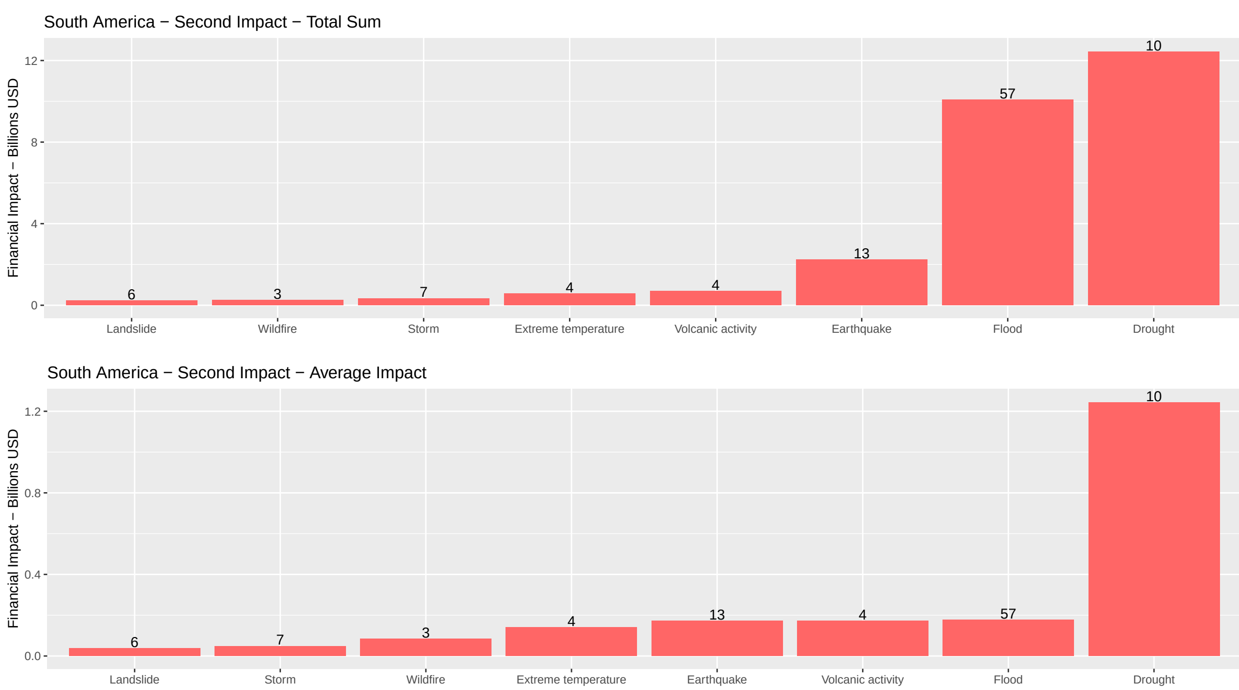

Figure 4: Most impactful secondary disasters within disaster chains in South America, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

4.1.2 South-Eastern Asia

The countries in South-Eastern Asia with entries in the database for consecutive disasters are: Brunei Darussalam, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Thailand, Timor-Leste and Vietnam. The predominating climate is tropical, temperate and dry. Figure 5 presents the sum and average impact of each individual impact, as well as their frequency. Figure 6 presents the same information, but limited to the secondary disasters from chains. Droughts represent a major danger for this region, as they are the second most damaging disaster and they are found in many chains. Particularly, Flood_Drought has the highest average impact, mainly due to the intense flooding in Thailand that started in August 2011 and lasted for 153 days, with an impact of 40 billion USD. The disaster type that has the highest impact is the storm, mostly due to the frequency (709 events as a secondary disaster, 355 as a single disaster), as storms are on the fourth place with regards to average impact for secondary events and fifth overall.

Conversely, the most damaging impact by itself is the wildfire. There have been 10 wildfire events in the period, with the most damaging ones being the two in Indonesia, with impacts of 8 billion USD in 1997 and 1.3 billion USD in 1998, respectively. These were part of a series called 1997 Indonesian forest fires, considered the most damaging series of fires in the past centuries [Harrison et al., 2009]. At origin, they were mostly started from illegal human activities, such as land clearing, resource extraction and land disputes. The human activities were of particularly high intensity during these years, but it was transformed into en ecological catastrophe by the fact that it was associated with an intense drought caused by the ENSO conditions [Davies and Unam, 1999]. This chain of events can also be seen in Figure 2, where there is a single event of Wildfire_Drought, second by severity, and two of Drought_Wildfire, fourth by severity. One of the proposed measures to protect against future wildfires is taxes on land clearing, which would deter from disorganised activities and fund the state for using technological means to clean the land [Varma, 2003]. Another proposed method is that of requesting international aid to retrain and finance agricultural workers.

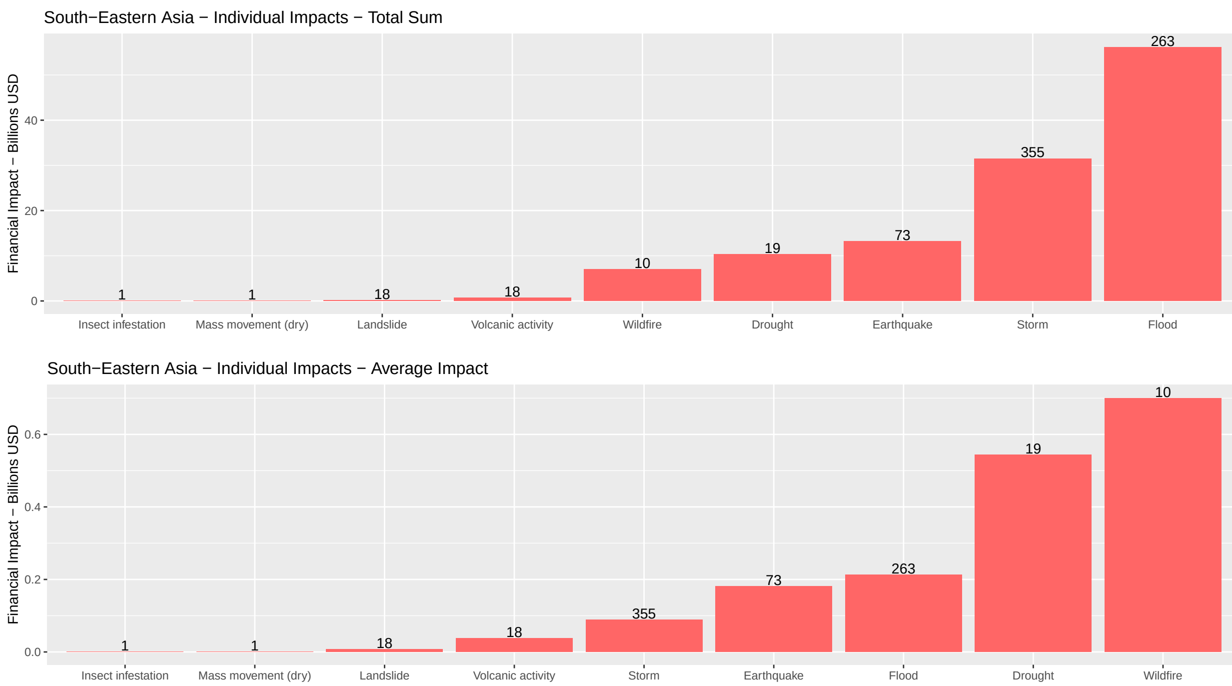

Figure 5: Most impactful disasters in South-Eastern Asia, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

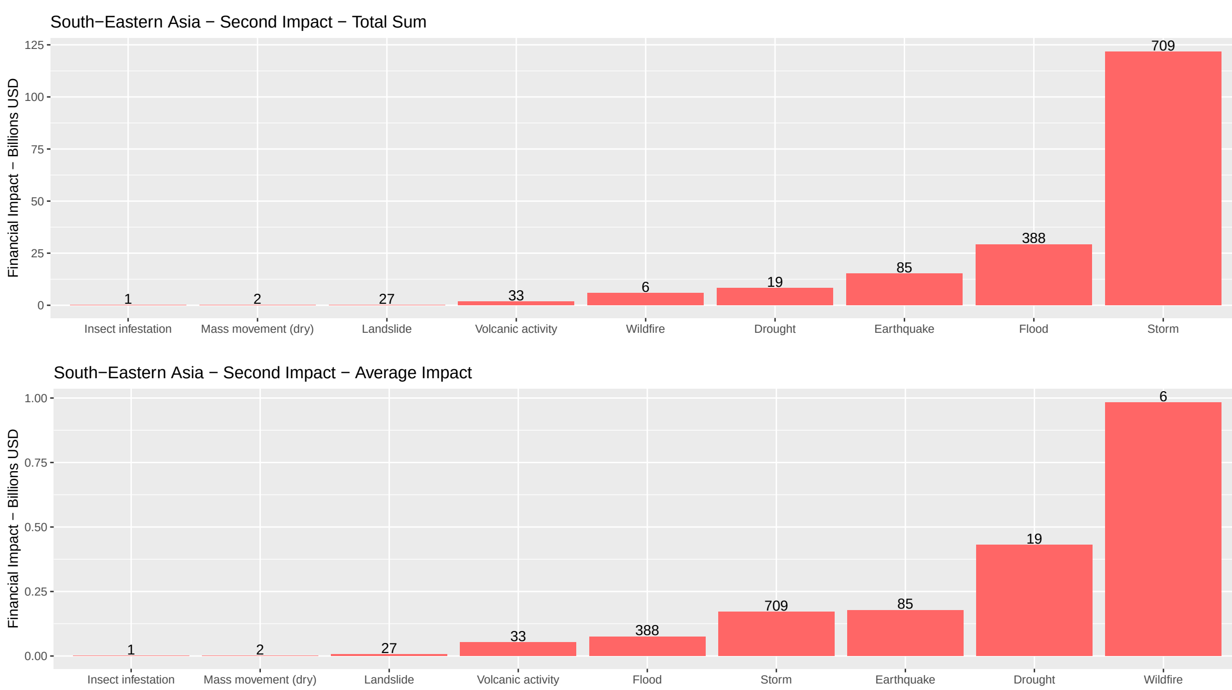

Figure 6: Most impactful secondary disasters within disaster chains in South-Eastern Asia, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

4.1.3 Western Europe

The countries in Western Europe with entries in the database for consecutive disasters are: Austria, Belgium, Switzerland, Germany, France, Luxembourg and the Netherlands. The predominating climate is temperate and continental. Figure 5 presents the sum and average impact of each individual impact, as well as their frequency. Figure 6 presents the same information, but limited to the secondary disasters from chains.

Floods and storms are the most frequent disasters in the region, with a frequency of 51 and 138 observed events. As such, there is no surprise that the most damaging combinations by aggregate impact and also the most frequent chains come from consecutive storms and floods. They are shown by total impact and in decreasing order, Storm_Storm, Flood_Storm, Storm_Flood, Flood_Flood, with the first one having an average impact of over 0.5 billion USD. Consecutive storms have had an impact of more than 40 billion USD over 87 events and Flood_Storm have had a similar impact, of almost 40 billion USD, but over a much smaller number of 13 disaster chains. The latter one, Flood_Storm, had an average impact of 3 billion dollars, with the two most impactful chains being in Germany, in 2013 and 2002, respectively. The first one had a total nominal damage of 17.7 billion USD, comprised of a flood in March-June 2013 followed by a storm at the end of July 2013. During the flood, the water reached record highs for the rivers Elbe and Danube [Merz et al., 2014]. The second one had a total nominal damage of 13.4 billion USD, comprised of a flood in August 2002 followed by a short storm at the end of October. For both of these events the most part of the chain damage was in the first event, the floods accounting for 73% and 86% of the chain damage. The impact of floods in the region can also be observed from Figure 6, where floods are the most damaging secondary event averaging 0.77 billion dollars per event.

The second most disruptive disaster by financial impact are the extreme temperatures. With only 8 observations, these events have been spread all over the continent and throughout time, with no temporal or geographic cluster. The most damaging one happened in France, in August 2003, which lasted for 20 days and had a net impact of 4.4 billion USD. The climate of the region is temperate and it is by the North Sea and the Atlantic Ocean, as well as traversed by an extensive river network. The general geography of the land, alongside efficient and proactive irrigation practices, have lead to droughts representing rare or minor events. Only two such disasters happened in the time frame of analysis, and drought has not been part on any significant chain of disasters. However, these events have the third highest average impact of individual events, as seen in Figure 5. Both of them happened in France, and the most impactful of them occurred in July-August 1997 and had an estimated nominal impact of 1.6 billion USD.

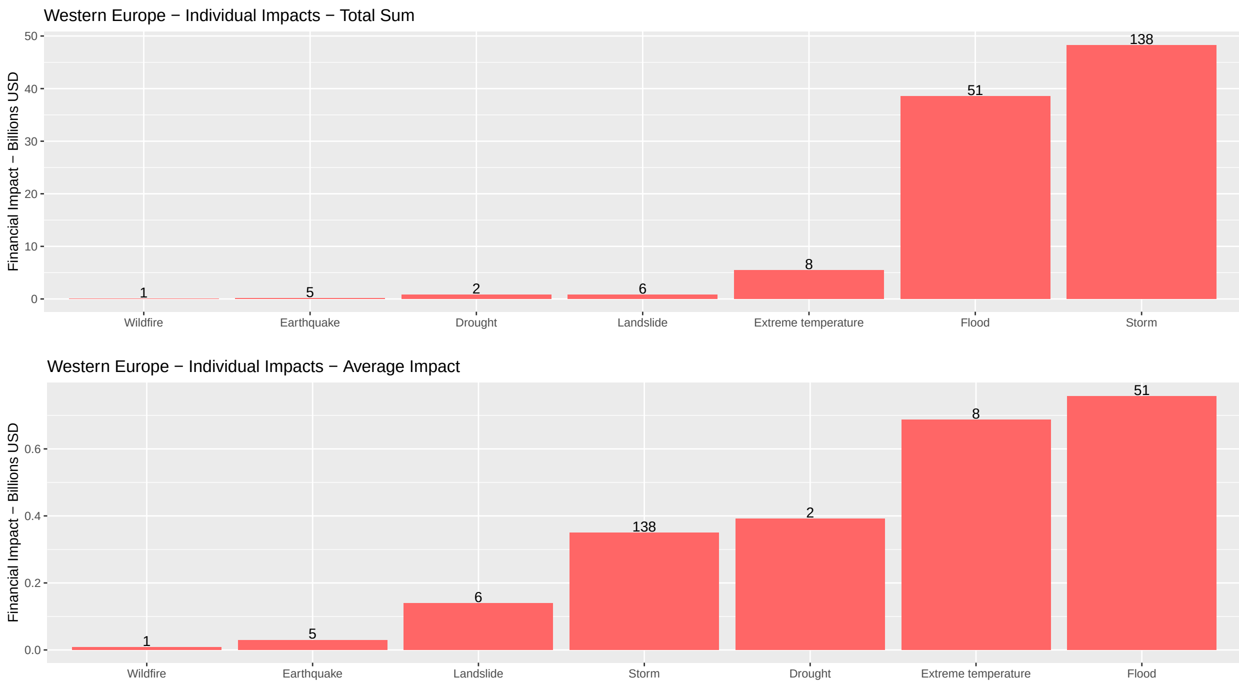

Figure 7: Most impactful disasters in Western Europe, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

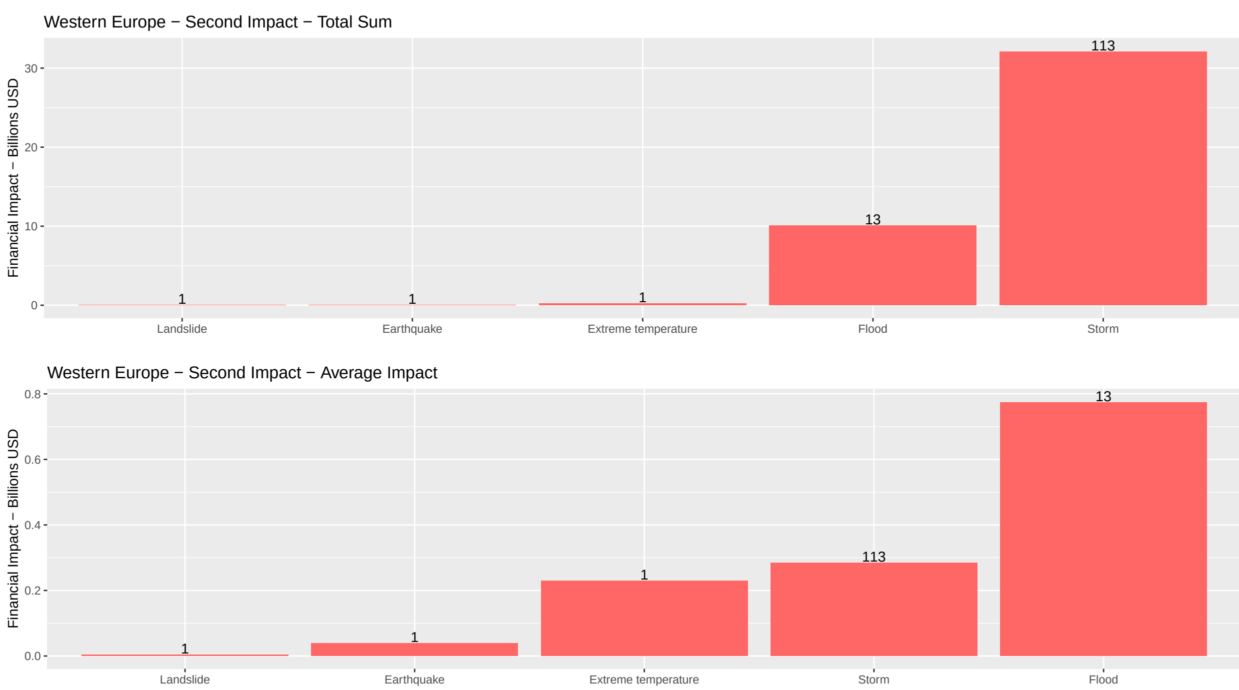

Figure 8: Most impactful secondary disasters within disaster chains in Western Europe, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

4.2 Disaster Analysis

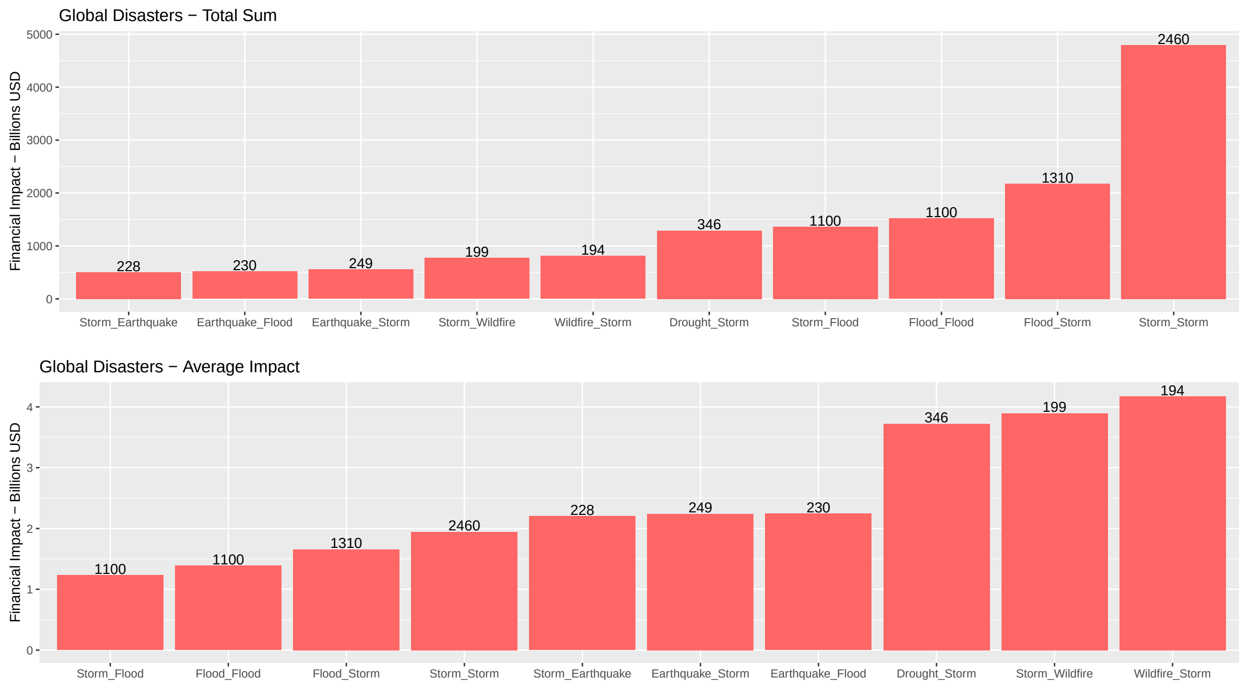

Figure 9: Global Disaster Distribution, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

This section analyses the distribution of the most damaging events worldwide. Figure 9 shows the global distribution of the most damaging disaster combinations, given the chosen definition of disaster chain. The first graph shows the aggregated sum of the impact damages, whereas the second one shows the average damage of the chains. For each combination, the frequency of the event is on top of the respective bar. Section 10 of the Appendix further describes the global distribution of the most damaging disaster chains. Each combination is broken down into the most damaged areas by it, for both sum of impact and average impact.

It can be observed that there is no consistent mapping from the top combinations by sum to the top for the average event. Storm_Storm, Flood_Storm and Flood_Flood are only present in the bottom part of the averages, but they hold the top three positions by sum. This is due to the repeated occurrence of such chains, fact accentuated by the high frequency observable for all these events. Conversely, Wildfire_Storm and Storm_Wildfire hold top places regarding average, meaning each impact was significant, but they are on the 6th and 7th place by aggregated sum. This is due to the moderate frequency of such events (194 and 199, respectively) combined with the high impact of each event (approximately 4 billion USD).

4.2.1 Time Interval

Throughout this study, one of the requirements for a series of disasters to form a chain is to have fewer than 100 days between the end of the first disaster and the beginning of the second one, representing a medium time interval. In this section, this condition is changed in order to observe the variations of the impact at the global scale if the definitions were to change.

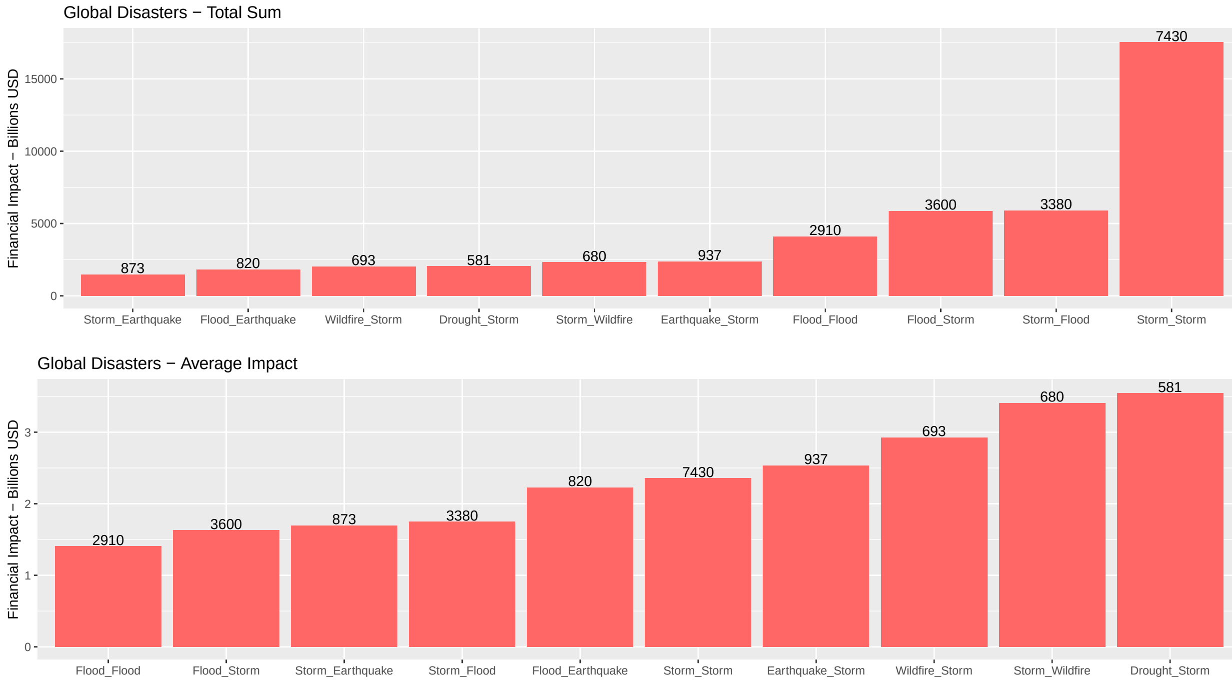

Figure 10: Global Disaster Distribution with a **large** time interval between events, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

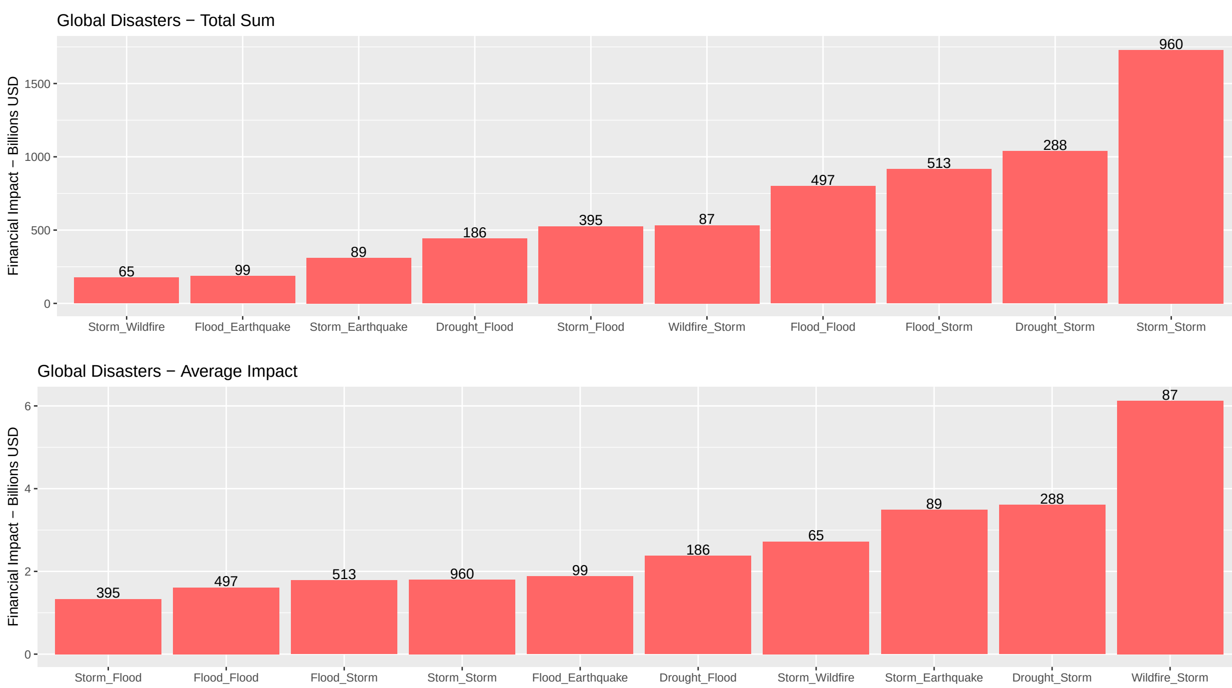

Figure 11: Global Disaster Distribution with a **small** time interval between events, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

Figure 10 shows the impacts if the condition becomes that events have to be fewer than 365 days apart, considered a long time interval. It is observable that the combinations of flood and storms remain in top as the most damaging pairs, with Storm_Flood having a significantly higher global aggregate impact when considering a large time interval, in line with the increase frequency (1100 versus 3380). When observing the average impact, one can notice that the most damaging three disasters (Storm_Wildfire, Drought_Storm, Wildfire_Storm) are shuffled in the top, but they maintain a similar hierarchy. A significant difference can be observed in the fact that the average disaster becomes less impactful in the long time interval. When looking at the scale of the bottom figure of Figure 10, we can observe that none crosses a 4 billion USD threshold. Numerically, the average drops from 2.57 to 2.43 billion USD, a 5.8% decrease, which points to the fact that disasters follow the same structure and trend, but the heaviest impact comes from the ones within a shorter time frame. The total damage of disasters amounts to 33560.34 billion USD, a linear increase by a factor of 2.55 from the value of 13144.83 billion USD, represented by the medium time interval.

Furthermore, Figure 11 shows the impacts if the condition becomes that events have to be fewer than 30 days apart, considered a short time interval. The hierarchy of disaster chains aggregated impact remains stable, with a similar structure as the previous figures and at similar ratios between the subsequent spots. However, the average impact is higher than the one for a time interval of 100 days, with a mean of 2.83 billion USD, an increase of almost 10%. Moreover, the most damaging chain, Wildfire_Storm, has an average impact of 6.47 billion USD, by far higher than the others, regardless of the time interval. The total damage of disasters amounts to 7500.5 billion USD, which makes the damages of the medium time interval 1.75 times higher. In the context where the variations of time are of the same scale, around an order of 3.5 (30/100/365 days), the aggregated damages increase by an ever smaller fraction (1/1.75/2.55). This points to the fact that most of the damages occur for chains with shorter interval between events

4.2.2 Drought_Flood

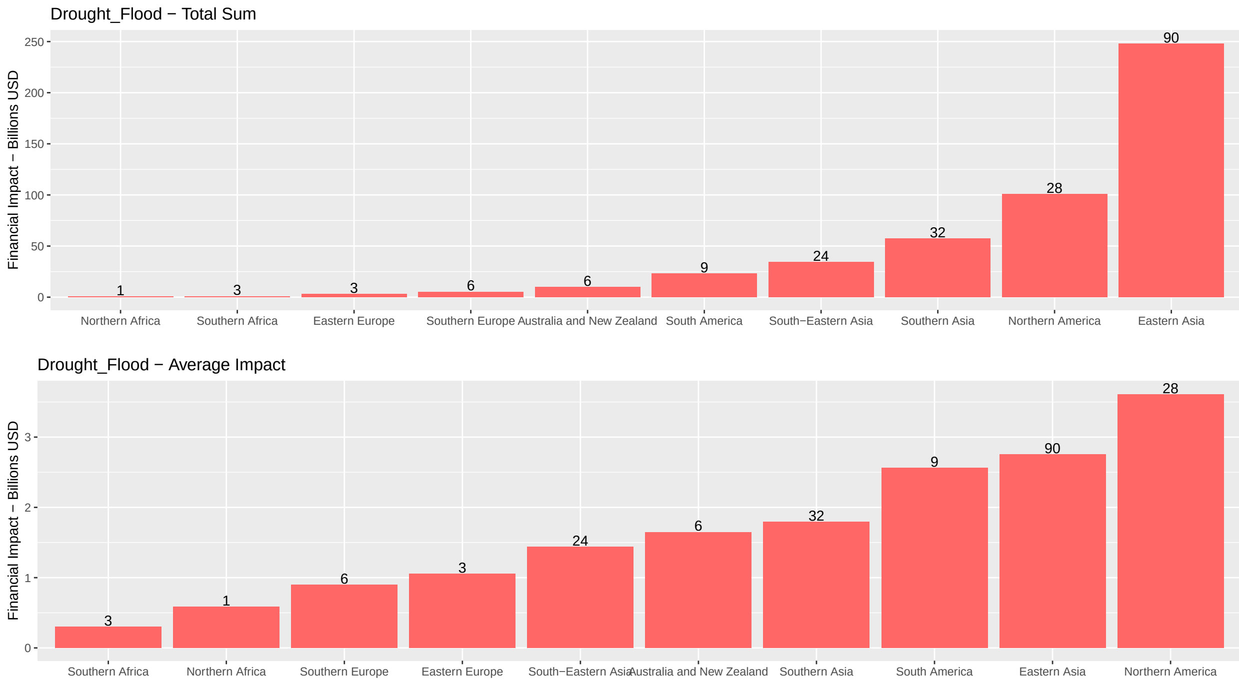

Figure 12: Drought_Flood disaster distribution segmented by regions, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure);

Figure 12 focuses the analysis on the Drought_Flood disaster chain and the distribution these events have globally. By total sum, the highest aggregate damage is felt by Eastern Asia, at a total of 250 billion USD, 2.5 times higher than North America. The role reverses when considering the average impact, where Northern America shows the highest average impact, mainly due to the frequency of events: 28 for North America and 90 for Eastern Asia. The climate and geographic conditions of the southern and eastern part of Asia might be facilitators for this particular disaster chain. Eastern Asia, Southern Asia and South-Eastern Asia all show high frequencies of this chain (90/32/24 events) and have amongst he highest aggregate impact and average impact, which underlines the regional propensity for droughts, floods and disaster chains from these consecutive events. As shown previously in Figure 2, the reverse chain (Flood_Drought) is a significant issue in South-Eastern Asia.

4.2.3 Flood_Storm

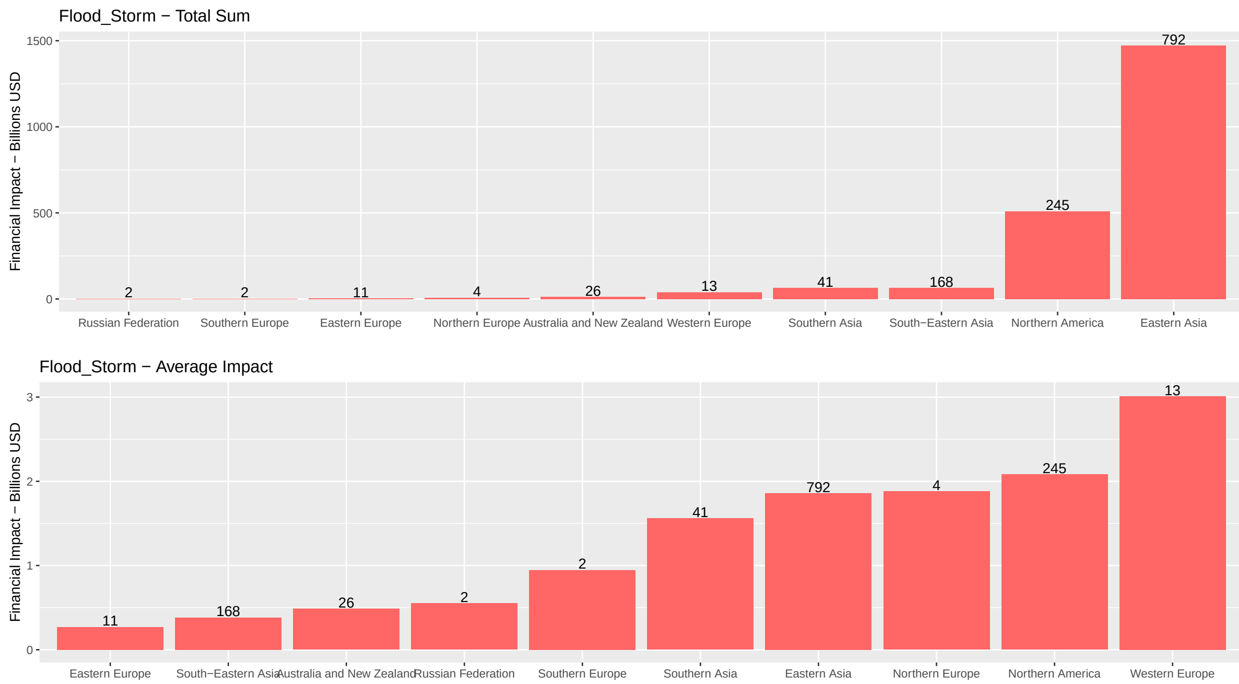

Figure 13: Flood_Storm distribution segmented by regions, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure);

Figure 13 focuses the analysis on the Flood_Storm disaster chain and the distribution these events have globally. By far, the most affected regions are Eastern Asia, which suffered almost 1500 billion USD in damages from this chain alone, and North America, which amounted 500 billion USD of impact damages. This comes from the extreme frequency of the chain in these regions, with 792 events in Eastern Asia and 245 in Northern America. Regarding the mean impact, the range is more balanced, from 3 billion USD for each event in Western Europe to 0.27 in Eastern Europe. Here, regions with a few number of recorded chains (13 in Western Europe and 4 in Northern Europe) have some of the highest impacts.

4.3 Significance Analysis

4.3.1 Secondary Event - Within or Outside Chain

	Mean			Frequency	
Disaster	Second	Single	Ratio	Second	Single
Flood	738166	148340	4.98	2795	718
Drought	2039934	169220	12.05	198	84
Storm	1012094	288300	3.51	4668	615
Landslide	145821	37729	3.86	123	33
Wildfire	974774	365846	2.66	388	40
Extreme temperature	1232828	374448	3.29	58	28
Volcanic activity	118385	39490	3.00	47	17
Earthquake	1221081	1313317	0.93	643	236

Table 1: Disaster means and frequencies for secondary events (Second) and single events (Single), as well as the ratio between the means

This subsection analyses if the impact is higher when the event comes second in a chain of disasters, compared to single events. This is done by measuring the average of the financial impacts of each disaster under each situation (secondary and single) and then comparing the means to observe for statistical relevance through T-tests and Wilcoxon test. The tables presented in this subsection are shown in increasing p-value of the resulting T-tests. Table 1 shows preliminary statistics about the disasters within the analysis. By 'Single' it is meant a disaster that is not part of a chain, whereas 'Second' symbolises that the secondary disaster from a chain. In terms of frequencies, we can observe that the numbers of appearances of disasters as secondary events is always higher than their appearances as singular. In particular, wildfires and storms appear 9.7 and and 7.6 times more often in a chain. This is due to the fact that some events are recorded as part of several chains, thus they are counted several times as chain disasters. When observing the mean differences, it is already clear that most disaster types are significantly more impactful as the secondary even of a chain than an intrinsic event, with range varying from 0.93 (earthquakes) to 12.05 (droughts). The observed number of events is considered sufficient to have pertinent observations through both T-test and Wilcoxon test.

Disaster	t-value	df	p-value	W-statistic	p-value
Flood	13.04	3504	< 0.001	1466740	< 0.001
Drought	8.2	215	< 0.001	14914	< 0.001
Storm	5.74	1126	< 0.001	2070490	< 0.001
Landslide	3.98	154	< 0.001	2456	0.032
Wildfire	3.3	201	0.001	8822	0.077
Extreme temperature	2.52	72	0.007	1110	0.003
Volcanic activity	2.3	46	0.013	545	0.014
Earthquake	-0.11	286	0.544	92726	< 0.001

Table 2: Statistical test results

Table 2 shows the results of the T-test and the Wilcoxon test done in order to see if the differences are statistically significant. The a-priori hypothesis is that impacts are significantly more damaging as part of a chain. As such, the tests are one-sided, with the alternative hypothesis being that the disaster has a higher impact if it comes the second in a chain, rather than as a singular event, and the null hypothesis being that there is no significant variation in the averages. The benchmark for rejecting the null is having a p-value less than 0.05 (5%), as is standard practice.

Regarding the p-value of the statistical test results, we can observe a tendency for agreement between the results of the T-test and the Wilcoxon test. It can be noticed that for floods and storms the mean ratio is large (4.98 and 3.51, respectively), with chain events being multiple times more impactful than singular event, and there are numerous observations (2795 chain and 718 single events for floods, 4668 chain and 615 single events for storms), which lead to a very low p-value for both tests. Whereas the scale of frequencies decreases for droughts (198 chain and 84 single events), it is sufficient for observing the effects. Furthermore, the very high ratio determines a very low p-value for both tests. We note, however, the difference in scale between the W-statistic for drought and the ones for floods and storms, which are hundreds of times larger. The results are similar for landslides, volcanic activity and extreme temperature, where both tests agree on the fact that the difference is significant. This shows that in the case of floods, droughts, storms, landslides, volcanic activity and extreme temperature disasters there is sufficient data and the means vary sufficiently high to have an agreement between the tests that the disasters are much more impactful when they are part of a chain.

The results from the T-test analysis on wildfire indicate that the difference is extremely significant (p-value = 0.001). This is due to the large mean ratio, 2.66, and due to the rather large number of observations. On the other hand, the result from the Wilcoxon test indicate that the difference is not significant, at p-value = 0.077. Nevertheless, the fact that it is lower than 0.1 indicates some level of validity in the statistical power, and, alongside the very low p-value of the T-test, indicates sufficient validity in interpreting the hierarchy of the means. This is potentially due to the large imbalance in the number of observations, where there are 388 observations of secondary wildfire and only 40 observations of single wildfire events. For earthquakes, the t-test shows that the means do not vary significantly, at a p-value of 0.544. This might be due to the fact that there are several significant outliers in the earthquake data, with some events being on the extreme end of the tail, alongside the fact that the mean ratio is 0.93, lower than 1. Conversely, the Wilcoxon test points to the fact that secondary earthquakes are significantly more impactful, at an extremely low p-value of less than 0.001. Thus, there is disagreement between the test results and we either do not have sufficient data to reach a conclusion, or the mean difference is not large enough. As such, the results are inconclusive to determine whether the disasters are significantly more impactful as secondary events when compared to single events.

With regards to volcanic activity, the ratio is relatively high, that of 1.76, but the number of events is too low for the results to be conclusive. The p-value 0.013 for the t-test is higher than the benchmark, thus we conclude that the variation is not statistically significant. This is further backed up by the even larger p-value of 0.279 for the Wilcoxon test. Nevertheless, we note that this is mainly due to the low number of observations (33 and 32), as the volcanic activities that come secondary in a chain are three times more damaging than the same type of disaster as a single event.

Thus, given the current analysis, we reject the null hypothesis for floods, droughts, storms, landslides, volcanic activities and extreme temperature disasters. For this category, events are shown to be significantly more damaging when being the secondary event of a chain. For earthquakes, there are several issues the deter from confirming this claim: there might be insufficient data to have sufficient testing power, the two tests might be in disagreement or the mean ratio of the observed events is not sufficiently high. As such, we accept the null hypothesis for earthquakes only. Overall, the disasters are shown to be more damaging when being part of a chain.

4.3.2 Chains versus Single

Disaster	Mean			Frequency	
	Chain	Single	Ratio	Chain	Single
Storm_Storm	1941175	576599	3.37	2327569	378225
Storm_Flood	1357054	436639	3.11	629625	441570
Storm_Drought	3939990	457520	8.61	7832	51660
Storm_Wildfire	4520503	654146	6.91	28171	24600
Flood_Storm	1543155	436639	3.53	616200	441570
Flood_Flood	1317694	296679	4.44	534852	515524
Drought_Storm	2733856	457520	5.98	23856	51660
Drought_Flood	2056704	317560	6.48	15450	60312
Wildfire_Storm	3194733	654146	4.88	13192	24600
Flood_Drought	2710636	317560	8.54	3780	60312
Flood_Wildfire	1644813	514186	3.20	3975	28720
Drought_Wildfire	3490017	535067	6.52	924	3360
Wildfire_Flood	1297720	514186	2.52	3773	28720
Storm_Earthquake	2237234	1601616	1.40	40812	145140
Storm_Extreme temperature	1915603	662747	2.89	868	17220
Flood_Landslide	793896	188392	4.21	2024	22258
Storm_Landslide	769752	328352	2.34	1936	19065
Wildfire_Wildfire	1615404	731692	2.21	1700	1600
Landslide_Flood	1233929	188392	6.55	1392	22258
Landslide_Storm	657393	328352	2.00	720	19065
Drought_Extreme temperature	1983914	543668	3.65	81	2352
Extreme temperature_Storm	2477235	662747	3.74	504	17220
Drought_Drought	3496022	338441	10.33	100	7056

Table 3: Disaster means and frequencies for chain events (Chain) and single events (Single), as well as the ratio between the means - Part 1

Disaster	Mean Chain	Mean Single	Mean Ratio	Frequency Chain	Frequency Single
Wildfire_Drought	3951386	535067	7.38	100	3360
Drought_Landslide	1526483	209273	7.29	81	2604
Earthquake_Flood	1874128	1461656	1.28	22600	169448
Extreme temperature_Flood	2144072	522787	4.10	315	20104
Earthquake_Storm	1927277	1601616	1.20	25647	145140
Flood_Volcanic activity	291866	192135	1.52	315	10770
Flood_Extreme temperature	882866	522787	1.69	100	20104
Extreme temperature_Drought	1090597	543668	2.01	25	2352
Flood_Earthquake	1587989	1461656	1.09	44880	169448
Earthquake_Drought	2183263	1482537	1.47	323	19824
Extreme temperature_Earthquake	17635747	1687764	10.45	36	6608
Storm_Volcanic activity	493095	332095	1.48	196	9225
Wildfire_Earthquake	2510512	1679163	1.50	144	9440
Extreme temperature_Wildfire	1035810	740294	1.40	48	1120
Volcanic activity_Storm	350060	332095	1.05	170	9225
Volcanic activity_Flood	154929	192135	0.81	64	10770
Earthquake_Extreme temperature	938111	1687764	0.56	16	6608
Earthquake_Landslide	973335	1353369	0.72	225	7316
Drought_Earthquake	1250108	1482537	0.84	1312	19824
Landslide_Landslide	44017	80105	0.55	16	961
Earthquake_Volcanic activity	441023	1357112	0.32	16	3540
Earthquake_Earthquake	1903559	2626634	0.72	8364	55696
Earthquake_Wildfire	436402	1679163	0.26	90	9440
Landslide_Earthquake	156659	1353369	0.12	81	7316

Table 4: Disaster means and frequencies for chain events (Chain) and single events (Single), as well as the ratio between the means - Part 2

This subsection analyses if the disasters provoked by the chain of events are larger than the sum of the components as single events. This is done by measuring the average of the financial impacts of each disaster chain, noted as Chain, and comparing it to the average of the sum for the two individual disasters, noted as Single. Afterwards, the means are analysed for statistical relevance through T-tests and Wilcoxon test. In order to obtain the distribution of the sum of single events, a Cartesian product was done for each individual type of hazard. In this way, every pseudo-primary event was added with every pseudo-secondary event, thus obtaining a synthetic distribution for single events that maps the disaster chains and it statistically comparable to it. The chains and combinations that did not ammount to 10 observations were excluded from the analysis.

The tables presented in this subsection are shown in increasing p-value of the resulting T-tests. Table 3 and Table 4 show preliminary statistics about the disasters within the analysis such as the means for the chains (Chain) and for individual disasters (Single), as well as the ratio obtained by dividing the mean of the chain with that of the single events (Ratio), alongside the frequencies of events. The ratio of means is significantly over 1 in Table 3 and it halfway decreases below 1 in Table 4, averaging 3.34, with a maximum of 10.45 for 'Extreme temperature_ Earthquake' and a minimum of 0.12 for Landslide_Earthquake. As such, there is a reasonable a-priori intuition that chains are, on average, significantly more impactful than single events. We can also observe the large imbalance in frequencies found for many combinations, such as most of the ones in Table 4, where chain events have a much lower count than single events.

Disaster	t-value	df	p-value	W-statistic	p-value
Storm_Storm	177.32	884580	< 0.001	$639.4*10^{10}$	< 0.001
Storm_Flood	174.64	929713	< 0.001	$207.8*10^{10}$	< 0.001
Storm_Drought	41.97	8164	< 0.001	366609602	< 0.001
Storm_Wildfire	50.59	31320	< 0.001	536289860	< 0.001
Flood_Storm	203	971011	< 0.001	$208*10^{10}$	< 0.001
Flood_Flood	248.08	605729	< 0.001	$210.7*10^{10}$	< 0.001
Drought_Storm	48.33	27172	< 0.001	1008983588	< 0.001
Drought_Flood	64.06	15782	< 0.001	757215376	< 0.001
Wildfire_Storm	31.5	14532	< 0.001	238860034	< 0.001
Flood_Drought	27.76	3787	< 0.001	199232174	< 0.001
Flood_Wildfire	22.52	4063	< 0.001	73525252	< 0.001
Drought_Wildfire	18.23	938	< 0.001	2682676	< 0.001
Wildfire_Flood	16.08	3862	< 0.001	66919412	< 0.001
Storm_Earthquake	12.66	107248	< 0.001	3902704724	< 0.001
Storm_Extreme temperature	11.54	935	< 0.001	11489244	< 0.001
Flood_Landslide	10.63	2039	< 0.001	27980937	< 0.001
Storm_Landslide	10.53	3102	< 0.001	26191392	< 0.001
Wildfire_Wildfire	9.89	2001	< 0.001	1579619	< 0.001
Landslide_Flood	9.76	1394	< 0.001	21693147	< 0.001
Landslide_Storm	9.25	1442	< 0.001	10497663	< 0.001
Drought_Extreme temperature	11.38	83	< 0.001	165771	< 0.001
Extreme temperature_Storm	8.92	514	< 0.001	6374532	< 0.001
Drought_Drought	9.86	99	< 0.001	660817	< 0.001

Table 5: Statistical test results - Part 1

Disaster	t-value	df	p-value	W-statistic	p-value
Wildfire_Drought	8.77	99	< 0.001	302180	< 0.001
Drought_Landslide	9.06	81	< 0.001	181250	< 0.001
Earthquake_Flood	7.14	40980	< 0.001	$2.7 * 10^{10}$	< 0.001
Extreme temperature_Flood	6.58	314	< 0.001	4339453	< 0.001
Earthquake_Storm	5.71	54809	< 0.001	$2.5 * 10^{10}$	< 0.001
Flood_Volcanic activity	4.5	350	< 0.001	2407937	< 0.001
Flood_Extreme temperature	3.68	100	< 0.001	1305042	< 0.001
Extreme temperature_Drought	3.85	25	< 0.001	45819	< 0.001
Flood_Earthquake	3.29	174974	< 0.001	$5.4 * 10^{10}$	< 0.001
Earthquake_Drought	3.31	465	0.001	5216829	< 0.001
Extreme temperature_Earthquake	3.51	35	0.001	177592	< 0.001
Storm_Volcanic activity	2.84	337	0.002	1175141	< 0.001
Wildfire_Earthquake	1.91	170	0.029	924216	< 0.001
Extreme temperature_Wildfire	1.92	50	0.030	32348	0.008
Volcanic activity_Storm	0.37	374	0.356	839499	0.057
Volcanic activity_Flood	-1.55	69	0.937	369085	0.164
Earthquake_Extreme temperature	-1.95	21	0.967	46797	0.786
Earthquake_Landslide	-2.08	1363	0.981	1161381	< 0.001
Drought_Earthquake	-2.42	16934	0.992	18415595	< 0.001
Landslide_Landslide	-3.68	19	0.999	8159	0.337
Earthquake_Volcanic activity	-3.52	103	1	31037	0.254
Earthquake_Earthquake	-7.18	31433	1	276971587	< 0.001
Earthquake_Wildfire	-8.29	959	1	382509	0.948
Landslide_Earthquake	-8.26	7145	1	292700	0.575

Table 6: Statistical test results - Part 2

Tables 5 and 6 show the results of the T-test and the Wilcoxon test done in order to see if the differences are statistically significant. The a-priori hypothesis is that impacts are significantly more damaging if they are part of a chain. As such, the tests are one-sided, with the alternative hypothesis being that the chain disasters has a higher than the sum of single events, and the null hypothesis being that there is no significant variation in the averages. The benchmark for rejecting the null is having a p-value less than 0.05 (5%), as is standard practice.

The combinations shown in Table 5 and at the top of Table 6 are rather straightforward in interpretation: the p-value of the T-test are extremely low and the p-value of the Wilcoxon test are also extremely low. For these combinations, it is also shown in Table 3 that the mean ratio is significantly over 1 and there are enough observations to regard the results as representative. Afterwards, there is a series of combinations for which the tests contradict each other, mainly due to low mean ratio (Earthquake_Landslide ratio 0.72, Drought_Earthquake ratio 0.84, Earthquake_Earthquake ratio 0.72). Lastly, there are several combinations (Volcanic activity_Flood, Earthquake_Extreme temperature , Landslide_Landslide, Earthquake_Volcanic activity, Earthquake_Wildfire, Landslide_Earthquake) for which the tests agree on the fact that the null hypothesis is not rejected, with reasons being both data size imbalance and a mean ratio lower than 1.

Overall, the hazard combinations are shown to be significantly more damaging in the context of a chain, rather than as separate single events.

4.3.3 Chains - The Relevance of Order

Disaster	Mean			Frequency	
	Chain	Inverse	Ratio	Chain	Inverse
Storm_Flood	1233884	1657568	0.74	1104	1313
Drought_Landslide	1526483	3305557	0.46	9	2
Earthquake_Landslide	973335	156659	6.21	15	9
Extreme temperature_Drought	1090597	1983914	0.55	5	9
Extreme temperature_Flood	2125794	882866	2.41	21	10
Earthquake_Wildfire	384286	2510512	0.15	11	12
Extreme temperature_Earthquake	17635747	938111	18.8	6	4
Volcanic activity_Flood	154929	284939	0.54	8	21
Drought_Earthquake	1323771	2086038	0.63	41	19
Earthquake_Flood	2243724	1718126	1.31	230	240
Landslide_Flood	1323327	764640	1.73	48	46
Extreme temperature_Storm	2520371	1933565	1.30	39	31
Flood_Drought	2681306	2319542	1.16	63	209
Storm_Volcanic activity	493095	416669	1.18	14	17
Storm_Landslide	769752	695401	1.11	44	41
Storm_Wildfire	3894428	4171948	0.93	199	194
Drought_Storm	3723534	3931732	0.95	346	89
Drought_Wildfire	3722861	3951386	0.94	42	10
Wildfire_Flood	1554654	1633709	0.95	80	75
Extreme temperature_Wildfire	1517115	1399366	1.08	8	2
Storm_Earthquake	2202439	2240277	0.98	228	249

Table 7: Disaster means and frequencies for chain events (Chain) and the inverse chain event (Inverse), as well as the ratio between the means

Throughout this section the order in which disasters present shall is analysed. Firstly, several statistics regarding the disasters and their inverse are shown, afterwards the T-test and Wilcoxon test are performed to observe statistical significance between means. Finally, a simulation is run in order to validate the results of the initial tests. Disaster chains for which two or fewer observations were recorded are excluded from the analysis. Table 7 contains general statistics regarding the way each disaster chain relates to its inverse, including the means and their ration, as well as the frequencies. Information pertaining to the disaster chain shown on the first column is noted as ‘Chain’, while the same information for the inverse chain is noted as 'Inverse'. For example, the mean of Storm_Flood is 1233884 and the mean of Flood_Storm, its inverse, is 1657568. Some expectations regarding the statistical results can already be made by observing the table. Most mean ratios are between 0.66 and 1.5, particularly in the bottom half of the table, which already does not hint to meaningful variations of the mean. Moreover, most samples have fewer than 50 observations, with some even having lower counts than 10, which forecast the low power of discrimination of the statistical tests.

Disaster	t-value	df	p-value	W-statistic	p-value
Storm_Flood	-3.78	2403	< 0.001	657590	< 0.001
Drought_Landslide	-3.05	9	0.014	5	0.436
Earthquake_Landslide	1.74	15	0.103	98	0.073
Extreme temperature_Drought	-1.49	12	0.163	14	0.257
Extreme temperature_Flood	1.42	25	0.168	133	0.250
Earthquake_Wildfire	-1.44	11	0.177	29	0.025
Extreme temperature_Earthquake	1.15	5	0.303	19	0.171
Volcanic activity_Flood	-0.98	21	0.337	50	0.102
Drought_Earthquake	-0.94	22	0.356	301	0.163
Earthquake_Flood	0.81	377	0.420	26646	0.517
Landslide_Flood	0.79	80	0.434	1341	0.074
Extreme temperature_Storm	0.68	68	0.498	662	0.497
Flood_Drought	0.52	77	0.602	6763	0.744
Storm_Volcanic activity	0.27	25	0.786	146	0.297
Storm_Landslide	0.26	65	0.794	794	0.344
Storm_Wildfire	-0.26	391	0.798	20035	0.516
Drought_Storm	-0.23	141	0.820	14820	0.585
Drought_Wildfire	-0.15	15	0.886	160	0.255
Wildfire_Flood	-0.14	148	0.892	3015	0.959
Extreme temperature_Wildfire	0.09	1	0.939	9	0.889
Storm_Earthquake	-0.05	472	0.961	27520	0.565

Table 8: Statistical test results

Table 8 shows the results of the T-test and the Wilcoxon test done in order to see if the differences are statistically significant. The results are shown in increasing value of the T-test p-value. There is no a-priori hypothesis regarding the hierarchy between the means, which renders the T-test two-tailed with the null hypothesis that the means are not statistically different. As such, the tests are two-sided, with the alternative hypothesis being that the means are statistically different, and the null hypothesis being that there is no significant variation in the averages. The benchmark for rejecting the null is having a p-value less than 0.05 (5%), as is standard practice.

The only chain that shows significant results is Storm_Flood, for which both tests indicate extreme significance, with p-values lower than 0.001, and with a mean ratio of 0.74. This indicates that storms followed by floods (Flood_Storm) are significantly more impactful than floods followed by storms (Storm_Flood). Thus, for most chains, the null hypothesis is accepted and the means are considered to not be significantly different.

In order to test the validity of the tests, a simulation is run where the data is sampled 10 times, in order to observe if the lack of data has skewed the significance of the analysis. The same pairs as in Table 8 were kept, with the purpose of a more direct comparison. The results shown in Table 9 reveal that that there are many more pairs for which the test would have shown a significant difference between several other means. This follows the intuition provided by the Ratio column of Table 7, where it can be noticed that the means of the top chains are significantly different from 1. Nevertheless, the fact that the simulation shows statistical relevance in mean comparison invalidates the claims obtained previously. As such, we conclude that the order of the disasters in a chain does not have a statistically significant relevance.

Disaster	t-value	df	p-value	W-statistic	p-value
Storm_Flood	-11.94	24047	< 0.001	65758950	< 0.001
Drought_Landslide	-10.35	97	< 0.001	500	0.002
Earthquake_Landslide	5.67	157	< 0.001	9800	< 0.001
Extreme temperature_Drought	-5.04	138	< 0.001	1350	< 0.001
Landslide_Wildfire	-6.79	19	< 0.001	< 0.001	< 0.001
Earthquake_Wildfire	-4.73	124	< 0.001	2900	< 0.001
Extreme temperature_Flood	4.61	257	< 0.001	13300	< 0.001
Wildfire_Volcanic activity	-5.2	19	< 0.001	< 0.001	< 0.001
Extreme temperature_Earthquake	3.94	59	< 0.001	1900	< 0.001
Earthquake_Mass movement (dry)	-3.73	29	0.001	200	0.11
Volcanic activity_Flood	-3.24	241	0.001	5000	< 0.001
Drought_Earthquake	-3.05	233	0.003	30100	< 0.001
Storm_Mass movement (dry)	3.26	29	0.003	200	0.110
Storm_Insect infestation	-3.11	19	0.006	100	1
Earthquake_Flood	2.56	3782	0.011	2664600	0.04
Landslide_Flood	2.51	813	0.012	134100	< 0.001
Extreme temperature_Storm	2.18	696	0.029	66250	0.029
Flood_Drought	1.67	782	0.096	676300	0.299
Storm_Volcanic activity	0.89	269	0.372	14600	0.001
Storm_Landslide	0.84	668	0.403	79400	0.003
Storm_Wildfire	-0.81	3928	0.416	2003500	0.04
Drought_Storm	-0.73	1425	0.468	1481950	0.084
Drought_Wildfire	-0.48	176	0.633	16050	< 0.001
Wildfire_Flood	-0.43	1501	0.665	301500	0.865
Extreme temperature_Wildfire	0.39	27	0.702	900	0.389
Storm_Earthquake	-0.15	4736	0.878	2752050	0.068

Table 9: Statistical test results - Simulation

4.4 Regression

This section uses statistical modelling methods to analyse which factors increase the impact of a chain of disasters. The model family that best fits this analysis is the regression, as it is an efficient way of extracting main contributors to the information of the target variable and the outputs and estimates are easy to interpret. The types of regressions used are OLS, LASSO, RIDGE and Elastic Net, for the purpose of parameter calibration and parsimonious modelling.

The 8926 observations are split as 7000 for the training data and 1926 for the testing data. The dependant variable is the logarithm of the impact, after adjustment to purchasing parity (PPP) and inflation (CPI). This and all the other variables are standardised through Z-scoring them, by de-meaning the variables and dividing by the standard deviation. Thus, the regressions are log-linear. The variable selection was done through matching the results of the step-up procedure with the step-down procedure. Step-up refers to a model starting with only the most relevant variable (lowest p-value, in this case population) and then adding the most relevant variable of the remaining regressors until none is statistically relevant anymore. Step-down refers to starting with the model that has all variables within it and removing the variable with the lowest significance (highest p-value) until all variables are statistically relevant. Both these procedures converged to the current variable selection, which includes Year (year of the chain start), Duration (duration of the first disaster), Duration_second (duration of the second disaster), Population (population of the country at the start of the chain), GDP (nominal GDP of the country at the start of the chain) and OECD (binary variable representative of the country's OECD membership).

4.4.1 Model Selection

Table 10 shows the estimates for the parameters for all the models used, OLS, LASSO, RIDGE and Elastic Net, for the entire data set, in order to be able to compare the parameter estimates. The value of λ is relatively low for both regressions, with $\lambda_{RIDGE} = 0.053$, λ_{LASSO}

Variables	OLS	LASSO	Elastic Net	RIDGE
Intercept	-0.375	-0.370	-0.369	-0.293
Year	0.293	0.291	0.290	0.254
Duration	0.129	0.128	0.128	0.121
Duration_second	0.085	0.083	0.084	0.080
Population	0.459	0.454	0.453	0.380
GDP	0.097	0.100	0.102	0.167
OECD	0.989	0.977	0.974	0.774

Table 10: Estimates Output

= 0.0013 and $\lambda_{ElasticNet}$ = 0.0021. The alpha level that optimises the Elastic Net is $\alpha = 0.4$. Most variable estimates decrease, in absolute value, as the penalty increases, including the intercept. The notable exception is GDP, which increases in line with the penalty magnitude, from 0.097 in case of OLS to 0.167 in case of RIDGE regression. Variables don't have significant changes in magnitude, which point toward consistency in modelling and accurate estimates with regards to minimising the residuals, which is further enhanced by the fact that none of the regularisation models have excluded any variable on grounds of multicollinearity or statistical irrelevance. There is no change of sign for any variable, thus the interpretability is clear for all models. Overall, the low change in parameters and the small values of λ show that the variables chosen are significant and there is little evidence for multicollinearity.

Table 11 shows the R^2 coefficients and the loss functions for each model, for all subsets of the data (training data, testing data and the whole dataset). The best value is bolded: that is, the model with the highest R^2, the lowest MSE and the lowest MAE. As observable, there are many points where there is the same level for OLS, LASSO and the Elastic Net results, rounded to the third decimal. RIDGE consistently under-performs, having the lowest R^2 and the highest MSE and MAE out of all models. This further hints to the fact that the variables chosen do not show multicollinearity and the penalty factor is not essential. Moreover, OLS is the model with the highest number of bolded values, consistently being the best model in

Loss	OLS	LASSO	Elastic Net	RIDGE
R^2_train	**0.408**	**0.408**	**0.408**	0.398
R^2_test	**0.297**	0.296	0.296	0.288
R^2_all	**0.424**	**0.424**	**0.424**	0.412
MSE_train	**0.606**	0.607	0.607	0.619
MSE_test	**0.475**	**0.475**	**0.475**	0.486
MSE_all	**0.576**	**0.576**	**0.576**	0.590
MAE_train	**0.599**	**0.599**	**0.599**	0.607
MAE_test	**0.532**	**0.532**	0.533	0.539
MAE_all	**0.583**	**0.583**	**0.583**	0.591

Table 11: Efficiency Comparison

terms of the chosen standards, which further emphasises the accuracy of the linear model with no penalties. As such, the model that is going to be analysed and interpreted is the OLS version.

4.4.2 OLS Output Analysis

Variables	Estimate	Std. Error	t-value	p-value
Intercept	-0.375	0.014	-26.27	<0.001
Year	0.293	0.011	25.21	<0.001
Duration	0.129	0.008	15.91	<0.001
Duration_second	0.085	0.008	10.54	<0.001
Population	0.458	0.012	37.44	<0.001
GDP	0.097	0.014	6.58	<0.001
OECD	0.989	0.031	31.78	<0.001

Table 12: OLS Regression Output

Table 12 shows the estimates of the OLS regression, alongside the respective p-values.

All variables are very relevant, having extremely low p-values. In fact, GDP has a p-vale of approximately $5*10^{-11}$ and the other have p-values lower than 10^{-16}, which point to the fact that they are essential elements of regressions with this target value. The regression has a residual standard error of 0.7591 on 8919 degrees of freedom with an aggregate p-value <0.001 and an F-statistic of 1095 on 6 and 8919 degrees of freedom. The multiple R^2 is equal to 0.4242 and the adjusted R^2 is equal to 0.4238.

All coefficient estimates are positive, which means that an increase in any of them will lead to an exponential increase in the estimated impact of the disaster chain. The value for Year is particularly worrying in this context. The value of the impact was adjusted to the purchasing power of the country, as well as the inflation. As such, there is no significant increase in expected impact due to inflation. This means that the high value of the Year coefficient and the extremely relevant coefficient imply that there is strong evidence that impacts are becoming higher as time passes by. The coefficients of Duration and Duration_second are positive, thus it is expected that impacts that last longer have a higher financial impact. Intriguingly, the coefficient for the first event (0.129) is higher than for the second one (0.085) by 51.7%, which means that the length of the second disaster is only two thirds as important than the length of the first one. Population is a proxy for the size of the country and the density of the people living in it. As expected, a higher population leads to an increase in impact estimates. Similarly, GDP also incorporates the size of countries, but it is a stronger indicator of the aggregate wealth of the country and the level of development. The positive value of the coefficient, even if it is the lowest of all variables, still means that countries with a higher GDP are expected to have increased impacts. The fact that GDP is the only variable for which the coefficient increases in value as more penalty is added in Table 10 potentially indicates that GDP has, in fact, a higher role in impact forecasting. Lastly, OECD has the highest estimate and also an extremely low p-value, which means we are very confident that countries part of the OECD are expected to have significantly more damaging impacts. As these countries are well developed and the infrastructure is very expensive, it can be assumed that such countries might suffer more financial damage in the presence of any disaster chain.

Breusch-Pagan test is a method to observe if the residuals of a regression, such as the one in question, are heteroskedastic [Breusch and Pagan, 1979]. By analysing the p-value, if it falls bellow 0.05 then we consider there is considerable evidence that the residuals are not homoskedastic and have a fluctuating volatility. In our case, the test shows a value of 338.48 with 6 degrees of freedom and a p-value <0.001. Thus, there is considerable evidence to reject the null hypothesis that the residuals are homoskedastic and we conclude that the residuals have a heteroskedastic distribution. This factor, alongside the rather low value of 0.424 for R^2, point to the fact that there are still significant elements that determine the expected impact value outside of the current variables.

5 Discussion

The results of this thesis are in line with several studies that tackled consecutive impacts and multi-hazard theory, as well as research on climate disasters and climate change. The analysis has underlined that each region has their own issues prompted by the geographic and demographic context. South America suffers from the disaster chains done through combinations of droughts and floods, as well as from earthquakes as single events. Colombia is one of the most exposed countries to earthquakes due to its tectonic structure and is at risk from erosion, landslides, and floods. They have targeted awareness measures involving disaster education at an early age, structuring a four stage educational programme for high school students where they go through theoretical concepts and practical activities regarding mitigation, prevention and response [Cardona, 2007]. Pan-continental efforts to mitigate and prevent climate risk has guided their activities according to the Sendai Framework and the 2030 agenda, with each national and regional entity pursuing specific tasks and priorities [Mollar, 2019] [Mollar, 2021].

South-Eastern Asia suffers from the disaster chains done through combinations of storms, droughts and floods, as well as from wildfires as single events. Thailand was affected very intensely by two floods in the last decades, the 2004 Indian Ocean Tsunami and the 2011 Great Flood. In response to that, they have started implementing flood-specific DDR policies and general climate risk awareness and prevention campaigns [Kitagawa, 2020]. Both Thailand and the Philippines directed their efforts towards children education and risk awareness [Mitchell[1] et al., 2009]. Western Europe suffers from the disaster chains done through combinations of storms and floods, as well as from extreme temperatures as single events. As one of the most developed regions in the world, some of the ways they introduced DDR measures are innovative, through awareness and education on social media and web platforms [Alexander, 2014], and through nature-based solutions [Anderson and Renaud, 2021].

A clear distinction throughout the analysis was done between the sum of disaster impacts and the average disaster impact. Combinations of storms and floods are by far the most frequent type of chain observed and the very high frequency of these chains, relative to the others, have made them consistently score amongst the disaster sequences with the highest aggregate impact. Chains that include wildfires and earthquakes have the some of the highest average impact per event, due to the tendencies to be catastrophic events and due to the extreme outliers found in some cases that were several orders of magnitude higher than the mean. Droughts are the events with the longest duration, meaning they had generated financial impacts for longer periods of time and they were also associated with other disasters within the same time frame. Thus, droughts were found among the more frequent chains of events, as well as in some chains of significantly higher average, one example of this being Drought_Storm, as seen in Figure 9.

When changing the time interval between disasters that would be regarded as a chain, it was observed that the time between impacts is a relevant variable, as most of the damage is produced within a shorter amount of time. The most damaging chains remain relatively static, as there is little change in the hierarchy for aggregate sum and also for average impact. However, the total damage done globally by disasters does not increase in line with the time interval, which leads to a hypothesis that most of the damage is done in the case of consecutive events that have fewer days in between.

Statistical analysis showed that the second impact of a chain is more damaging than the same type of event as a single impact. With the notable exception of earthquakes, all other disasters were, on average, at least 2.6 times more damaging if they came after any other disaster, regardless of the primary one. This again follows the results of several research articles that observed this tendency [de Ruiter et al., 2020] [Gill and Malamud, 2014] [Gissing et al., 2021]. As such, regional and national entities should observe which disasters have a tendency to appear as secondary events and make a hierarchy between them to observe the most damaging ones and the most frequent ones. On the basis of that, it would be cautious to target DDR policies such that they decrease their vulnerability against the more damaging ones first, if synergies are not easily obtained. Building on that, impacts of disaster chains are more damaging than the sum of the individual events. Thus, the efforts of disaster impact minimisation of each country should prioritise the types of hazards that have a tendency to follow in chain structure. Especially with hazards that have positive causal link, a potentially effective method to decrease impacts would be to decrease the intensity of the secondary hazard and decrease the possibility of the primary one happening in the first place.

Analysing the order of disaster has proven that there is insufficient data to determine if, at a global scale, it is to be expected that the order of the disasters in a chain is relevant. The notable exception is the combination of floods and storms, where it was determined, at a very high level of statistical confidence, that storms that follow floods are much more damaging than the other way around, by up to 35%. To a certain degree, this is counter intuitive, as there is at least some degree of causation between a primary storm and a secondary flood, and one would also expect an increase in the intensity of the floods [de Ruiter et al., 2020] [Gill and Malamud, 2014]. Moreover, there are recorded events where heavy storms have triggered floods of a particularly damaging intensity, such the Carlisle floods in January 2005 or the Cumbrian floods in December 2009 [Convery and Bailey, 2008] [Miller et al., 2013] [Burt et al., 2016]. The other chains showed little statistical relevance in the initial results mainly due to the low count of recordings. The fact that many of these events started showing extreme confidence in results after simulating the data 10 time simply points to the inconsistency of the results. As such, for the vast majority of the types of chains the number of recorded observations do not allow for a statistical interpretation and they should be analysed as case-studies.

6 Limitations and Future Research

The analysis had several simplification of the approach to hazard impacts and hazard interaction, in order to allow for a global framework. Firstly, causality and directionality were disregarded, as the causal link was not accounted for any of the disaster types. By omitting this dimension, the same treatment is taken for hazards with no direct link that are identified by the chain definition as for chains where the secondary event is triggered by the primary one. Future research could better segment this approach by causality, in order to have better preventive measure taken against any primary hazard that increases the probability or the intensity of secondary events. Similarly, the only aspect that quantified the intensity of the impact is the financial impact of the respective hazard. This means that the hazard intensity itself was not taking into account, which dismissed potentially relevant information when considering chains. For example, a moderate earthquake (Richter magnitude 5) and a major earthquake (Richter magnitude 7) with the same adjusted impact are treated identically, even if the geological effects are vastly different, and so are the probabilities of such events. Moreover, when quantifying impact, the casualties or the number of injured people were not taken into account, which biased events towards the ones that produced mostly material damage. Making hierarchies between financial impact and human casualties raises serious ethical issues, and so would attempting a mapping between the two, but future research could also take the human injury factor into consideration when ranking disaster chains. A potentially difficult extension, but extremely impactful, could be accounting for mental health on top of physical health, as mental health issues after climate disasters are common, intense and costly [Papanikolaou et al., 2011].

For simplicity of analysis and ease of interpretation and categorisation, the present definition of disaster chain limits the number of consecutive events to two. As shown in previous research, disaster cascades may very well have several linked events, especially if causality is taken into account [Gill and Malamud, 2014]. The spatial dimension was taken to be the national scale and the analysis taken at the supra-national regional scale. Given the shifting borders of the last century, several assumptions had to be made, as well as removing data points (for example, disasters located in Yugoslavia). More importantly, it is not uncommon for disasters to have effects which extend far beyond the national scale, as well as some that have a direct effect over only a local area. As such, future research could implement GIS methods and consider different administrative boundaries for land segmentation [Rosvold and Buhaug, 2021]. The methods of analysis were chosen for their simplicity and interpretability. In particular, this was due to the fact that it was first desired to compare the means of distributions under different conditions, such as in Section 4.3, or to draw the important factors in disaster impact, such as in Section 4.4. For a better forecast of the impact, more advanced and complex methods could be used, such as neural networks and LSTM algorithms, and future research could compare the accuracy of supervised and unsupervised methods [Balti et al., 2021] [Ding et al., 2019].

7 Conclusion

Within this study, each element of the analysis has brought in a different perspective on the relation between consecutive impacts and the variables and contexts it is linked to. Having a global view of disasters allowed for a more general conceptualisation of the factors involved in multi-hazard and disaster estimation.

Section 4.1 has shown that each region has their own issue prompted by the geographic and demographic context, focusing on South America, South-Eastern Asia and Western Europe. While all of these regions suffered from different hazards and at different intensities, is was observed that there was a tendency for the highest aggregate impact to come from combinations of droughts, storms and floods, while the highest individual impact would come from wildfires, extreme temperatures and earthquakes. Section 4.2 observed the most damaging types of chains, concluding that the combinations of storms and floods have the highest aggregate impact, but chains that include wildfire, droughts and earthquakes have the highest impact per event. Time between impacts is a relevant variable, as most of the damage is produced within a shorter amount of time. The most damaging chains have a stable hierarchy between timeframes, both by aggregate and by average.

Section 4.3 proposed a statistical analysis of the mean impact of disaster chains. It was observed that the second impact of a chain is more damaging than the same type of event taken as a single impact. Building on that, impacts of disaster chains are more damaging than the sum of the individual events. The order of disasters in a chain is not proven to be statistically relevant. Section 4.4 observed the main variables that affect the result of impacts, analysing various their impact and their interaction. It was concluded that disasters have become significantly more impactful financially as time passed by, which underlines the effects of climate change and anthropomorphic interaction. Furthermore, the value of the assets exposed to hazard is a crucial element in determining the disaster impact, which has determined OECD membership to be an extremely relevant variable in forecasting the financial impact of disasters.

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8 Appendix 1

		Australia and New Zealand		
Australia	New Zealand			
		Caribbean		
Antigua and Barbuda	Barbados	Cayman Islands (the)	Cuba	Dominica
Dominican Republic (the)	Grenada	Haiti	Jamaica	Martinique
Montserrat	Puerto Rico	Saint Kitts and Nevis	Saint Lucia	Trinidad and Tobago
Turks and Caicos Islands (the)	Virgin Island (British)	Virgin Island (U.S.)		
		Central America		
Belize	Costa Rica	El Salvador	Guatemala	Honduras
Mexico	Nicaragua	Panama		
		Central Asia		
Kazakhstan	Kyrgyzstan	Tajikistan	Turkmenistan	Uzbekistan
		Eastern Africa		
Burundi	Comoros (the)	Djibouti	Eritrea	Ethiopia
Kenya	Madagascar	Malawi	Mauritius	Mozambique
Rwanda	Seychelles	Somalia	Uganda	Zambia
Zimbabwe				
		Eastern Asia		
China	Hong Kong	Japan	Mongolia	
North Korea	South Korea	Taiwan		
		Eastern Europe		
Belarus	Bulgaria	Czech Republic (the)	Ukraine	Hungary
Moldova (the Republic of)	Poland	Romania	Russian Federation (the)	Slovakia
		Micronesia		
Fiji	New Caledonia	Papua New Guinea	Solomon Islands	Vanuatu
		Melanesia		
Guam	Marshall Islands (the)			
		Middle Africa		
Angola	Cameroon	Central African Republic	Chad	
		Northern Africa		
Algeria	Egypt	Libya	Morocco	Sudan (the)
Tunisia				
		Northern America		
Bermuda	Canada	United States of America (the)		
		Northern Europe		
Denmark	Estonia	Finland	Iceland	Ireland
Latvia	Lithuania	Norway	Sweden	United Kingdom
		Polynesia		
American Samoa	Cook Islands (the)	French Polynesia	Niue	Samoa
Tokelau	Tonga			
		South-Eastern Asia		
Cambodia	Indonesia	Laos	Malaysia	Myanmar
Philippines (the)	Thailand	Timor-Leste	Viet Nam	
		South America		
Argentina	Bolivia	Colombia	Ecuador	Guyana
Paraguay	Peru	Suriname	Uruguay	Venezuela
		Southern Africa		
Botswana	Lesotho	Namibia	South Africa	
		Southern Asia		
Afghanistan	Bangladesh	Bhutan	India	Iran (Islamic Republic of)
Maldives	Nepal	Pakistan	Sri Lanka	
		Southern Europe		
Albania	Bosnia and Herzegovina	Croatia	Greece	Spain
Italy	Northern Macedonia	Portugal	Serbia	Slovenia
		Western Africa		
Benin	Burkina Faso	Cabo Verde	Ghana	Liberia
Mauritania	Niger (the)	Nigeria	Senegal	Sierra Leone
Togo				
		Western Asia		
Armenia	Azerbaijan	Cyprus	Georgia	Iraq
Israel	Jordan	Lebanon	Oman	Qatar
Saudi Arabia	Turkey	Yemen		
		Western Europe		
Austria	Belgium	France	Germany	Luxembourg
Netherlands (the)	Switzerland			

Table 13: Countries - Regional Allocation

9 Appendix 2 - Regional Analysis

This subsection presents the disaster chains most impactful for each of the regions analysed.

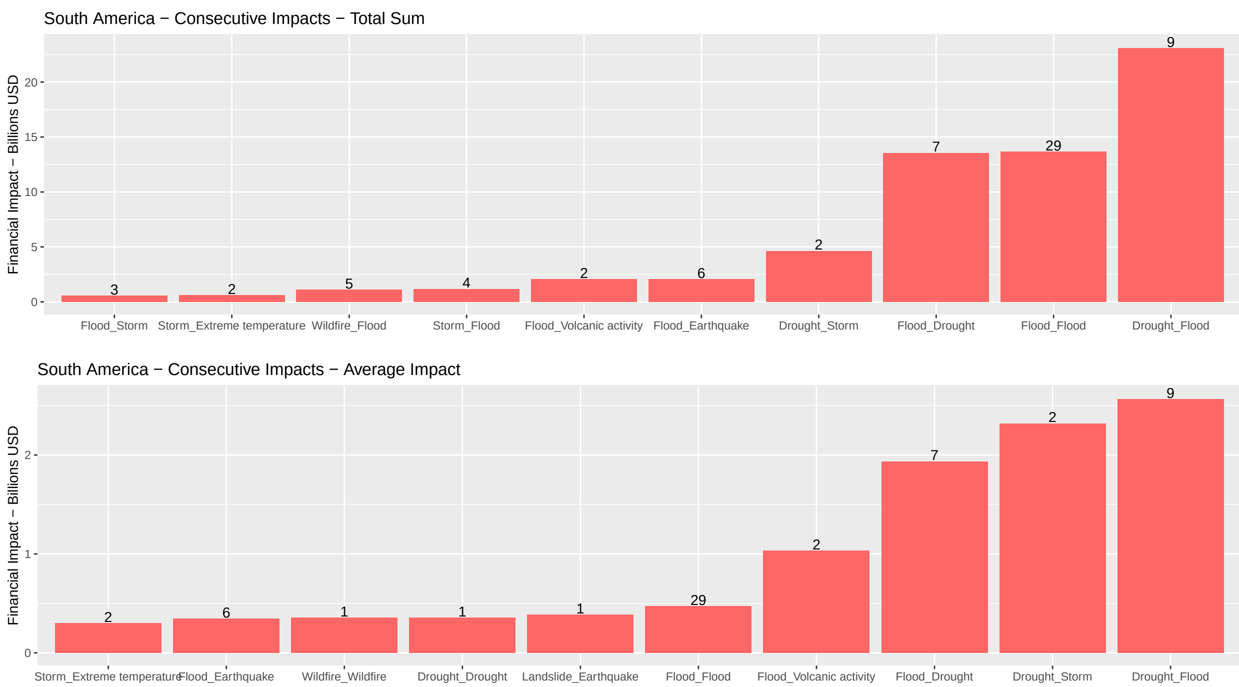

Figure 14: Most impactful disaster chains in South America, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

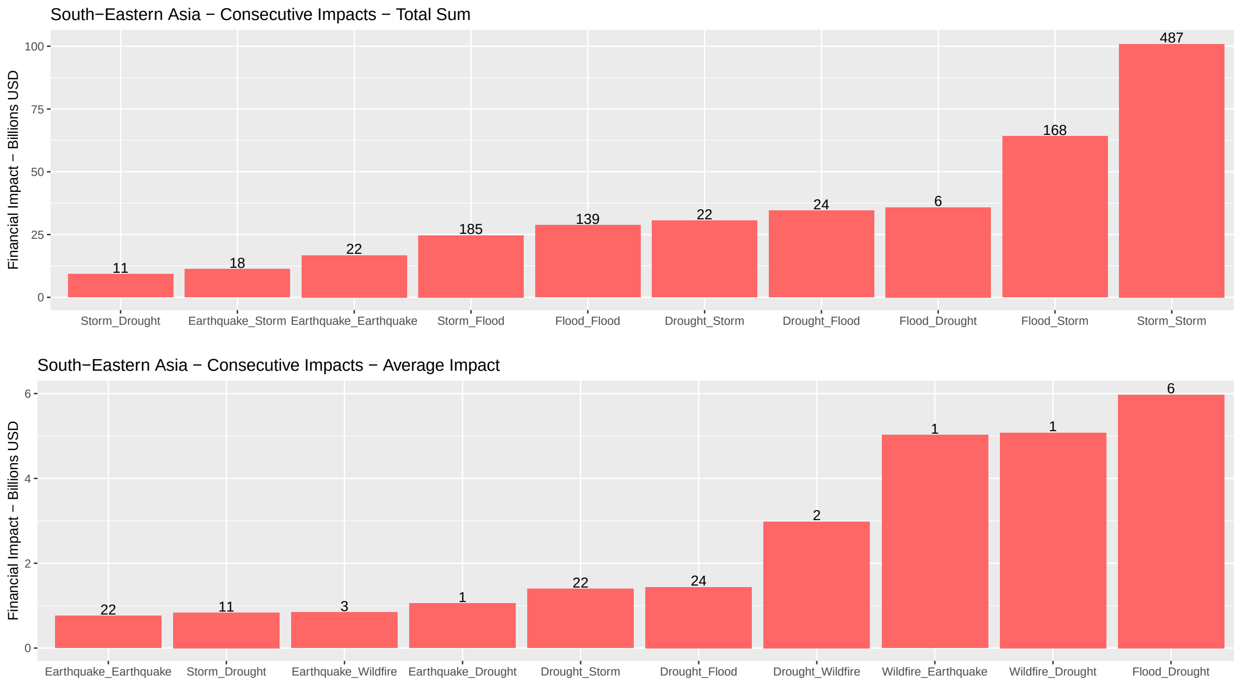

Figure 15: Most impactful disaster chains in South Eastern Asia, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

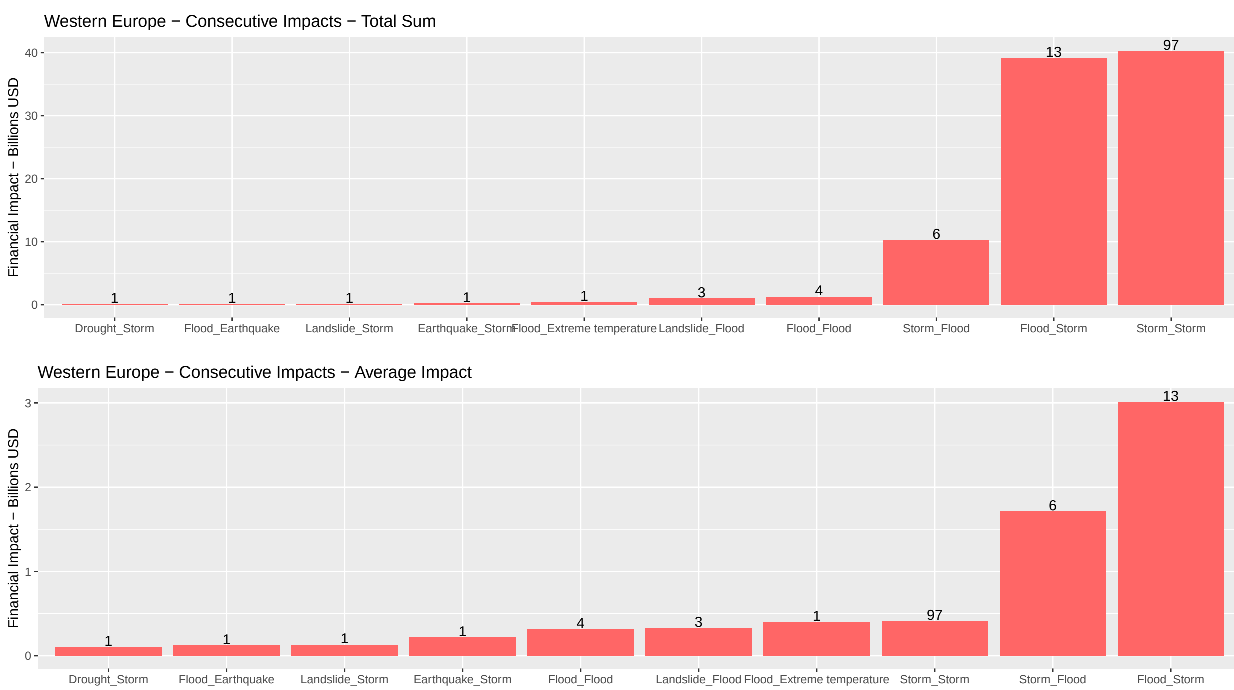

Figure 16: Most impactful disaster chains in Western Europe, representing aggregated sums of impacts (top figure) and averaged over the number of occurrences (bottom figure)

10 Appendix 3 - Disaster Chain Distribution

10.1 Medium Time Range - Top 10

This subsection presents the most impactful chains globally, segmented by region. The time interval between hazards is taken as 100 days.

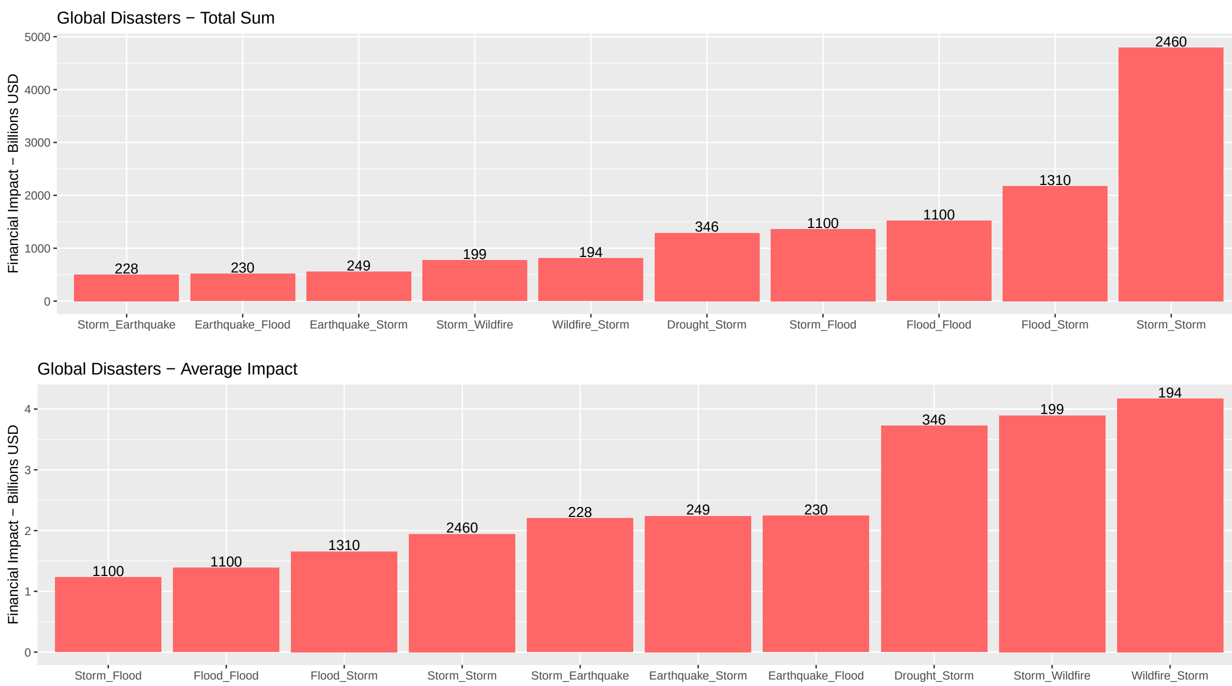

Figure 17: Global disaster distribution - Medium time range

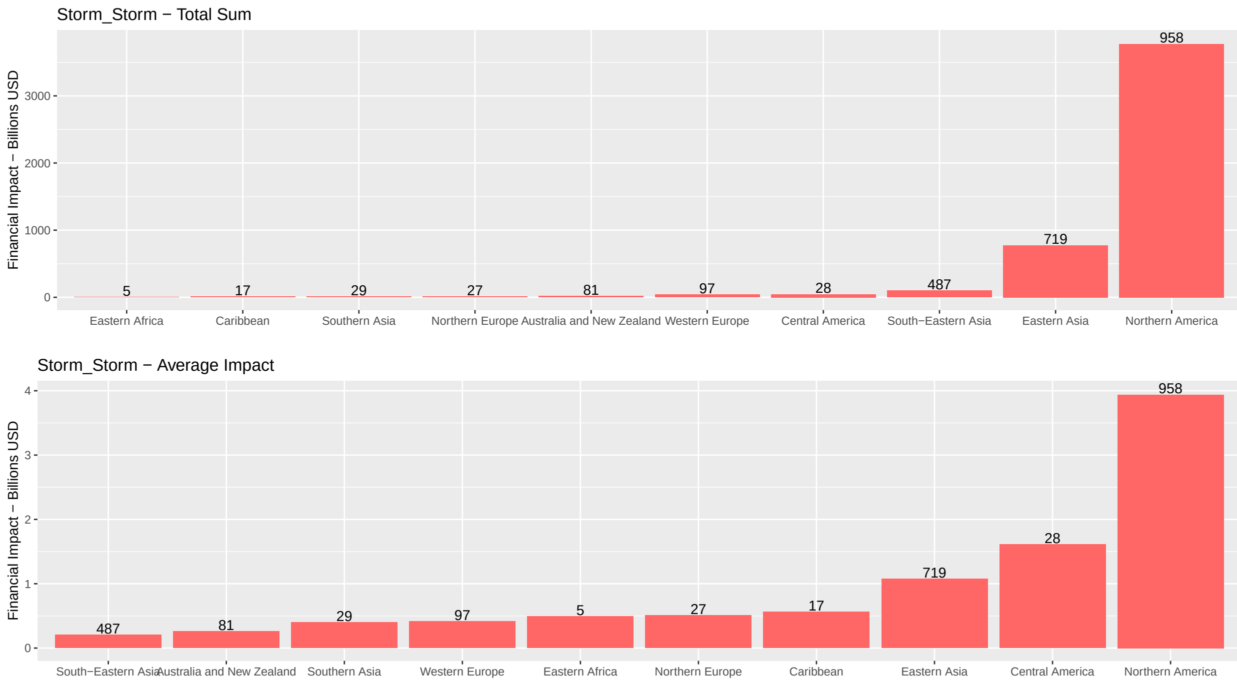

Figure 18: Storm_Storm disaster distribution - Medium time range

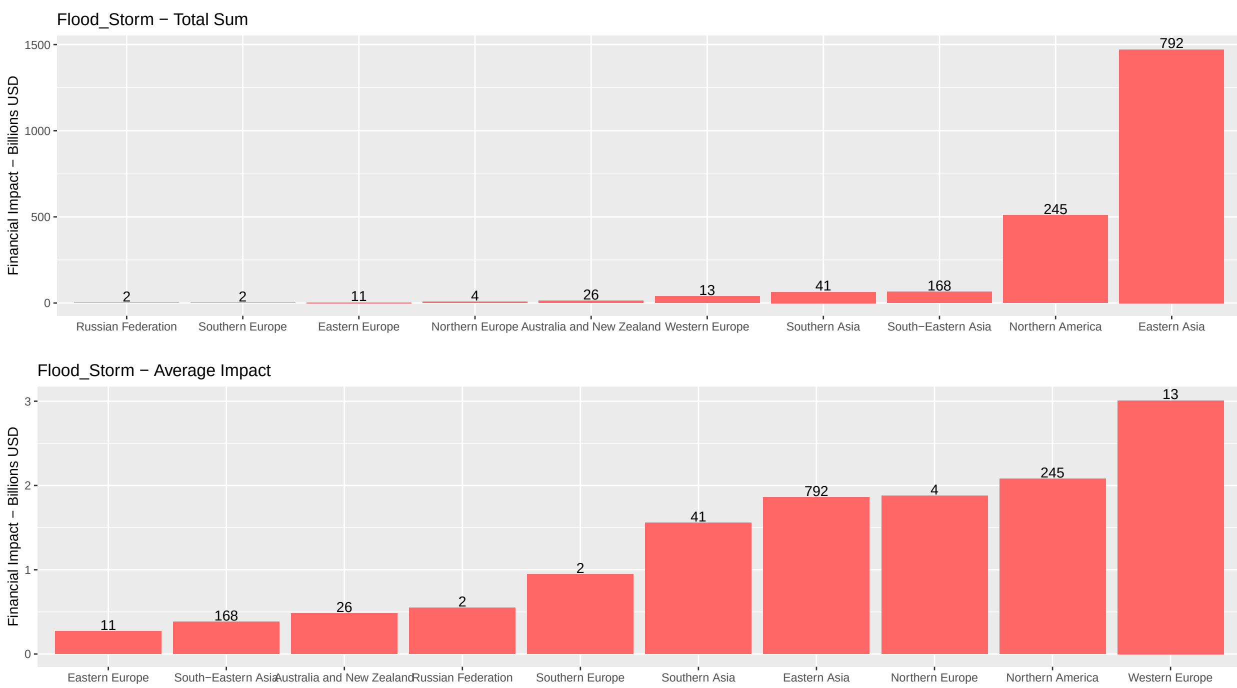

Figure 19: Flood_Storm disaster distribution - Medium time range

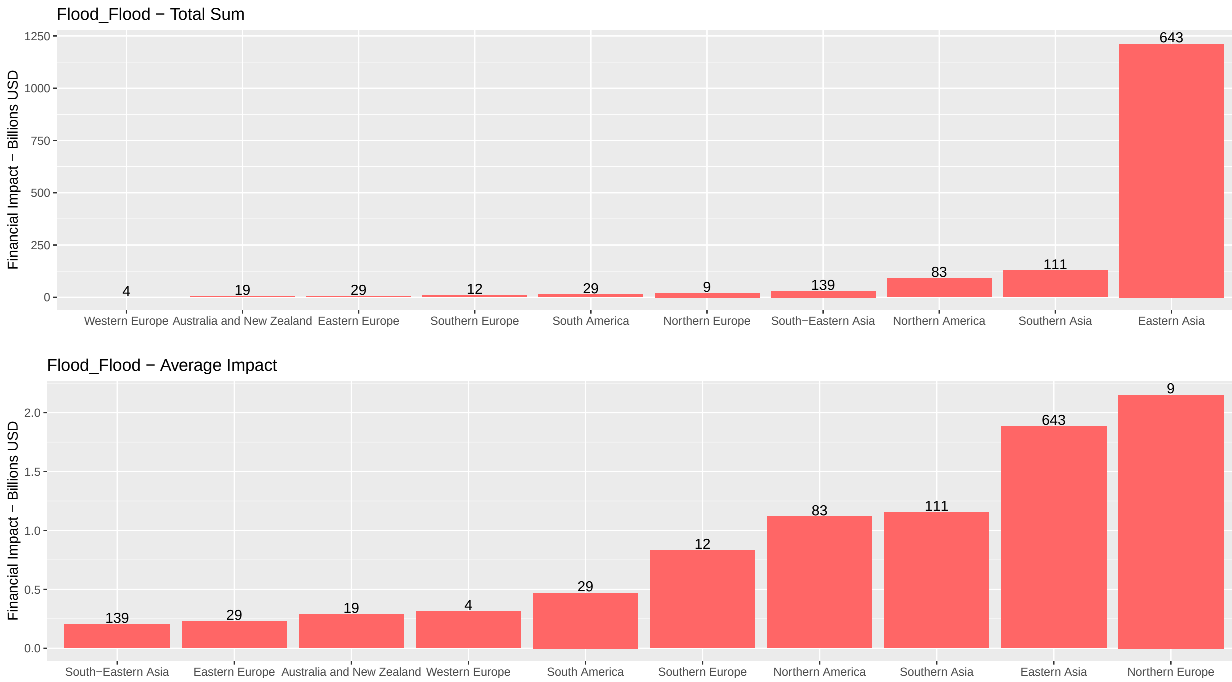

Figure 20: Flood_Flood disaster distribution - Medium time range

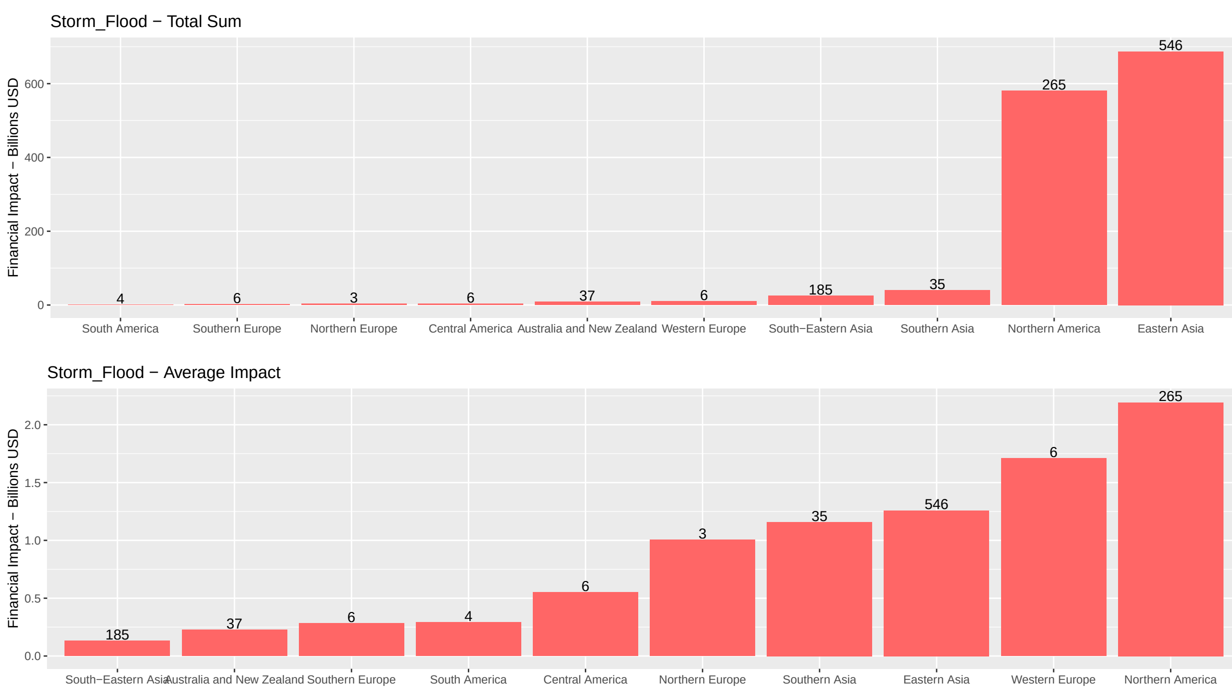

Figure 21: Storm_Flood disaster distribution - Medium time range

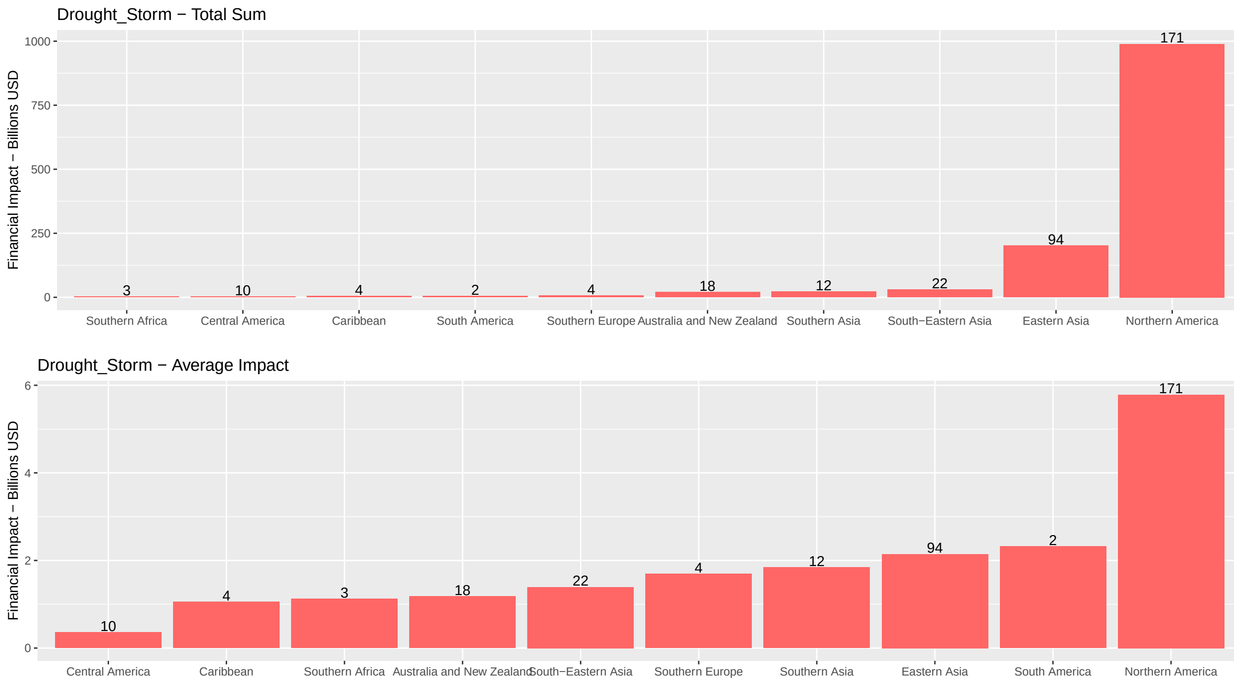

Figure 22: Drought_Storm disaster distribution - Medium time range

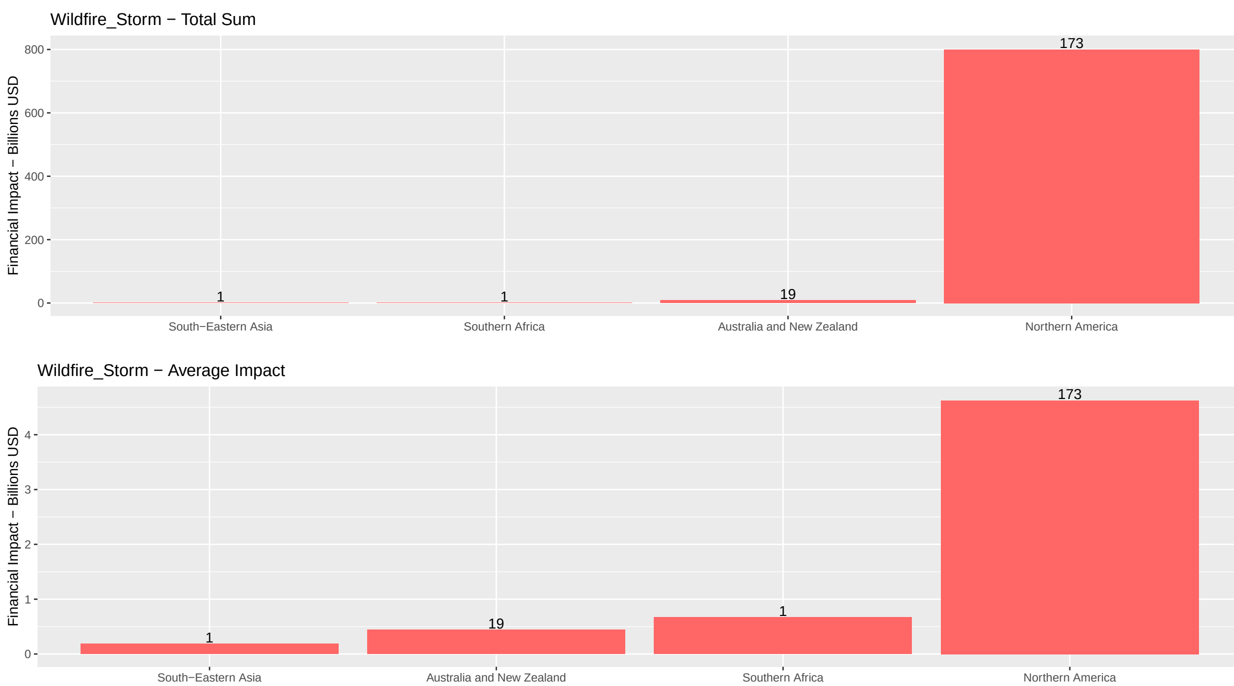

Figure 23: Wildfire_Storm disaster distribution - Medium time range

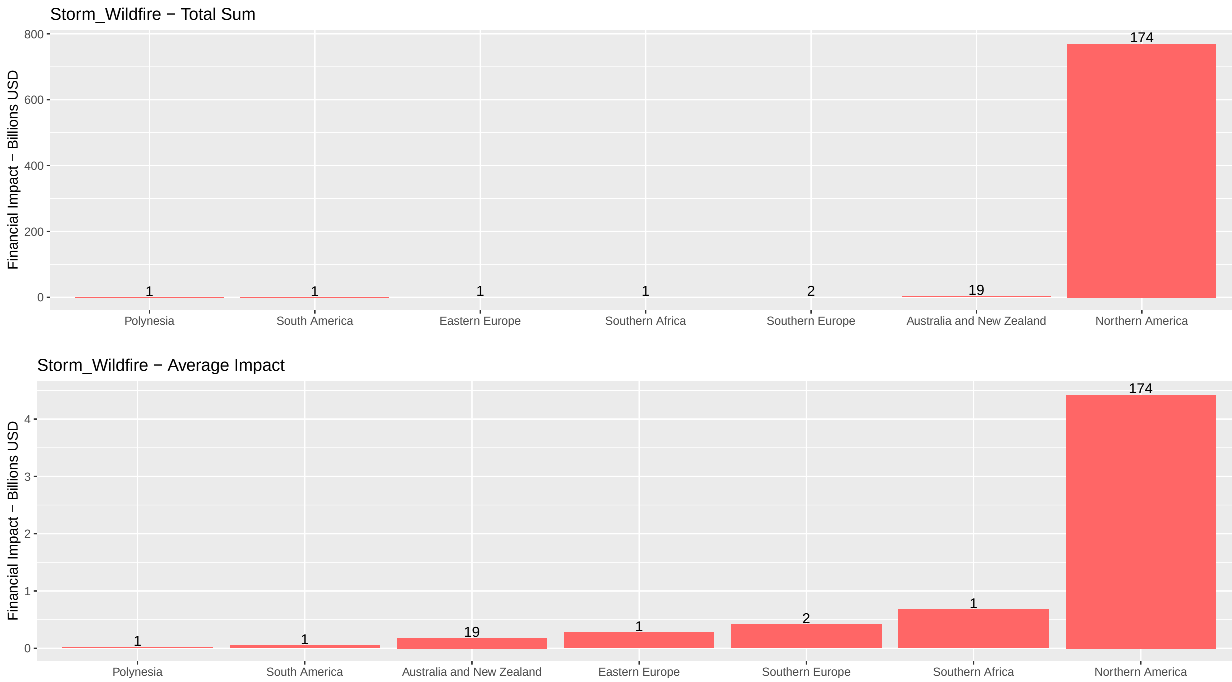

Figure 24: Storm_Wildfire disaster distribution - Medium time range

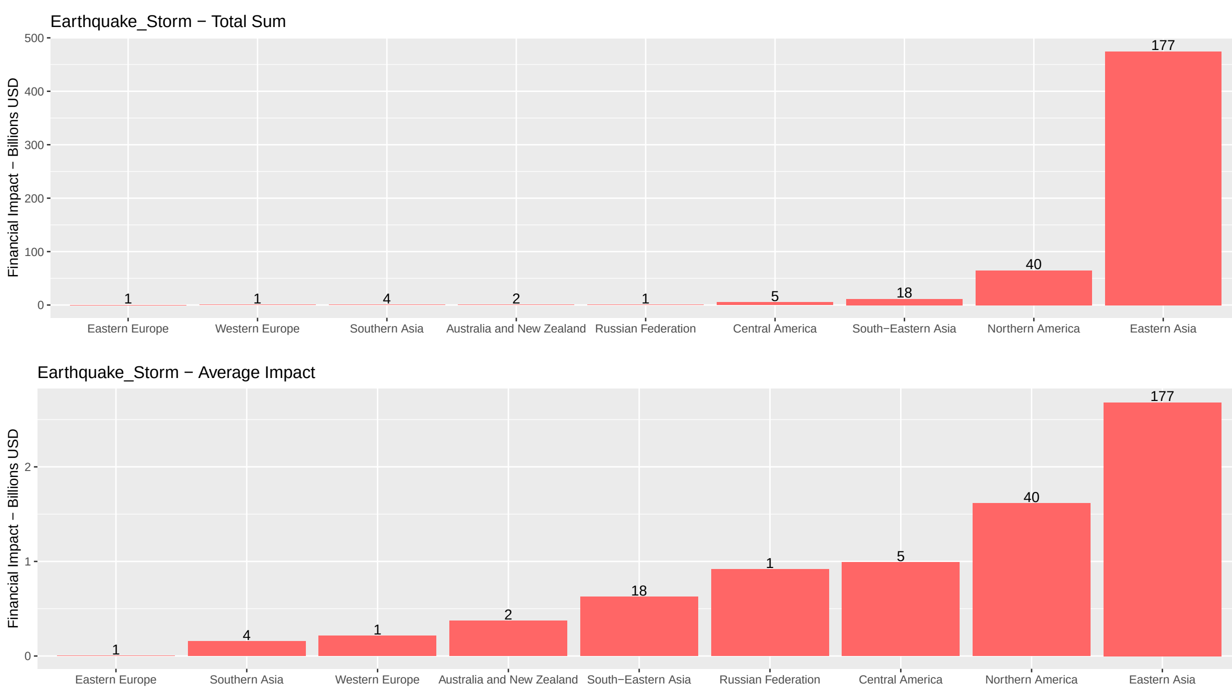

Figure 25: Earthquake_Storm disaster distribution - Medium time range

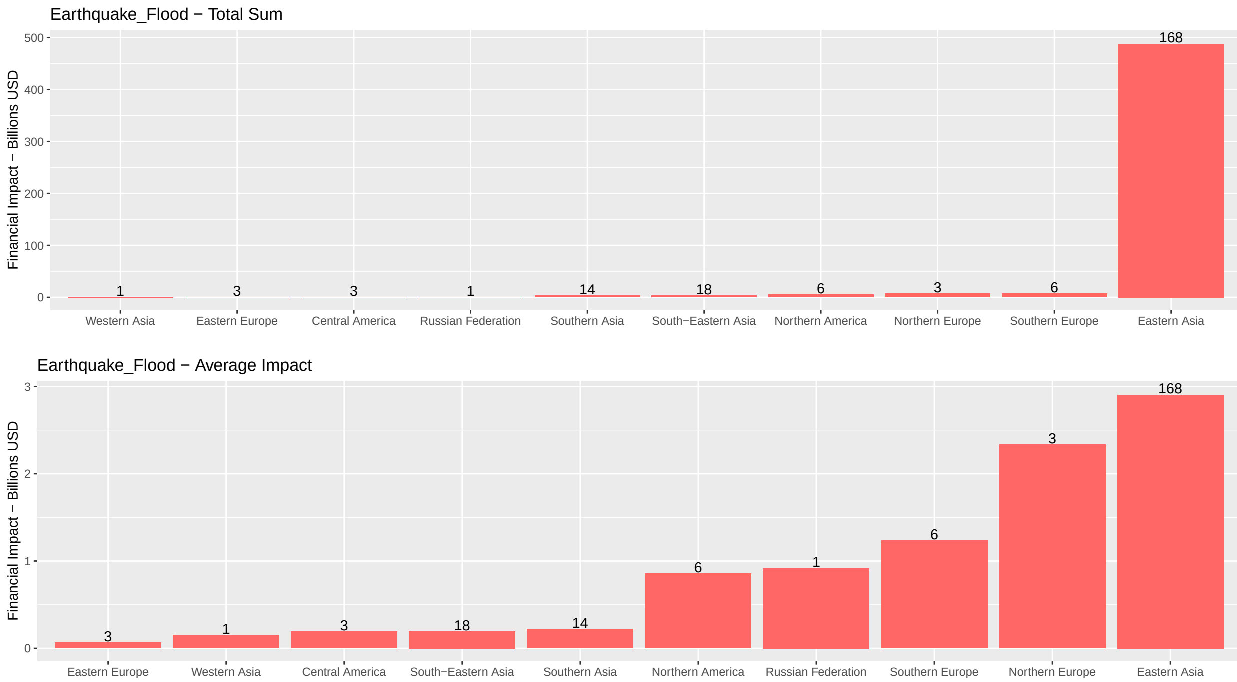

Figure 26: Earthquake_Flood disaster distribution - Medium time range

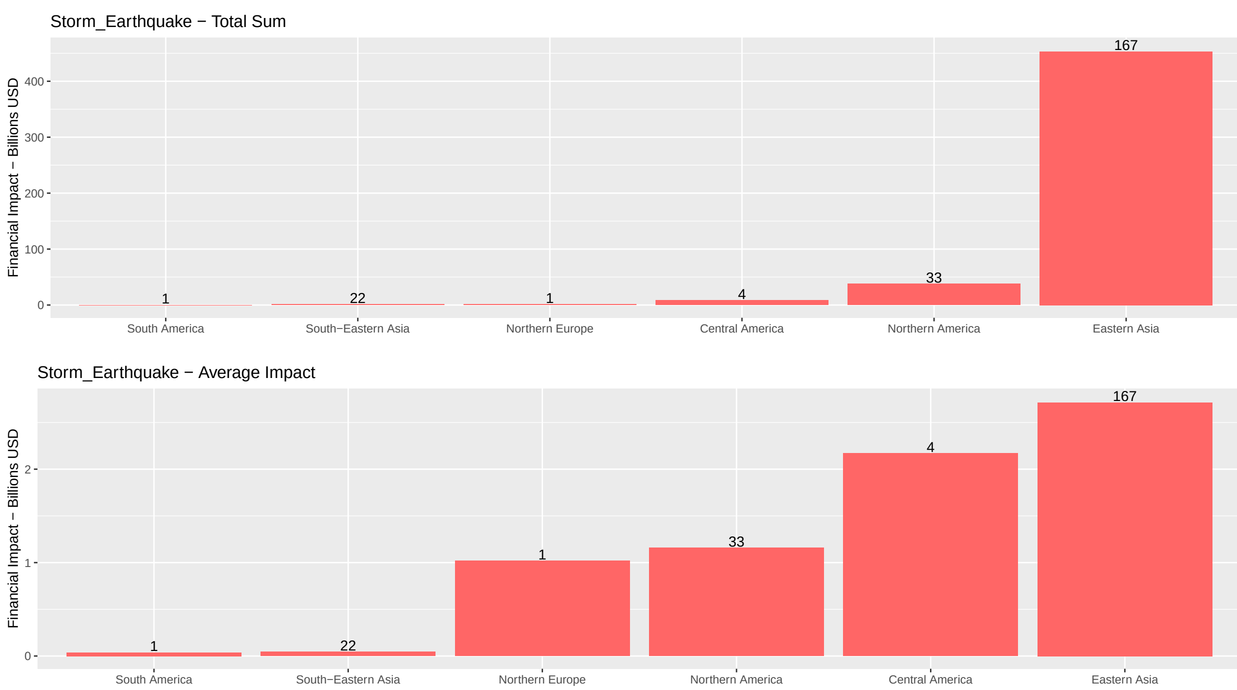

Figure 27: Storm_Earthquake disaster distribution - Medium time range

10.2 Long Time Range - Top 10

This subsection presents the most impactful chains globally, segmented by region. The time interval between hazards is taken as 365 days.

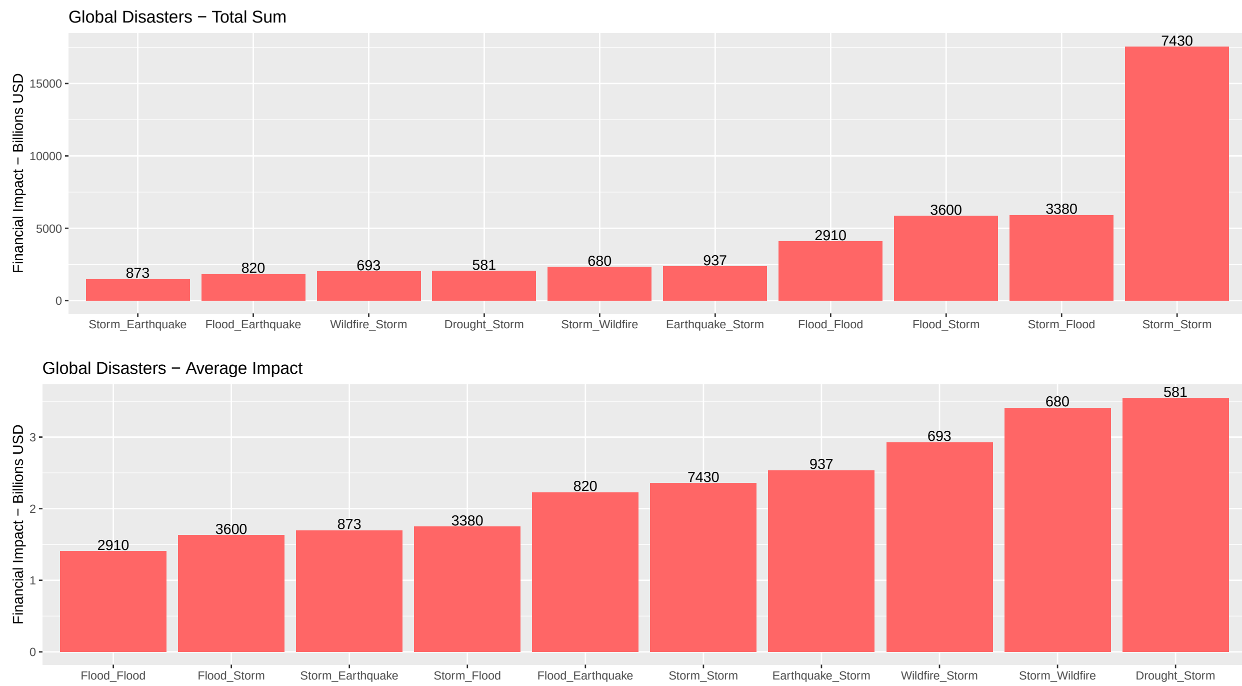

Figure 28: Global disaster distribution - Long time range

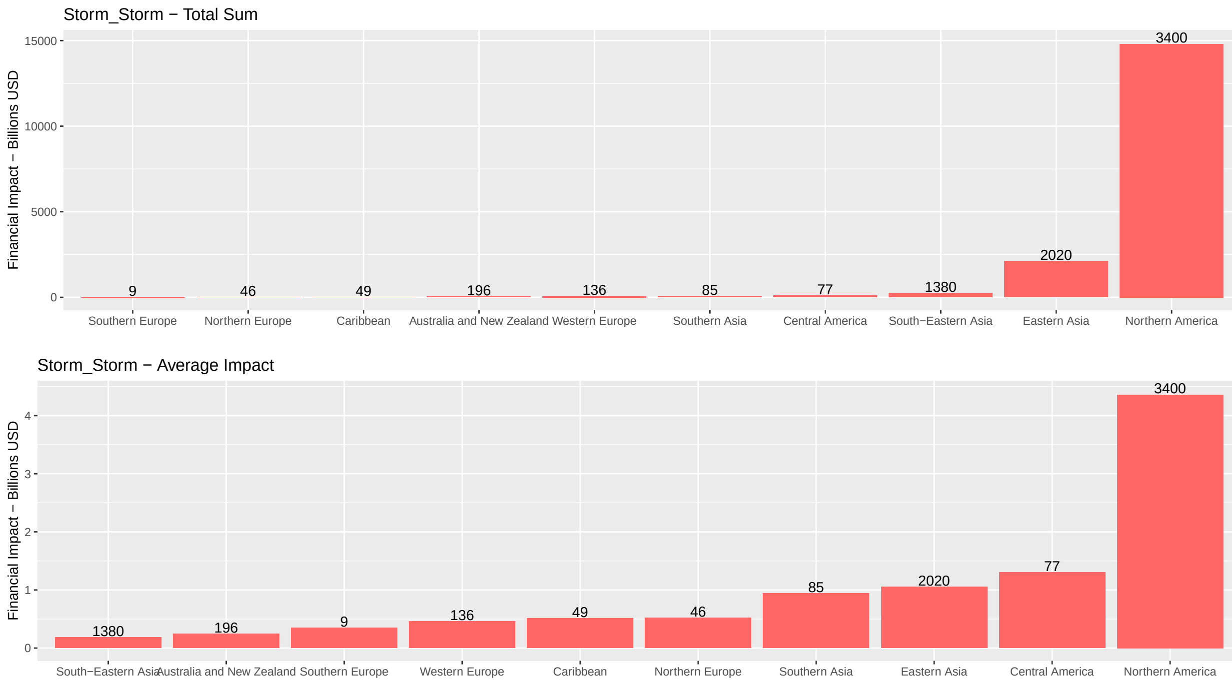

Figure 29: Storm_Storm disaster distribution - Long time range

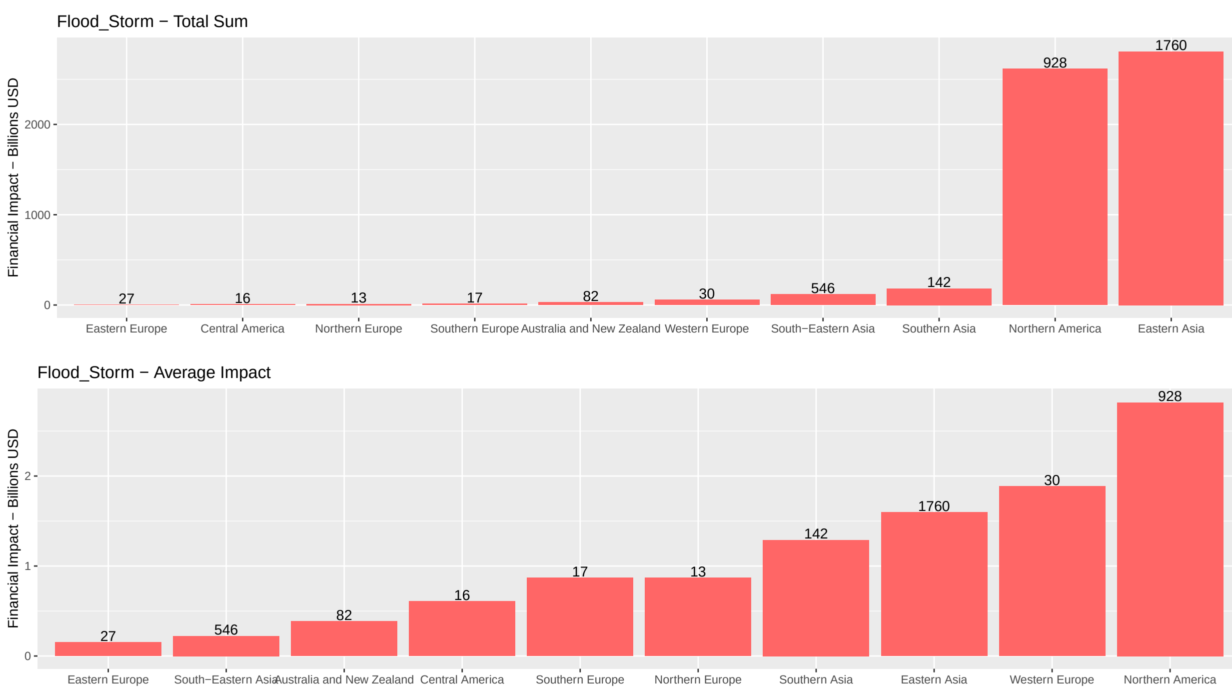

Figure 30: Flood_Storm disaster distribution - Long time range

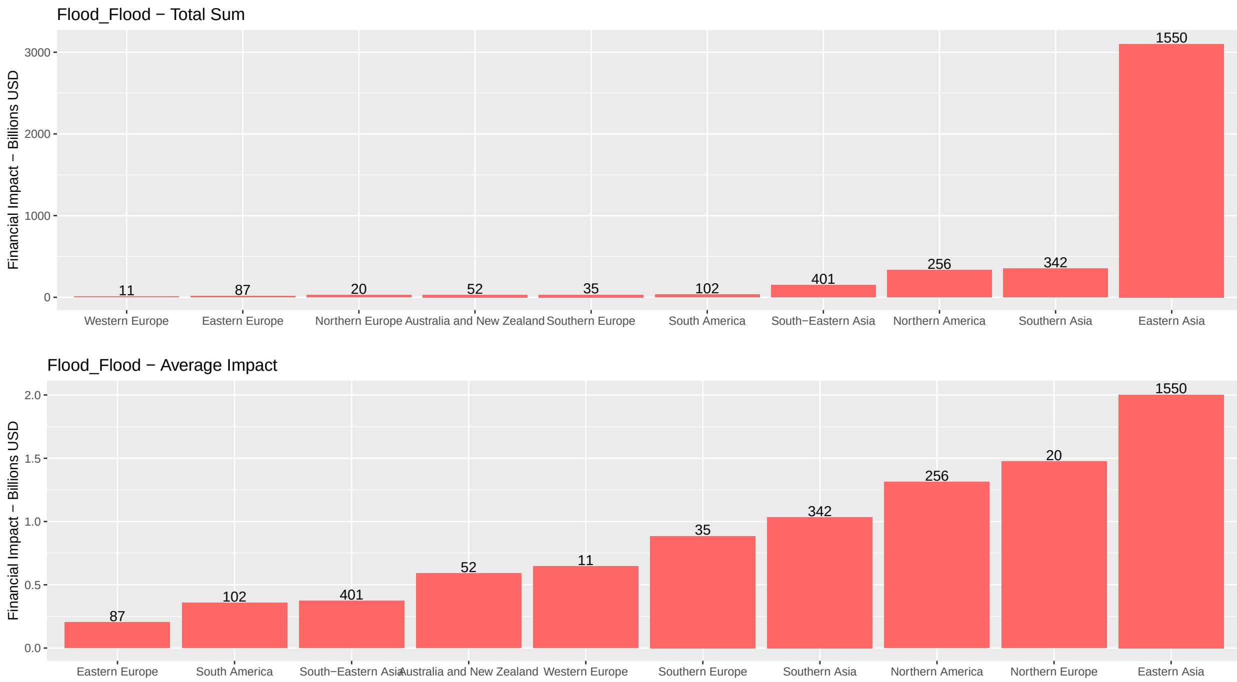

Figure 31: Flood_Flood disaster distribution - Long time range

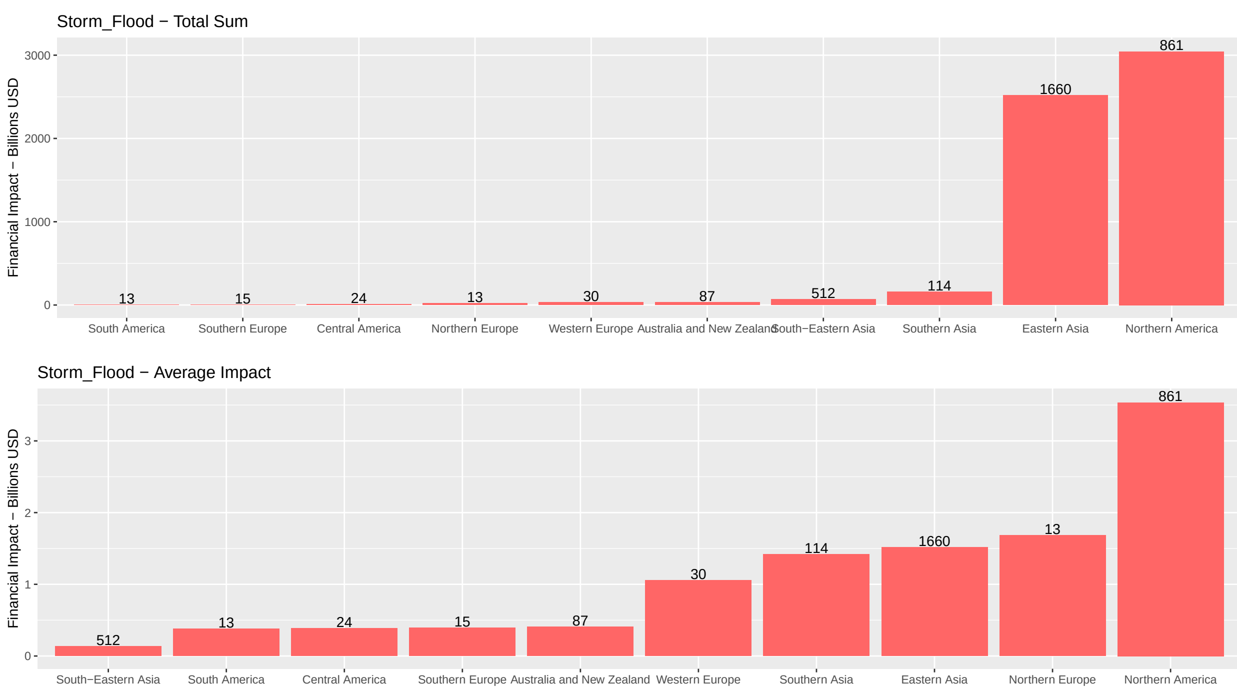

Figure 32: Storm_Flood disaster distribution - Long time range

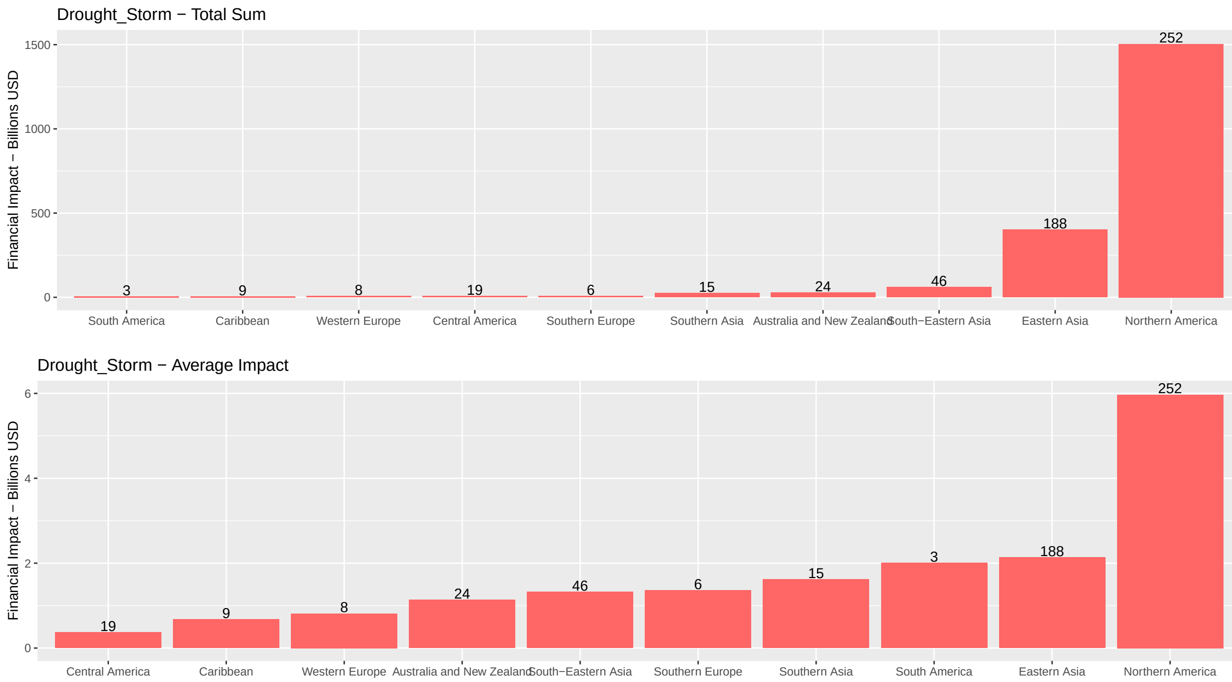

Figure 33: Drought_Storm disaster distribution - Long time range

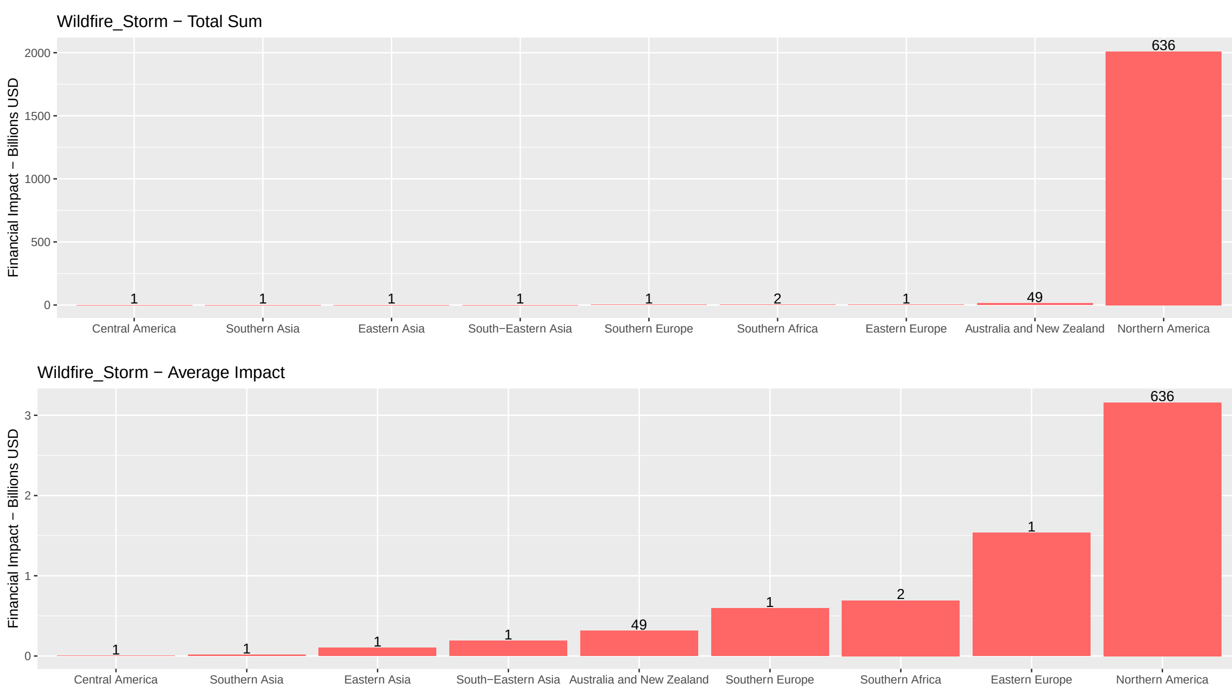

Figure 34: Wildfire_Storm disaster distribution - Long time range

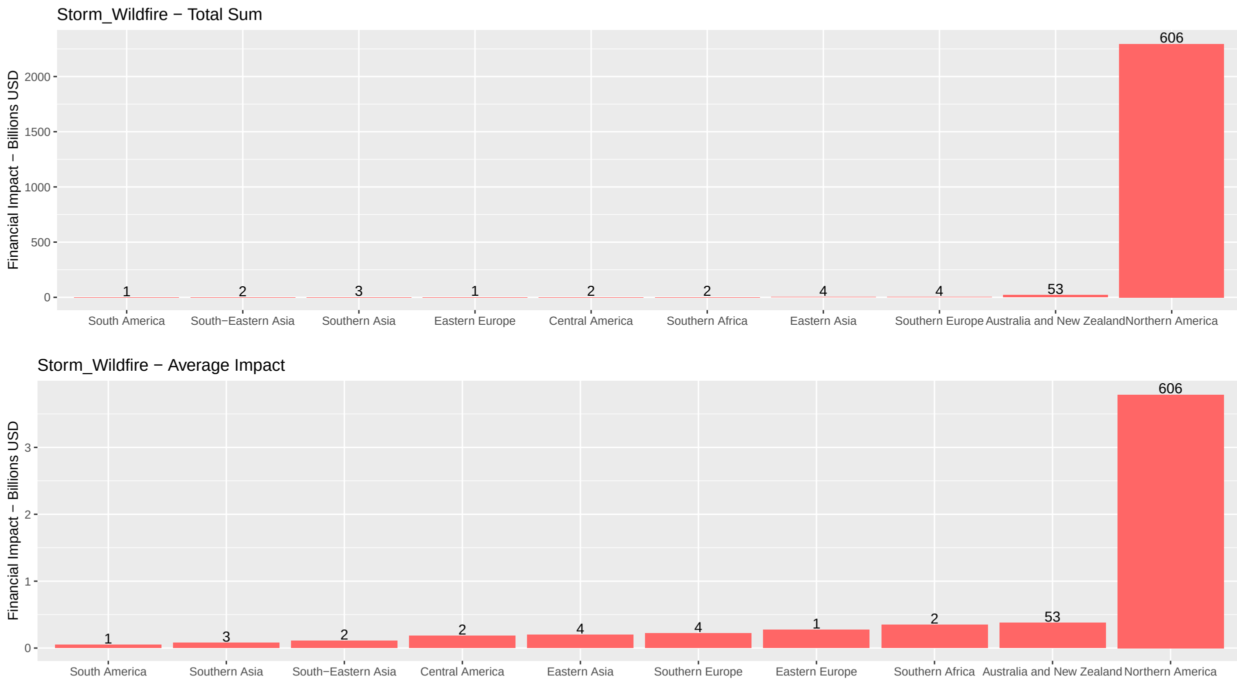

Figure 35: Storm_Wildfire disaster distribution - Long time range

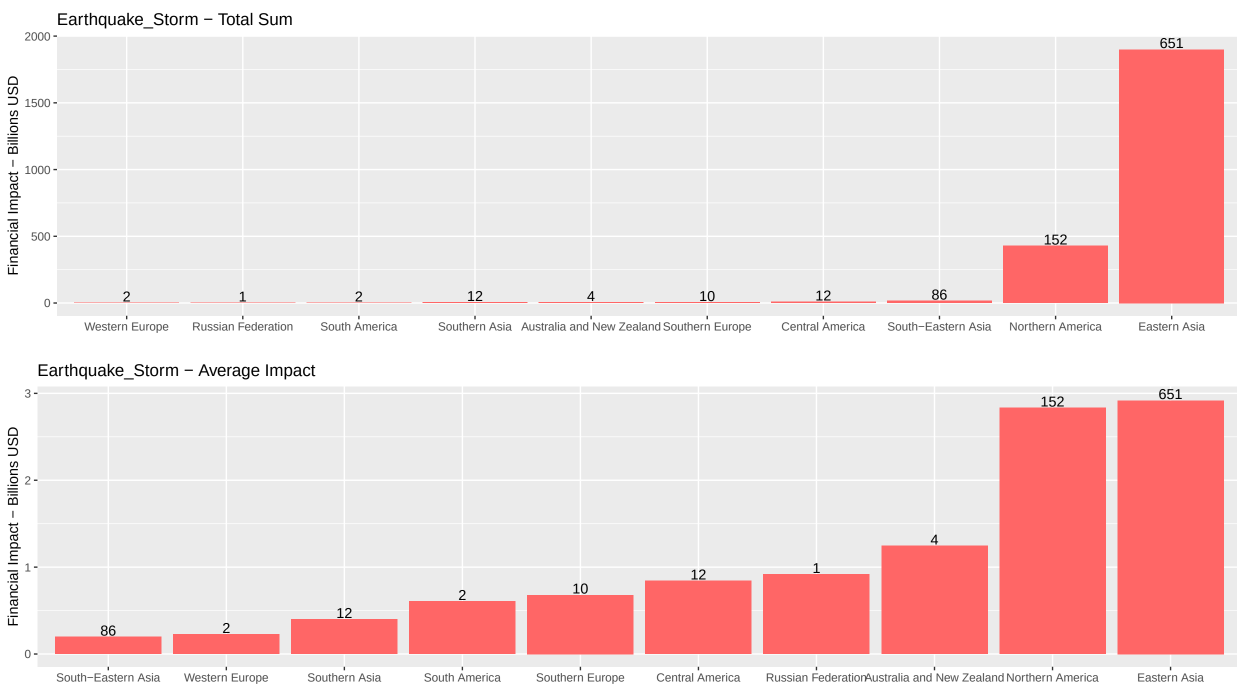

Figure 36: Earthquake_Storm disaster distribution - Long time range

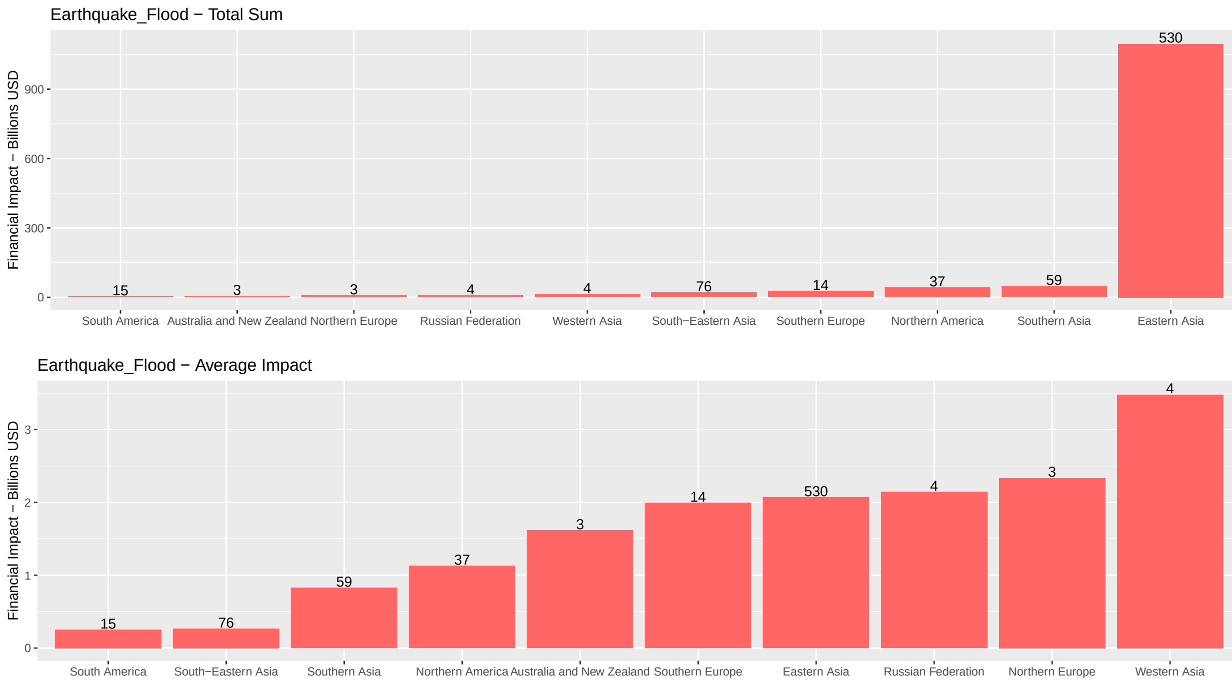

Figure 37: Earthquake_Flood disaster distribution - Long time range

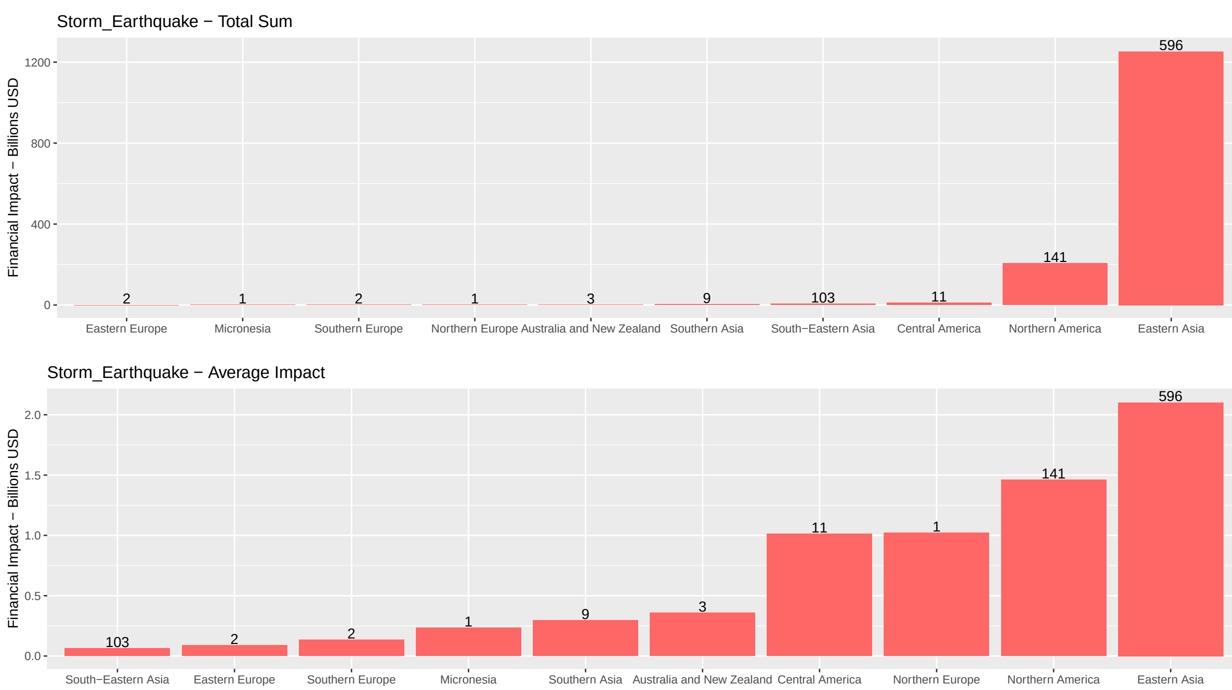

Figure 38: Storm_Earthquake disaster distribution - Long time range

10.3 Short Time Range - Top 10

This subsection presents the most impactful chains globally, segmented by region. The time interval between hazards is taken as 30 days.

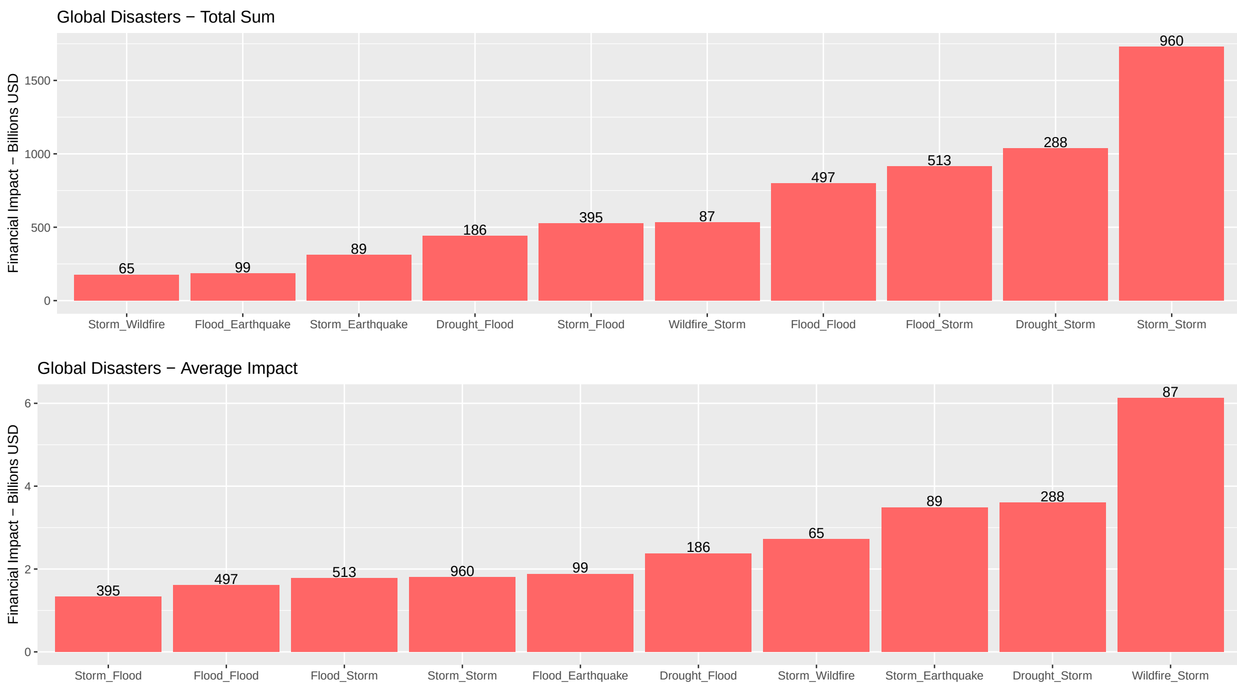

Figure 39: Global disaster distribution - Short time range

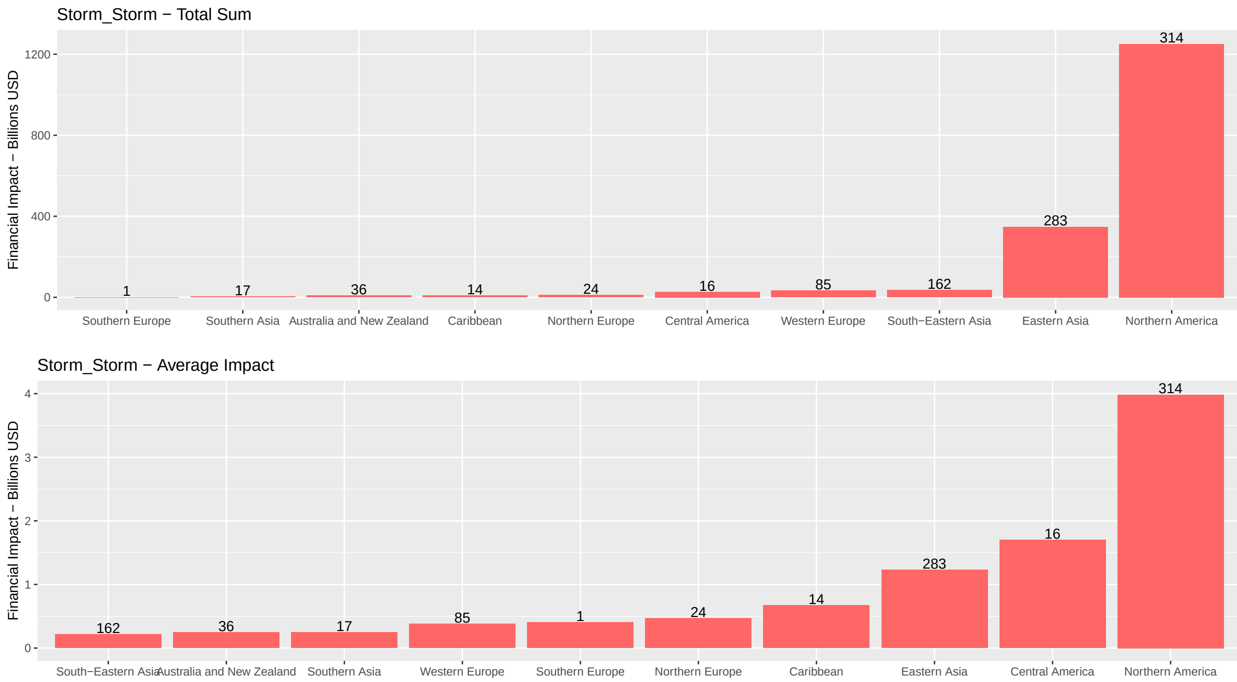

Figure 40: Storm_Storm disaster distribution - Short time range

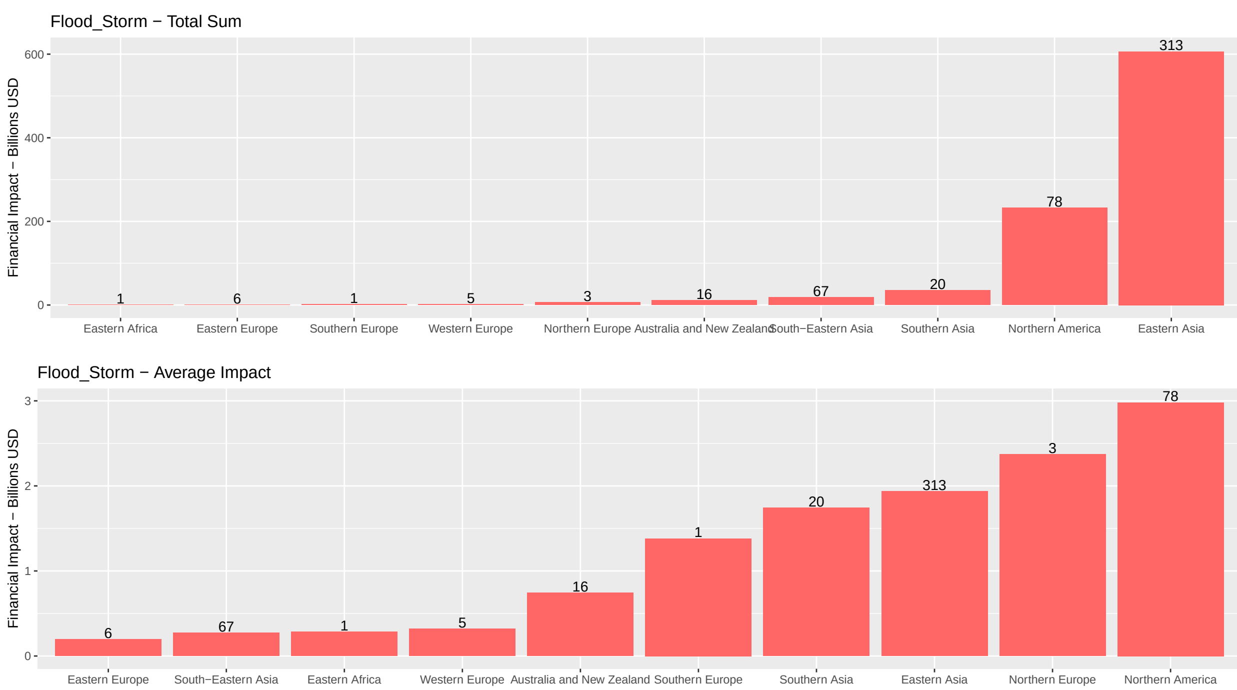

Figure 41: Flood_Storm disaster distribution - Short time range

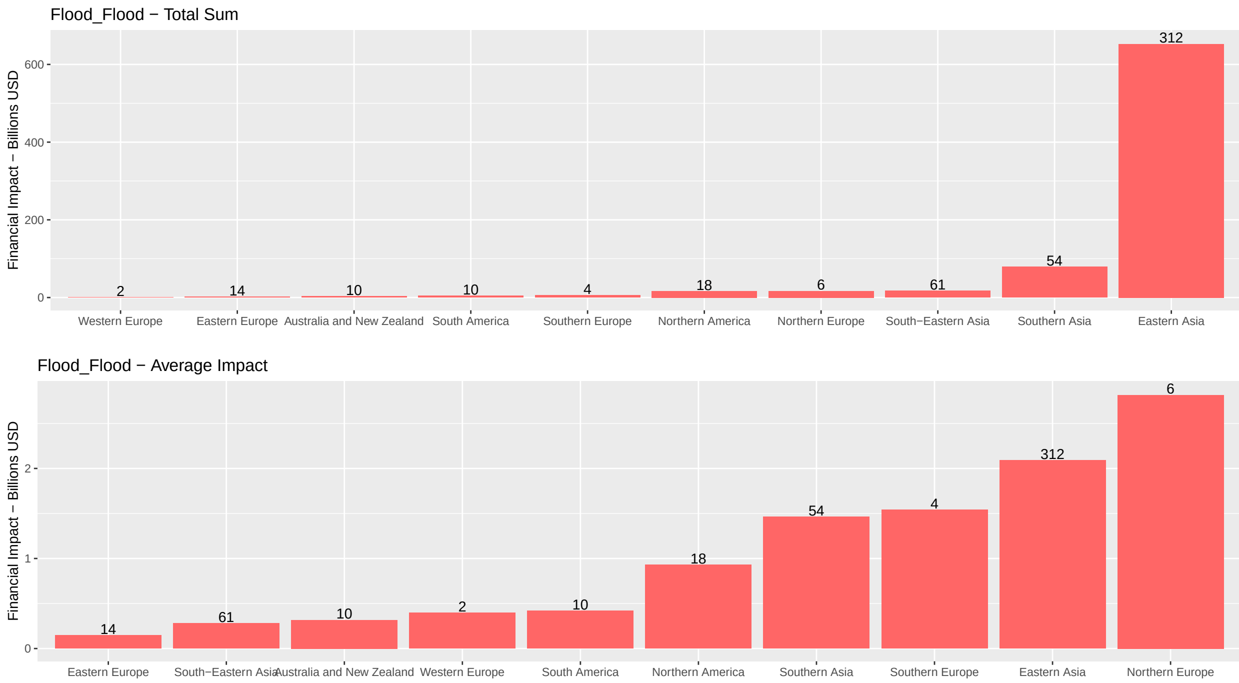

Figure 42: Flood_Flood disaster distribution - Short time range

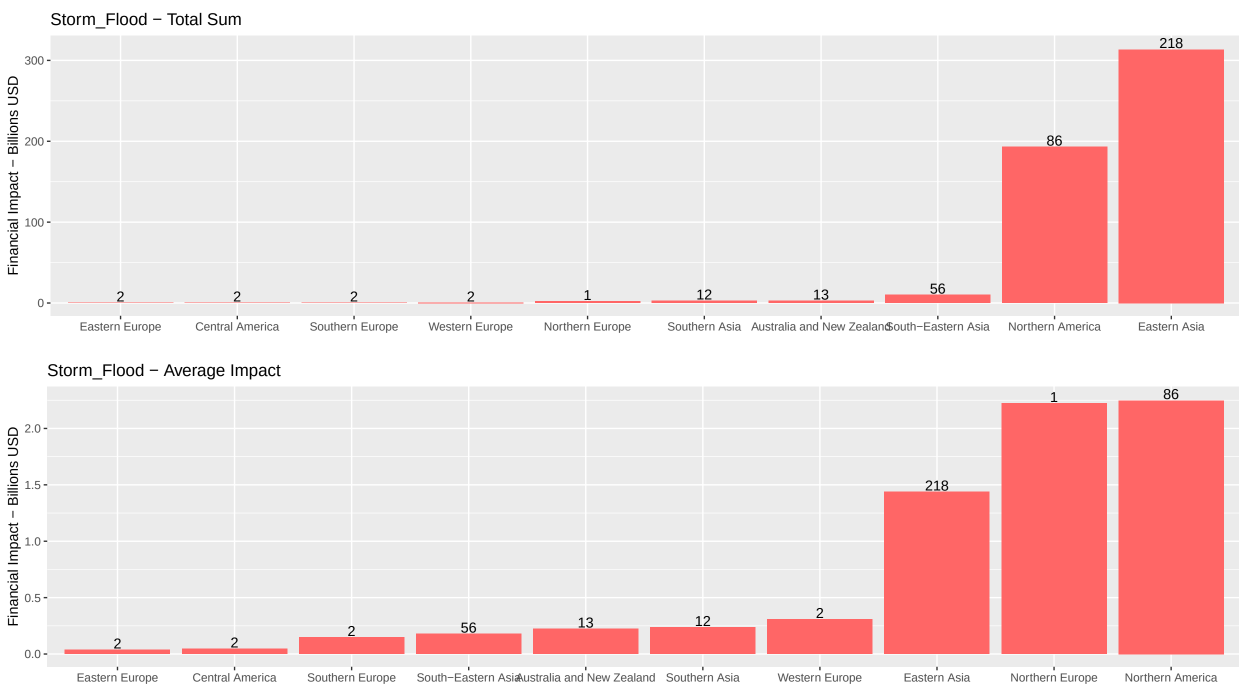

Figure 43: Storm_Flood disaster distribution - Short time range

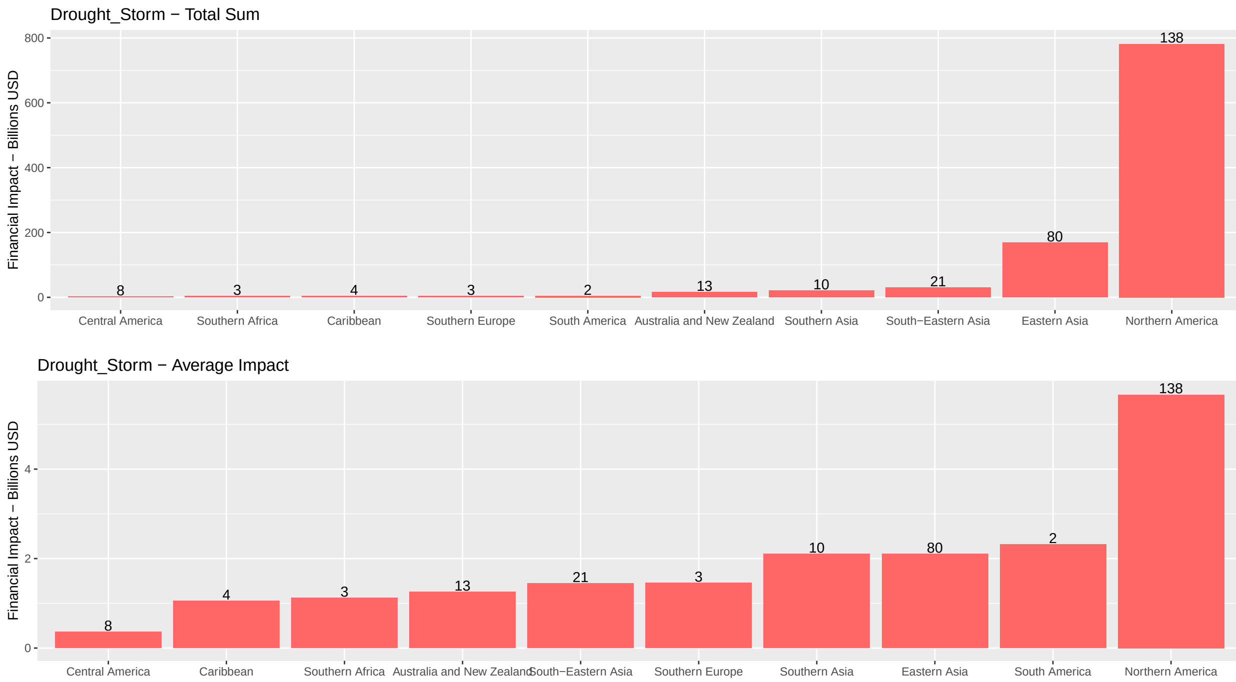

Figure 44: Drought_Storm disaster distribution - Short time range

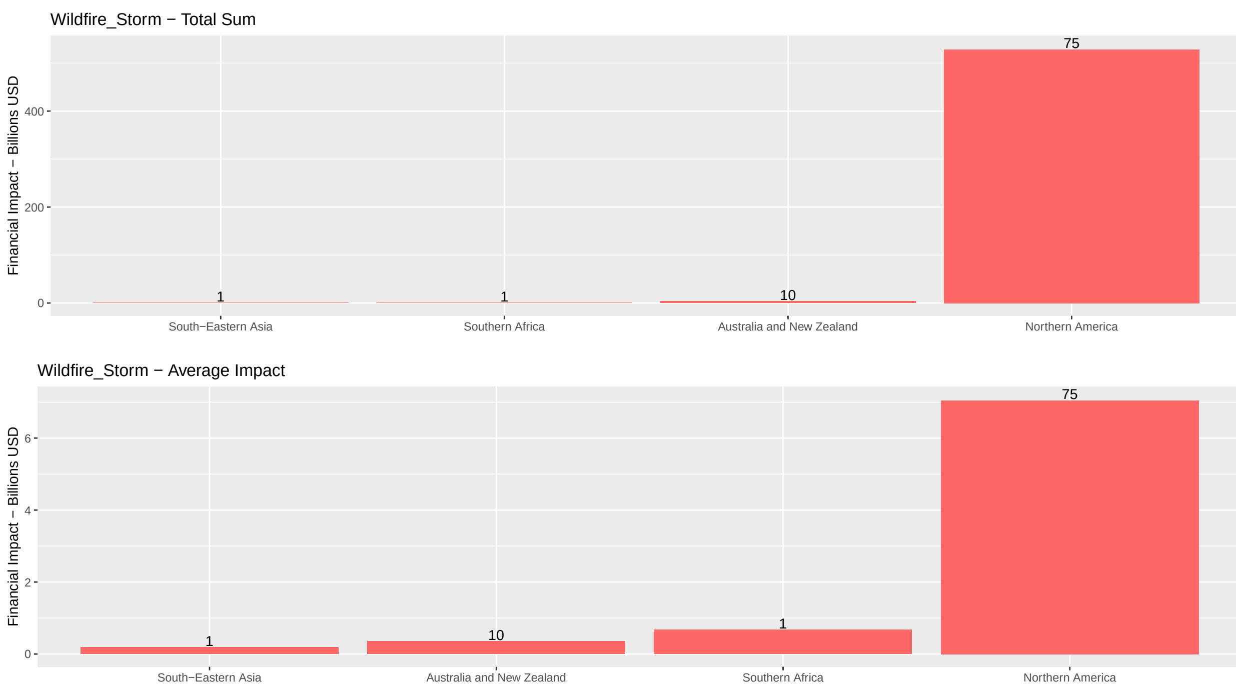

Figure 45: Wildfire_Storm disaster distribution - Short time range

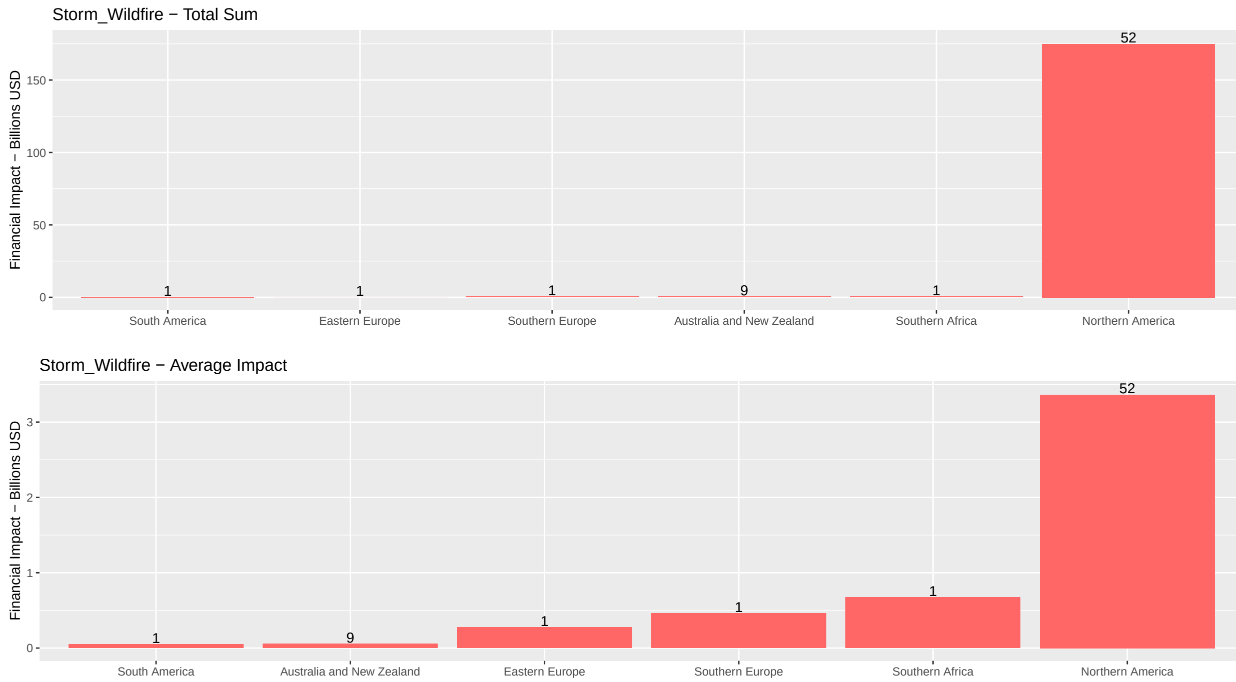

Figure 46: Storm_Wildfire disaster distribution - Short time range

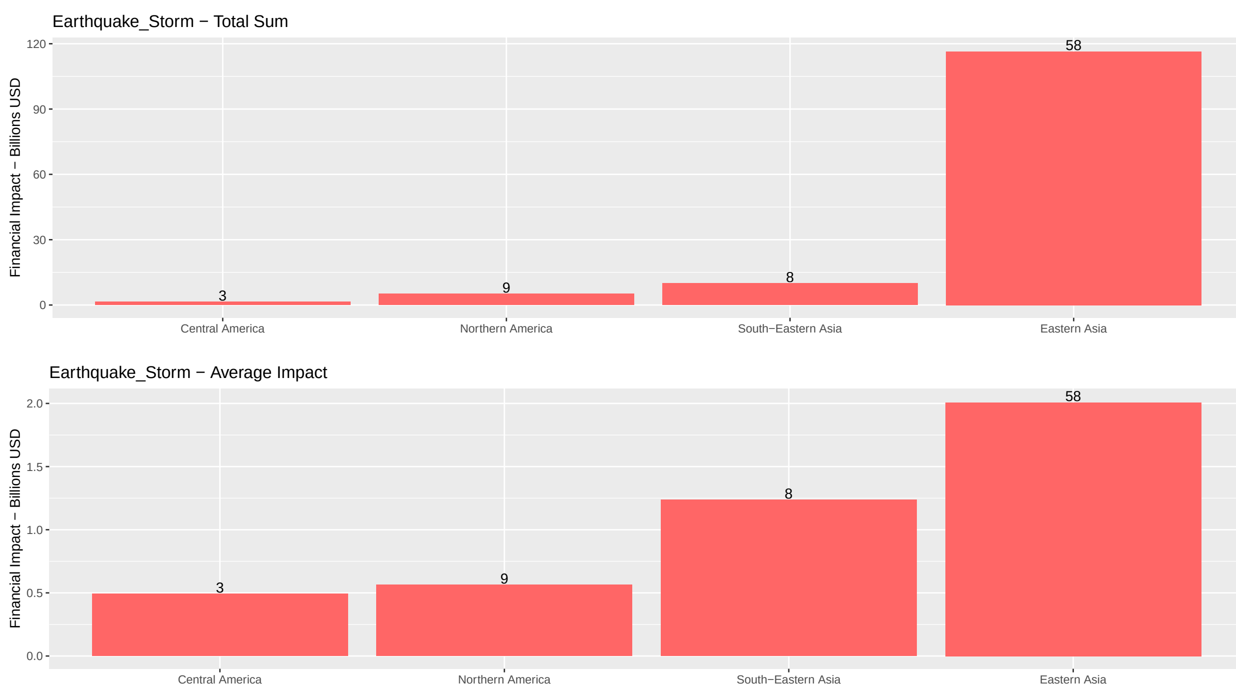

Figure 47: Earthquake_Storm disaster distribution - Short time range

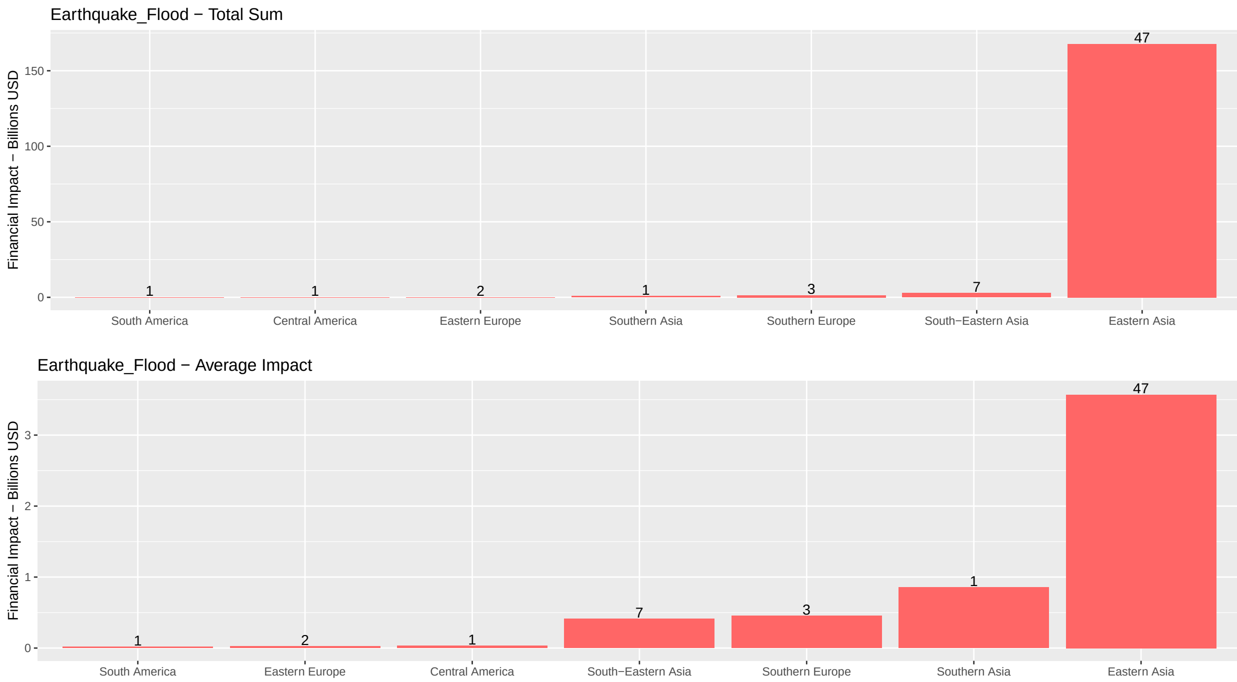

Figure 48: Earthquake_Flood disaster distribution - Short time range

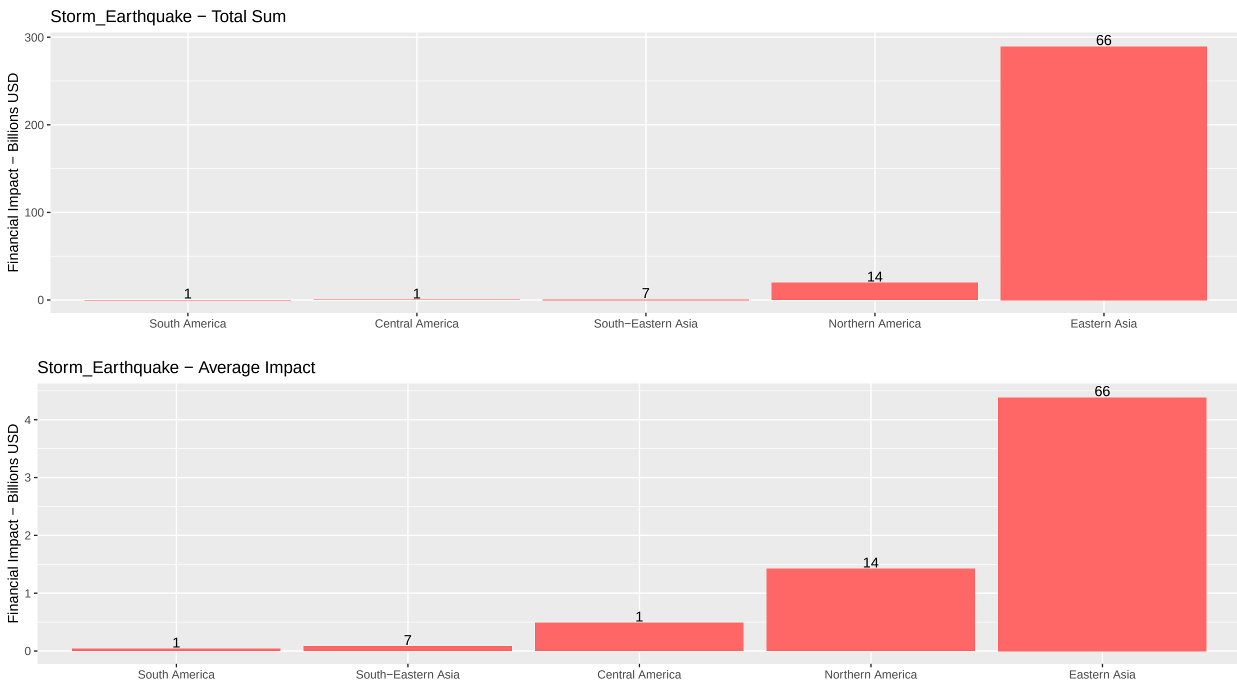

Figure 49: Storm_Earthquake disaster distribution - Short time range

10.4 Medium Time Range - Remaining Disaster Chains

This subsection presents the disaster chains that were not shown before, segmented by region. The time interval between hazards is taken as 100 days.

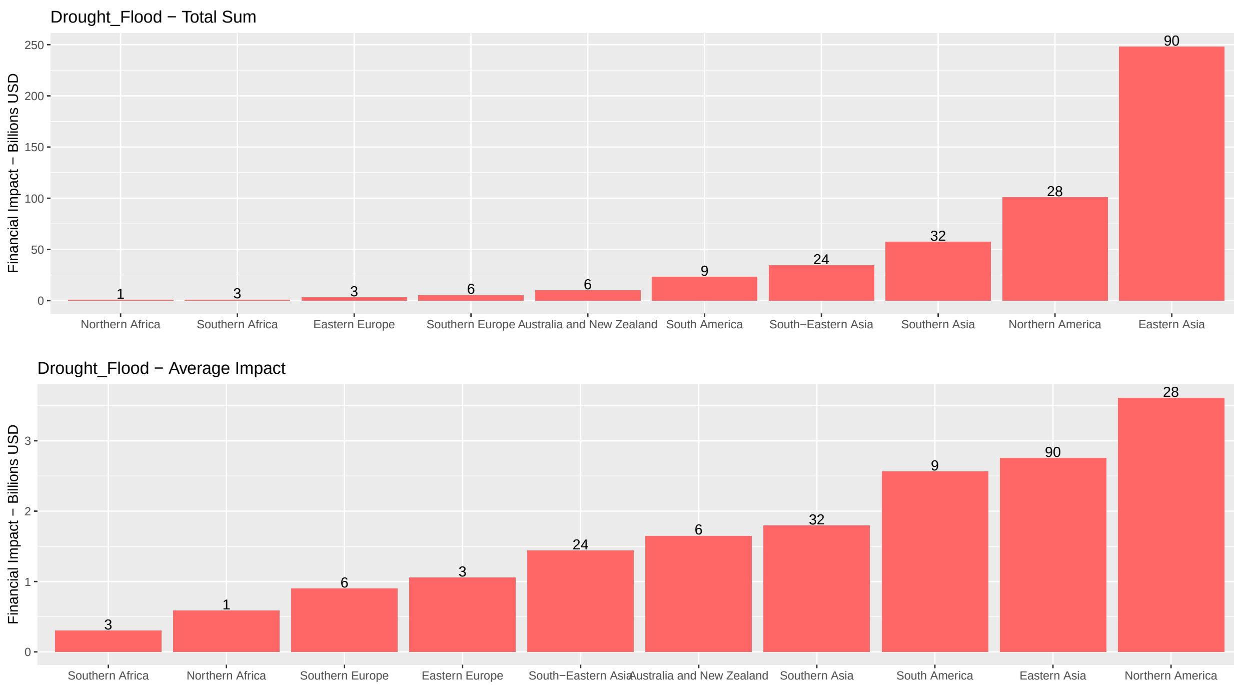

Figure 50: Drought_Flood disaster distribution - Medium time range

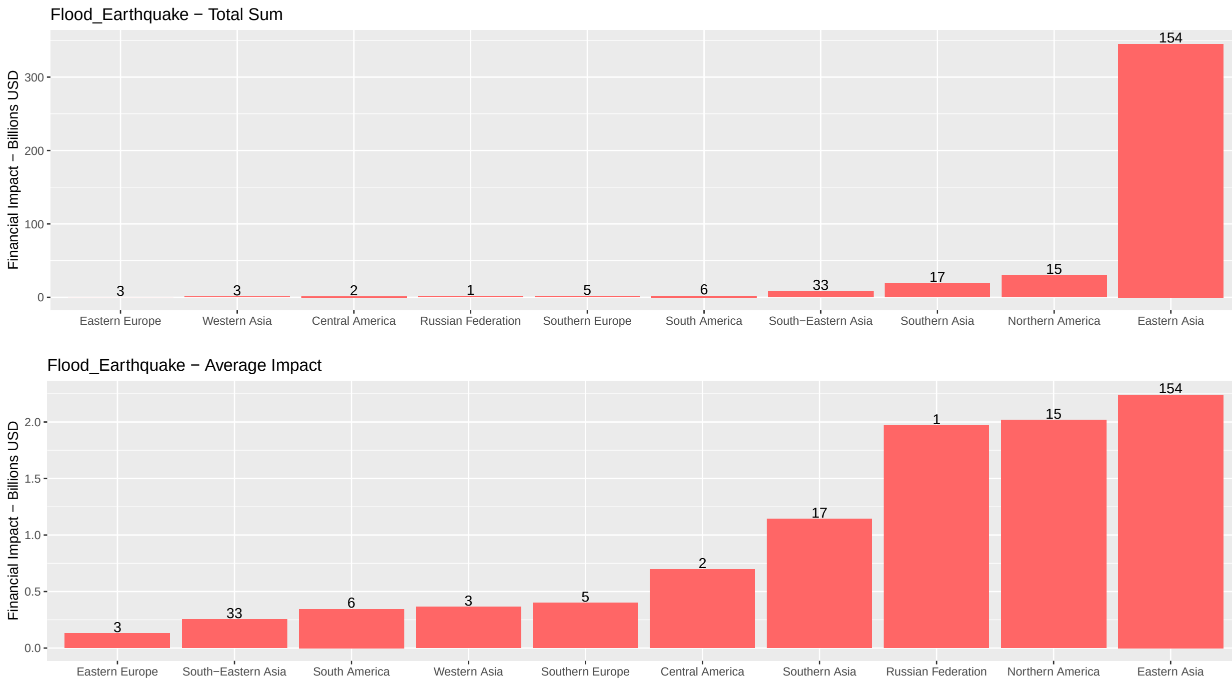

Figure 51: Flood_Earthquake disaster distribution - Medium time range

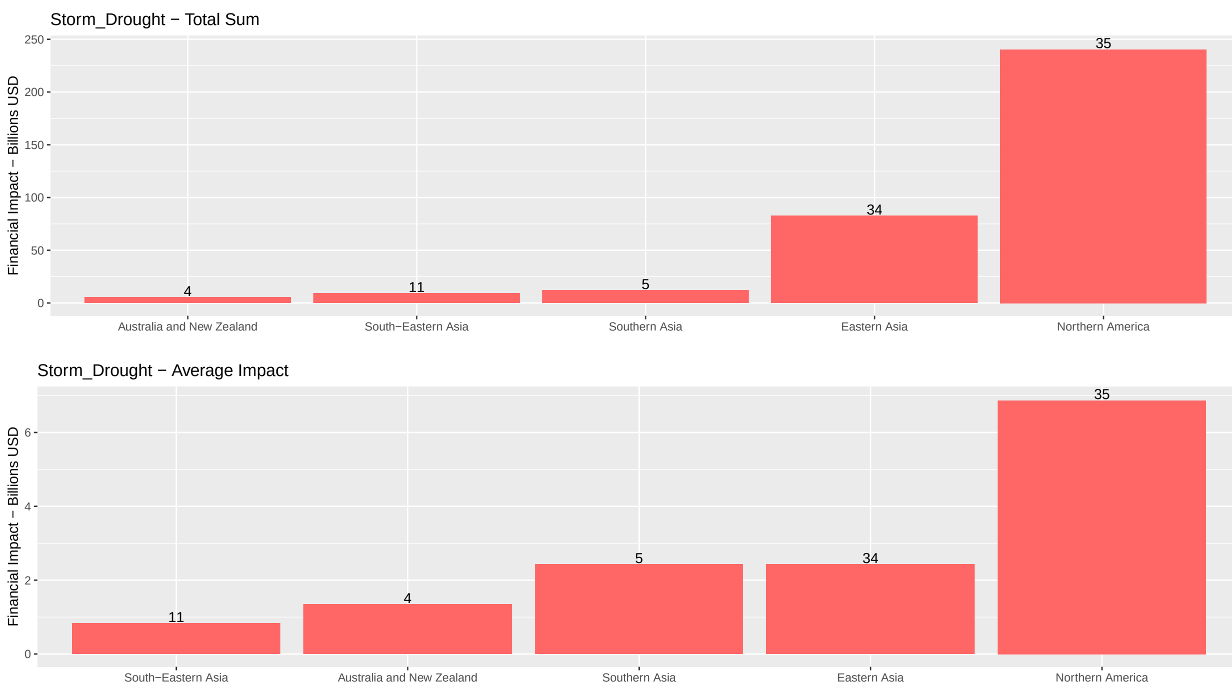

Figure 52: Storm_Drought disaster distribution - Medium time range

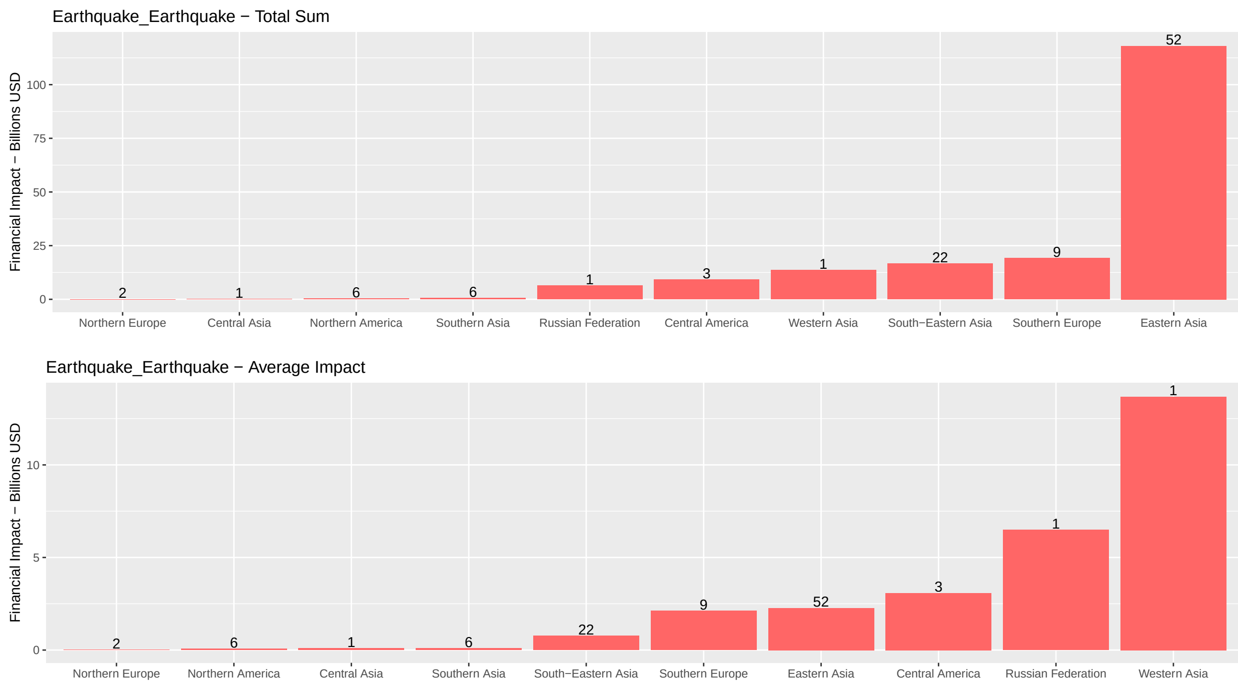

Figure 53: Earthquake_Earthquake disaster distribution - Medium time range

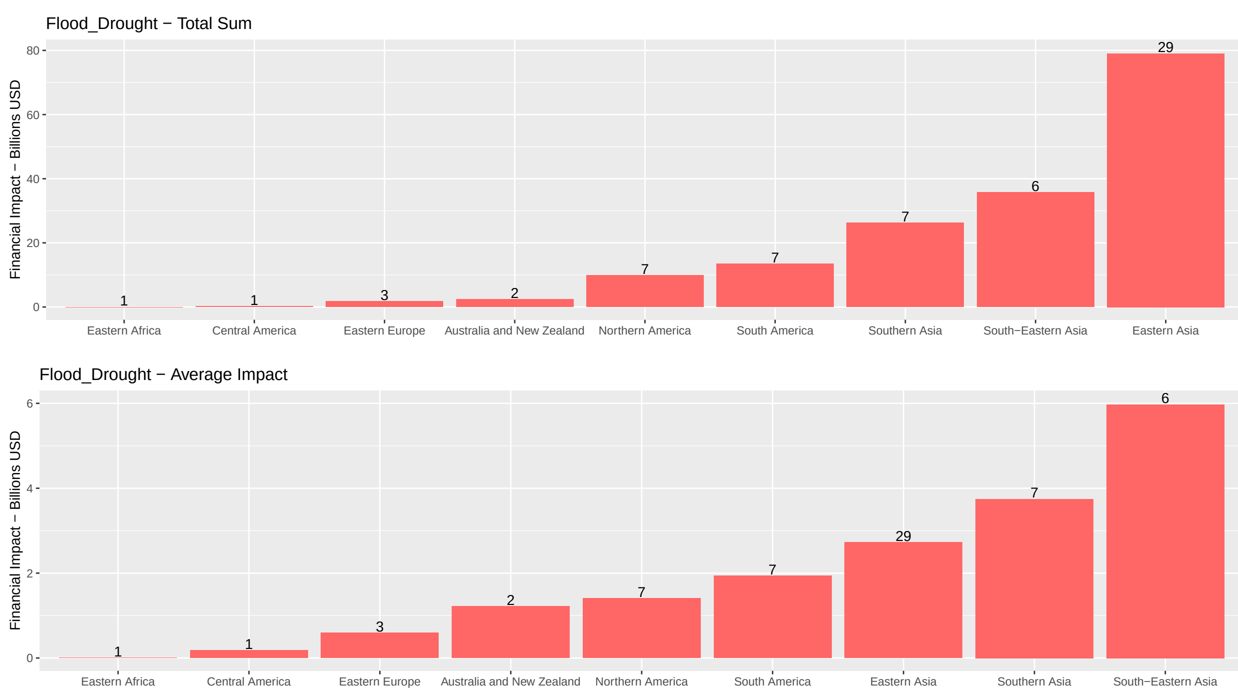

Figure 54: Flood_Drought disaster distribution - Medium time range

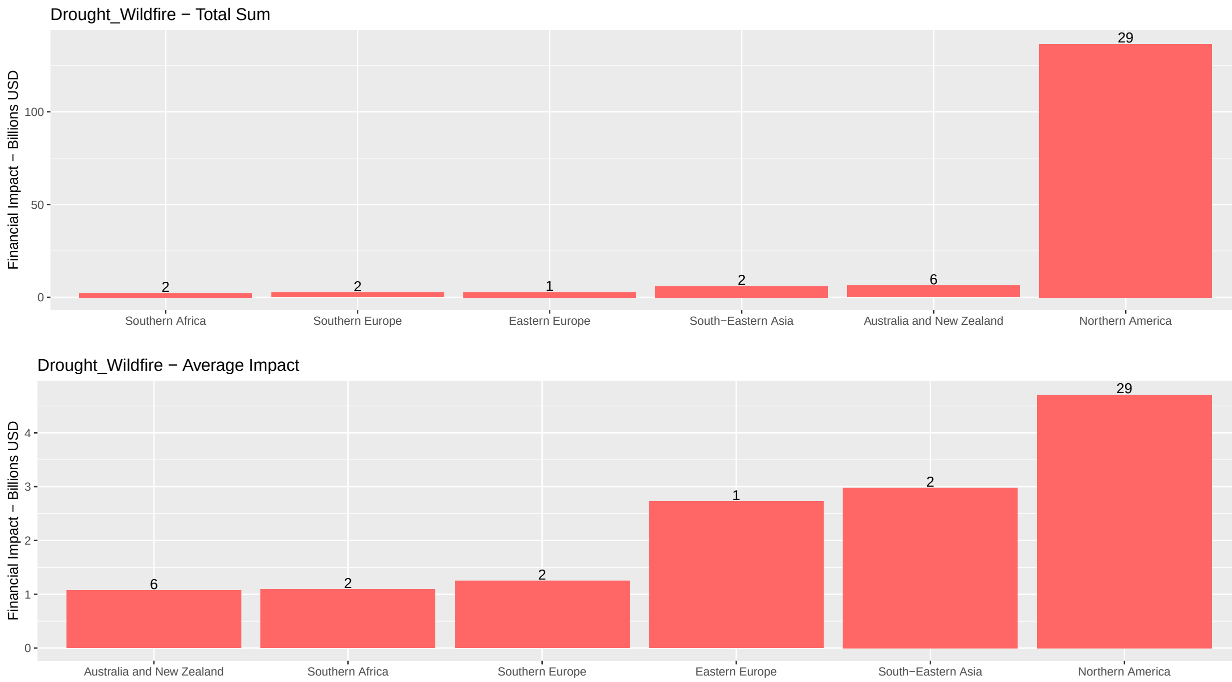

Figure 55: Drought_Wildfire disaster distribution - Medium time range

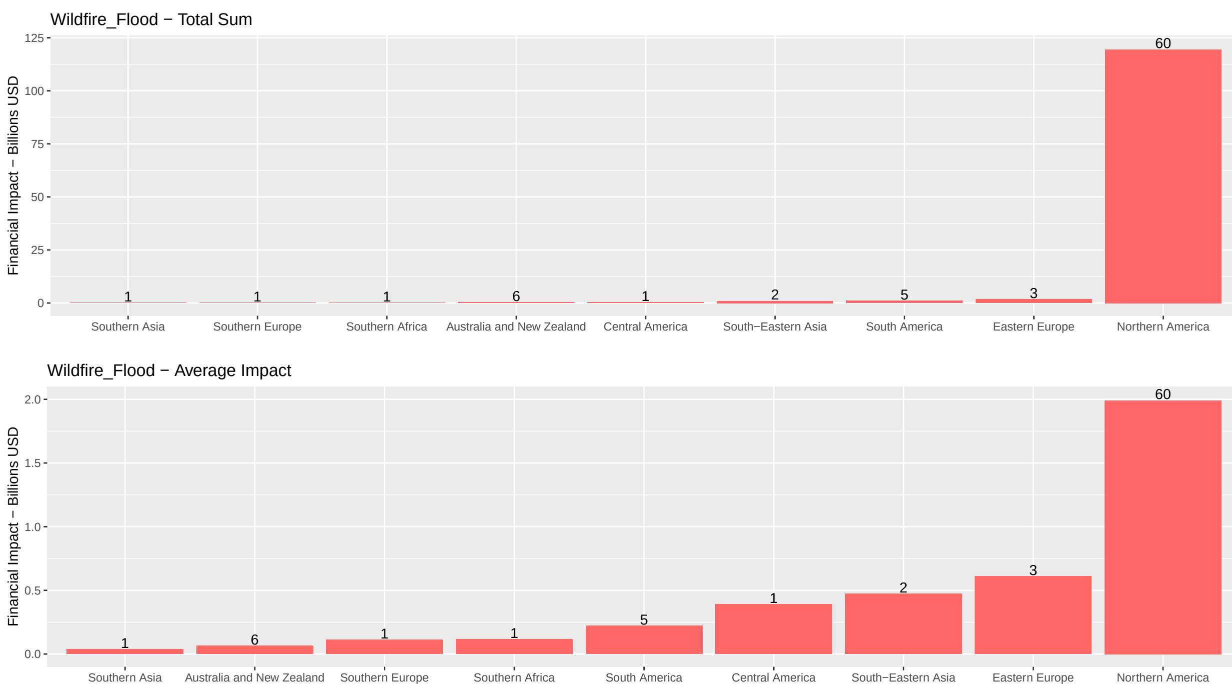

Figure 56: Wildfire_Flood disaster distribution - Medium time range

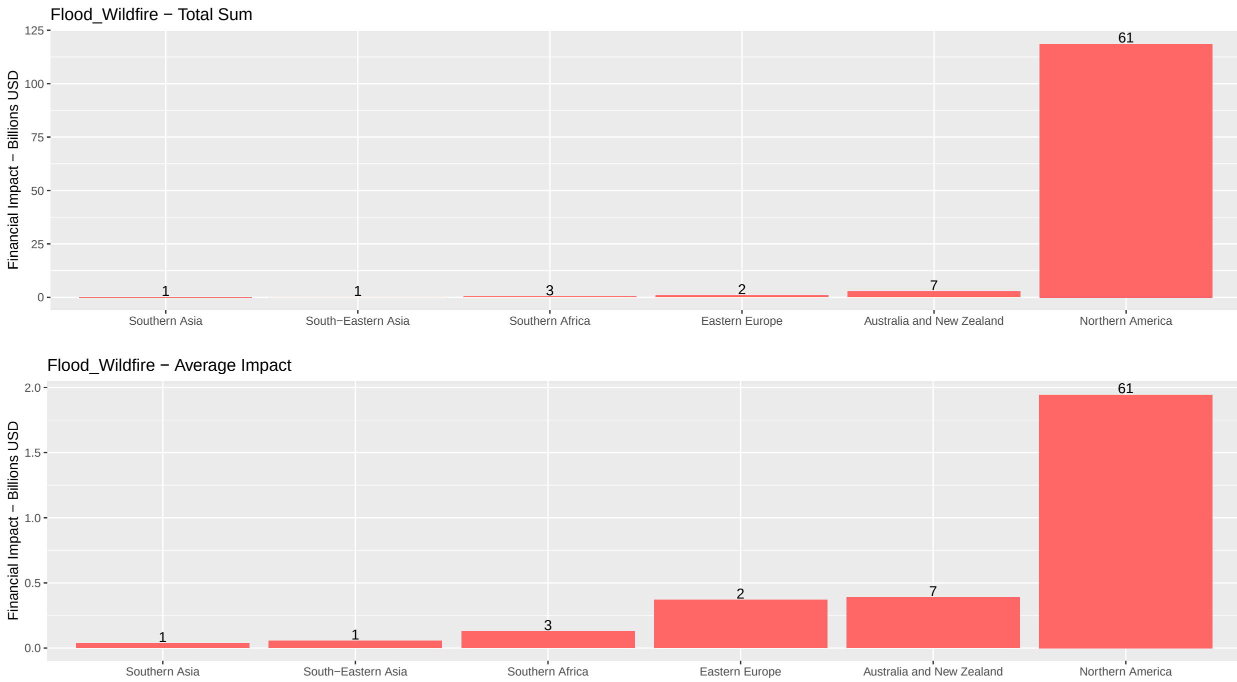

Figure 57: Flood_Wildfire disaster distribution - Medium time range

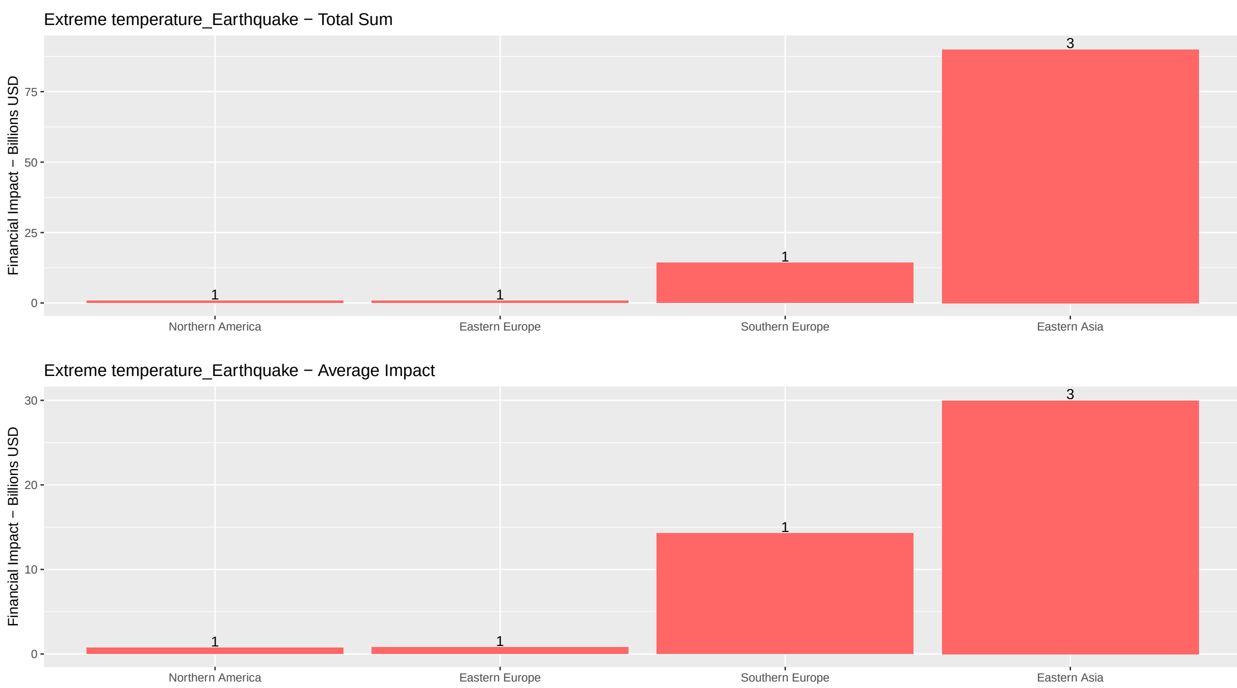

Figure 58: Extreme temperature_Earthquake disaster distribution - Medium time range

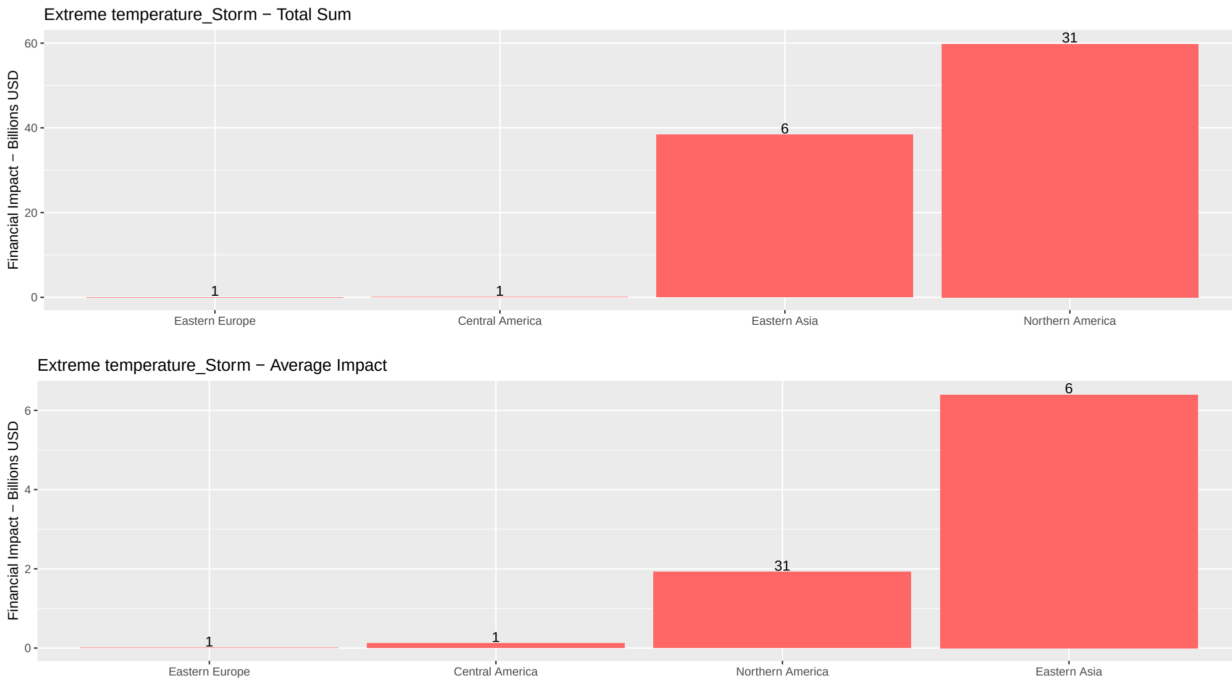

Figure 59: Extreme temperature_Storm disaster distribution - Medium time range

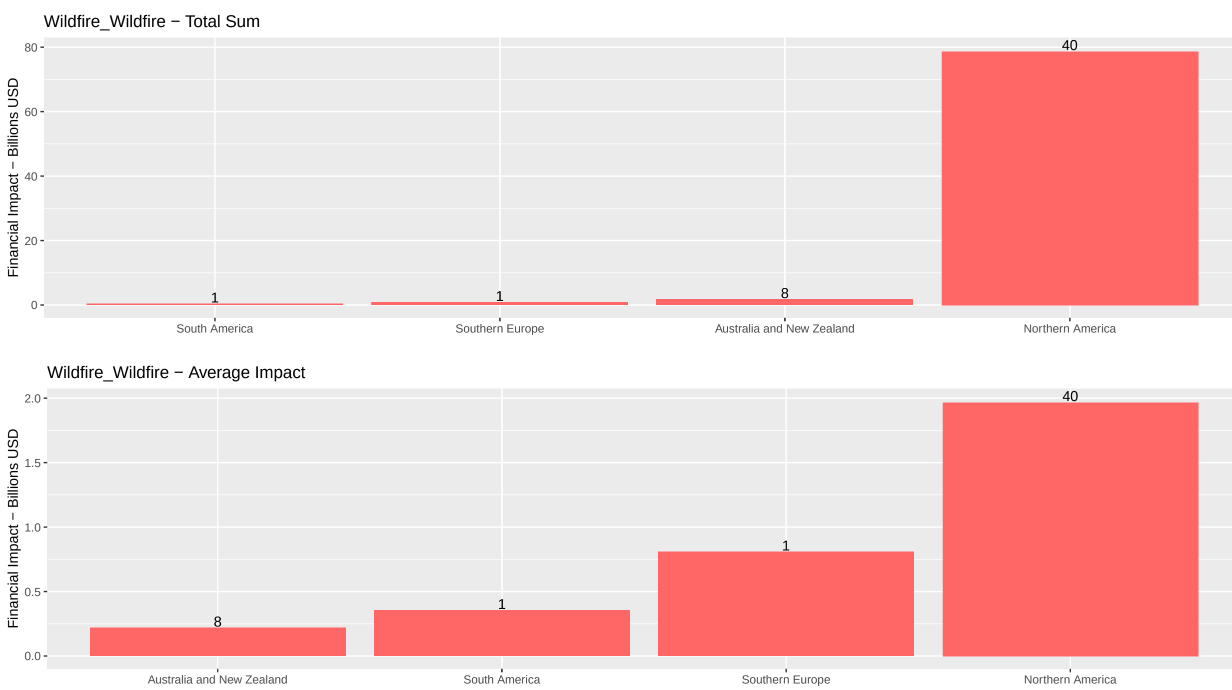

Figure 60: Wildfire_Wildfire disaster distribution - Medium time range

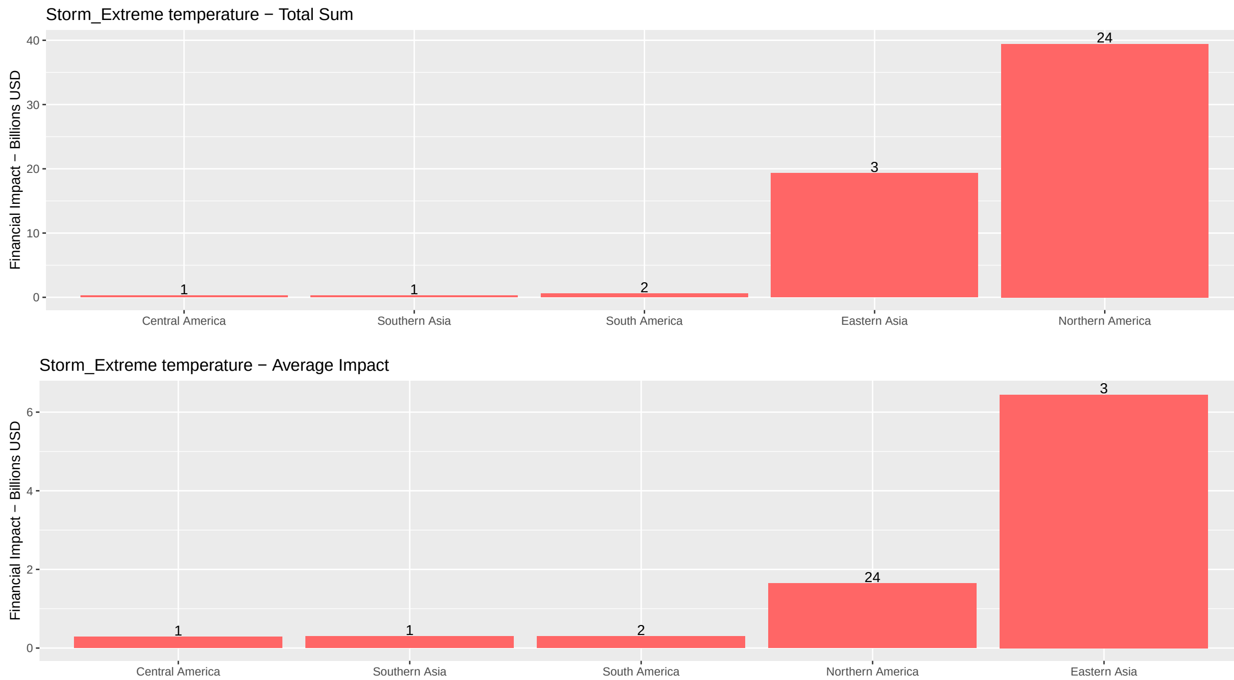

Figure 61: Storm_Extreme temperature disaster distribution - Medium time range

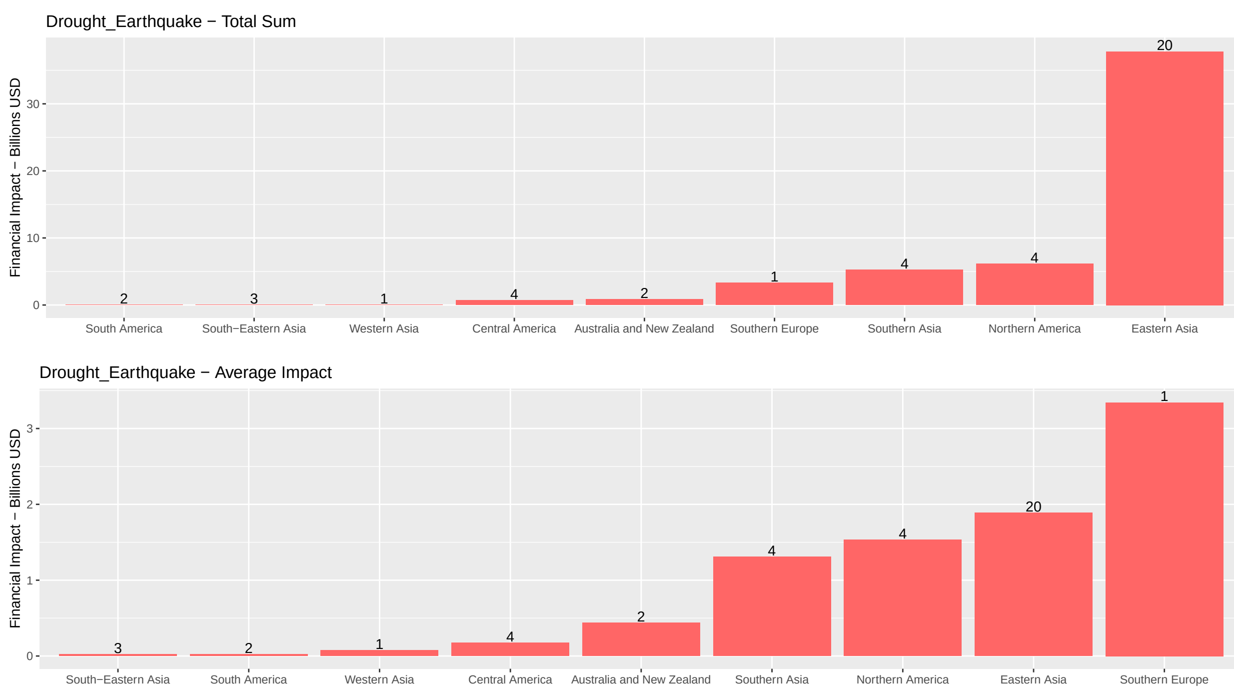

Figure 62: Drought_Earthquake disaster distribution - Medium time range

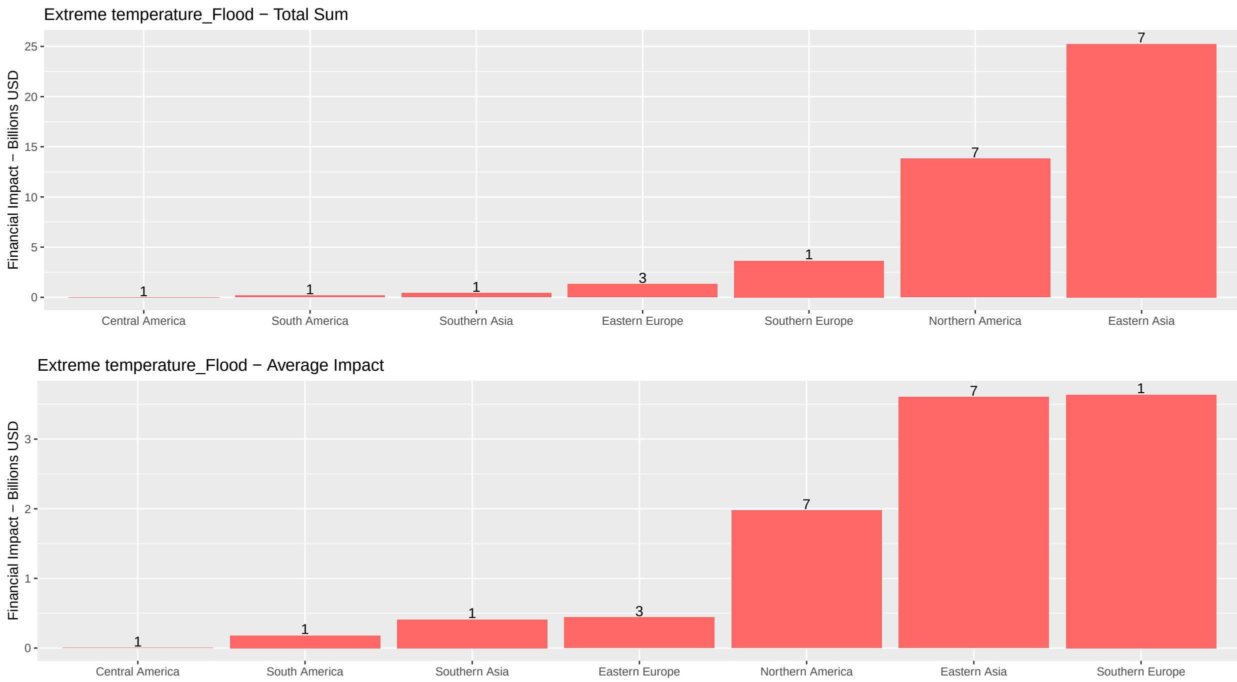

Figure 63: Extreme temperature_Flood disaster distribution - Medium time range

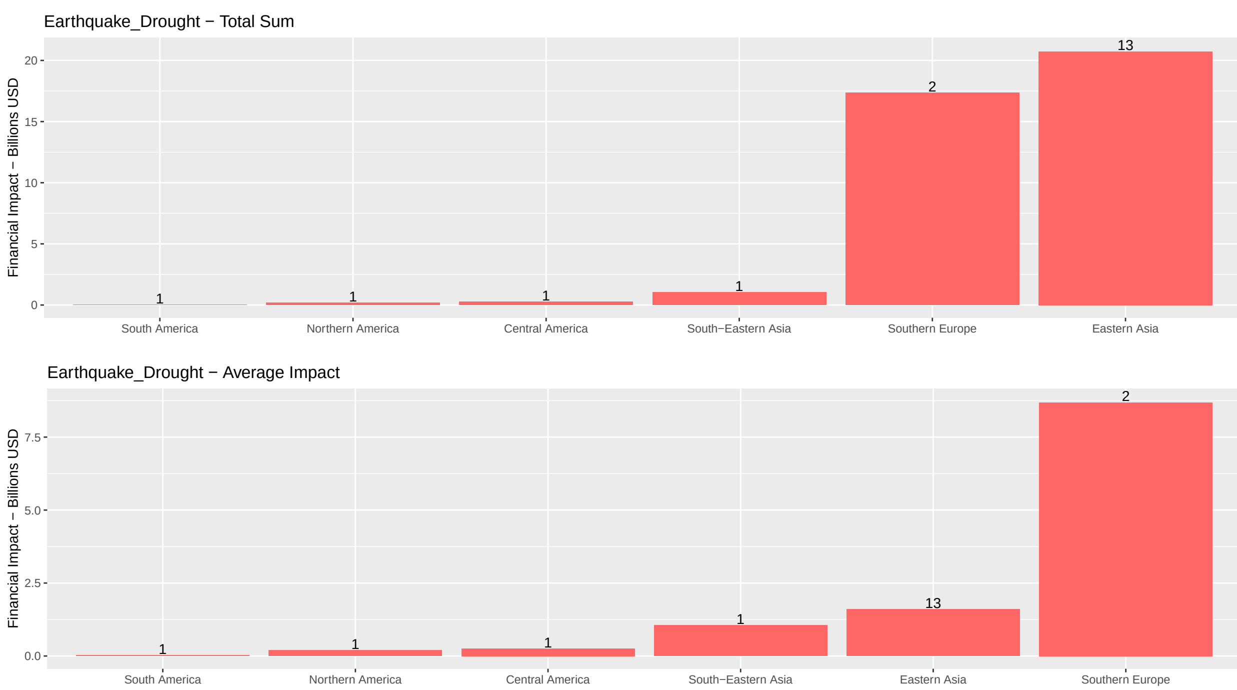

Figure 64: Earthquake_Drought disaster distribution - Medium time range

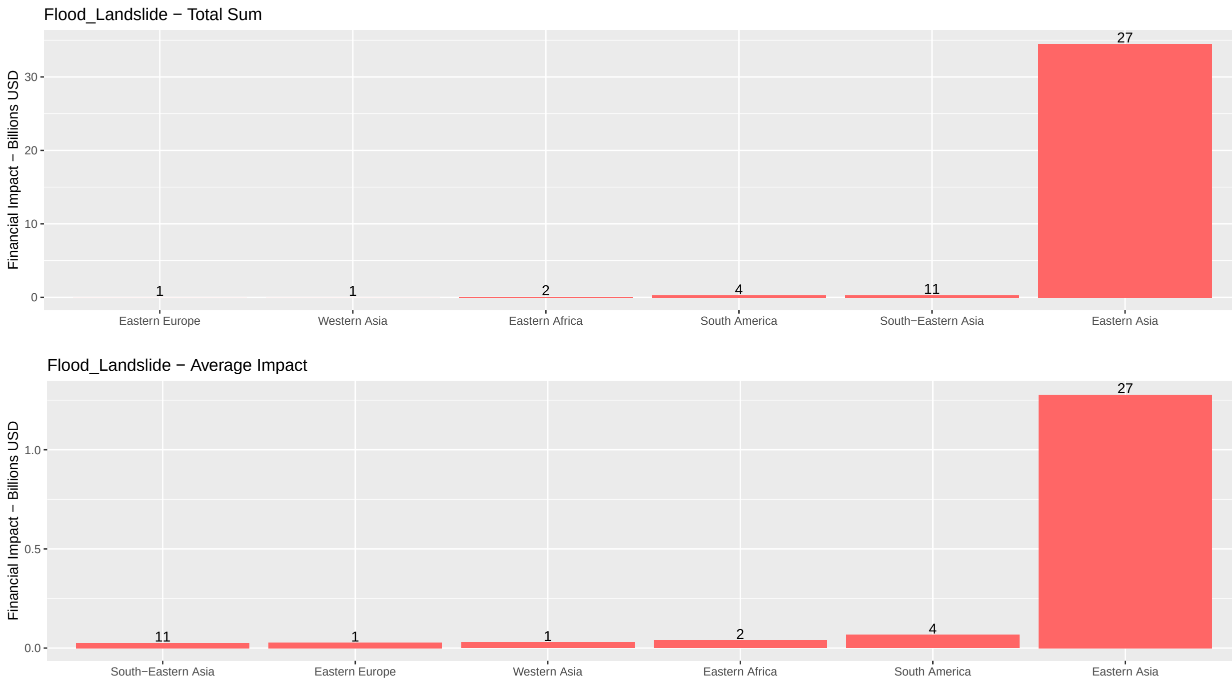

Figure 65: Flood_Landslide disaster distribution - Medium time range

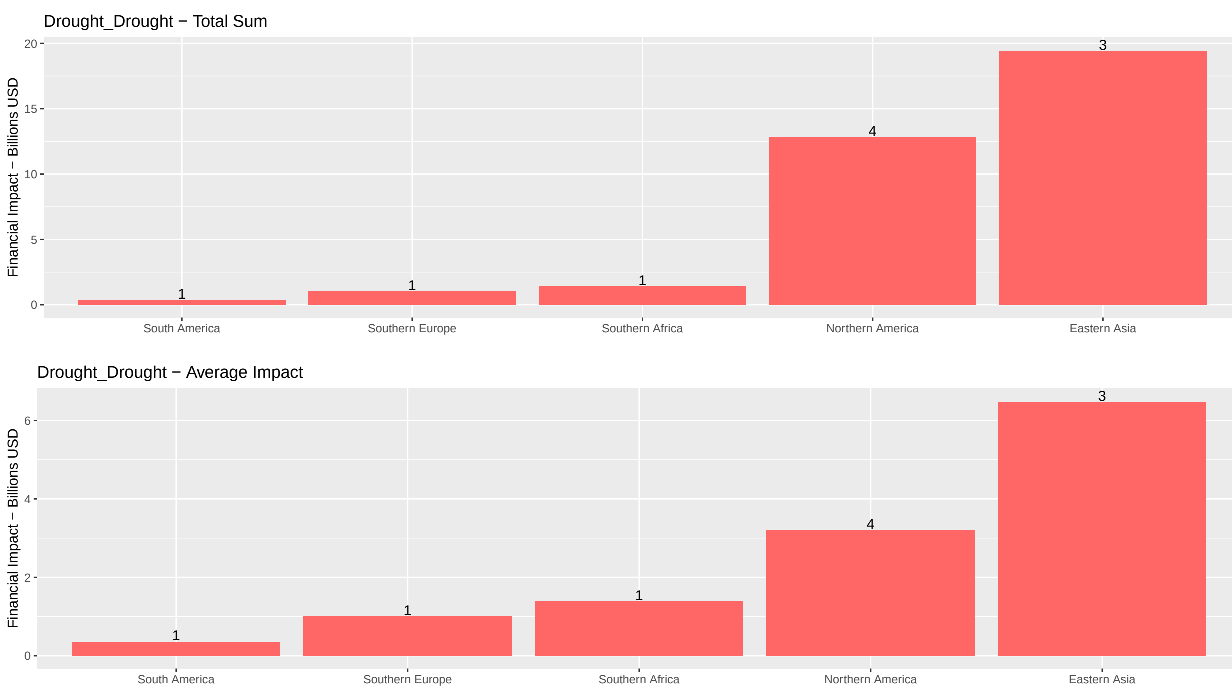

Figure 66: Drought_Drought disaster distribution - Medium time range

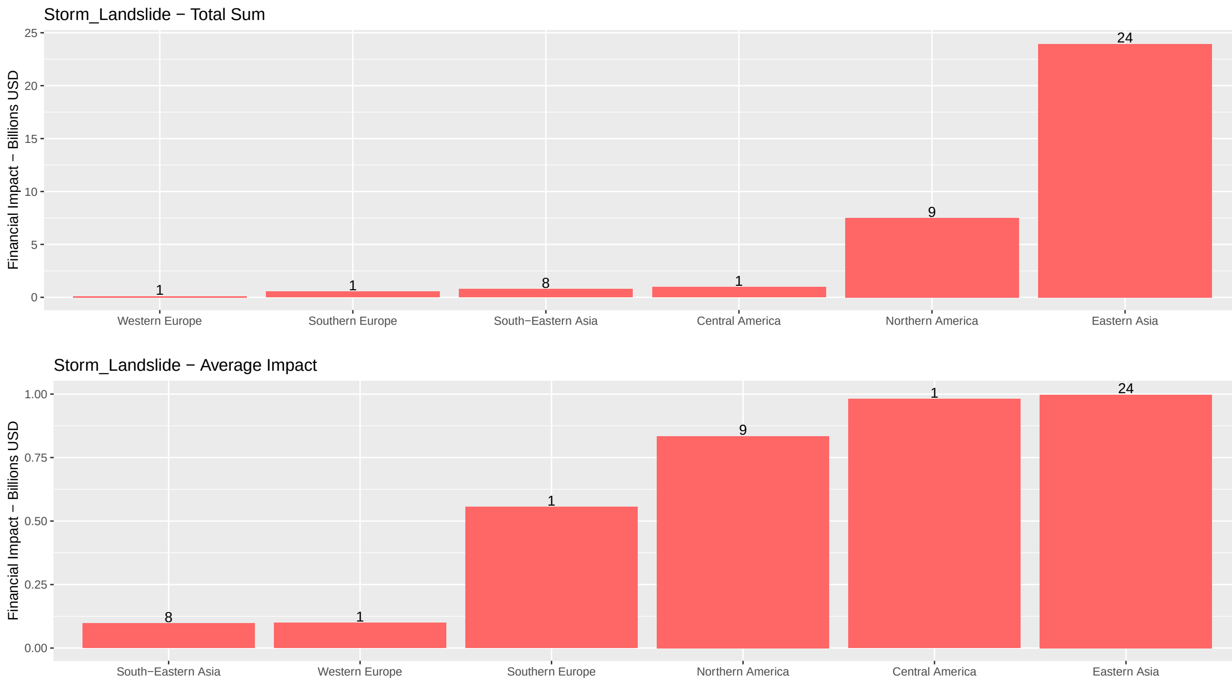

Figure 67: Storm_Landslide disaster distribution - Medium time range

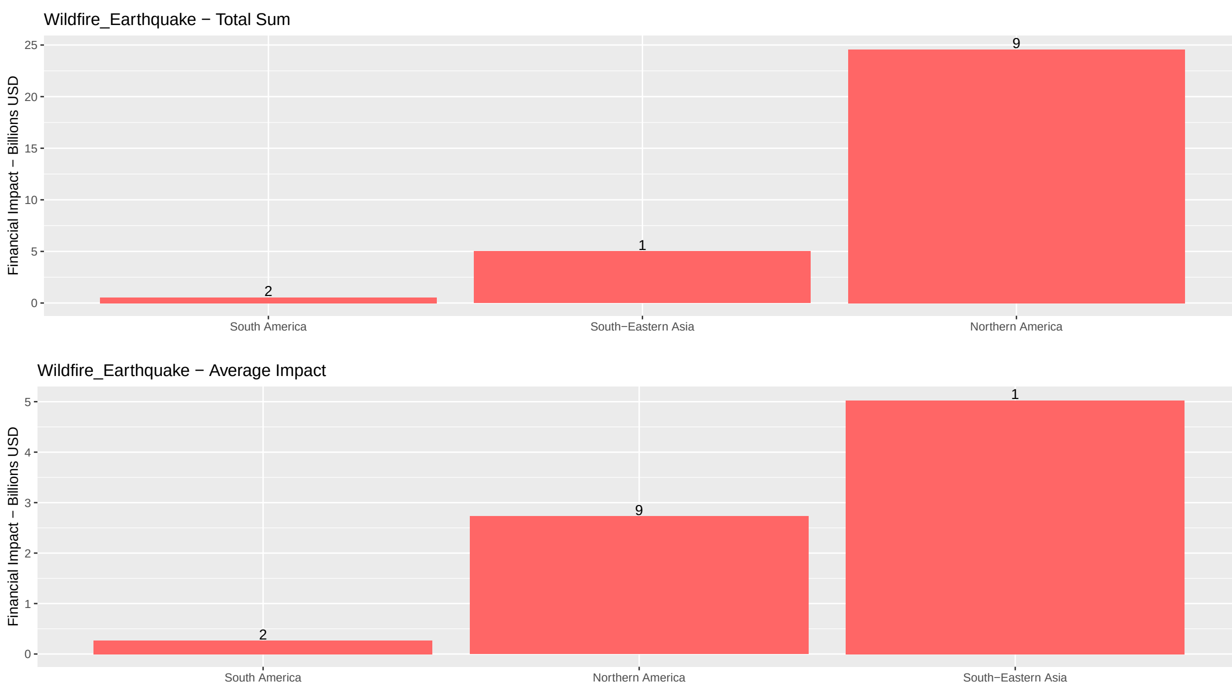

Figure 68: Wildfire_Earthquake disaster distribution - Medium time range

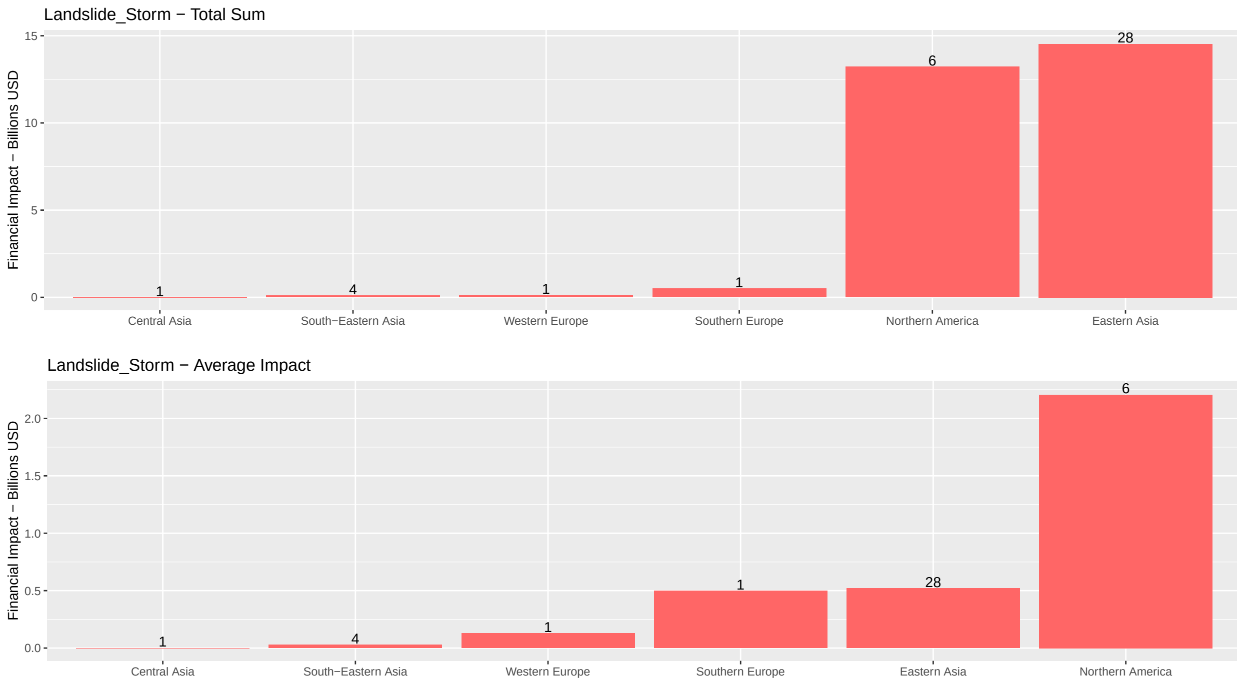

Figure 69: Landslide_Storm disaster distribution - Medium time range

Figure 70: Volcanic activity_Wildfire disaster distribution - Medium time range

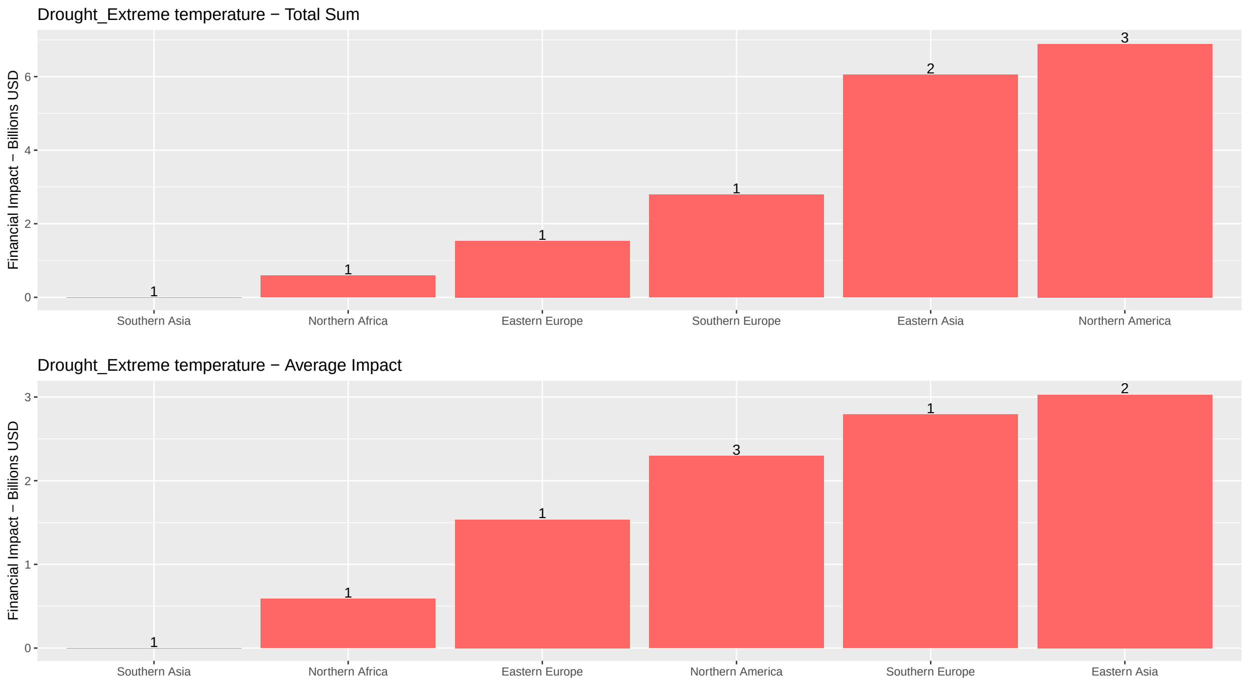

Figure 71: Drought_Extreme temperature disaster distribution - Medium time range

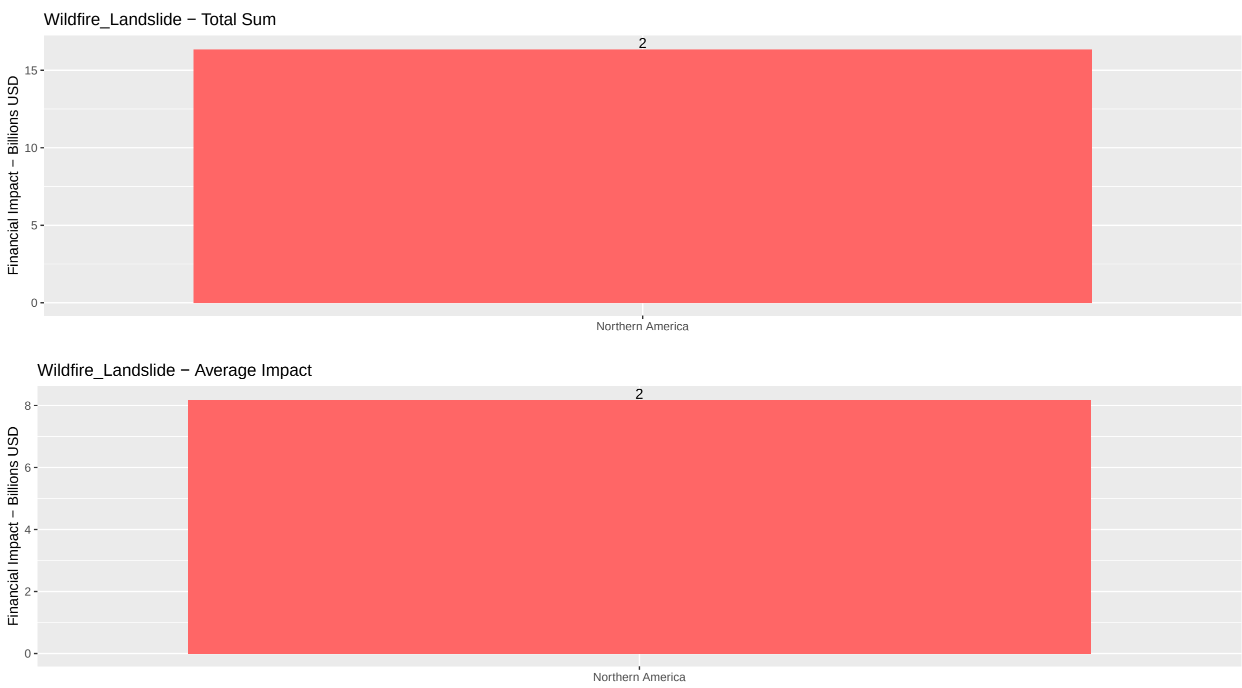

Figure 72: Wildfire_Landslide disaster distribution - Medium time range