ISYS 5050 Final Project

Abstract

This report analyzes global flood data from 1985 to 2022 sourced from the Dartmouth Flood Observatory. It addresses data quality issues, calculates Flood Magnitude indices, identifies seasonal patterns, assesses flood impacts, and explores driving factors, including climate change effects. Findings are supported by visualizations and structured discussions.

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1 Introduction

Floods are among the deadliest natural disasters, causing a considerable quantity of death, displacement, and global economic damage. The amplification of the global water cycle by climate change is expected to result in increased frequency and intensity of flooding in many locations. Limiting flood risk effectively requires a close analysis of past flood data as well as a knowledge of the main factors that contribute to and affect these catastrophes.

This study examines data recorded by the Dartmouth Flood Observatory on floods globally from 1985 until 2022. Data quality problems are addressed, seasonal patterns are identified, Flood Magnitude indexes are calculated, the impact of floods are assessed, and the causes including the impact of climate change are investigated.

2 Pre-processing & Data Preparation

In this project, we were given a Dartmouth Flood Observatory dataset which contains details about major floods worldwide from 1985 to 2022. In this section, we would first analyze the data, finding its error and problem, then apply corresponding method for Pre-processing.

2.1 Data Analysis & Problem Analysis

By examining the dataset, we observed that there are 14 different attributes and 5156 events recorded. And we listed all the potential issues and expectations for each attribute according to their characteristic and meaning. It is important to noted that in the context of this project, it is considered unnecessary to perform verification of data correctness.

- **ID** is an attribute to give each events an Identifier. ID is an integer number that should be unique to each event. The data should be stored in the order of ascending in terms of ID.
- **Glide Number** is a series of text consist of lettes and numbers. GLIDE stands for "GLobal unique disaster IDEntifier number"[1]. A GLIDE number starts with the first two letter indicates the type of disaster, followed by the year of occurring, then a four-digit sequential disaster number, in the end a three-letter ISO code refer to the country of occurrence[1]. It sort of data shouldn't affect the result of any knowledge managing actions. It is optional to filled out any missing glide number or to verify them. However, the value of this attribute should be the same type.
- **Country** is an attribute with text value that indicates the country of flood occurrence. Every country here should has a one and only name. The same name might appear more than once. Verification for data correctness of this attribute shouldn't be necessary considering the context of this project. However, issues like spelling error, wrong name, multiple name of representations of the same country should be considered.
- **Other Country** is an attribute with text value that indicates the secondary affected country of flood incident. It shares the same characteristic as the "Country" attribute. What should be specially care for is that value in this attribute can be none or null, and the value can't be the same as the value in "Country" for an item.
- **Long/Lat/Area** are some attributes with float type of number that together, indicates the occurrence location, and size of affecting area in square of meter. These attributes should be checked for empty values or wrong type of data.
- **Began/Ended** are two attributes that shows the start data and end data of a flood incident. Each value should be in the format of Y/M/D, and when month or day is in one digit, it stays that way. It should be checked if the end date has a later time than the start date.

- **Validation** is an attribute showing the validation of data source. The value should be text, start with capital letter. Issues like multiple representations of the same type of source, wrong spelling or wrong datatype should be checked.

- **Dead** is a numeric attribute that shows the number of dead people in the incident. Type of data should be checked for each value.

- **Displaced** is also a numeric attribute. It shows the number of displaced people that are forced to flee, leaving their residence during the incident[2].

- **MainCause** is a text attribute indicates the main cause of the flood. The value start with a Upper letter. The value in this attribute should be checked for spelling, multiple-representations of the same type of main cause, and use of same format to represent the "and" relation.

- **Severity** is a float type of data that indicates the severity of a flood. The value in this attribute should be checked for datatype and empty value.

2.2 Methods

Based on the analysis above, we perform ETL processes on each attribute. We use Python as the programming language to pre-process our dataset. We used df and other modules from **pandas**[3] library in python to help us read and write dataset. General pre-processing procedure for each attribute is to check whether the value is in a matching datatype and whether there is a empty value or value with empty (0, None, Null) meaning that need datatype transformation. After datatype unification and empty(missing) value had been dealt with, we moved on to more specific pre-processing for each attribute.

For **Country** and **Other Country**, we use the python package **pycountry**[4] to validate every value in these two attributes, see if the value matches within a list of valid country names in pycountry.

```python
# Generate a list of all valid country names using pycountry
valid_countries = [country.name for country in pycountry.countries]

# Extract unique country names from your DataFrame
unique_countries = df['Country'].unique()

# Find which entries are not in the valid_countries list using set difference
invalid_countries = [country for country in unique_countries if country not in valid_countries]
```

Figure 1: Python code on country name validation & correction part 1

If a value is invalid, it means that there is spelling error, mistype, or multiple representations of the same country. To solve this issue, we use the process module from **fuzzywuzzy**[5] library in python to match these invalid values to its closest correct valid country name. Then, we use df module to replace all invalid values with their correct representations.

```python
# For each invalid country, find the closest valid country name
corrections = {country: process.extractOne(country, valid_countries)[0] for country in invalid_countries if process.extractOne(country, valid_countries)[1] >= 80}
print("Corrections to be made:", corrections)
```

```
Corrections to be made: {'Phillipines': 'Philippines', 'Comoros islands': 'Comoros', 'Bolivia': 'Bolivia, Plurinational State of', 'West Germany': 'Germany', 'Venezuel
```

```python
# Replace incorrect spellings with correct ones
df['Country'] = df['Country'].replace(corrections)
df
```

Figure 2: Python code on country name validation & correction part 2

For similar text errors shown in **MainCause**, we first viewed all unique values in this attribute then manually create a dictionary of corrections to made for each types of MainCause. We also used df module to make corrections.

```python
# Rain-related events
'Heavy rain': 'Heavy Rain',
'heavy rain': 'Heavy Rain',
'Heavy Rain': 'Heavy Rain',
'Torrential rain': 'Torrential Rain',
'torrential rain': 'Torrential Rain',
'Torrential Rain': 'Torrential Rain',
'Brief torrential rain': 'Brief Torrential Rain',
'Brief Torrential Rain': 'Brief Torrential Rain',
'Heavy seasonal rains': 'Heavy Rain',
'Heavy monsoon rains': 'Monsoonal Rain',
'heavy Rain': 'Heavy Rain',
```

Figure 3: Sample section of correction dictionary

For **ID** attribute, we spotted there are two pairs of duplicated IDs, and after observation of these rows' value, we considered they are different flood incident and therefore, should be allocate with different ID. All IDs after duplication's occurrence were reassigned in order accordingly.

For **Began** and **Ended** column, we use to_datetime[6] module in pandas library to convert the value of time in a format that allows calculation operations for following questions.

The dataset was then imported into Tableau for further operations.

3 Flood Magnitude

In this section, we need to calculate Flood Magnitude using the given formula LOG(Duration x Severity Class x Affected Area) and rank top five countries in terms of the total number of floods of different levels of magnitude.

3.1 Flood Magnitude Calculation & Classification

First, we created a new calculation field for duration. It was calculated by subtracting the value of Began from Ended.

```
df['Duration'] = (df['Ended'] - df['Began']).dt.days
```

Figure 4: Python code for calculating duration

Using the above formula, we create another calculation field to store the calculated Flood Magnitude for each row. Then, we used **Mean and Standard Deviation** to classify flood magnitudes into ”Low”, ”Medium”, and ”High” categories. The classification is based on statistical analysis to understand and categorize the data effectively.

3.1.1 Understanding Mean and Standard Deviation

1. **Mean (Average):** The mean is the sum of all the values divided by the number of values. It gives a central value that represents the typical flood magnitude in our dataset.

$$\text{Mean} = \frac{\sum \text{Flood Magnitude}}{N} \tag{1}$$

   Where sum(Flood Magnitude) is the sum of all flood magnitudes and N is the number of values.

2. **Standard Deviation:** The standard deviation measures the variability of the data from the mean. It indicates how spread out the values are around the mean.

$$SD = \sqrt{\frac{\sum(\text{Flood Magnitude} - \text{Mean})^2}{N}} \tag{2}$$

3.1.2 Classification Logic

The classification logic is designed to leverage these statistical properties to divide the flood magnitudes into three categories:

1. **Low:**

$$\text{Flood Magnitude} \leq \text{Mean} - SD \tag{3}$$

2. **Medium:**

$$\text{Mean} - SD < \text{Flood Magnitude} \leq \text{Mean} + SD \tag{4}$$

3. **High:**

$$\text{Flood Magnitude} > \text{Mean} + SD \tag{5}$$

3.2 Visualisation

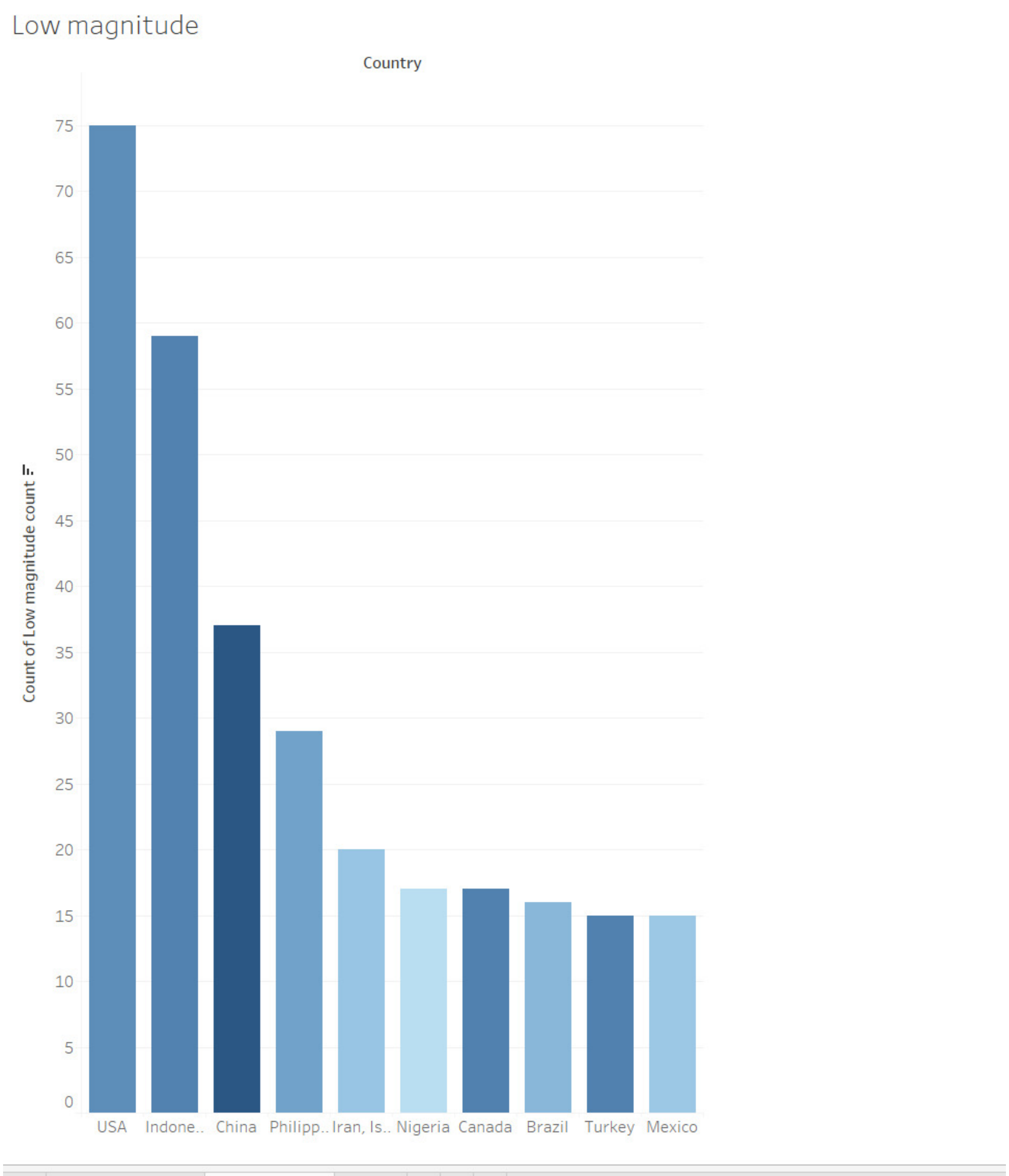

Figure 5: Top countries for low level

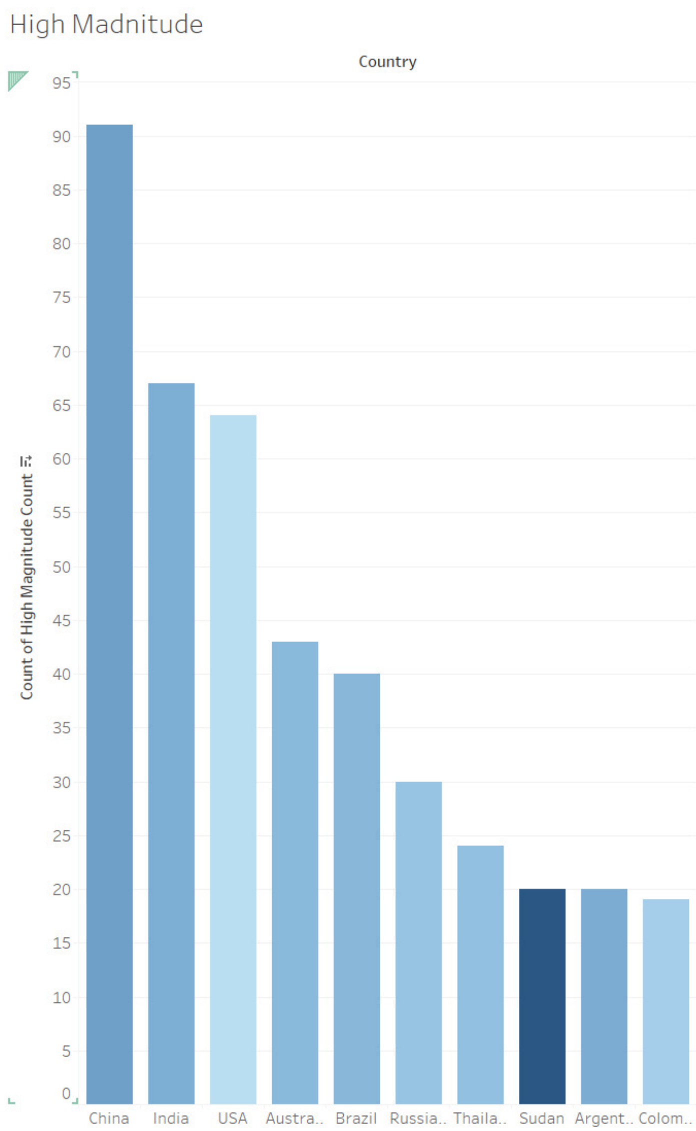

Figure 6: Top countries for high level

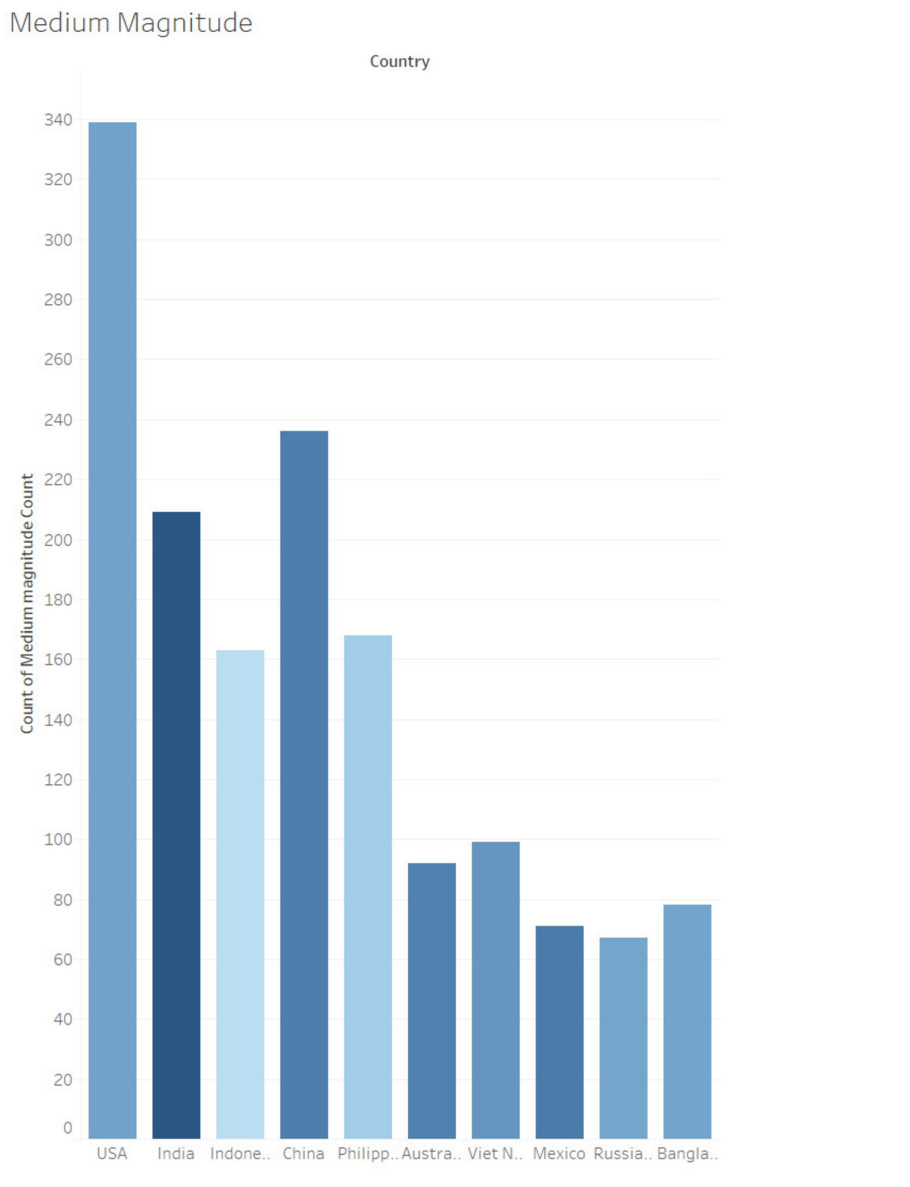

Figure 7: Top countries for medium level

3.3 Discussion

From the result above, it can be observed that USA and China are two countries that suffered the most from all levels of floods. India is the third most frequent country that has floods mainly in medium and high level while Indonesia mainly has floods in low and medium levels.

4 Seasonal Patterns

In this section, we derived into finding seasonal patterns of floods using Tableau for visualisations. It needs to be mentioned that considering the differ of seasons for countries in North Sphere and those in South Sphere, here we used the combination of season and month as the main time factors when conducting analysis.

First, we started with counting total numbers of floods worldwide for each month. We used the information of month in Began column to identify the month of a flood incident. The result are shown below in plot chart. It can be observed that June, July, August are the peak time of flood occurrence as July being the month with the most accumulated flood of 655 incidents recorded from 1985 to 2022.

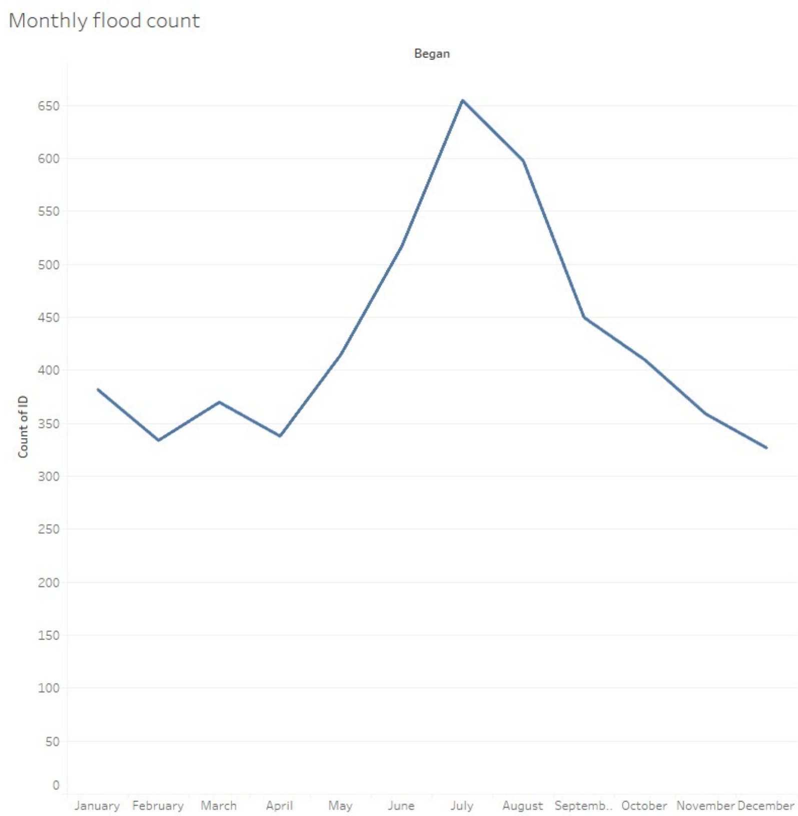

Figure 8: Monthly flood count

Next, from the chart of Monthly Average Severity, we discovered that the average severity level of floods of each month is all range in between of 1.23 and 1.26 with little differences.

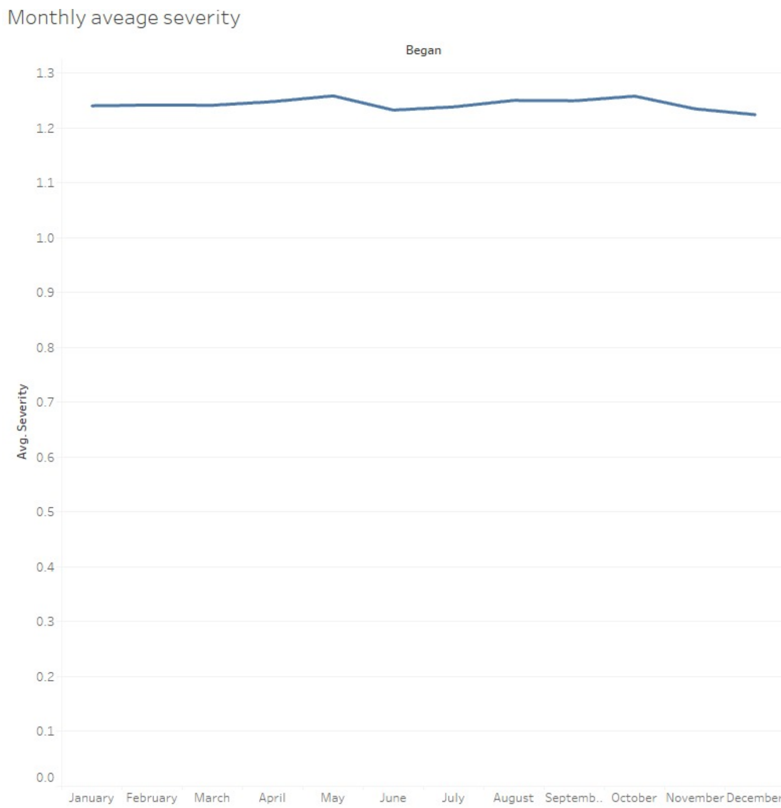

Figure 9: Monthly average severity

Then, used year and month as two main factors, we conducted analysis that gives a comprehensive view of floods incidents among years with portions per month. It can be seen that all years share a similar structure of floods occurrence: more flood incidents in the middle months (Summer and Autumn for North Sphere countries, Winter and Spring for South Sphere countries.)

Last but not the least, using North Sphere as guideline of seasons, we conducted analysis of total number of recorded flood incidents of four seasons.

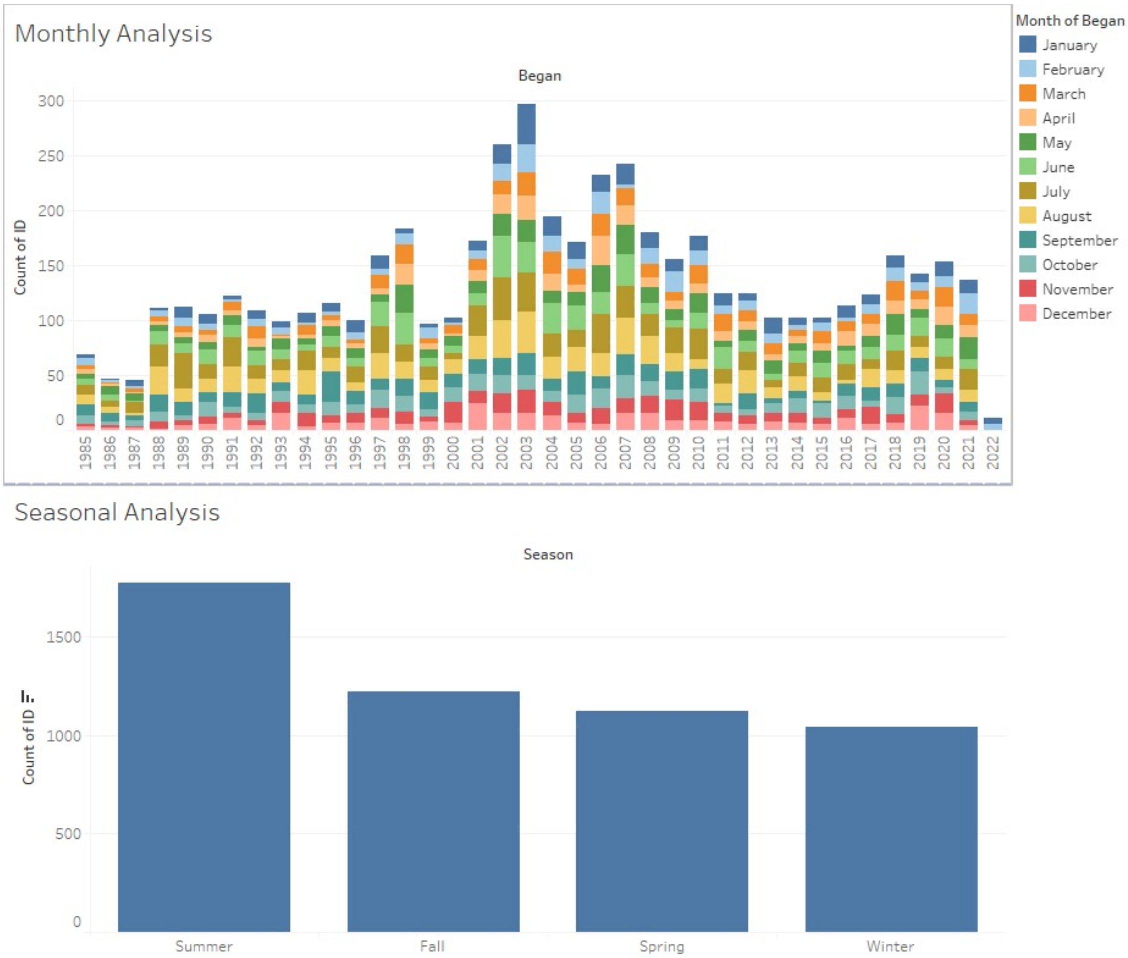

Figure 10: Monthly-year analysis & Seasonal analysis

In summary, the frequency of flood occurrence is affected by time factor. In seasonal terms, Summer is the season that flood is most likely to happen. And it shows no correlation between season(month) and the severity of floods. It can be assume the severity of floods could be affected by other factors like geographic location. A further analysis of the outcome of floods will be discussed in the following section.

5 Damage and Impact of Floods

In this section, we explore the impact of Floods and the damage done on the economy based countries and people. This analysis shall oversee the impact of floods which has changed over time, identifying the most affected areas (countries). We define our measurement of impact, constructing formula, also focus on further processing of the data like the normalisation of values of Area, Dead and Displaced in the comparative analysis.

5.1 Methodology:

The impact is measured by the formula our team internally decided about is:

$$\text{Impact} = (\text{Dead} + \text{Displaced}) \times \frac{\text{Severity}}{\text{Area}} \tag{6}$$

These values are taken directly from the dataset. Following which, it provides a standardized approach to compare the impact of the different countries over a certain time-period. Comparative analysis is the only mode of analysis that uses the normalization of Dead , displaced and area to compare the impact across different economic grouping.

For the comparative analysis , normalized values for the 'Dead', 'Displaced' and 'Area' are used for calculating the following formula:

$$\text{Normalized (Dead)} = \frac{\text{Dead} - \text{MIN(Dead)}}{\text{MAX(Dead)} - \text{MIN(Dead)}} \tag{7}$$

$$\text{Normalized (Displaced)} = \frac{\text{Displaced} - \text{MIN(Displaced)}}{\text{MAX(Displaced)} - \text{MIN(Displaced)}} \tag{8}$$

$$\text{Normalized (Area)} = \frac{\text{Area} - \text{MIN(Area)}}{\text{MAX(Area)} - \text{MIN(Area)}} \tag{9}$$

This data is also filtered further on the basis of economic groupings which is used to compare the impact across the developed, developing and underdeveloped countries using the custom grouping field.

The segmentation for the economic grouping is generally done by the creation of the calculated field as mentioned below:

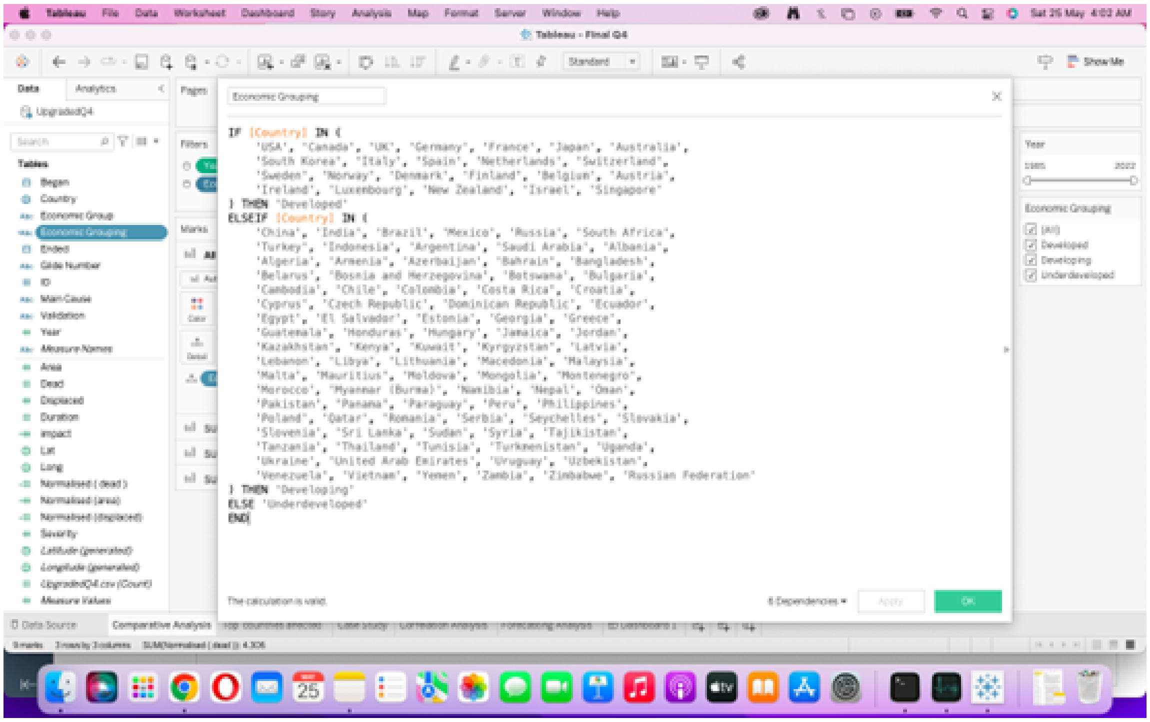

Figure 11: Economic Grouping

The reason of considering the economic grouping instead of the continents which our group planned earlier was because the continents are a lot and are a geographical representaton of our solution, but eventually we need a solution that can be considered as a factor of good understanding, such as in this case we considered economic level of the country, by this way we ensure that the economy of the country is indirectly a factor for the impact and this has been mentioned in the following part.

5.2 Comparative Analysis

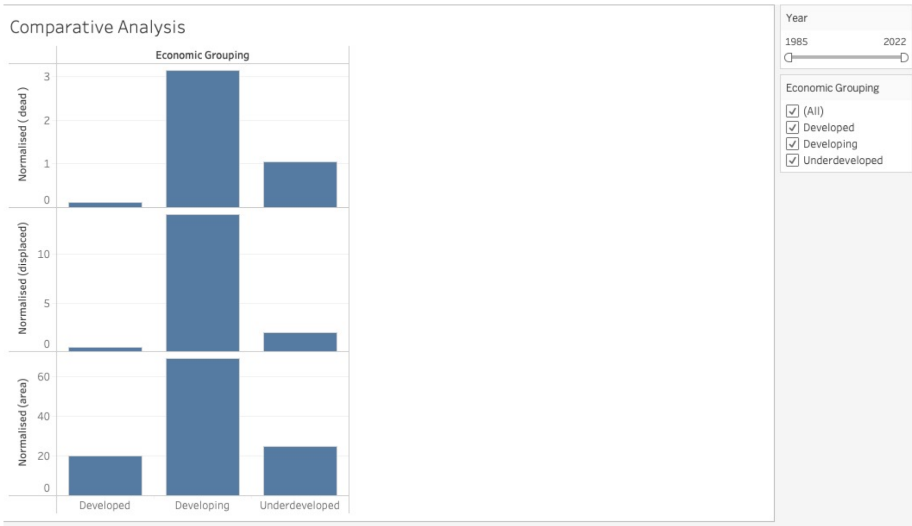

Figure 12: Economic Grouping 1985-2022

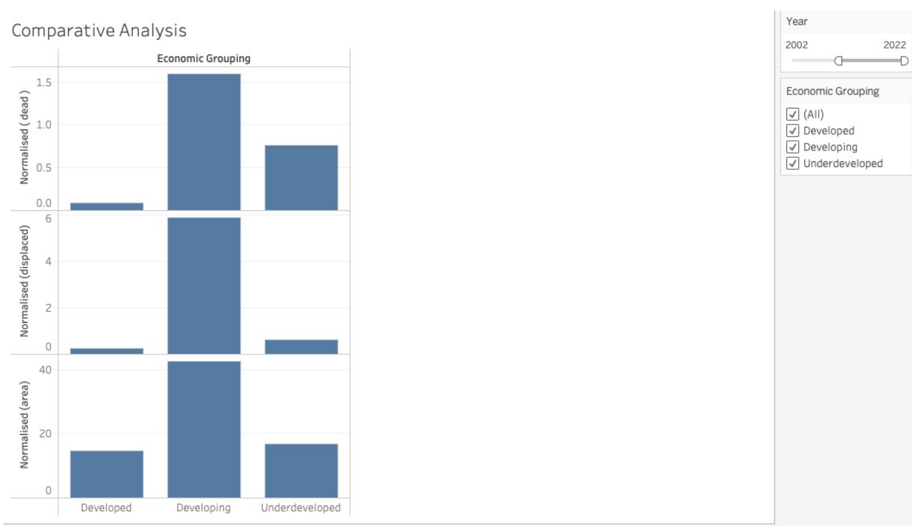

Figure 13: Economic Grouping 2002-2022

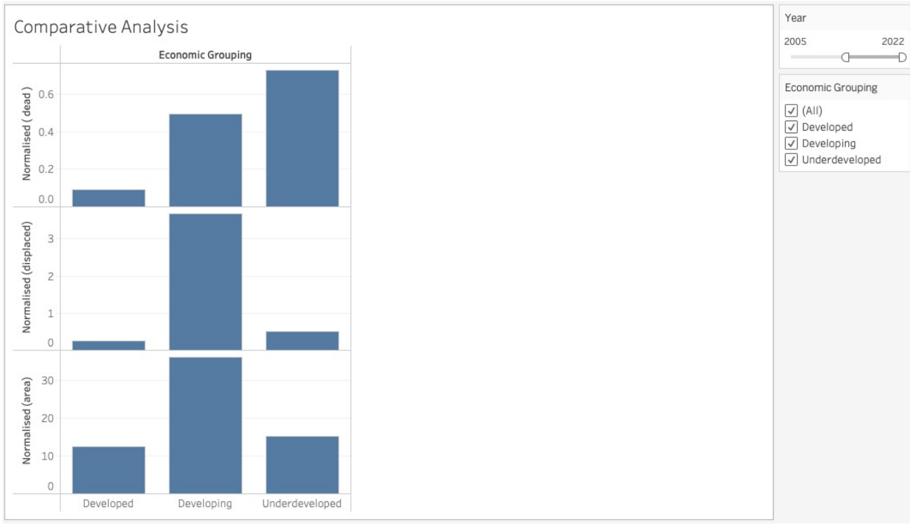

Figure 14: Economic Grouping 2005-2022

5.2.1 Description

The comparative analysis showcases the impact of floods along the lines of different economic groupings uses normalized values of 'Dead', 'Displaced' and 'Area'. Developing countries showcase the highest normalised values of Dead and Displaced people, indicating a significant impact in comparison to developed and underdeveloped countries . This proves that developing countries are more vulnerable to impact of floods, most probably because of less modification in the infrastructure and disaster management systems (UpgradedQ4 dataset, 2024). In addition to the same, we find that the economic grouping analysis gives the idea about the issues faced by the developing countries such as the challenges in mitigation and recovering from the flood events because of the limited resources and the infrastructure. But from the 2005 onwards you would see that the SUM of the normalized dead is the most in the underdeveloped countries than the developed countries and developing countries but still the rest of the parameters like the displaced and area affected are still more in the developing countries.

Secondly we also observe that the data of Dead and Displaced fluctuates for the Developed countries as from the 2011 onwards we see that the displaced in normalized value increases in the developed countries more than the underdeveloped countries.

5.2.2 Justification

The bar chart is decided in this case for providing clear understanding between the difference in flood impact across different economic grouping. The use of the normalized values permits for a proper comparison irrespective of absolute values of dead, displaced and area affected in each grouping.

5.3 Top Countries Affected

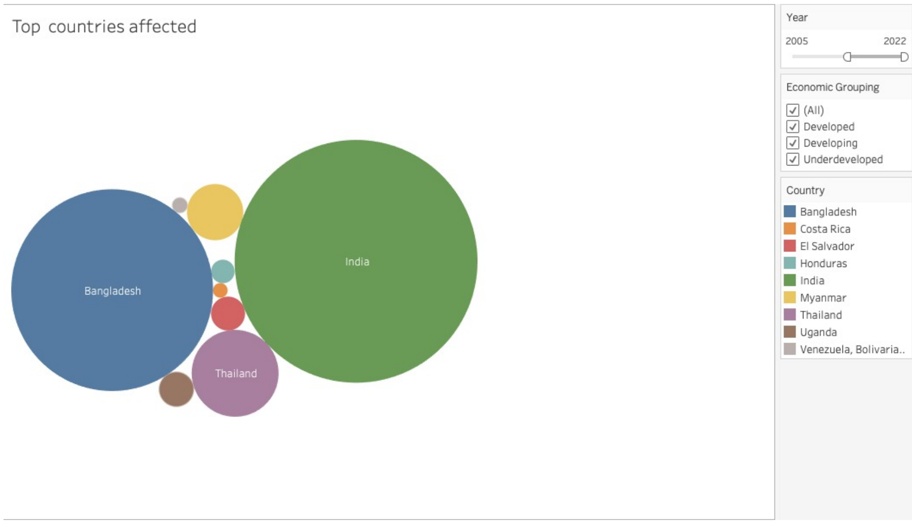

Figure 15: 2005-2022

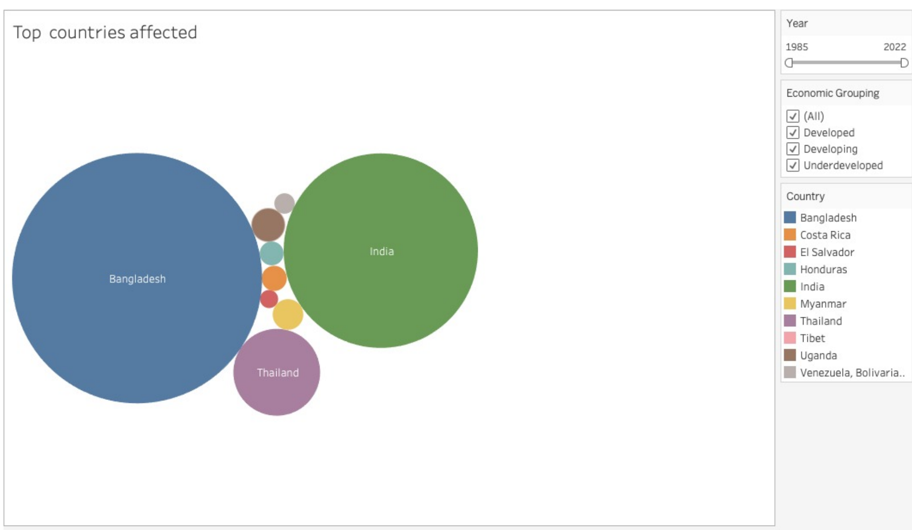

Figure 16: 1985-2022

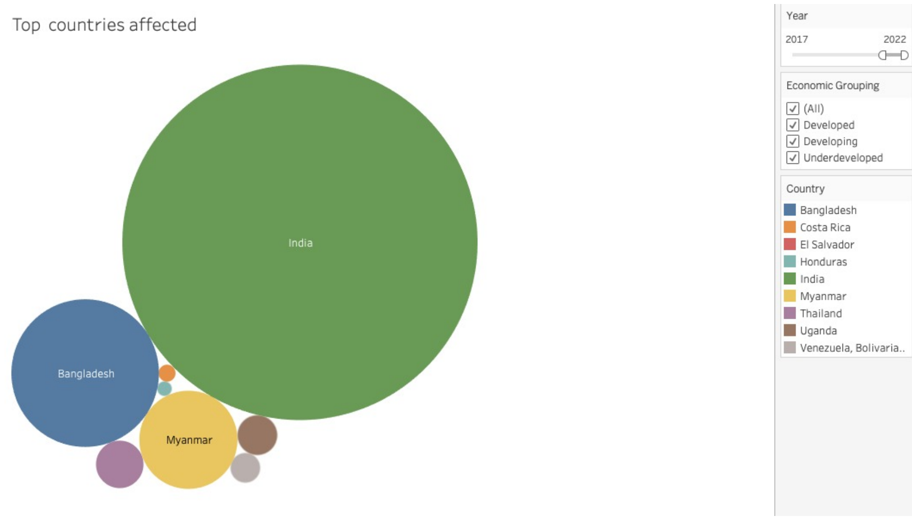

Figure 17: 2017-2022

5.3.1 Description

The bubble chart illustrates the top countries that are affected by the floods on the basis of sum of impact as per the formula (Dead+Displaced) * Severity/Area. Bangladesh, India and Thailand are overall the most affected countries. The visualization showcases the concentration of flood impacts in the South Asia, which shall be aligned with the weather which is monsoon patterns and river systems in the region (UpgradedQ4 dataset, 2024). The data signifies that the following countries experience frequent and severe floods, further deteorated by the climate change and increasing poplulation density in flood prone areas.

5.3.2 Justification

The bubble chart is mostly used for representing top countries because it allows visualization of three variables simultaneously (impact, country and relative size of impact). Therefore it makes the scene conducive to compare the severity of impact across different countries in one showcase.

5.4 Case Study

Figure 18: Case study map

5.4.1 Description

The case study map propagates the idea of the geographic distribution of flood impact. Countries like the ones in South and South-east Asia, as well as parts of Africa ica and South America, experience a significant change. This map gives the idea of identifying regional patterns and areas that require targeted flood management and mitigation which is essential (UpgradedQ4 dataset, 2024). Considering the data, it indicates that the flood – prone regions often coincide with areas of rapid urbanization, giving a hint of urban planning which includes the proper flood management plans as well.

5.4.2 Justification

The map visualizes geographic distribution of flood impact, making it conducive for identifying regional hotpots and trends. There is a crucial need for understanding the spatial aspect and accordingly assist in planning of mitigation efforts.

5.5 Correlation Analysis

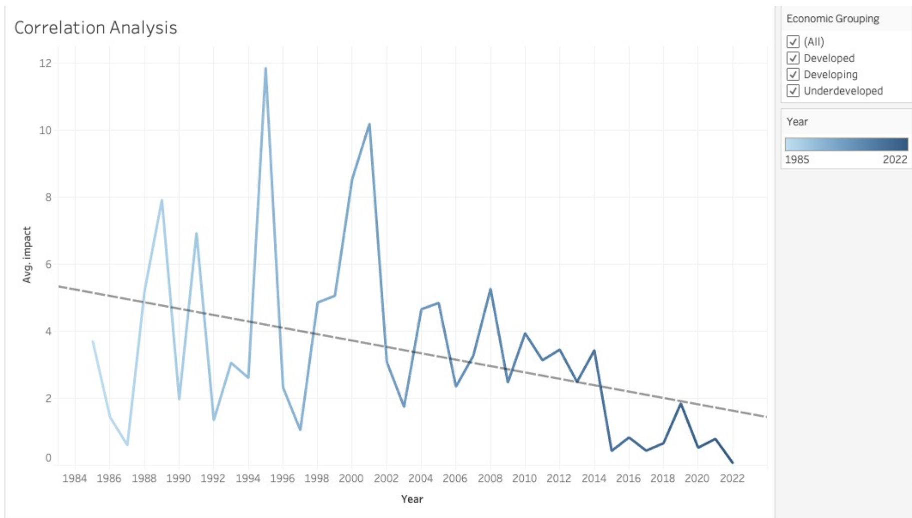

Figure 19: Correlation analysis

5.5.1 Description

The correlation analysis ranges between the average impact and year showcasing the declining trend in average impact during the years. This showcases improvements aligned with the flood management and disaster response mechanism over time. Although, the variation in the data showcases taht the overall impact may be decreasing, several flood events are still occuring (UpgradedQ4 dataset, 2024). This trend might suggest the implementation for better forecasting, early warning system development and enhanced infrastructure for resilience. Inspite of the advancements, the frequency of extreme weather followed by drastic climate change is still a significant aspect of concern.

5.5.2 Justification

A line graph is used and preferred as it shows trend over time. This type of graph helps in easy understanding of the patterns, trends and change in data across the year, providing clear visualization.

5.6 Forecasting Analysis

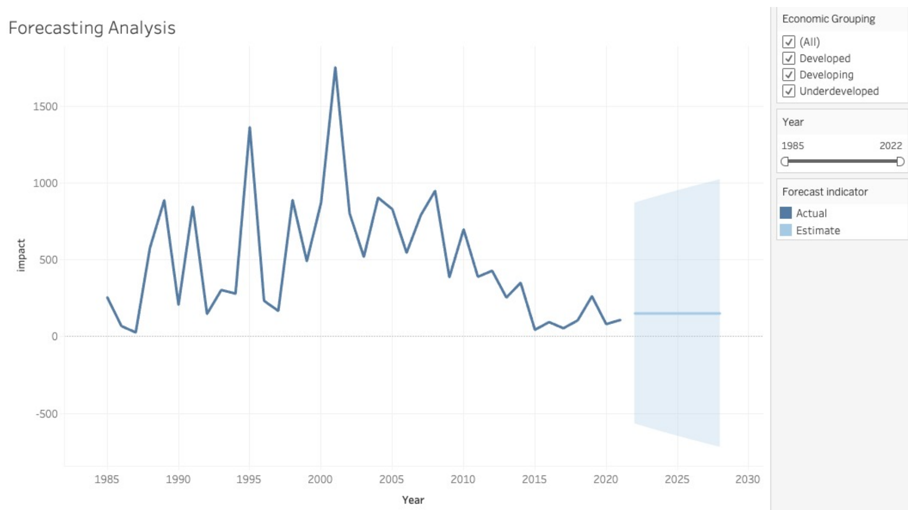

Figure 20: Forecasting analysis

5.6.1 Description

The forecasting analysis predicts the future impact of floods using the formula (Dead + Displaced)*Severity/Area. The forecast indicates stabilization in the impact, but the uncertainty range indicates potential for both decrease and increase in flood impact. These signifies the need for the continuous improvement in flood prevention and climate resilient strategies (UpgradedQ4 dataset, 2024). The forecast highlights the importance of adaptive strategies to counter the challenging flood situations, patterns, intensities and especially in the vulnerable regions.

5.6.2 Justification

The forecasting chart is helps in providing future predictions. This inclusion of confidence interval assists to understand the uncertainty in prediction, which is why the crucial planning and risk management is essential.

5.7 Interactive Dashboards

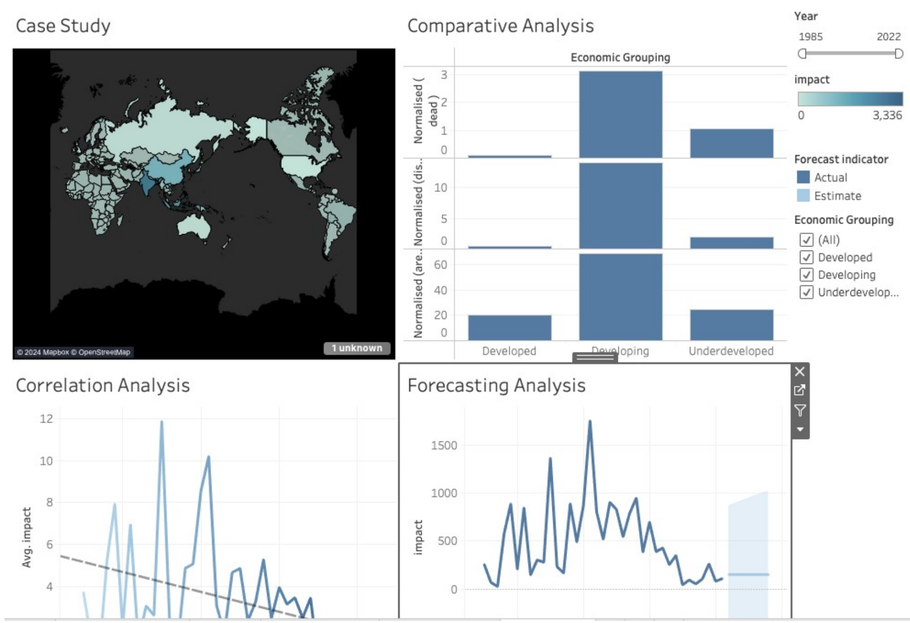

Figure 21: Dashboard

5.7.1 Description

The interactive dashboards are providing a comprehensive view of analysis conducted. Users here can filter by economic grouping and year to understand the trends. This tool assists in proper understanding of the flood impact and supports the data-driven decision-making process (UpgradedQ4 dataset, 2024) . The dashboard's interactive nature permits the stakeholders to define their specific analysis on the basis of their interests, such as analyzing the impact of latest flood events comparing the historical trends along different regions.

5.7.2 Justification

An interactive dashboard is best because it permits the user to understand the data in a dynamic way. By provisioning the filters and interactive merger of elements, users are able to customize their view and focus on specific areas of interests, improving the usability and proper analysis.

5.8 Evidences in Relations to The Incidents

Based on the analysis performed from insights we find that few significant incidents of floods followed with high deaths and displacements among the nations like Bangladesh, Indian and Nepal have news based evidences and are mentioned below:

1. **Bangladesh (June 2022)[7]**
    - **Incident:** One fo the worst floods in the last 20 years[7].

- **Impacts:** Over 7.2 million people were affected directly, there was a huge displacement and significant damage to the infrastructure[7].
- **Details:** The flood was expected to be because of heavy monsoon rains and runoff as per the seasonal understanding from response of Question 3 and runoff from the Indian mountains. Sylhet and Sunamganj were among the worst-hit regions following the most of the areas were submerged and cut off from the rest of the country[7].

2. **Bangladesh (1998)[8]**
   - **Incident:** Catastrophic Flood[8].
   - **Impacts:** Over 900 deaths and $2.5 billion in damages[8].
   - **Details:** The floodwaters swamped Dhaka and affected a significant part of the population living in flood- prone areas. The incident showcased the vulnerability of densely populated area with inadequate infrastructure[8].
3. **Bangladesh, India and Nepal (August 2017)[9]**
   - **Incident:** Monsoon Floods and landslides[9].
   - **Impacts:** Millions affected, with thousands being displaced and a great loss of lives[9].
   - **Details:** A large rainfall led to severe flooding through these countries. In the Nepal, the floods lead to 123 lives and displaced 51,244 families. UNICEF proved immediate relief, including the hygience kits to prevent disease outbreaks[9].
4. **India (Assam, June 2022)[10]**
   - **Incident:** Severe flooding leads to torrential rains[10].
   - **Impacts:** At least 9 reported deaths, nearly 2 million displaced[10].
   - **Details:** The flooding in Assam was so bad that the armed forced were called to rescue people. Landslides and continuous rains were causing widespread damage and displacement[10].
5. **Bangladesh (1988)[8]**
   - **Incident:** Major floods[8].
   - **Impacts:** Over 2000 deaths[8].
   - **Details:** The flood swamped large parts of the Dhaka, capital of Bangladesh and caused extensive damage. This event underlines the risk faced by the population in low lying areas[8].

5.9 Summary of Insights & Conclusion

The above incidents tell us that the severe impact of the monsoon floods in the South Asia, in particular the countries like Bangladesh and India and also as per the area, specifically Bangladesh. The nature of these floods which are exacerbated by the climate change and the inadequate infrastructure, leads to loss of human and economy. The data points out the need for improvement in flood management, early warning processes and infrastructure resillence in the specific regions considering that these are the developing economies.

The analysis highlights that the developing countries are the most affected by the floods, along with the significant human and economic issues. The overall impact of the floods signifies a declining trend, severe events still indicate a big threat. Continuous improvement in flood management, infrastructure and climate resilience is important to mitigate effects of flood (UpgradedQ4 dataset, 2024) . Ancillary to this the data also marks the importance of international cooperation and support the developing countries to improve the flood resilience and response facilities.

6 Insights

Floods are one of the most catastrophic natural disasters that has a long lasting impact on the economy and the environment of that region.It is very important for us to understand the factors that cause this phenomenon and what role is being played by the climate change so that we can come up with strategies to safeguard ourselves in the future.The below aims to visualise some of the main causes of flooding and the impact of climate change[11].

We have categorised the main causes of flooding as follows: Monsoonal Rain, Torrential Rain, Heavy Rain, Dam or Levee Break, Tropical Cycle , Storm Surge, Unknown, Ice Jam, Miscellaneous, Snow Melt, Avalanche.

6.1 Visualisations

6.1.1 Bar Chart

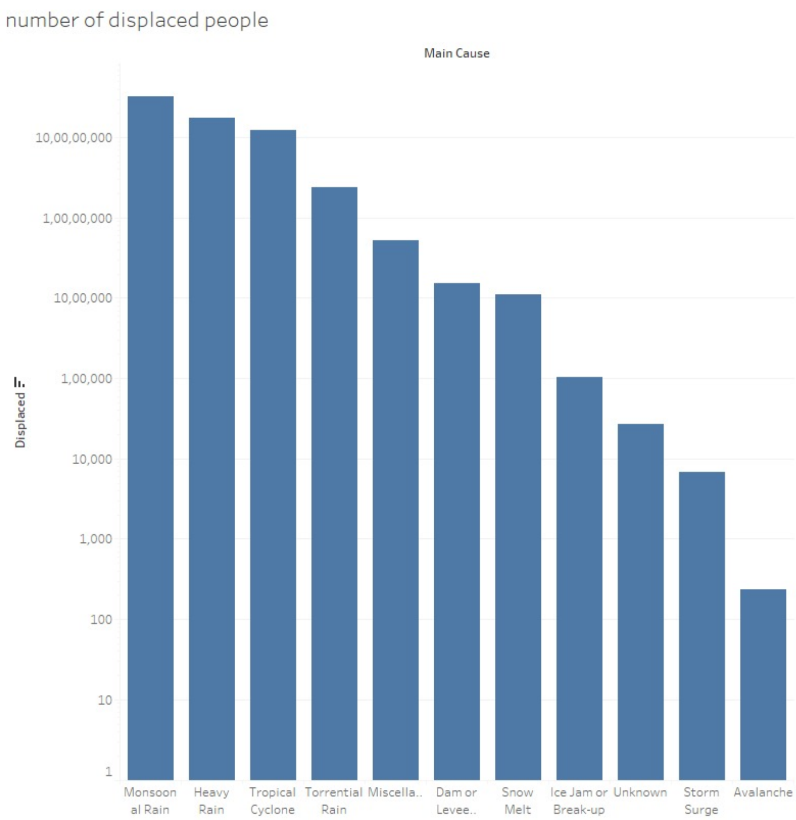

Figure 22: The Number of People displaced due to the main cause

This chart illustrates the number of people that have been displaced due to the various causes of flooding. The Key Finding we noticed that Monsoonal Rains and Heavy Rain are the main reasons behind the people being displaced.

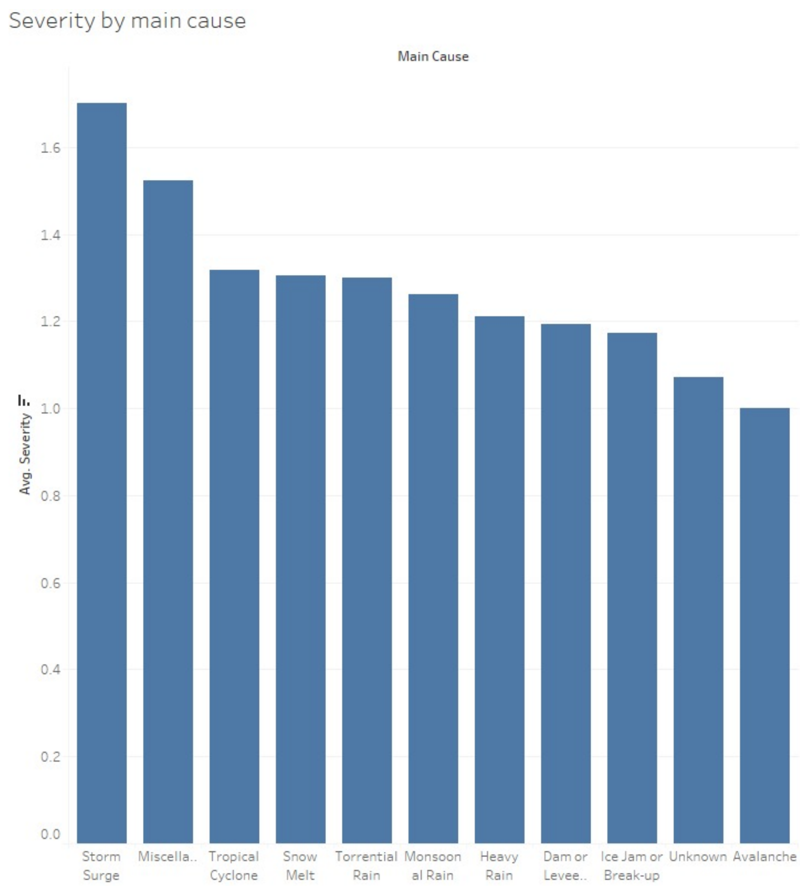

Figure 23: The Severity of the Cause

Here we display the severity(average) of floods that are caused by the various triggers. It is found that Storm Surge and Miscellaneous cause have the highest average rating which indicates the impact they have.

6.1.2 Identifying Climate Change and Trends

From Figure 88, it shows the number of floods every month so as to highlight the peak flood periods. Finding: We notice that the floods mostly occur in July and August this is due to it being monsoon swanson in most parts of the world.

From Figure 99, This provides insights into how severe the floods are every month to give us data about the seasonal flood trend. Finding: We find that the severity remains almost stable throughout the year with some slight changes.

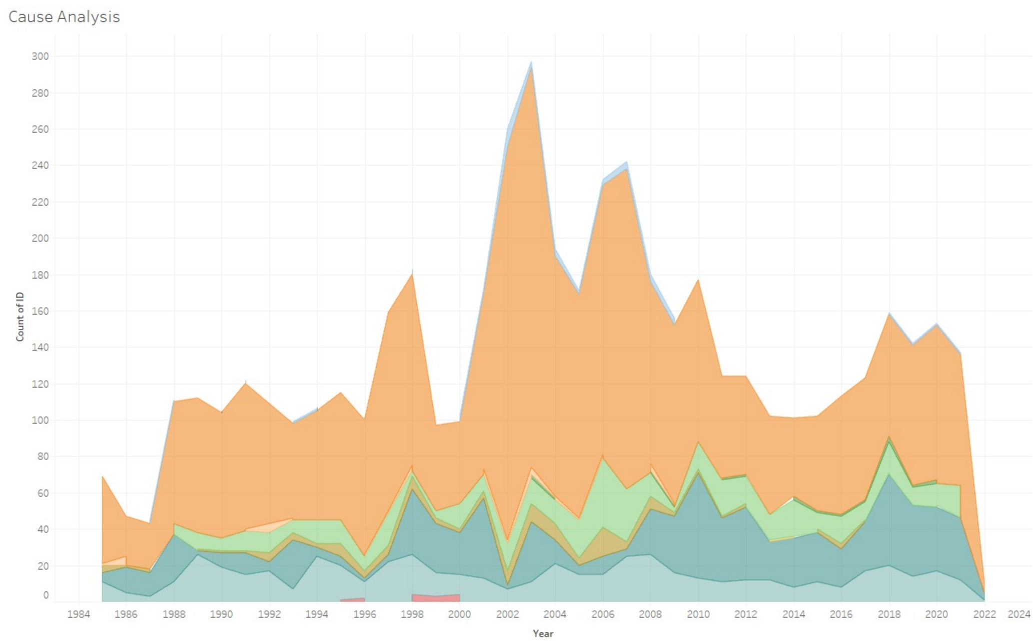

Figure 24: Area Chart

We have chosen an area chart to illustrate the flood events that happened over a period of time, this lets us to find the most number of occurrences. We can see that there is a rise in floods in the past years which suggest there might be a connection between the floods and the change in climate. This is a very important find as it can form the basis of our understanding between the change in climate, the effect it has on the environment and the people.

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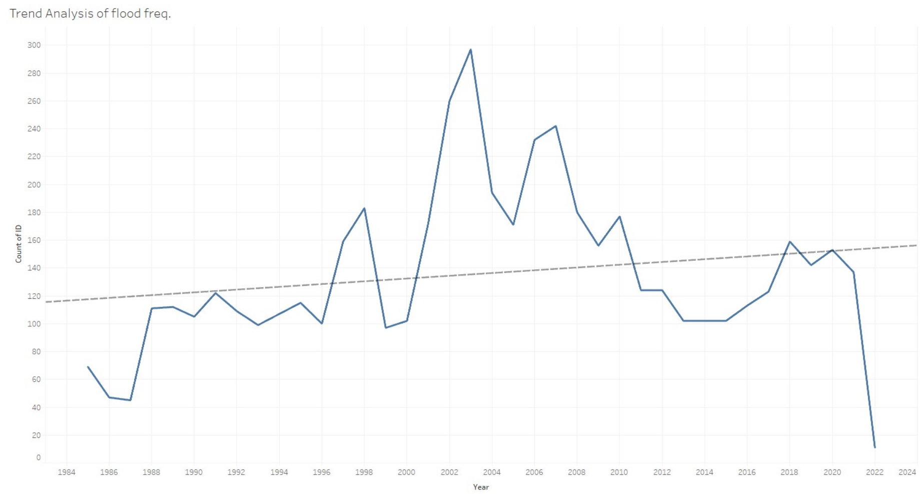

Figure 25: Flood frequency

The Line here shows the flood frequency over the years and it is noted that the Trend Line is gradually increasing. This upward line is an indication that the floods are occurring more frequently and we can correlate this to the impact of climate change.

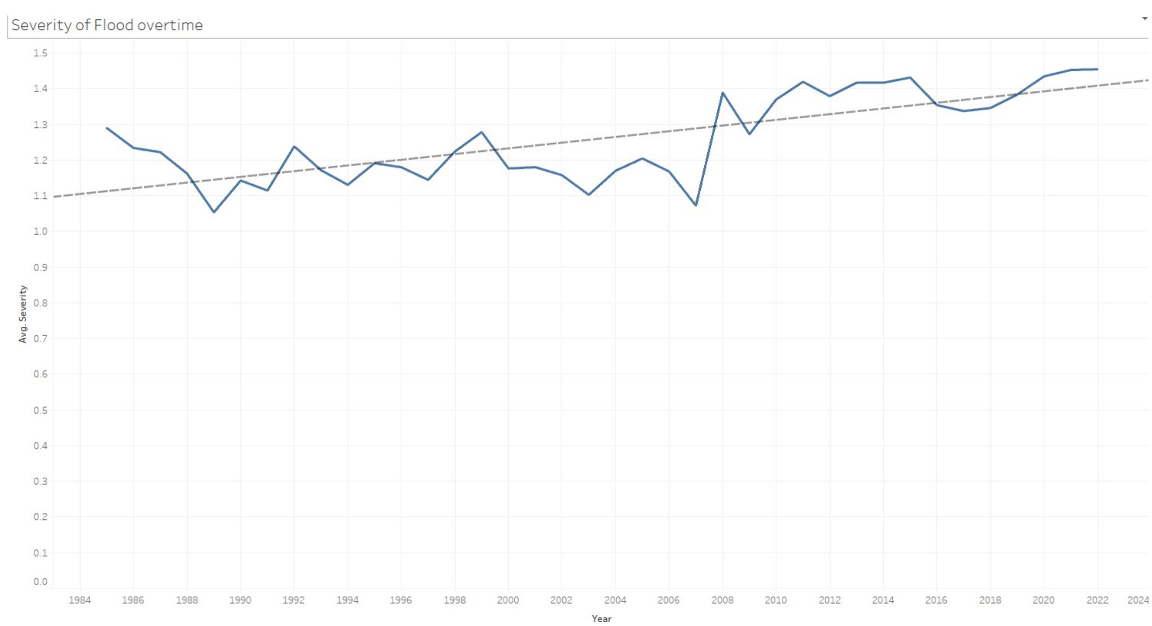

Figure 26: Severity of the floods over time

This Graph displays the Severity of the floods over time, with the trend line showing a clear increase in trend. This Upward trend is an indication that the floods are getting more destructive with every year and this can be used to connect the dots of climate change to the impact it has on floods.

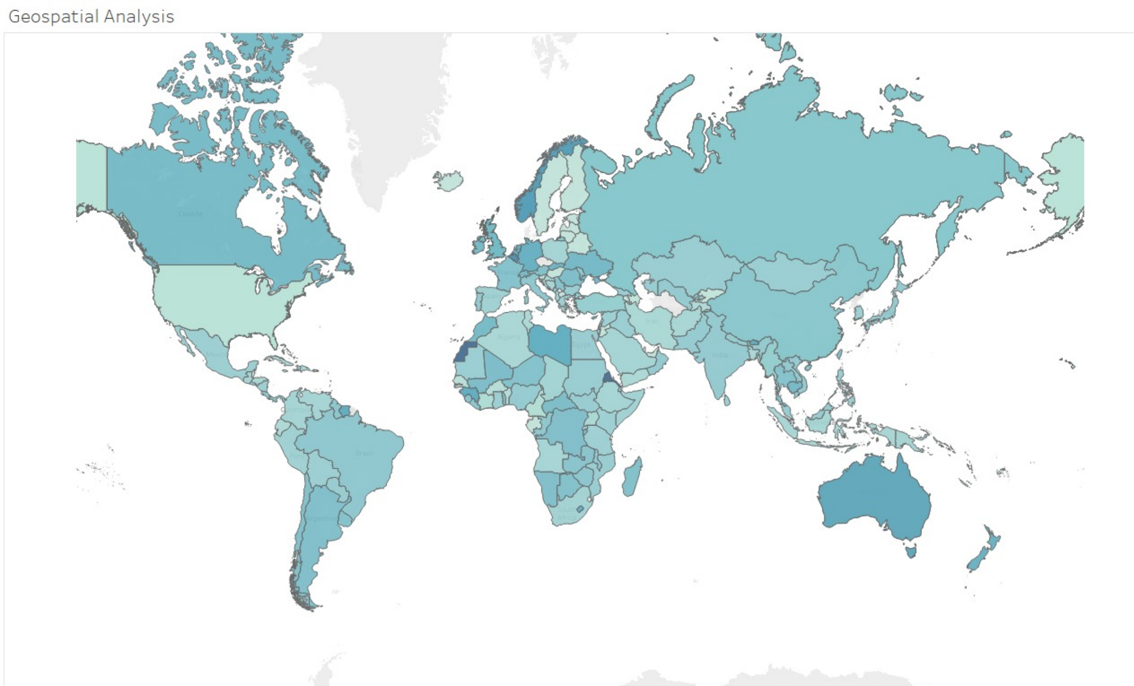

Figure 27: Severity of the floods over time

The map gives us the average severity of floods and the impact it has on the different countries from a geographical standpoint. We find that the countries in Asia and parts of the North US specifically the tropic areas seem to experience more severe floods, we can suggest that this is due to the regional specific weather conditions like the tropical cyclones and rains.

6.2 Summary of The Section

The Analysis has provided insights that Monsoonal Rain,Heavy rains seems to be the main cause of flooding with Ice Jams as the cause due to climate change be the other main factor.We can relate this to the rise in temperature because of Global warming that causes the Ice caps to melt and raise the level of water.The Increase in Trend of the frequency of floods over the past decades raises a cause for concern on how the climate change might be playing a significant hand in the cause of floods[12].

Some Takeaways from this Analysis: 1.We find that most of the floods that are caused are by the rains, so the areas that have high probability of rainfall must be kept monitored. 2.With the help of bar chart we can see the different reasons for floods, this calls for the people to have a variety of strategy to counter all possible situations. 3.In the charts we also saw how the frequency of floods had an upward slope, this can be in relation to the climate change caused by global warming. 4.Overall we should form some mitigation plans so that there is no loss to resources.

7 Conclusion

This extensive analysis of global flood statistics from 1985 to 2022 highlights the different impact of floods on developing countries, the pressing need for ongoing improvements in flood prevention, and the criticality of climate change adaptation. Through the application of data cleaning techniques, the computation of Flood Magnitude Indices, the identification of seasonal patterns, and the evaluation of flood impacts, the report offers vital insight into the complex dynamics of flood events and their aftermath.

The findings emphasise the importance of funding early warning systems, improving methods for responding to disasters, and promoting sustainable land management techniques. International cooperation and assistance for developing countries are essential for enhancing their capacity to mitigate and recover from flood disasters. Climate change will continue to alter rainfall patterns and raise the probability of catastrophic weather, thus it is critical that governments, organisations, and communities concentrate on flood risk reduction and preparedness. By taking a proactive approach to flood prevention, we may endeavour to build a future that is more resilient to this worldwide catastrophe.

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