



FEMA Disaster Impact Analysis

Group 01

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FEMA Disaster Declaration Raw Dataset

- **Dataset Name:** OpenFEMA Dataset: Disaster Declarations Summaries - v2
- **Dataset Size:** 28 columns and 67,361 rows
- **Data Origins:**
 - Older data manually entered or transferred from written spreadsheets
 - FEMA declarations date back to the 1950s
 - Labels and formats have evolved over decades
- **Challenges:**
 - Many columns were initially unreadable or lacked clarity
 - Abbreviated meanings and government-based definitions complicated comprehension

Declaration Type:

- FM = Fire Mgmt
- DR = Major Disasters
- EM = Emergency Disasters

Fed. Relief Program:

- ih = Individuals & Households
- ia = Individual Assistance
- pa = Public Assistance
- hm = Hazard Mitigation

FIPS Codes:

- Federal Information Processing System (States and Counties)
- Uniquely identify geographic areas

This is not readable - shown here for emphasis on raw format and necessary transformations

[illegible]

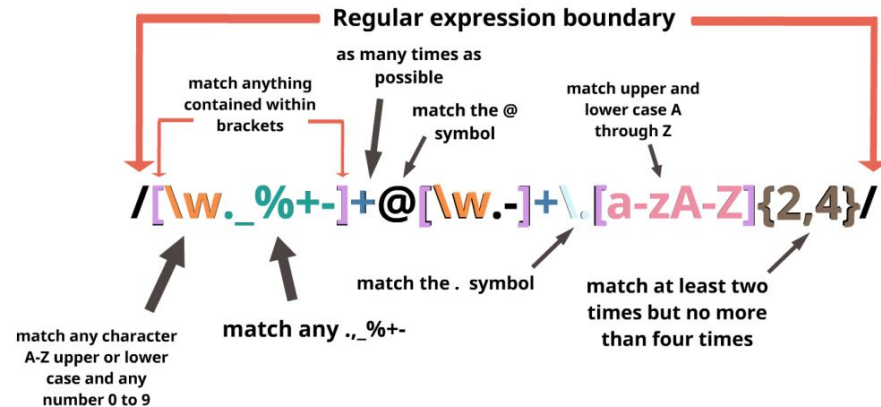
FEMA Data - Initial Filtering

Filter 1: Basic - Parsing, Merging,

- Dates included times @ midnight -> Remove times
- Geographic codes (ie. FIPS) deemed less helpful -> Remove FIPS codes
- Created DataFrame with only desired incident types to merge with original
- Drop columns that are mostly NaN

Filter 2: Advanced (Regex) - Areas

- “designatedArea” - separated by `()` to create area and area types
- “areaType” containing more area info -
Cleaned and duplicated with new areas
- Match “areaType” by keywords for accuracy and then by bins to create granularity in data (26 types originally)
- Granularity was not used for project, but with theoretical repurposing in mind



The Geoapify API Call...

Is actually just the concept of geocoding that we've all done as a class already!

Geoapify was given freeform location info in the form of an area name, and the state it's in. It was also restricted to finding coordinate pairs only in the US and its territories within a given rectangle.

This is how we retrieved the coordinate pairs for every incident and then filtered the resultant DataFrame to only rows that had coordinates.

The intricacies are found in how the call was performed...

Limitations were:

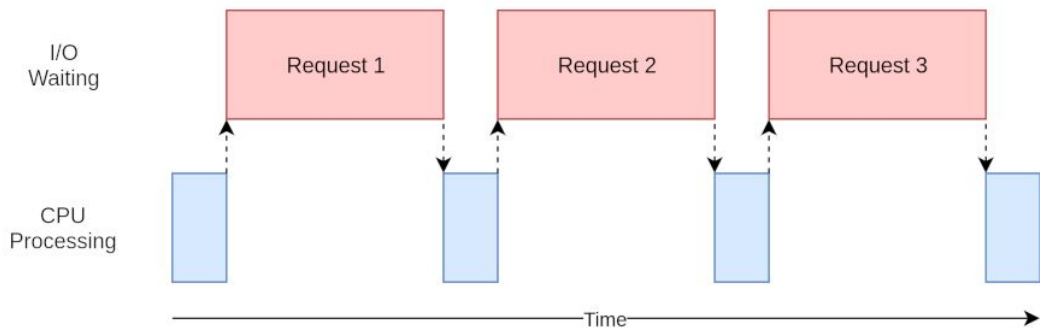
- 5 calls/second
- 3000 calls/day
- 3427 data points

→ **38 minutes, 38 seconds (runtime)**

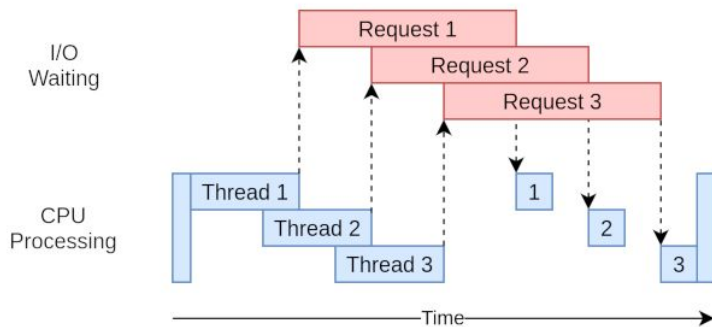
By integrating my call with the “concurrent.futures” library I was able to utilize the 9 keys I acquired to create **9 different threads**, all of which made API calls every 0.2 seconds

→ **4 minutes, 20 seconds (runtime)**

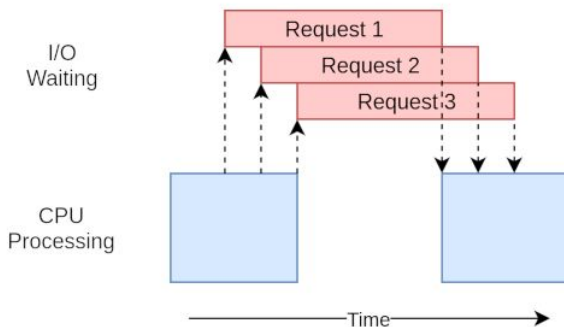
Multi-Threading Conceptually



(a) Single-threaded process



(b) Multi-threaded process
with GIL acquired by current thread



(c) Single-threaded process
with async

Final & Summary DataFrames

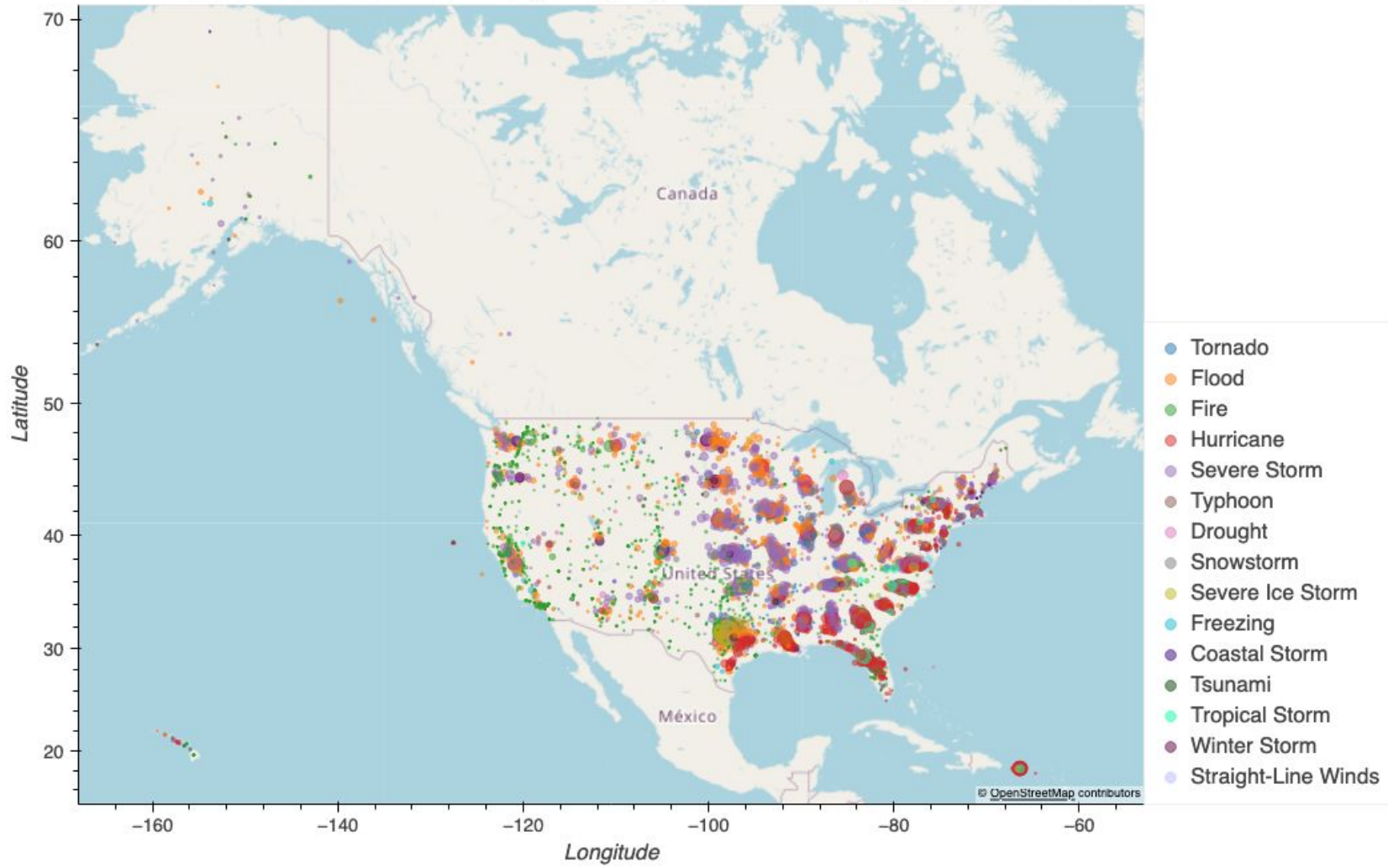
Final DF

disasterNumber	declarationRequestNumber	declarationTitle	area	areaType	state	incidentType	declarationType	declarationDate	incidentBeginDate	latitude	longitude	tribalRequest	ihProgramDeclared	iaProgramDeclared	paProgramDeclared	hmProgramDeclared
0	5530	24123	GOLD RANCH FIRE	Washoe	County	NV	Fire	FM	2024-08-12	2024-08-11	40.584905	-119.613161	0	0	0	1
1	5529	24122	LEE FALLS FIRE	Washington	County	OR	Fire	FM	2024-08-09	2024-08-08	45.560188	-123.058791	0	0	0	1
2	5528	24116	ELK LANE FIRE	Jefferson	County	OR	Fire	FM	2024-08-06	2024-08-04	44.722434	-123.007389	0	0	0	1
3	5527	24111	MILE MARKER 132 FIRE	Deschutes	County	OR	Fire	FM	2024-08-02	2024-08-02	44.156923	-121.258700	0	0	0	1
4	5522	24102	BOREL FIRE	Kern	County	CA	Fire	FM	2024-07-27	2024-07-25	35.314570	-118.753822	0	0	0	1
...
58138	1967	11042	TSUNAMI WAVES	Honolulu	County	HI	Tsunami	DR	2011-04-08	2011-03-11	21.304547	-157.855676	0	0	0	1
58139	1967	11042	TSUNAMI WAVES	Maul	County	HI	Tsunami	DR	2011-04-08	2011-03-11	20.758059	-156.310523	0	0	0	1
58140	1964	11029	TSUNAMI WAVE SURGE	Coos	County	OR	Tsunami	DR	2011-03-25	2011-03-11	43.218414	-124.109621	0	0	0	1
58141	1964	11029	TSUNAMI WAVE SURGE	Curry	County	OR	Tsunami	DR	2011-03-25	2011-03-11	41.858425	-74.581269	0	0	0	1
58142	1964	11029	TSUNAMI WAVE SURGE	Lincoln	County	OR	Tsunami	DR	2011-03-25	2011-03-11	42.108750	-122.403078	0	0	0	1

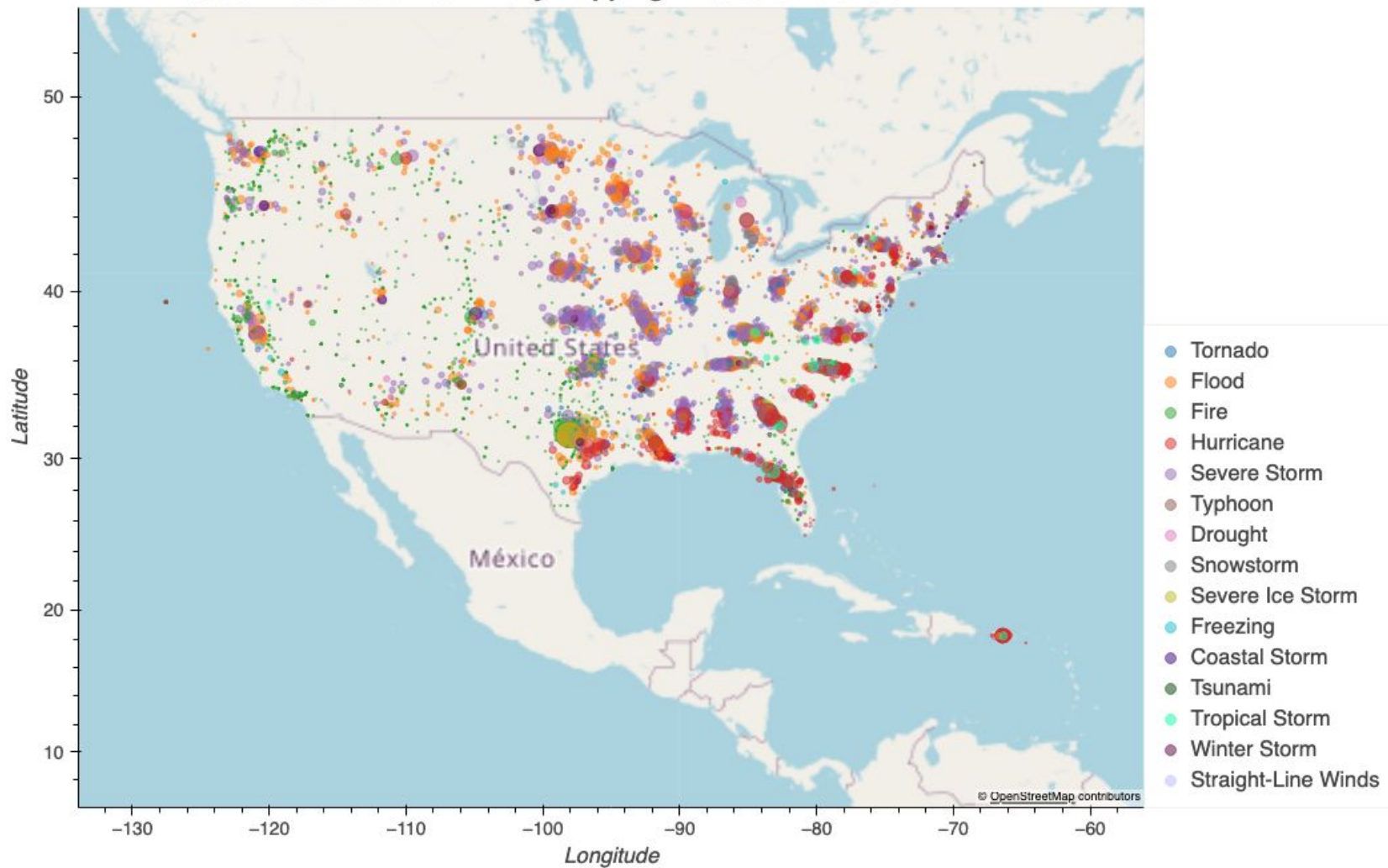
Disaster Number		Title	Number of Requests	Declaration Request Number	Incident Type	Incident Begin Date (First)	Incident Begin Date (Last)	Declaration Date (First)	Declaration Date (Last)	Latitude	Longitude
0	1	TORNADO	1	53013	Tornado	1953-05-02	1953-05-02	1953-05-02	1953-05-02	30.876607	-84.200199
1	2	TORNADO & HEAVY RAINFALL	1	53003	Tornado	1953-05-15	1953-05-15	1953-05-15	1953-05-15	29.396013	-94.917548
2	3	FLOOD	1	53005	Flood	1953-05-29	1953-05-29	1953-05-29	1953-05-29	32.787346	-91.904878
3	4	TORNADO	1	53004	Tornado	1953-06-02	1953-06-02	1953-06-02	1953-06-02	42.233092	-84.327177
4	5	FLOODS	1	53006	Flood	1953-06-06	1953-06-06	1953-06-06	1953-06-06	46.540855	-111.946345
...
4713	5547	JENNINGS CREEK FIRE	1	24199	Fire	2024-11-08	2024-11-08	2024-11-15	2024-11-15	41.539816	-74.098199
4714	5548	FRANKLIN FIRE	1	24204	Fire	2024-12-09	2024-12-09	2024-12-10	2024-12-10	34.053691	-118.242766
4715	5549	PALISADES FIRE	1	25002	Fire	2025-01-07	2025-01-07	2025-01-07	2025-01-07	34.053691	-118.242766
4716	5550	EATON FIRE	1	25003	Fire	2025-01-07	2025-01-07	2025-01-08	2025-01-08	34.053691	-118.242766
4717	5551	HURST FIRE	1	25004	Fire	2025-01-07	2025-01-07	2025-01-08	2025-01-08	34.053691	-118.242766

Summary DF

FEMA Disaster Declaration Summary Mapping - Includes Outlying US Territories



FEMA Disaster Declaration Summary Mapping - Focus on the U.S.





File Organization

CSV Breakdown:

- Original
- Cleaned Using Basic Methods
- Geocoded File gained from API
- Cleaned Using Regex and validated with geocoding
- Summary

Assets:

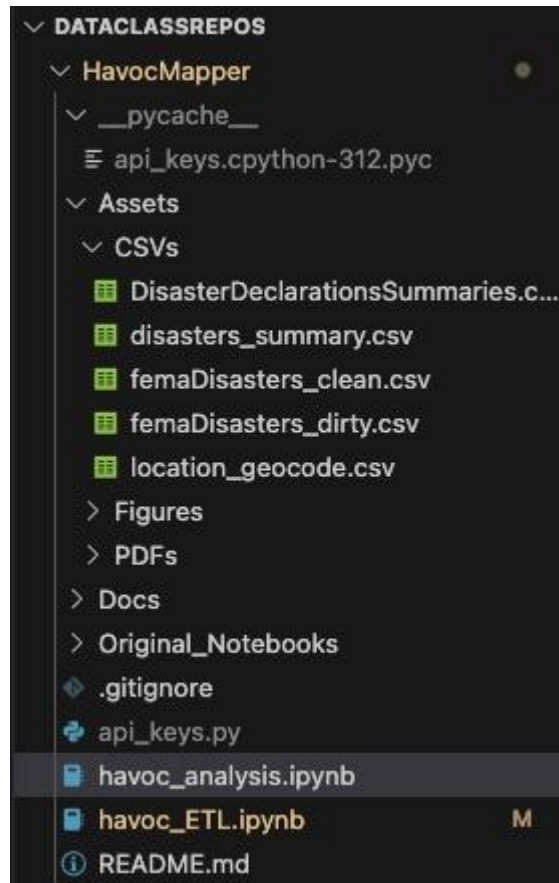
- CSVs
- Figures (exported images by Name)
- PDFs (resources)

Docs:

- For source linking and additional documentation

Original Notebooks:

- Each collaborator's individual notebook



Data Engineering Rabbit Holes

- Learning to use Regex and vectorized function for DataFrames
- `areaType` pitfall of cleaning data that wasn't needed/used
- Deciding on API and how to use
- Encountering heavy limits on API and runtime issues/long wait time
- Deciding on group workflow



The fearsome rabbit from Monty Python and the Holy Grail

Federal Emergency Management Agency (FEMA) Data Statistical Analysis - summary

Natural Disasters Focused on the FEMA data-set

- Severe Storms - 18,399
- Hurricane - 13,721
- Flood - 11,093
- Fire - 3759
- Snowstorms - 3707
- Severe Ice Storms - 2942
- Tornado - 1623
- Drought - 1292
- Tropical Storm - 1047
- Coastal Storm - 637
- Freezing - 301
- Earthquake - 228
- Typhoon - 130
- Winter storm - 117
- Volcanic Eruption - 51
- Mud/Landslide - 43
- Tsunami - 9
- Straight-Line Winds - 2

Declaration Types

- Major Disasters - 41,116
- Emergency Declarations - 15,991
- Fire Management - 1994

Total Number of Natural Disasters
Declared over the last 72 years is

59,101



Most Common and Least Common Natural Disasters Declared

- Most Common Natural Disaster Declared

- Severe Storms
- Hurricane
- Flood



- Least Common Natural Disaster Declared

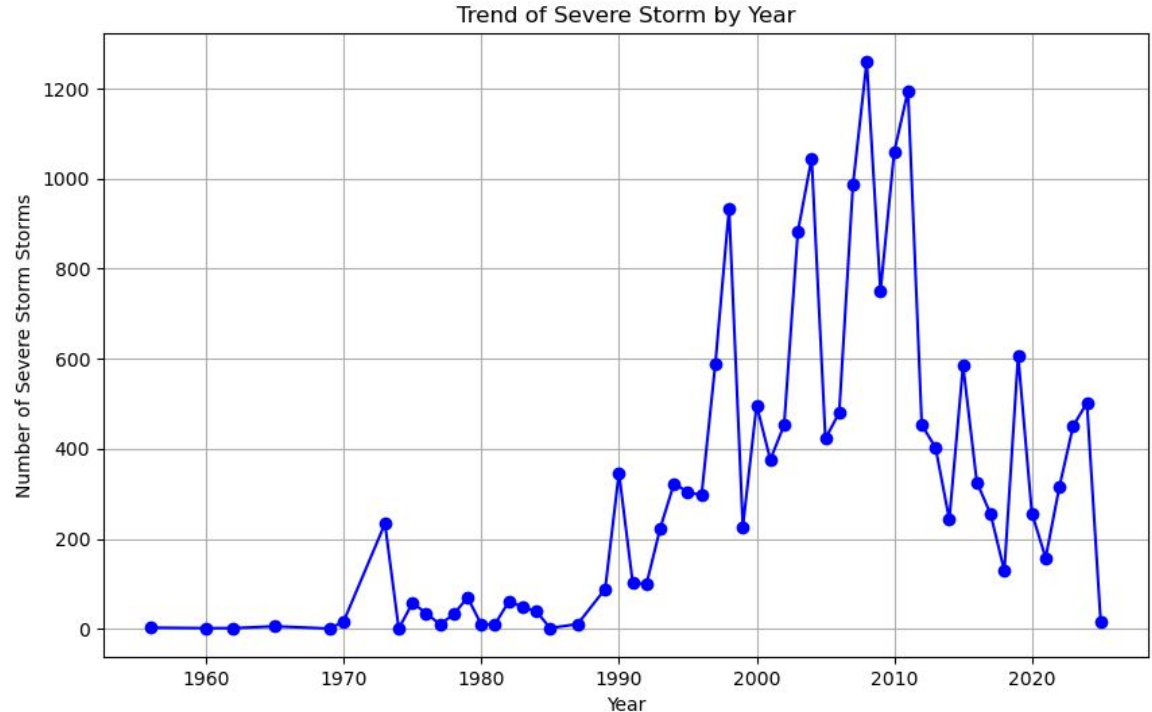
- Straight line winds
- Tsunami
- Mud/Landslides



Severe Storms - Trends Over the last Seven Decades

Trends:

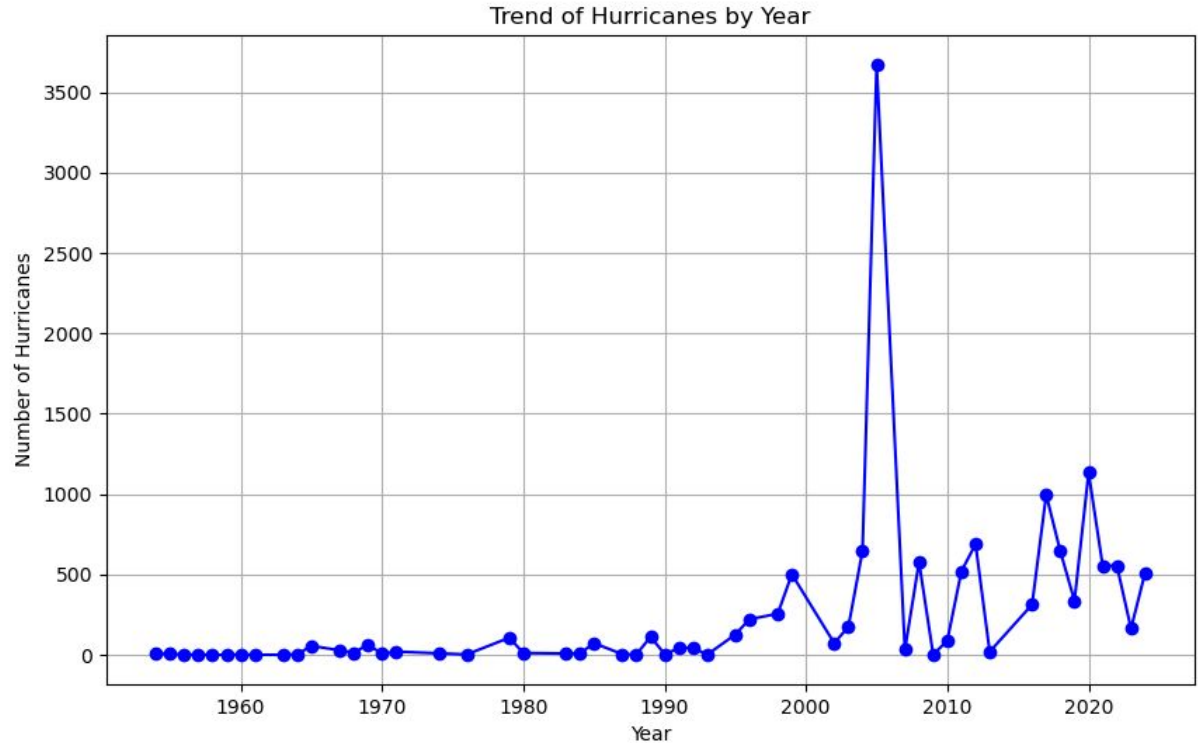
- Average Storms per year is 342.1
- Most number of Severe storms in a given year was 1263
- Least number of storms in a given Year was 1
- 2008 had the highest number of storms
- In general there was a spike in the number of storms between 2000 - 2010



Hurricanes - Trends Over the last Seven Decades

Trends:

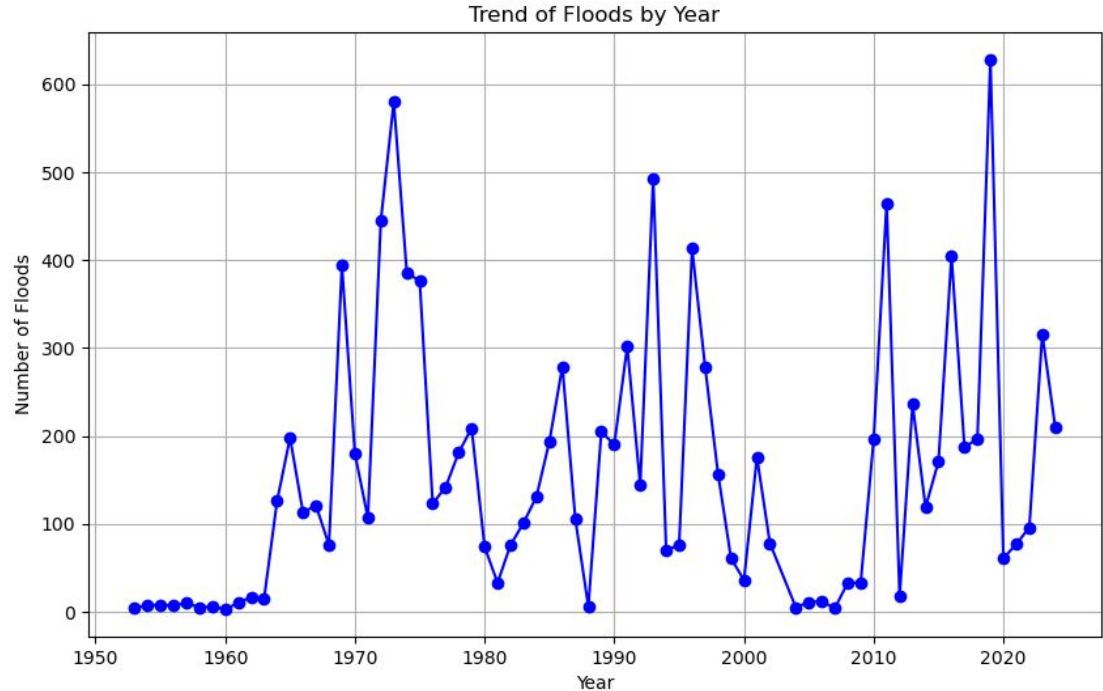
- Average Hurricanes per year is 254.09
- Most number of Severe storms in a given year was 3714
- Least number of Hurricanes in a given Year was 1
- 2005 had the highest number of storms
- Overall there was a consistent increase in hurricanes after 2005 with no major spikes



Floods - Trends Over the last Seven Decades

Trends:

- Average Floods per year is 124.1
- Most number of Floods in a given year was 3714
- Least number of Floods in a given Year was 1
- Floods have been consistent throughout the last seven decades with two spikes in the early 70's and late 2010's
- 1950's and 1960's were two decades that had the least amount of Floods.

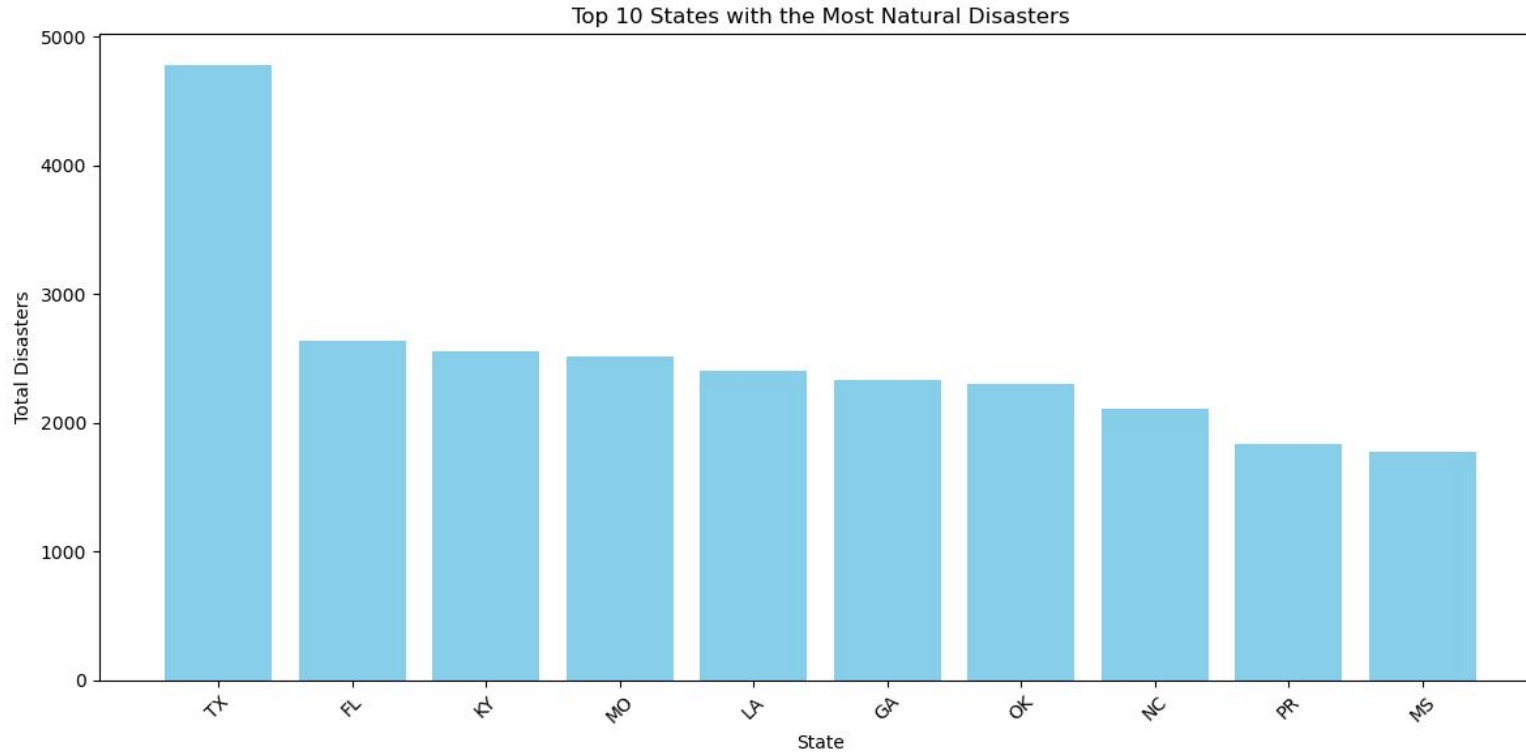


Geographical Data

Question: What US locations experience the most natural disasters? Why?



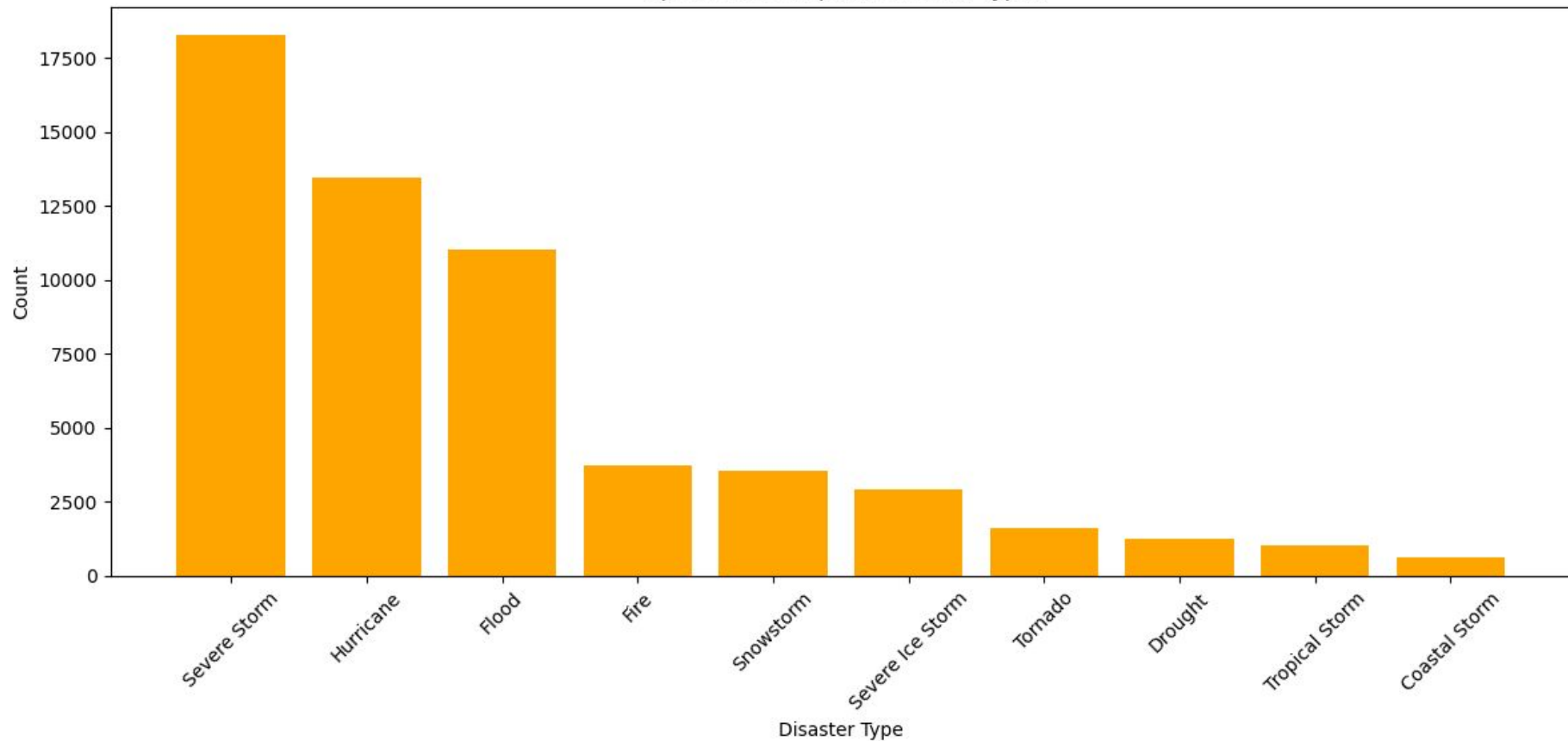
Graphs Based on FEMA Disaster Declaration Data Set



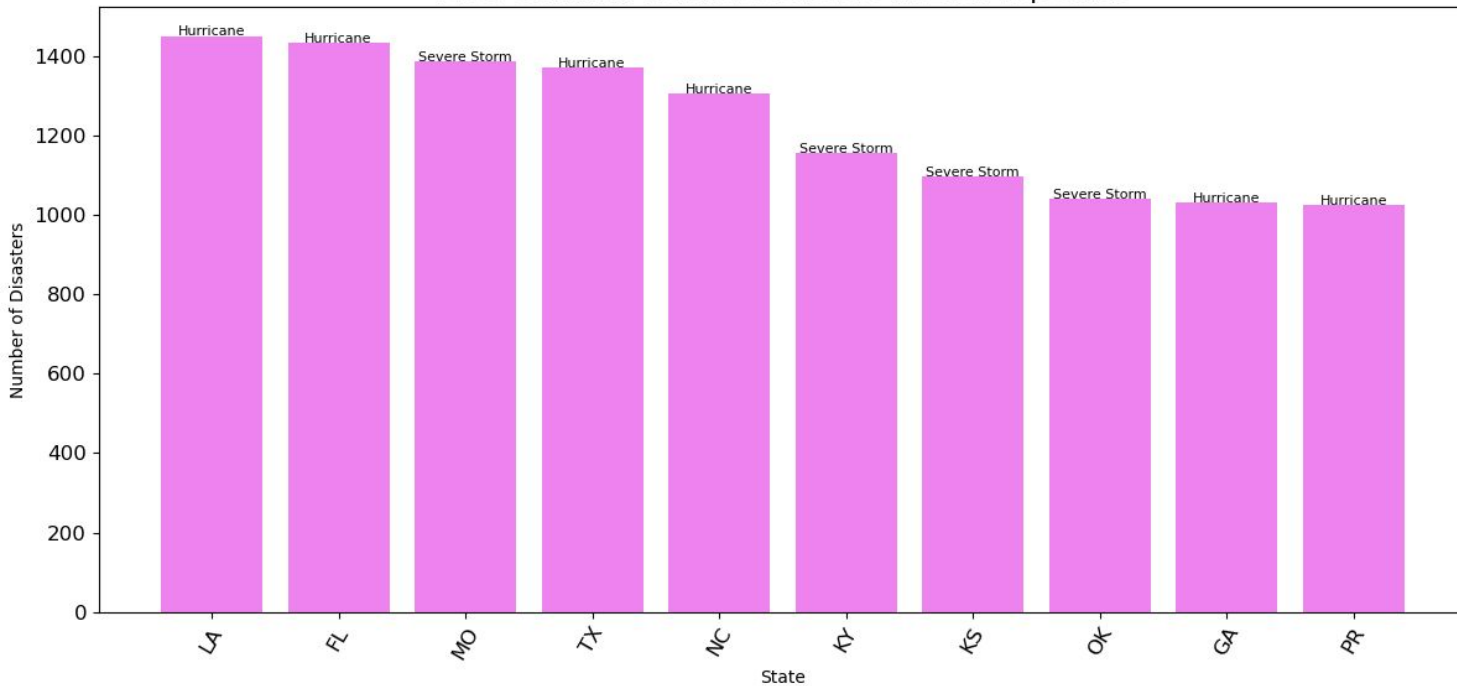
TX:
4,779
total
disasters

FL: 2,635
total
disasters

Top 10 Most Frequent Disaster Types



Most Common Natural Disasters in Each Top State



**LA: most hurricanes
declared out of all
the states (1,450
total)**

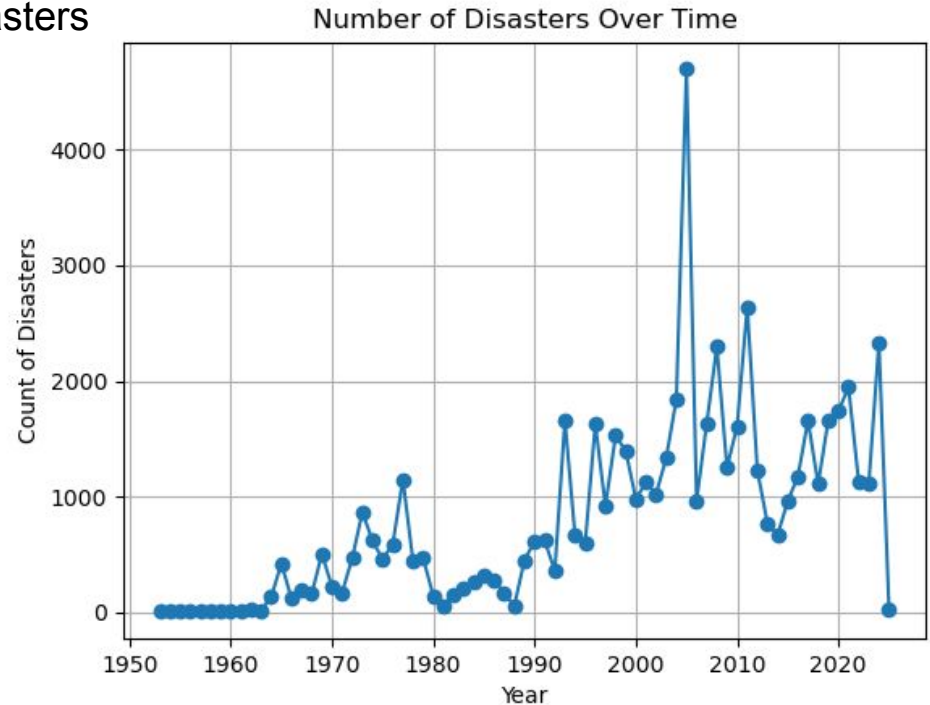
**MO: most severe
storms declared
(1,387 total)**

Why?

- Texas:
 - Broad coastline, making it more vulnerable to hurricanes and severe storms.
 - It is a very big state with lots of land that covers multiple climate zones.
- Florida:
 - Situated between the Gulf of Mexico, Atlantic Ocean, and the Straits of Florida, making the state susceptible to hurricanes from many directions.
 - Low elevation can increase the risk of floods.
- Southeast Regions (LA, GA, KY):
 - Highly exposed to Atlantic hurricanes and storms.
 - Moisture from the Gulf of Mexico can lead to frequent thunderstorms.

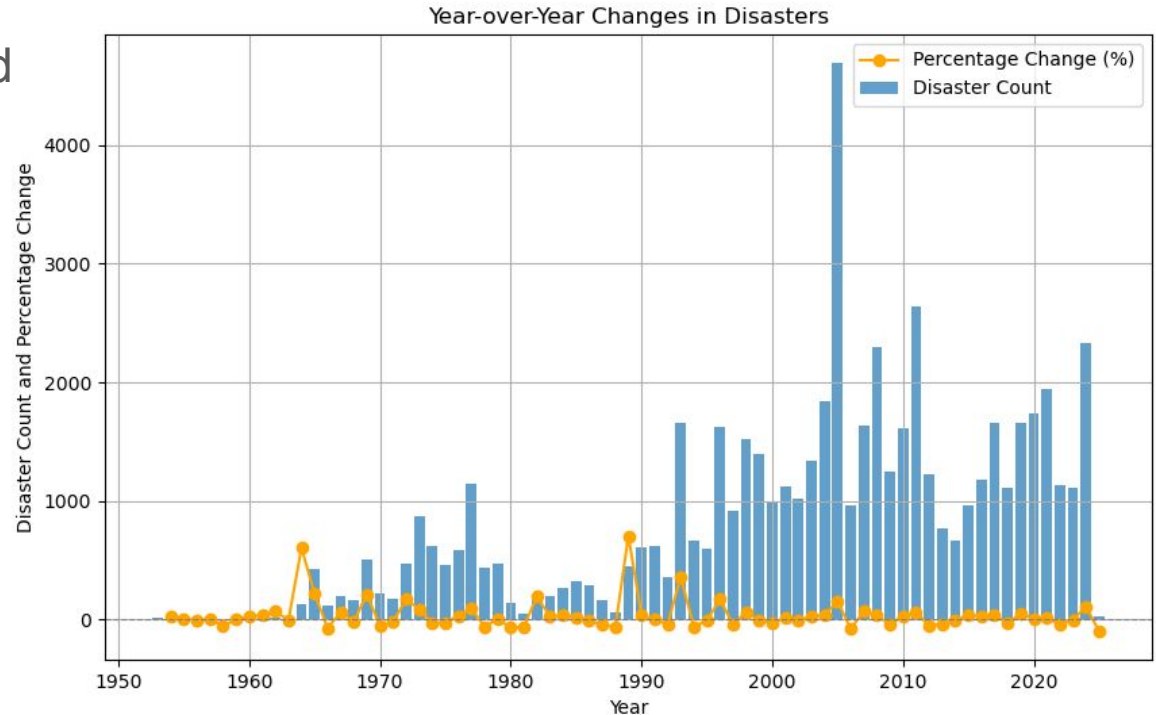
Natural Disaster Impact trend Analysis

- Year 2005 had 41 natural disasters
- 38.99% change over time of natural disasters



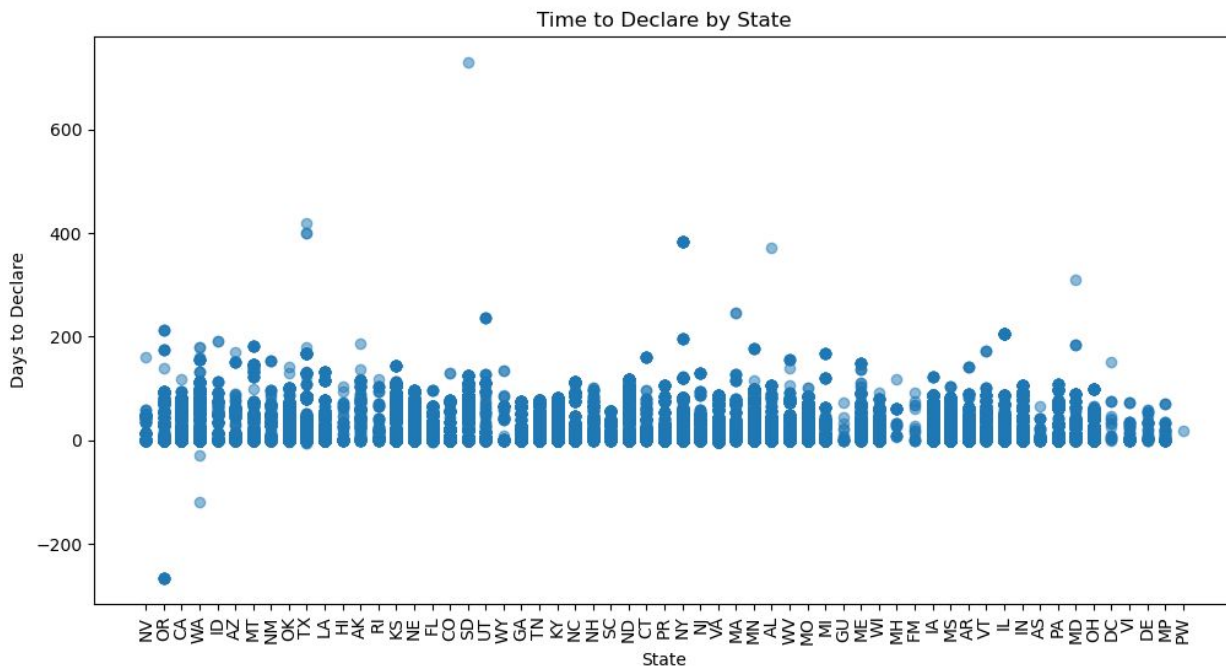
YOY Trend Analysis

- Hurricane Katrina and Rita impacted large spike in 2005 in LA and TX
- Spring: 22636
- Fall: 17310
- Summer: 15721
- Winter: 11689



Time to Declare by State

- PR and FL are the states that take the shortest time to declare a disaster with about ~ 8 days
- AK the longest at about 52 days



Utilized Libraries

FEMA Data Pipeline for ETL

Dependencies

```
1 # Main ETL Libraries
2 import pandas as pd
3 import requests
4 from concurrent.futures import ThreadPoolExecutor
5 from itertools import cycle
6 from time import sleep
7
8 # Formating and Display Libraries
9 from pprint import pprint
10
11 # File Library
12 from pathlib import Path
13
14 # Personal API Key File (Please use your own or comment out)!
15 import api_keys
```

HavocMapper Analysis and Visuals By Multiple Collaborators

Imports and bringing in cleaned CSV file

```
1 # Dependencies
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5 import hvplot.pandas
6 import dataframe_image as dfi
7
8 # Seaborn, hvplot, and pyplot silencing
9 import warnings
10 warnings.filterwarnings('ignore')
```

[1]

✓ 5.0s

Additional Sources

- <https://www.ncei.noaa.gov/>
- <https://www.spc.noaa.gov/publications/>
- <https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2> (Main Dataset)
- <https://www.fema.gov/flood-maps/products-tools/national-risk-index>
- <https://www.usgs.gov/programs/natural-hazards>
- <https://www.fema.gov/openfema-data-page/fima-nfip-redacted-claims-v2>