Results

Our aim was to analyze how FEMA allocates funding aid to states, based on the type of natural disaster that occurs. Though there are many other factors that may come into play regarding funding allocation, natural disaster type clearly plays a significant role and it's important to dissect these allocations. Figure 1 represents the correlation between disaster type and allocated funding. For example, in this linear regression model, coefficients represent the relationship between natural disasters (under "Feature") and the funding amount (represented by the "Coefficient") as follows: If the coefficient for Earthquake is is 6.78 x 106, it means that for each additional earthquake in a state during a given year (all else being equal), the model predicts an additional \$6,580,000 in disaster relief funding. A negative coefficient is associated with a decrease in predicted disaster relief funding (this could occur due to prioritization or other complex funding dynamics). It's important to note that these coefficients do not imply causation, only statistical association. It's also important to note that if disaster types are highly correlated (e.g., hurricanes often cause floods), the coefficients might not reliably isolate the effect of each variable.

To further analyze how state funding is allocated and understand how natural disasters play a role in funding, we conducted a k-cluster analysis. Figure 5 demonstrates 3 clusters pulled from the 50 states based on disaster type, frequencies, and allocated funding. As seen in Cluster 0, there are a high average number of disasters, and this represents areas with frequently occurring disasters. Cluster 1 has fewer disasters than Cluster 0, and moderate funding levels which probably represents regions with moderate disaster frequency. Cluster 3 has high values for

specific disasters (such as Freezing), which suggests a focus on areas prone to specific but impactful disasters.

This data provides crucial insights into patterns of disaster frequency, severity, and associated funding, allowing for a more strategic approach to resource allocation (reference Figure 6 for a visualization of the disaster clustering). By clustering disasters into groups based on their characteristics, decision-makers can identify regions or disaster types that require the most attention. For instance, Cluster 0, with the highest total number of disasters and significant funding allocation, likely represents areas with frequent and severe events, such as floods or fires, necessitating sustained investment. Conversely, Cluster 1, with fewer disasters and lower funding, may highlight regions where resources can be allocated more efficiently. The funding discrepancies across clusters suggest opportunities to reassess how resources are distributed, ensuring that high-impact but less frequent disasters (e.g., tsunamis in Cluster 2) are not underfunded. Overall, this analysis enables targeted disaster preparedness and relief strategies, ensuring funding aligns with the unique needs of each cluster to maximize resilience and minimize long-term recovery costs.

Appendix

```
→▼ Mean Squared Error: 75236351229713.56
R-squared: -1.6420160847190273
              Feature
                        Coefficient
13
                Other 7.458012e+06
5
           Earthquake 6.578130e+06
19
     Toxic Substances 3.527077e+06
3
      Dam/Levee Break 2.175235e+06
6
                 Fire 2.714233e+05
18
              Tornado 6.178786e+04
8
                Flood 4.682506e+04
14
     Severe Ice Storm 3.367254e+04
11
            Hurricane 2.696142e+04
0
           Biological 8.313693e+03
15
         Severe Storm 1.473953e+03
1
             Chemical 2.997695e-09
10
          Human Cause 9.313226e-10
9
             Freezing 1.164153e-10
22
              Typhoon 0.000000e+00
17
            Terrorist 0.000000e+00
23
    Volcanic Eruption 0.000000e+00
20
       Tropical Storm 0.000000e+00
21
              Tsunami
                       0.000000e+00
7
       Fishing Losses -4.656613e-10
4
              Drought -2.153683e-09
16
            Snowstorm -4.004818e+04
24
         Winter Storm -1.177787e+05
        Coastal Storm -1.715085e+05
2
12
        Mud/Landslide -3.614730e+05
```

Figure 1. A linear regression demonstrating the correlation between natural disaster occurrence within a state and the expected change in funding allocated to that state as a result.

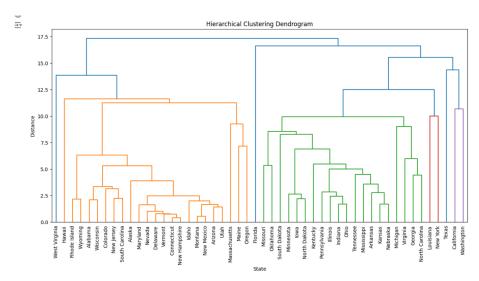


Figure 2. Hierarchical clustering of states based on natural disaster type, occurrence, and FEMA Funding allocation.

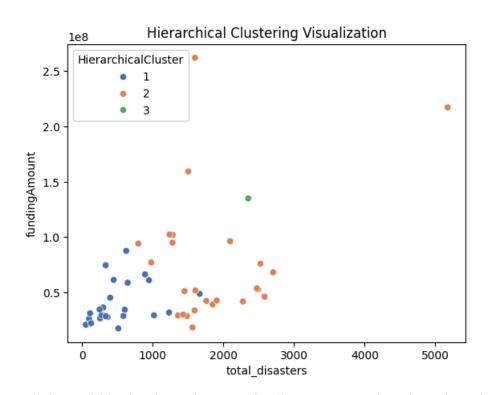


Figure 3. Correlations within the cluster between funding amount and total number of disasters.

	Biological	Chemi	.cal Co	astal Sto	orm Dam	/Levee B	reak	Drought \	
state					_				
Alabama	139		0		0		0	67	
Alaska	121		0		2		0	0	
Arizona	73		0		0		0	8	
Arkansas	152		0		0		0	32	
California	116		0		43		5	47	
	Earthquake	Fire	Fishin	g Losses	Flood	Freezin	g	. Terrorist	t
state									
Alabama	0	11		0	104		ə	. (3
Alaska	13	30		0	50	1	4	. (3
Arizona	0	88		0	82		1	. (3
Arkansas	0	0		0	271		o	. (9
California	32	460		4	448	5	7	. (3
						_			
	Tornado To	xic Su	bstance	s Tropio	al Stor	m Tsuna		yphoon \	
state	Tornado To	xic Su	bstance	s Tropio	al Stor	m Tsuna		yphoon \	
state Alabama	Tornado To	oxic Su		s Tropio		m Tsuna		yphoon \	
		oxic Su					mi Ty		
Alabama	62	oxic Su		0		0	mi Ty 0	0	
Alabama Alaska	62 Ø	oxic Su		0 0		0 0	mi T <u>y</u> 0 0	0	
Alabama Alaska Arizona	62 0 0	oxic Su		0 0		0 0 0	mi Ty 0 0 0	0 0 0	
Alabama Alaska Arizona Arkansas	62 0 0 113			0 0 0 0		0 0 0 0	mi Ty 0 0 0 0 3	0 0 0 0	
Alabama Alaska Arizona Arkansas	62 0 0 113 0			0 0 0 0		0 0 0 0	mi Ty 0 0 0 0 3	0 0 0 0	
Alabama Alaska Arizona Arkansas California	62 0 0 113 0		Winte	0 0 0 0		0 0 0 0	mi Ty 0 0 0 0 3	0 0 0 0	
Alabama Alaska Arizona Arkansas California	62 0 0 113 0	ruption	Winte	0 0 0 0 0 0		0 0 0 0 0	mi Ty 0 0 0 0 3 fund 4.8	0 0 0 0 0 dingAmount	
Alabama Alaska Arizona Arkansas California state Alabama	62 0 0 113 0	ruption 0	Winte	0 0 0 0 0 0 r Storm		0 0 0 0 0 isasters	mi Ty 0 0 0 0 3 fund 4.8	0 0 0 0 0 0 dingAmount	
Alabama Alaska Arizona Arkansas California state Alabama Alaska	62 0 0 113 0	ruption 0 0	Winte	0 0 0 0 0 0 r Storm		0 0 0 0 0 isasters 1665 318	mi Ty 0 0 0 0 3 fund 4.8 2.9	0 0 0 0 0 0 dingAmount 887564e+07	

Figure 4. Example of State mapping of natural disasters, total disaster occurrence, and funding allocated to each state

∓÷		Biological	Chemical	Coasta	1 Storm	Dam/Lev	oe Bres	k Drought	\	
Ĺ	Cluster	DIOIOGICUI	CHCHILCUI	Cousta	1 5001111	Dulli) LCV	cc bi ca	k Drought	`	
	0	569.000000	0.000000	25	.500000		0.00000	74.500000		
	1	135.829787	0.191489		.914894		0.27659			
	2	150.000000	0.000000	25	.000000		0.00000	0.000000		
		Earthquake	Fi	re Fish	ing Loss	es	Flood	Freezing		١
	Cluster									
	0	0.000000	613.5000	00	8.0000	000 299.	500000	13.500000		
	1	2.319149	44.7446	81	0.5531	191 205.	085106	2.702128		
	2	0.000000	277.0000	00	0.0000	000 73.	000000	147.000000		
		Tornado	Toxic Sub	stances	Tropica	al Storm	Tsuna	mi Typhoon	\	
	Cluster									
	0	25.000000		.000000		0.0		0.000000		
	1	31.510638		.191489		0.0	0.1914			
	2	38.000000	0	.000000		54.0	0.0000	0.000000		
	-1 .	Volcanic Er	uption W	inter St	orm tot	al_disas	ters f	undingAmount	\	
	Cluster									
	0		000000	0.000		3096.00		1.233323e+08		
	1		085106	0.914		1132.23		5.596522e+07		
	2	0.	000000	0.000	000	2352.00	00000	1.350564e+08		
		Hierarchica	lCluster							
	Cluster									
	0	1.500000								
	1	1.510638								
	2		3.000000							
	[3 rows	x 28 columns]							

Figure 5. Mapping of unique natural disasters, total disaster occurrence, and allocated funding per 3 clusters of the 50 states (reference Figure 2)

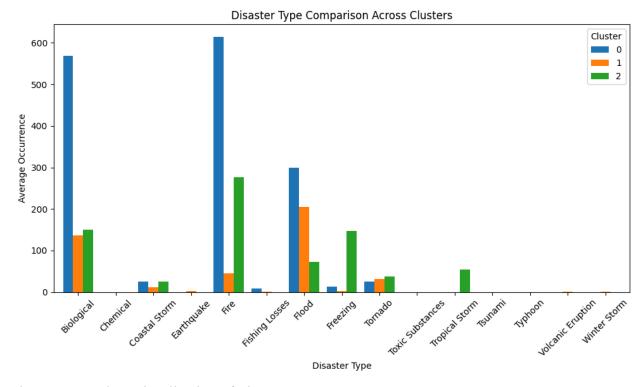


Figure 6. Bar chart visualization of Figure 5

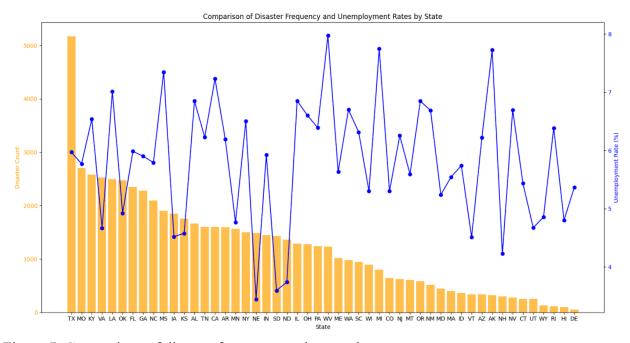


Figure 7. Comparison of disaster frequency and unemployment per state