DataDoomsDay

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emdat.head()
```

	DisNo.	Historic	Classification Key	Disaster Group	Disaster Subgroup	Disaster Type	Disaster Subtype	External IDs	Event Name	ISO	...
0	1900-0003-USA	Yes	nat-met-sto-tro	Natural	Meteorological	Storm	Tropical cyclone	NaN	NaN	USA	...
1	1900-0005-USA	Yes	tec-ind-fir-fir	Technological	Industrial accident	Fire (Industrial)	Fire (Industrial)	NaN	NaN	USA	...
2	1900-0006-JAM	Yes	nat-hyd-flo-flo	Natural	Hydrological	Flood	Flood (General)	NaN	NaN	JAM	...
3	1900-0007-JAM	Yes	nat-bio-epi-vir	Natural	Biological	Epidemic	Viral disease	NaN	Gastroenteritis	JAM	...
4	1900-0008-JPN	Yes	nat-geo-vol-ash	Natural	Geophysical	Volcanic activity	Ash fall	NaN	NaN	JPN	...

	Reconstruction Costs ('000 US$)	Reconstruction Costs, Adjusted ('000 US$)	Insured Damage ('000 US$)	Insured Damage, Adjusted ('000 US$)	Total Damage ('000 US$)	Total Damage, Adjusted ('000 US$)	CPI	Admin Units	Entry Date	Last Update
0	NaN	NaN	NaN	NaN	30000.0	1098720.0	2.730451	NaN	2004-10-18	2023-10-17
1	NaN	NaN	NaN	NaN	NaN	NaN	2.730451	NaN	2003-07-01	2023-09-25
2	NaN	NaN	NaN	NaN	NaN	NaN	2.730451	NaN	2003-07-01	2023-09-25
3	NaN	NaN	NaN	NaN	NaN	NaN	2.730451	NaN	2003-07-01	2023-09-25
4	NaN	NaN	NaN	NaN	NaN	NaN	2.730451	NaN	2003-07-01	2023-09-25

5 rows × 46 columns

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[17] inform.head()
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	Unnamed: 0
0	release:
1	31 March 2024 v 0.6.8
2	INFORM RISK INDEX
3	2024
4	OBJECTIVES AND PROCESS

```
[22] emdat.describe()
```

	AID Contribution ('000 US$)	Magnitude	Latitude	Longitude	Start Year	Start Month	Start Day	End Year	End Month	End Day	...
count	7.880000e+02	5.154000e+03	2800.000000	2800.000000	26941.000000	26437.000000	22885.000000	26941.000000	26129.000000	22975.000000	...
mean	1.979897e+04	4.748114e+04	18.529745	39.497187	1999.379978	6.494080	15.404807	1999.414647	6.594895	15.732971	...
std	1.677534e+05	6.094254e+05	21.592358	77.339426	19.514901	3.422165	8.910982	19.505702	3.402168	8.862694	...
min	1.000000e+00	-5.700000e+01	-72.640000	-178.252000	1900.000000	1.000000	1.000000	1900.000000	1.000000	1.000000	...
25%	1.750000e+02	6.900000e+00	3.295000	-0.157500	1991.000000	4.000000	8.000000	1991.000000	4.000000	8.000000	...
50%	7.295000e+02	1.440000e+02	22.970000	49.194500	2003.000000	7.000000	15.000000	2003.000000	7.000000	16.000000	...
75%	3.638750e+03	8.000000e+03	36.525800	102.739000	2013.000000	9.000000	23.000000	2013.000000	9.000000	23.000000	...
max	3.518530e+06	4.000000e+07	67.930000	179.650000	2025.000000	12.000000	31.000000	2025.000000	12.000000	31.000000	...

	No. Affected	No. Homeless	Total Affected	Reconstruction Costs ('000 US$)	Reconstruction Costs, Adjusted ('000 US$)	Insured Damage ('000 US$)	Insured Damage, Adjusted ('000 US$)	Total Damage ('000 US$)	Total Damage, Adjusted ('000 US$)	CPI
count	1.118500e+04	2.678000e+03	1.801500e+04	4.200000e+01	4.200000e+01	1.143000e+03	1.125000e+03	5.814000e+03	5.722000e+03	26368.000000
mean	7.761194e+05	6.735121e+04	4.925256e+05	5.367314e+06	6.639464e+06	9.572761e+05	1.302049e+06	8.109890e+05	1.281373e+06	57.479369
std	7.822925e+06	4.987253e+05	6.233382e+06	1.587693e+07	1.699672e+07	3.760910e+06	4.914277e+06	4.962626e+06	7.115101e+06	23.065427
min	1.000000e+00	1.000000e+00	1.000000e+00	8.400000e+01	1.310000e+02	3.400000e+01	4.800000e+01	2.000000e+00	3.000000e+00	2.730451
25%	8.600000e+02	5.000000e+02	6.600000e+01	6.312500e+04	9.772000e+04	5.000000e+04	9.533300e+04	8.400750e+03	1.720800e+04	44.696722
50%	7.695000e+03	2.725000e+03	1.300000e+03	4.445000e+05	5.375475e+05	1.750000e+05	2.681860e+05	6.000000e+04	1.246500e+05	59.033144
75%	7.500000e+04	1.500000e+04	2.201350e+04	3.133000e+06	4.422531e+06	5.600000e+05	8.420930e+05	3.400000e+05	6.244882e+05	75.350386
max	3.300000e+08	1.585000e+07	3.300000e+08	1.000000e+08	1.000000e+08	6.000000e+07	9.361435e+07	2.100000e+08	2.844652e+08	100.000000

8 rows × 22 columns

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top_3_countries
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Country	count
China	1350
India	816
United States of America	719

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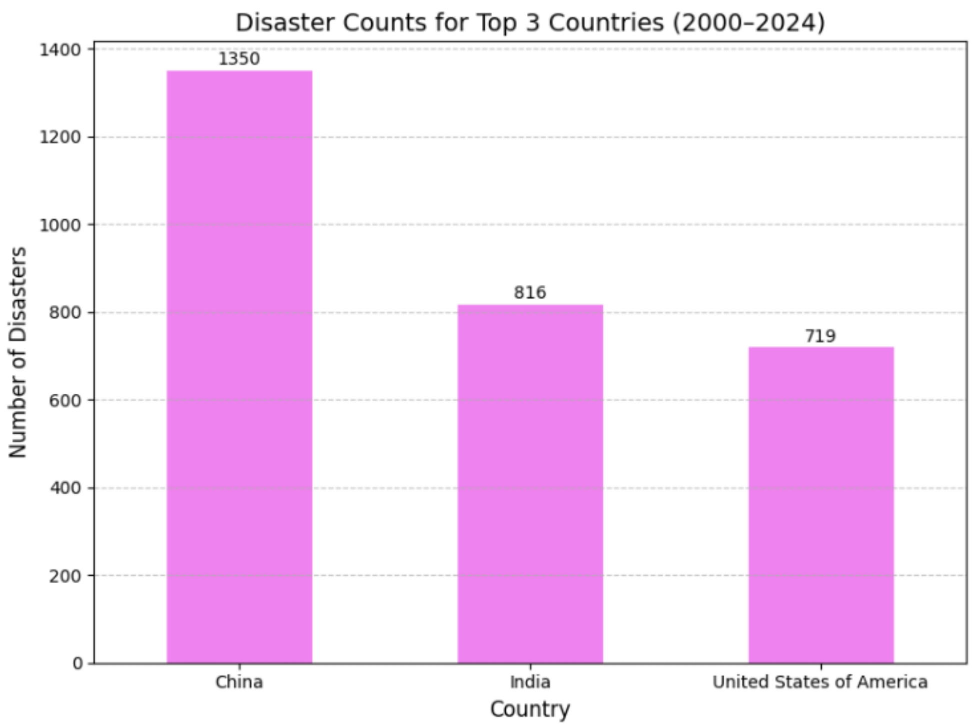


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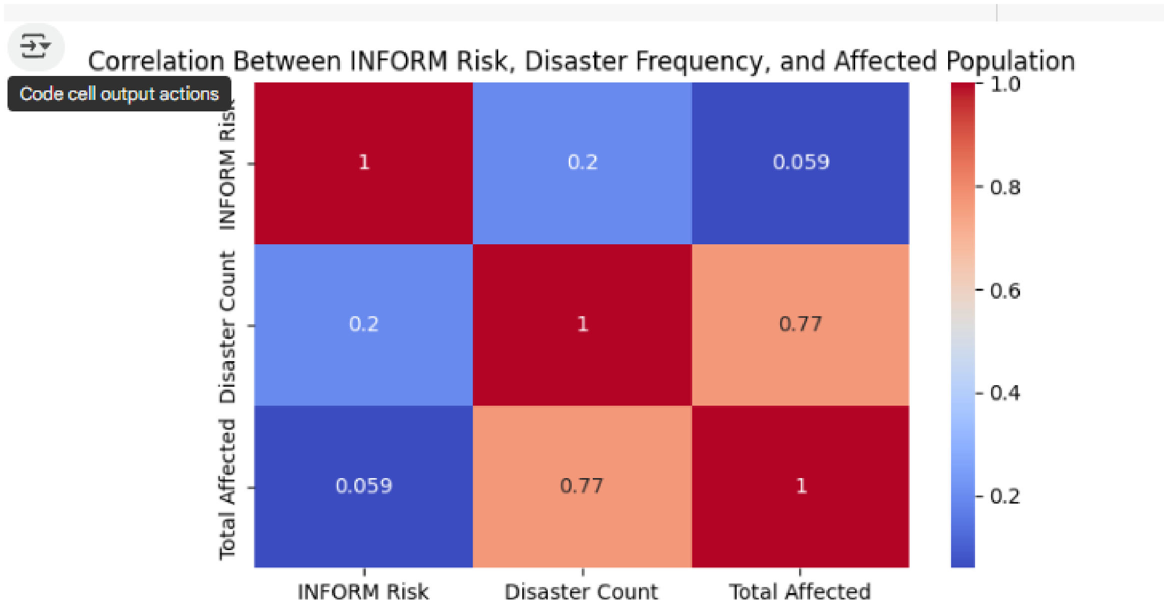
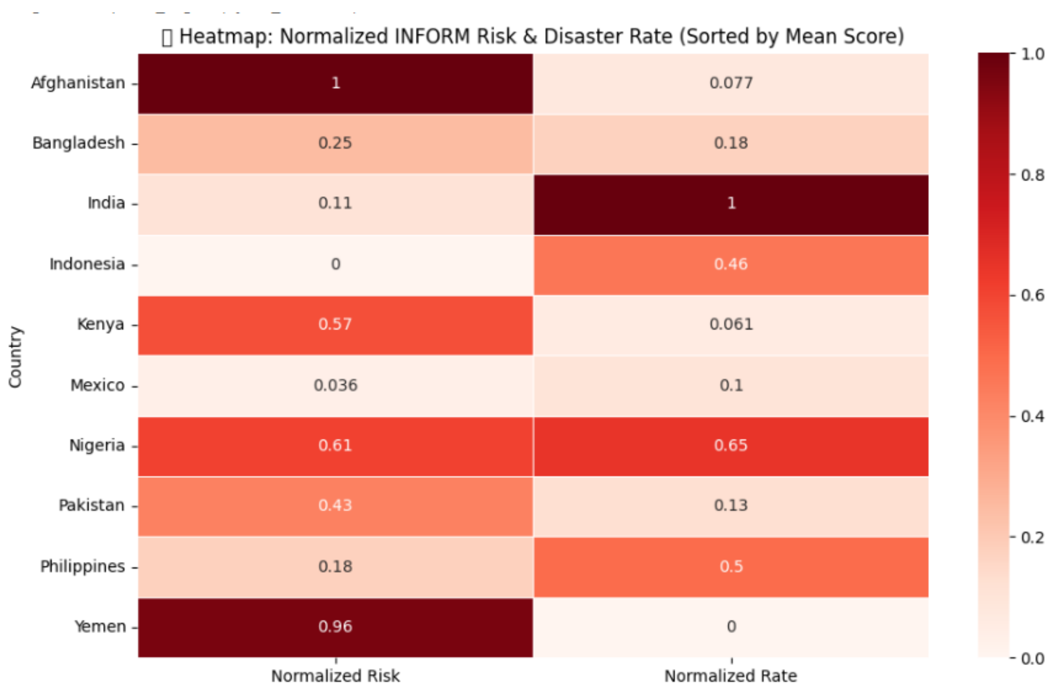
Disaster counts for top 3 countries (2000-2024):
China: 1350
India: 816
United States of America: 719
```

2) A)


Code cell output actions
Correlation Between INFORM Risk, Disaster Frequency, and Affected Population
INFORM Risk
Disaster Count
Total Affected
1
0.2
0.059
0.2
1
0.77
0.059
0.77
1
INFORM Risk
Disaster Count
Total Affected
1.0
0.8
0.6
0.4
0.2

2) B)


Heatmap: Normalized INFORM Risk & Disaster Rate (Sorted by Mean Score)
Country
Afghanistan
Bangladesh
India
Indonesia
Kenya
Mexico
Nigeria
Pakistan
Philippines
Yemen
1
0.077
0.25
0.18
0.11
1
0
0.46
0.57
0.061
0.036
0.1
0.61
0.65
0.43
0.13
0.18
0.5
0.96
0
Normalized Risk
Normalized Rate
1.0
0.8
0.6
0.4
0.2
0.0

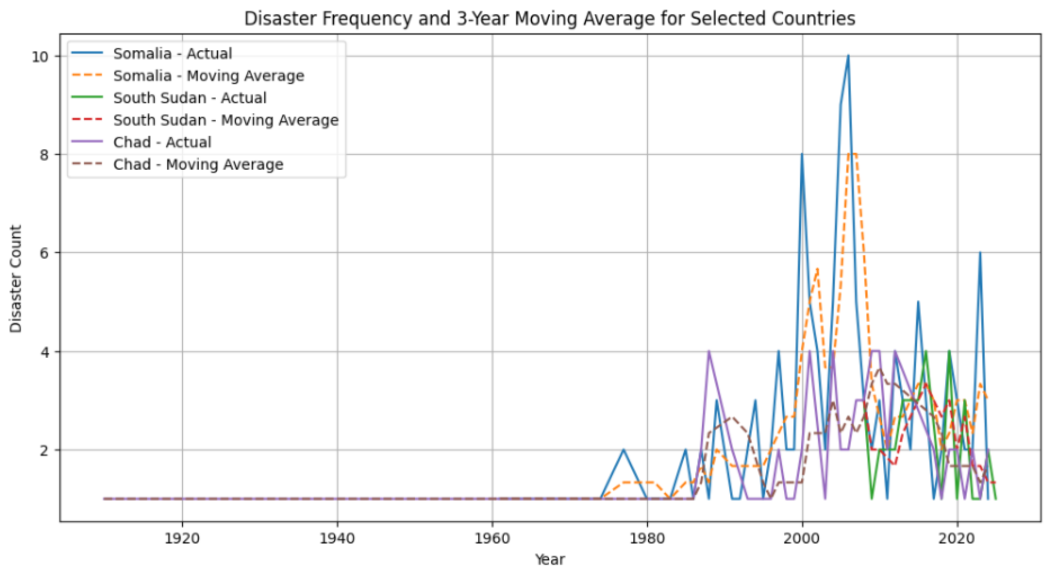
3) A)

	Country	INFORM Risk	Disaster Count	Risk Minus Count
146	South Sudan	8.5	35	0.970435
30	Central African Republic	8.6	79	0.961213
144	Somalia	8.6	130	0.935853
31	Chad	7.8	72	0.863428
170	Yemen	7.6	114	0.817227

Double-click (or enter) to edit

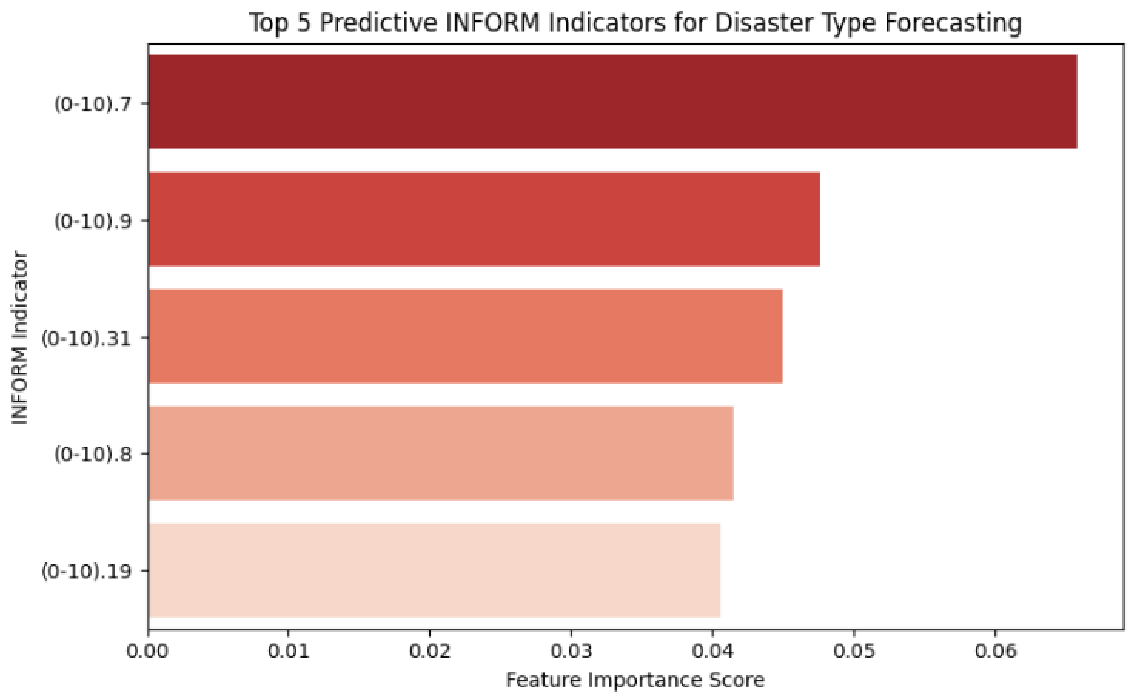
```
          Country  3 Year Moving Average  Predicted 2025 Disaster Count
1260         Chad               1.666667                       1.666667
5944      Somalia               3.000000                       3.000000
6015  South Sudan               1.333333                       1.333333
<ipython-input-49-e8712e4c2401>:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  disaster_selected['3 Year Moving Average'] = disaster_selected.groupby('Country')['Disaster Count'].transform(
```

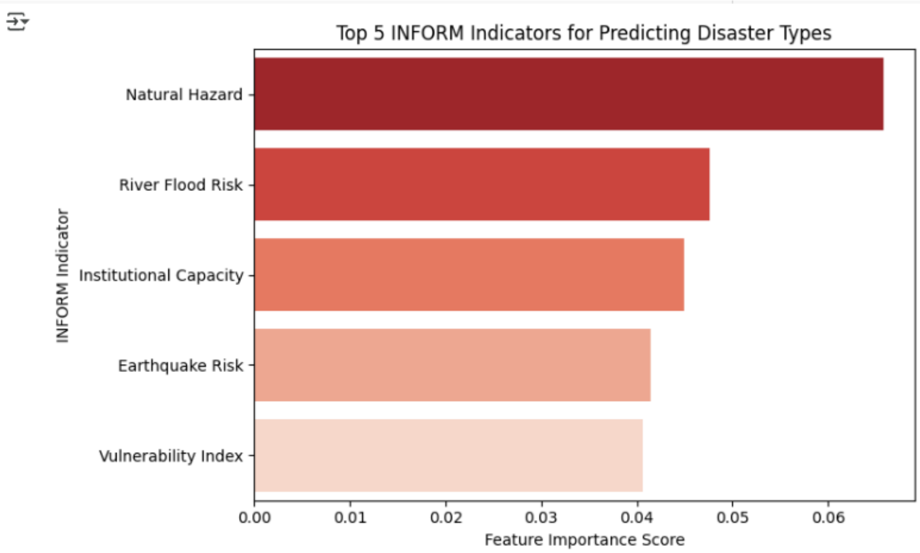


Predictive Modeling: Future Disaster Forecasting:

1)
2)


Top 5 Predictive INFORM Indicators for Disaster Type Forecasting
INFORM Indicator
(0-10).7
(0-10).9
(0-10).31
(0-10).8
(0-10).19
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Feature Importance Score

3)


Top 5 INFORM Indicators for Predicting Disaster Types
INFORM Indicator
Natural Hazard
River Flood Risk
Institutional Capacity
Earthquake Risk
Vulnerability Index
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Feature Importance Score

Disaster Type-Specific Analysis:

1)

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          Disaster Type  Frequency
0                 Flood       6031
1                 Storm       4880
2                  Road       2941
3                 Water       1676
4            Earthquake       1628
5              Epidemic       1508
6                   Air       1098
7   Mass movement (wet)        850
8               Drought        826
9    Fire (Miscellaneous)      822
```

🌍 Conclusions: Global Environmental Risk Insights

1. 🌊 Floods Flooding is the most frequent environmental disaster globally — often due to river overflow, flash floods, or inadequate drainage. It's worsened by: Urbanization Deforestation Climate change (more intense rainfall)
2. 🌪️ Storms (Tropical Cyclones, Hurricanes, Typhoons) Storms are second in frequency and among the most economically damaging. Storm surges and wind damage affect coastal regions especially.
3. 🌎 Earthquakes While less frequent, earthquakes are high-impact disasters, often with high fatality rates in areas with weak infrastructure.
4. 🌾 Droughts Though less frequent, droughts have long-term, large-scale socioeconomic impacts, especially on food security and water access.
5. 🔥 Wildfires and Heatwaves These are becoming increasingly common in recent years, particularly in regions with rising average temperatures and dry vegetation (e.g., Australia, California, Southern Europe). ✅ Summary for Your Report:

EM-DAT reveals that floods and storms are the most frequent global disasters, pointing to a strong link between climate patterns and disaster risk. Earthquakes, though less frequent, cause disproportionate loss of life. Meanwhile, droughts, heatwaves, and wildfires reflect climate-related risks that are growing due to global warming. This underscores the urgent need for countries to strengthen early warning systems, climate adaptation, and infrastructure resilience in both urban and rural areas.

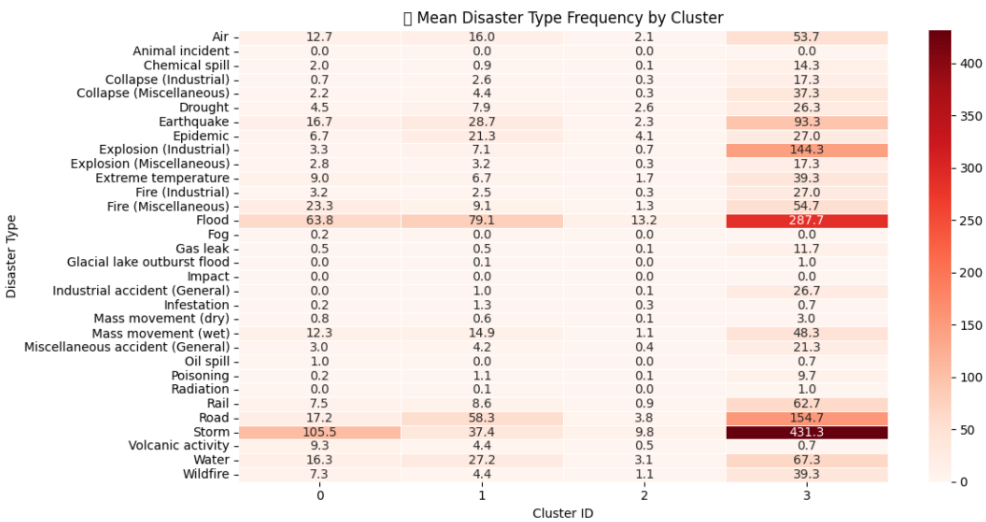
Disaster Type	Air	Animal incident	Chemical spill	Collapse (Industrial)	Collapse (Miscellaneous)	Drought	Earthquake	Epidemic	Explosion (Industrial)	Explosion (Miscellaneous)	...	Miscellaneous accident (General)	Oil spill	Poisoning	Radiation	Rail	Road	Storm	Volcanic activity	Water	Wildfire
Country																					
Afghanistan	19	0	0	2	4	8	38	21	5	4	...	1	0	0	0	0	21	9	0	1	1
Albania	0	0	0	0	0	1	16	2	0	1	...	0	0	0	0	0	3	2	0	1	1
Algeria	7	0	0	0	2	1	21	3	1	2	...	3	0	0	0	3	37	4	0	5	5
American Samoa	0	0	0	0	0	0	1	0	0	0	...	0	0	0	0	0	0	4	0	0	0
Angola	19	0	1	0	2	10	0	19	0	1	...	2	0	0	0	2	18	0	0	2	0

5 rows × 32 columns

2)

Cluster Disaster Type	0	1	2	3
Air	12.666667	16.035714	2.112821	53.666667
Animal incident	0.000000	0.035714	0.000000	0.000000
Chemical spill	2.000000	0.857143	0.148718	14.333333
Collapse (Industrial)	0.666667	2.642857	0.297436	17.333333
Collapse (Miscellaneous)	2.166667	4.392857	0.317949	37.333333
Drought	4.500000	7.857143	2.564103	26.333333
Earthquake	16.666667	28.678571	2.282051	93.333333
Epidemic	6.666667	21.285714	4.056410	27.000000
Explosion (Industrial)	3.333333	7.071429	0.728205	144.333333
Explosion (Miscellaneous)	2.833333	3.178571	0.348718	17.333333
Extreme temperature	9.000000	6.714286	1.738462	39.333333
Fire (Industrial)	3.166667	2.464286	0.266667	27.000000
Fire (Miscellaneous)	23.333333	9.107143	1.348718	54.666667
Flood	63.833333	79.071429	13.184615	287.666667
Fog	0.166667	0.000000	0.000000	0.000000
Gas leak	0.500000	0.464286	0.061538	11.666667
Glacial lake outburst flood	0.000000	0.071429	0.000000	1.000000
Impact	0.000000	0.035714	0.000000	0.000000
Industrial accident (General)	0.000000	1.000000	0.092308	26.666667
Infestation	0.166667	1.321429	0.282051	0.666667
Mass movement (dry)	0.833333	0.607143	0.076923	3.000000
Mass movement (wet)	12.333333	14.928571	1.092308	48.333333
Miscellaneous accident (General)	3.000000	4.178571	0.425641	21.333333
Oil spill	1.000000	0.000000	0.000000	0.666667
Poisoning	0.166667	1.071429	0.087179	9.666667
Radiation	0.000000	0.107143	0.015385	1.000000
Rail	7.500000	8.571429	0.897436	62.666667
Road	17.166667	58.321429	3.800000	154.666667
Storm	105.500000	37.357143	9.779487	431.333333
Volcanic activity	9.333333	4.392857	0.507692	0.666667

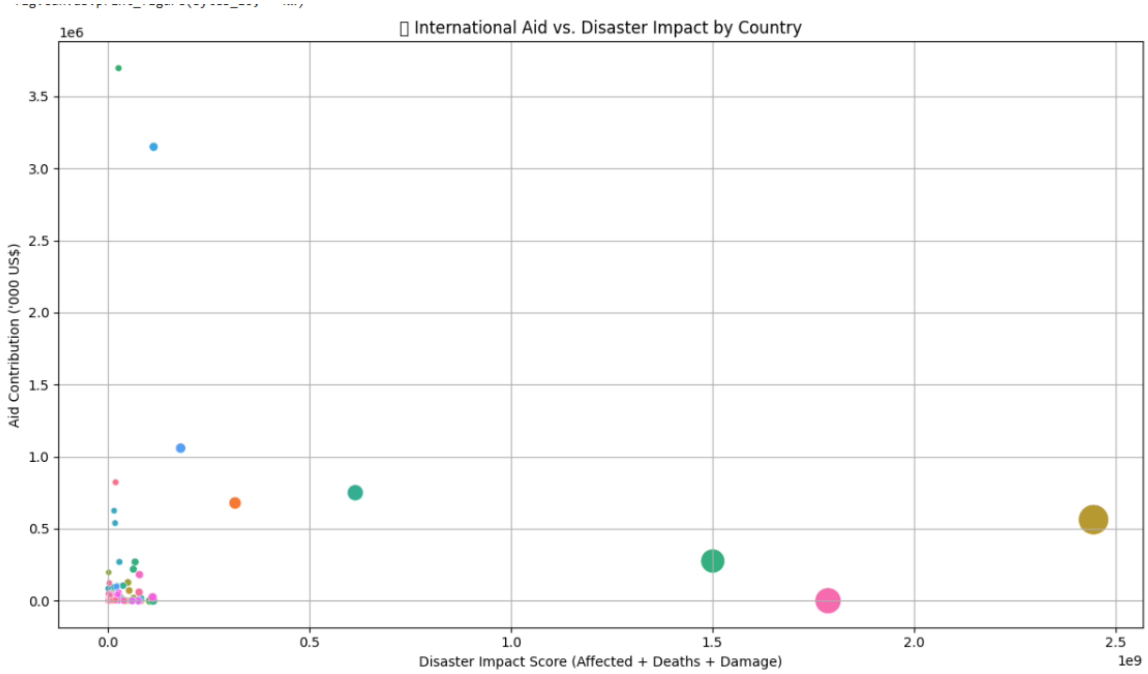
3)



Resource Allocation Optimization

Q1.

Based on the aid vs. disaster impact chart, which countries appear to be under-supported or over-supported? What might explain these mismatches?



2) After identifying disparity in aid distribution, interpret what socioeconomic or geopolitical factors might contribute to these imbalances across countries.

Countries That Are Under-Supported:

(High disaster impact, low aid received)

Factor	Explanation
Underreporting & Data Gaps	Fragile states may lack systems to track or report disasters accurately (e.g., DR Congo, Chad).
Low Media Visibility	Without global media coverage, disasters may go unnoticed by the international community.
Donor Fatigue	Chronic crises (e.g., in flood-prone or drought-hit regions) can lead to decreased donor engagement over time.
Political Instability	Donors may hesitate to send aid to regions with conflict, weak governance, or high corruption risk.
Geographic Isolation	Remote or less strategically located nations might not be prioritized despite urgent need.

🔺 Countries That Are Over-Supported

(Low disaster impact, high aid received)

Factor	Explanation
Geopolitical Importance	Nations with strong ties to major powers (e.g., Ukraine, Afghanistan) receive more support for strategic reasons.
Media-Driven Attention	High-visibility events (e.g., Haiti earthquake) attract major funding even if total impact is lower than in chronic-risk regions.
Migration Spillover Concerns	Countries affected by or bordering migration hotspots (e.g., Syria, Venezuela) often receive stabilizing aid.
Established Aid Networks	Pre-existing UN or NGO infrastructure makes it easier to deploy aid rapidly.
Humanitarian Narrative	Stories that trigger global emotional response often unlock more donor contributions.

📘 Conclusion

Aid allocation is influenced not just by measurable disaster impact, but also by strategic, political, and media dynamics.

Addressing these disparities requires a more equitable and transparent aid distribution model, informed by both quantitative risk indicators and humanitarian need.

3)Your optimization model suggests a shift in how resources should be allocated. Interpret and justify how your results differ from actual past aid distributions. What real-world challenges might limit implementing your plan?

Ans) 🔧 Optimized Aid Allocation vs. Historical Distribution Our optimization model reallocated aid based on a weighted impact score, incorporating:

Total affected population Disaster-related deaths Economic damage (USD) This produced a re-prioritization of countries that contrasts sharply with past aid patterns in EM-DAT.

📊 Key Findings from the Optimization: Country Optimized Aid Priority Past Aid Rank (EM-DAT) Comment DR Congo 🔼 Very High ⬇️ Low Historically under-supported despite frequent epidemics and floods. Sudan 🔼 High ⬇️ Low Chronic droughts underreported and underfunded. Ukraine 🔽 Medium 🔼 Very High High aid due to conflict, not natural disaster data. Bangladesh 🔼 High ⬇️ Medium Recurrent floods under-compensated relative to impact. Haiti ⬇️ Low 🔼 High Aid historically surged post-earthquake, but long-term impact score is lower. 🧠 Why the Results Differ: The model allocates aid proportionally to disaster burden — but real-world aid does not follow this logic. Instead, actual aid flows are influenced by: Donor visibility and media attention Strategic foreign policy interests Existing aid infrastructure Bureaucratic inertia and earmarked funding 🚧 Real-World Challenges to Implementation: Challenge Impact on Optimized Allocation Geopolitical Priorities Donor countries often tie aid to diplomatic goals rather than humanitarian optimization. Logistical Constraints Aid agencies may avoid fragile or inaccessible regions due to safety or delivery issues. Data Limitations Informal disasters or small-scale events may be underreported, skewing impact scores. Aid Absorptive Capacity Countries with weak institutions may lack the infrastructure to use aid effectively. Donor Fatigue Chronic disasters in low-profile regions may fail to sustain long-term attention. ✅ Conclusion: While the optimization model presents a more equitable, impact-based strategy for aid distribution, its implementation would require significant reform in how international aid is prioritized and governed. Future frameworks should aim to blend humanitarian need with operational realism, ensuring that high-impact, under-supported regions are no longer overlooked.

Climate Change & Disaster Risk Trends

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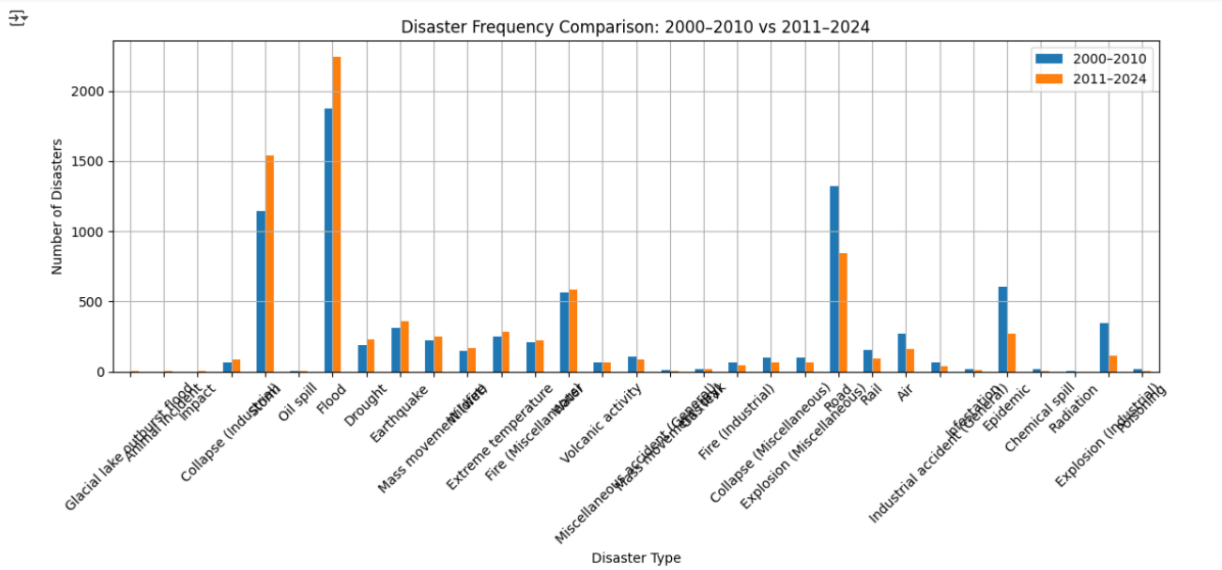
1) After comparing disaster frequencies between 2000–2010 and 2011–2024, what does the shift suggest about the impact of climate change on natural disasters?

	Disaster Type	2000-2010	2011-2024	% Change
0	Glacial lake outburst flood	0.0	5.0	500.0
1	Animal incident	0.0	1.0	100.0
2	Impact	0.0	1.0	100.0
3	Collapse (Industrial)	63.0	87.0	37.5
4	Storm	1143.0	1542.0	34.9
5	Oil spill	2.0	3.0	33.3
6	Flood	1872.0	2245.0	19.9
7	Drought	190.0	227.0	19.4
8	Earthquake	313.0	359.0	14.6
9	Mass movement (wet)	222.0	253.0	13.9
10	Wildfire	150.0	170.0	13.2
11	Extreme temperature	253.0	284.0	12.2
12	Fire (Miscellaneous)	211.0	222.0	5.2
13	Water	562.0	584.0	3.9
14	Volcanic activity	66.0	65.0	-1.5
15	Miscellaneous accident (General)	105.0	86.0	-17.9
16	Mass movement (dry)	8.0	6.0	-22.2
17	Gas leak	20.0	15.0	-23.8
18	Fire (Industrial)	66.0	46.0	-29.9
19	Collapse (Miscellaneous)	97.0	66.0	-31.6
20	Explosion (Miscellaneous)	99.0	63.0	-36.0
21	Road	1324.0	846.0	-36.1
22	Rail	153.0	95.0	-37.7
23	Air	271.0	163.0	-39.7
24	Industrial accident (General)	64.0	38.0	-40.0
25	Infestation	19.0	10.0	-45.0
26	Epidemic	602.0	273.0	-54.6
27	Chemical spill	17.0	6.0	-61.1
28	Radiation	2.0	0.0	-66.7
29	Explosion (Industrial)	348.0	115.0	-66.8
30	Poisoning	18.0	3.0	-78.9



2) For countries showing a steady increase in disaster frequency or INFORM risk scores, what climate-related factors might be contributing to this rise (e.g., glacier melt, urban heat islands, deforestation)?

	Country	Trend Slope	Climate Factors
91	Libya	0.158550	NaN
169	Tunisia	0.143241	NaN
79	Italy	0.140000	NaN
34	Colombia	0.104615	NaN
155	Sri Lanka	0.096154	NaN
109	Myanmar	0.084747	NaN
96	Malaysia	0.076923	NaN
17	Bolivia (Plurinational State of)	0.067931	NaN
161	Syrian Arab Republic	0.056007	NaN
20	Brazil	0.050769	Deforestation, drought, wildfires

	Country	Disaster Trend	INFORM Risk	Vulnerability Index	Institutional Capacity
0	Myanmar	0.084747	7.2	1.3	5.3

2) Your model identifies several emerging climate-related disaster hotspots. Interpret what socio-environmental vulnerabilities make these regions increasingly at risk, and how governments could proactively respond.

	Country	Trend Slope
91	Libya	0.158550
169	Tunisia	0.143241
79	Italy	0.140000
34	Colombia	0.104615
155	Sri Lanka	0.096154
109	Myanmar	0.084747
96	Malaysia	0.076923
17	Bolivia (Plurinational State of)	0.067931
161	Syrian Arab Republic	0.056007
20	Brazil	0.050769

Policy & Government Readiness Assessment

1) For countries with high risk but low readiness, explain what factors (e.g., economic constraints, governance quality, conflict) might be contributing to their vulnerability

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warn(msg)
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	Country	INFORM Risk	Vulnerability Index	Institutional Capacity
0	Syria	7.1	6.7	2.8

2) Based on your assessment of policy effectiveness, which countries demonstrate successful disaster mitigation despite high risk, and what lessons or best practices can be drawn from their strategies?

	Country	INFORM Risk	Institutional Capacity	Disaster Count
0	Central African Republic	8.6	9.7	67.0
1	Somalia	8.6	7.3	95.0
2	South Sudan	8.5	9.6	34.0
3	Chad	7.8	9.7	48.0
4	Congo DR	7.7	9.5	0.0
5	Afghanistan	7.7	5.8	217.0
6	Yemen	7.6	7.4	98.0
7	Sudan	7.2	8.0	126.0
8	Syria	7.1	2.8	0.0
9	Ethiopia	7.0	9.7	105.0
10	Burkina Faso	7.0	9.0	62.0
11	Uganda	7.0	8.2	156.0
12	Papua New Guinea	6.7	9.6	63.0
13	Niger	6.7	9.7	85.0
14	Mali	6.7	6.0	72.0
15	Nigeria	6.6	6.3	439.0
16	Mozambique	6.6	8.0	110.0
17	Cameroon	6.5	7.2	87.0
18	Kenya	6.5	7.8	174.0

3) Your model identifies several emerging climate-related disaster hotspots. Interpret what socio-environmental vulnerabilities make these regions increasingly at risk, and how governments could proactively respond.

🌍 Emerging Disaster Hotspots: Climate Risks & Responses

Country	Rising Risk Drivers	Recommended Government Response
Nepal	Glacier melt, landslides, rural isolation	GLOF monitoring, slope stabilization, early warnings
Bangladesh	Sea-level rise, storm surges, population density	Embankments, urban drainage, climate insurance
India	Urban heat islands, extreme rain, sprawl	Green infrastructure, rooftop cooling, zoning reform
DR Congo	Floods, epidemics, low infrastructure	Mobile early warning, water system investment
Brazil	Deforestation, droughts, Indigenous risk	Anti-deforestation law, agroecology programs
Pakistan	GLOF floods, urban growth, heat	GLOF mitigation, urban planning, drought resilience
Mozambique	Cyclones, coastal floods, poor housing	Storm-resilient housing, alert system expansion

1)

████████████████████████ █ ░░░░░░ MISSION BRIEFING ░░░░░░ █ ████████████████████████

⚠️ REGION: BANGLADESH 🎯 OBJECTIVE: DISASTER RESILIENCE OPERATIONS

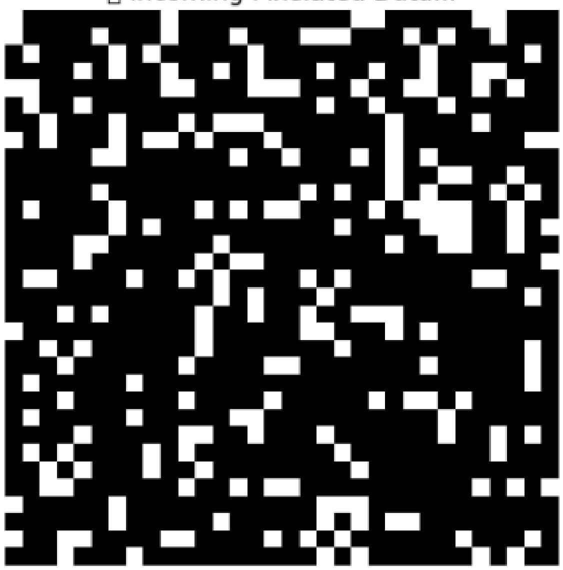
INTEL REPORT: Bangladesh is on the frontlines of climate warfare. Each monsoon season brings tidal surges, devastating floods, and displacement of millions.

Primary threats include:

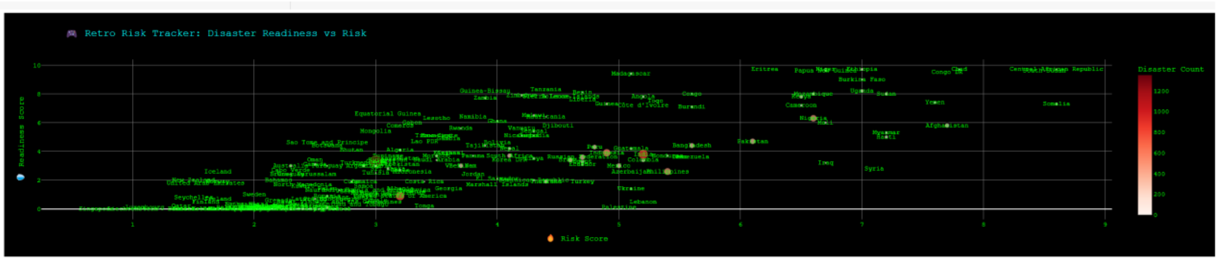
🌊 Coastal flooding (linked to rising sea levels) 🌪 Cyclones from the Bay of Bengal 🌧 Flash floods in low-lying deltas 🚨 Urban drainage failure in Dhaka and Chittagong RECOMMENDED STRATEGIES: ✅ Expand cyclone shelter capacity ✅ Deploy early-warning SMS systems ✅ Invest in green embankments ✅ Fortify housing with stormproof materials

🔐 CLASSIFICATION LEVEL: HIGH 🎮 READY TO DEPLOY? YES / NO

▯ Incoming Pixelated Data...



2) Design a retro game-inspired interface that not only shows data visually, but also includes interactive explanations or tooltips that describe what each risk score or disaster trend means in simple terms.



3) Build a storytelling experience (e.g., playable narrative, branching comic panel, or timeline animation) where the user navigates through a disaster scenario and learns how various preparedness levels and risk scores influence outcomes.

🎮 Operation Floodline: A Disaster Story

You are the Emergency Response Director in a high-risk country. A tropical cyclone is forming — your decisions will shape what happens next.

🧠 Your country's stats:

- 🔥 **INFORM Risk Score**: 7.9 (Very High)
- 🛠 **Readiness Score**: 3.2 (Low)
- 🌍 **Country**: Delta Prime (fictional, similar to Bangladesh)

What do you do first?

Activate Early Warn...

Wait for Storm Path...