



# Misinformation in Disaster Risk Reduction

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# Why misinformation matters in DRR



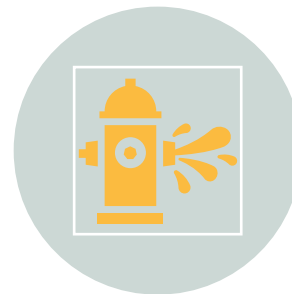
Disasters: High uncertainty, high emotions, high information needs.



People rely heavily on any available information, especially social media.



Rumors, false claims and conspiracies can distort risk perception and undermine trust.



Bad information can be as dangerous as bad infrastructure for disaster risk reduction.

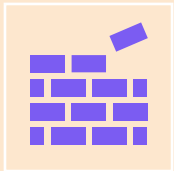
# Misinformation across the disaster risk management cycle



Prevention and preparedness: Climate denial, “hazard is a hoax”, “it won’t happen here”.



Early warning and response: False evacuation info, fake alerts, “engineered disaster” conspiracies.



Recovery and reconstruction: Scams, fake donation campaigns, misleading damage images.



Long-term mitigation: Narratives undermining climate adaptation and risk-reduction policies.

# Social media in DRR: Double-edged sword

- Opportunities: Real-time situational awareness, two-way communication, mutual aid.
- Risks: Data accuracy, representativeness, privacy and ethics challenges.
- Central challenge: Misinformation and conspiracy narratives spreading faster than corrections.
- Social media analytics can support DRR only if the information quality problem is addressed



# Forms of false information

**Misinformation** – false or inaccurate information shared without intent to harm.

**Disinformation** – false information created or shared with deliberate intent to deceive or achieve strategic goals.

**Malinformation** – genuine information used in a misleading or harmful way (e.g., taking disaster photos or quotes out of context).

**Rumors** – unverified information circulating in uncertainty (e.g., “huge aftershock tonight”).

**False claims** – incorrect statements presented as fact (e.g., “hurricane was engineered”).

**Conspiracy theories** – narratives about secret plots behind disasters (e.g., HAARP, geoengineering, “engineered earthquakes”).

**Misinterpretation of official statements** – misunderstanding or misreading warnings, maps, or technical terms.

**Hoaxes and pranks** – intentionally misleading “tips” or jokes (e.g., “shoot at the hurricane to weaken it”).

**Scams and fraudulent appeals** – fake donation campaigns, fundraisers, or aid organizations exploiting disasters.

**False or doctored images and videos** – old, miscaptioned, edited, or AI-generated footage reused in new crises.

# Case 1: Earthquake conspiracies and bots

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Seven conspiracy discourses on Twitter: Military tests, divine punishment, aliens, HAARP, CERN, fracking, Freemasons.

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More human-like accounts overall, but bot-like accounts tweeted more frequently.

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Higher bot scores correlated with more toxic content: Bots amplify disruptive discourse.

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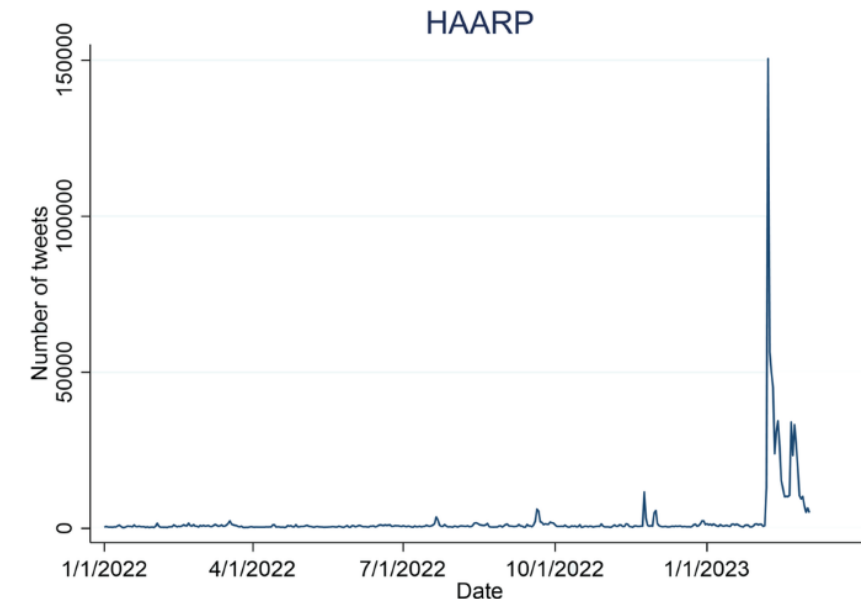
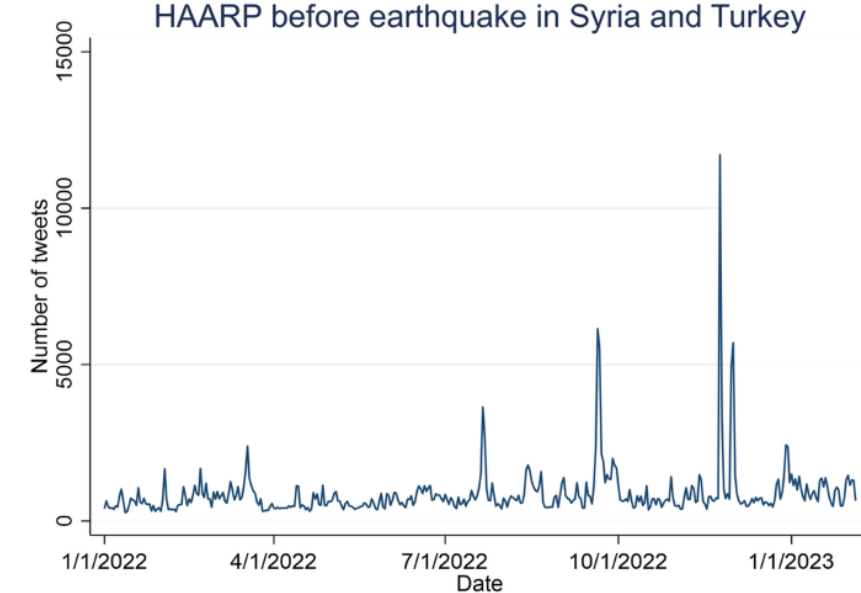
Implication: Conspiracies distort understanding of earthquake causes and predictability.

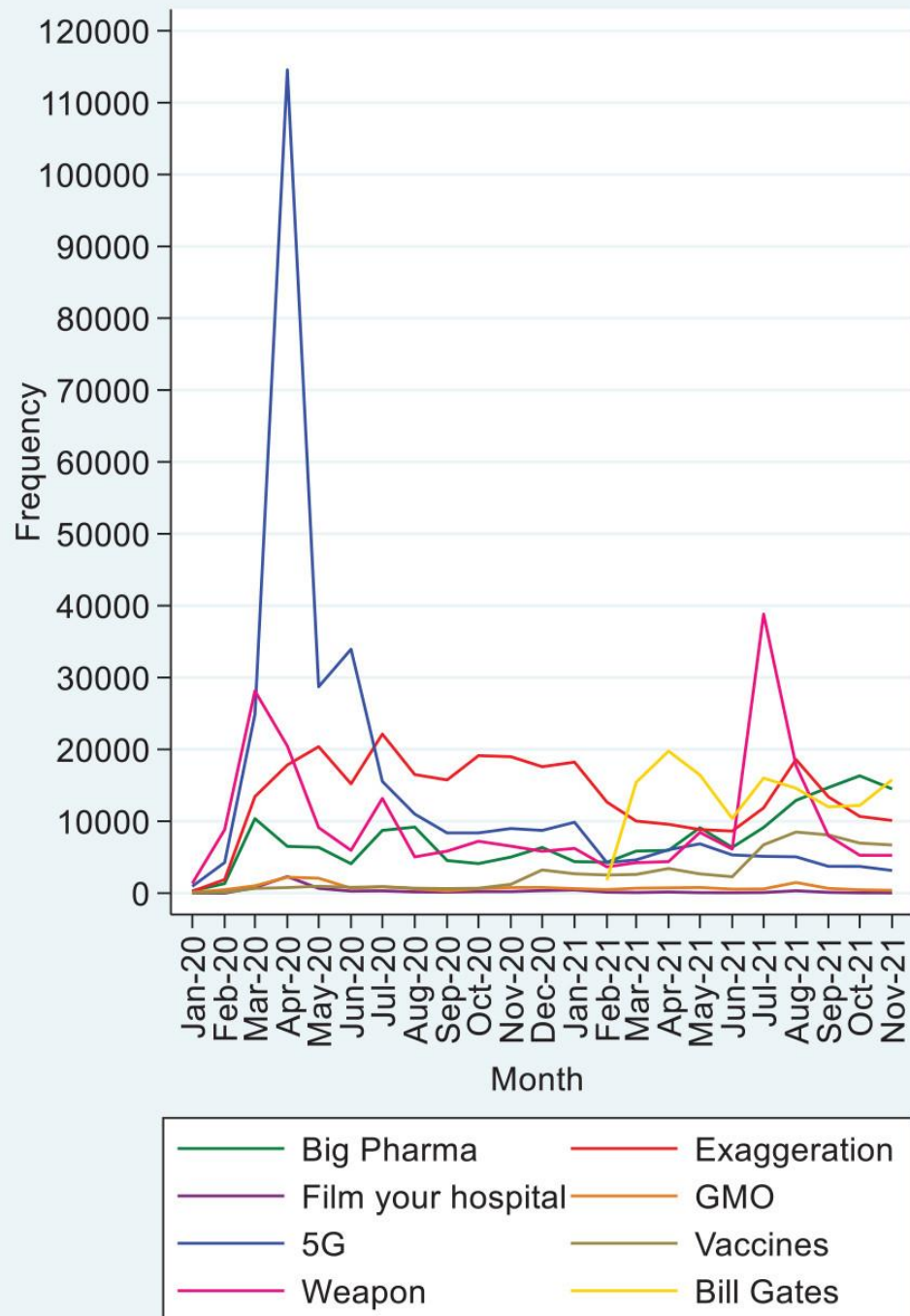
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Source: Erokhin, D., & Komendantova, N. (2024). Social media data for disaster risk management and research. *International Journal of Disaster Risk Reduction*, 114, 104980.

# Case 2: HAARP conspiracies and the 2023 Turkey–Syria earthquakes

- Dataset: Over 1 million tweets about HAARP from January 2022 to March 2023.
- Tweet volume spikes sharply after high-impact earthquakes, including Turkey-Syria 2023.
- Positive correlation between tweet sentiment and frequency suggests belief reinforcement.
- Large destructive events plus scientific uncertainty are fertile ground for conspiracies.
- Need for fast, clear, empathetic scientific communication after earthquakes.
- Source: Erokhin, D., & Komendantova, N. (2024). Earthquake conspiracy discussion on Twitter. *Humanities and Social Sciences Communications*, 11(1).

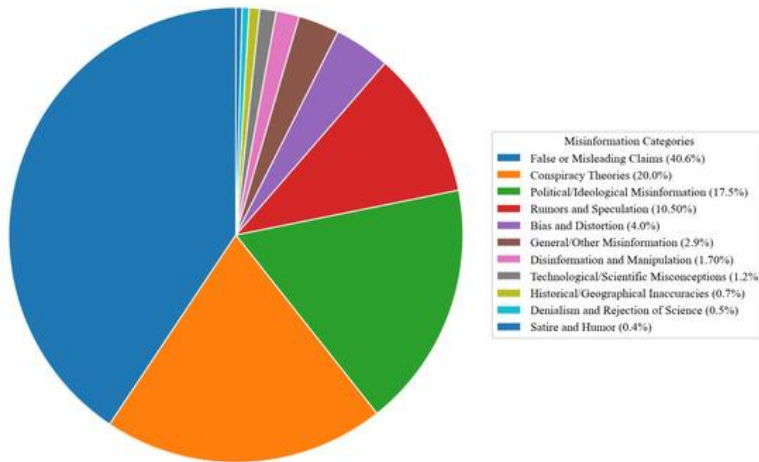




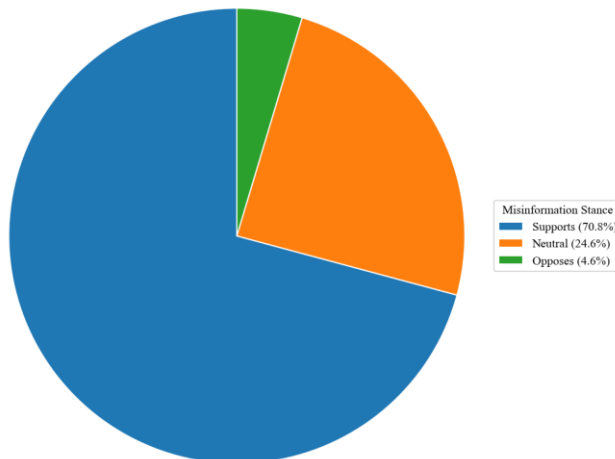
## Case 3: COVID-19 conspiracy theories on Twitter

- Pandemic as a prolonged global disaster with massive uncertainty.
- 1.27 million tweets on eight conspiracy theories (5G, GMOs, Bill Gates, Big Pharma, etc.).
- Different temporal patterns: Early spikes, persistent theories, and multiple peaks.
- New COVID-19 case numbers predict next week's conspiracy tweet frequency for most theories.
- Infodemic: Mix of facts, fear, rumors and conspiracies affects mitigation actions (e.g. vaccination).
- Source: Erokhin, D., Yosipof, A., & Komendantova, N. (2022). COVID-19 conspiracy theories discussion on Twitter. *Social media+ society*, 8(4), 20563051221126051.

Misinformation Category Distribution  
(Comments with has\_misinformation = Yes)



Misinformation Stance Distribution  
(Comments Containing Misinformation)

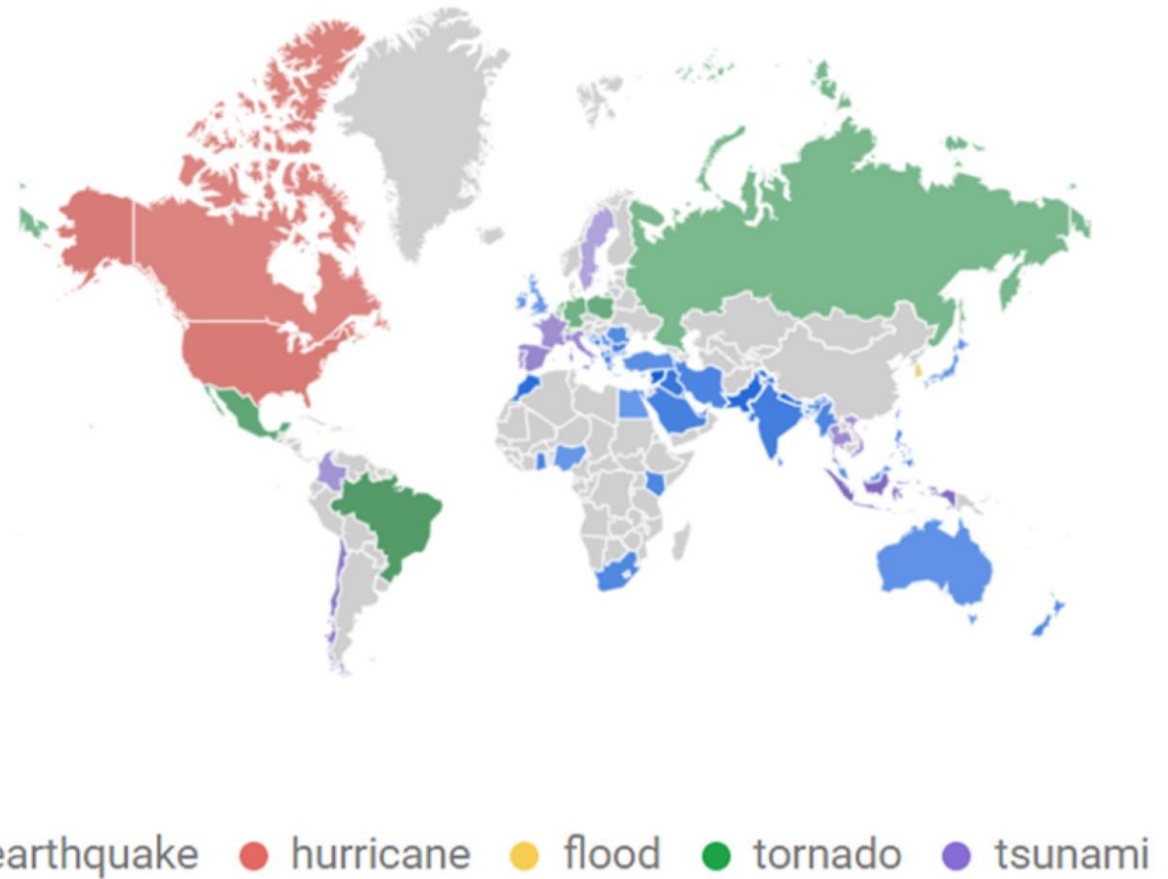


## Case 4: Iberian Peninsula 2025 blackout – YouTube discourse

- Dataset: 76,398 comments from 360 videos posted on the day of the blackout.
- Emotional climate: 43% of comments classified as angry, overall negative sentiment.
- Misinformation present in 46% of comments.
- Blame narratives targeted governments and politics rather than technical causes.
- Implication: Need for multilingual, real-time explanations in complex technical failures.
- Source: Erokhin, D. (2025). Analyzing Spanish-Language YouTube Discourse During the 2025 Iberian Peninsula Blackout. *Societies*, 15(7), 174.

# Case 5: Climate and geohazard narratives via Google Trends

- Searches for terms like “climate change”, “climate hoax”, “HAARP” show temporal and regional variability.
- Public interest spikes around major events and public statements about climate and hazards.
- Search data reveals public intrigue with hoax and conspiracy narratives.
- Geohazard searches (earthquakes, hurricanes, floods, etc.) spike after major events.
- Implication: Search data can provide early warning signals for misinfo-prone topics
- Sources: Erokhin, D., & Komendantova, N. (2024). Unveiling the dynamics of climate change narratives: A Google Trends analysis. *Observatorio (OBS\*)*, 18(5); Erokhin, D., & Komendantova, N. (2024). Analyzing Public Interest in Geohazards Using Google Trends Data. *Geosciences*, 14(10), 266.



# Cross-cutting lessons from the case studies

Triggers: High-impact events, uncertainty and inconsistent or delayed official communication.

Content patterns: Blame narratives, technological conspiracies, religious/moral explanations, misinterpreted uncertainty.

Consequences: Erosion of trust in experts, distraction from practical guidance, increased polarization.

Effective DRR must treat information ecosystems as critical infrastructure.

# Managing misinformation in DRR practice

Before disasters: Build trusted channels and spokespersons; invest in risk literacy.

Pre-bunking: Explain common myths and conspiracy themes before crises.

During disasters: Monitor social media and search trends in real time.

Provide clear, frequent, multilingual updates tailored to different platforms


Rapid rumor response:  
Short, shareable debunks embedded in operational messages.

After disasters:  
Transparent investigations, myth-busting and community dialogue to rebuild trust.

# Artificial intelligence for misinformation management

 AI can help classify and detect false disaster-related content at scale.

 Natural language processing enables real-time monitoring of posts, comments and videos.

 Platform-level tools: Fact-checking labels, downranking, spam and fake account detection.

 Experiments show AI assistants can reduce belief in conspiracies, but not eliminate them.

 Challenges: Context-specific vocabularies, multilinguality, false positives and bias.

 AI must complement and not replace human judgement and local knowledge in DRR.

# Conclusions and discussion

- Misinformation is a structural feature of contemporary disaster risk reduction.
- Disasters create information vacuums quickly filled by rumors and conspiracies.
- Case studies show how bots, belief communities, and platform dynamics amplify misinformation.
- Monitoring social media and search data offers early warning for misinformation surges.
- Effective DRR requires integrating risk communication, misinformation management, and AI tools.

Questions, comments, or examples from your  
own context?

Thank you!