

I WANT TO MAKE A DISASTER MOVIE THAT JUST SHOWS SCIENTISTS RUSHING TO UPDATE ALL THEIR DATA SETS.

Harnessing the Power of AI for Disaster Response and Preparedness





What words come to mind when you hear Al? 57 responses



bigger brother intelligence workflows vast ethical questions large machine learning terminator the future nebulous more int automated the future analysis bad data more info llms computer chat gpt skepticism blackbox exciting transformers schwarzenegger simplification future computer learning





The Promise of AI?

- When disaster strikes, we are overtaxed, under resourced
- Can AI help us to bring these curves into alignment?
- Can it help us to reduce the amplitude of the curve through preparedness?
- What role will AI have on the future public safety knowledge workforce?





Session Overview

- Big Challenges in Disasters
- The Landscape, Trends, and Research
- Design Methodology
- Workshop with your tables
- Observations
- Where you can learn more and stay informed

Big, Bad, and Slow: Quantifying problems in disaster management

Katie Picchione

November 16, 2023



DISTRIBUTION STATEMENT A. Approved for public release. Distribution is unlimited.

This material is based upon work supported by the Department of the Air Force under Air Force Contract No. FA8702-15-D-0001. Any opinions, findings, conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Department of the Air Force.

© 2023 Massachusetts Institute of Technology.

Delivered to the U.S. Government with Unlimited Rights, as defined in DFARS Part 252.227-7013 or 7014 (Feb 2014). Notwithstanding any copyright notice, U.S. Government rights in this work are defined by DFARS 252.227-7013 or DFARS 252.227-7014 as detailed above. Use of this work other than as specifically authorized by the U.S. Government may violate any copyrights that exist in this work.



- Outdated processes and worse disasters
- Lengthy damage assessments
- Large areas affected
- Long recovery times
- Workforce shortage

Severe disasters are occuring more frequently



Our emergency management system was not designed to handle the severity and frequency of current and future disasters.

Image Sources

- USAR: https://www.asce.org/publications-and-news/civil-enginee n/2015/07/26/red-cross-office-open-in-madison/
- - s/despire-risk-of-hurricanes-florida-coastal-population-keeps-growin

LINCOLN LABORATORY MASSACHUSETTS INSTITUTE OF TECHNOLOGY



How long do preliminary damage assessments take?



Public Assistance: 50% of preliminary damage assessments took <u>60 days or longer</u>





Individual Assistance: 50% of damage assessments took <u>17 days or longer</u>





Individual Assistance: 50% of damage assessments took <u>17 days or longer</u>





How large is the affected area per state?





Declared area per state: <u>9200 square miles</u> or more for 50% of disasters



Total area declared per disaster declaration (square miles)

Declaration data: <u>https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries.json</u> County area data (2010 Census): <u>https://www.openintro.org/data/index.php?data=county_complete</u>



How long does recovery take?



Recovery: Incident start to declaration closeout took 8.8 years for more than 50% of incidents





Summary





17 days to Individual Assistance Declarations

60 days to Public Assistance Declarations

9 years to closeout

While these are system problems, technology can help!





- Individual Assistance
 - 25% < 6 days</p>
 - 50% > 17 days
 - 25% > 42 days
- Average IA PDA: 27 days
- Public Assistance
 - 25% < 34 days
 - 50% > 62 days
 - 25% > 82 days

Average PA PDA: 60 days

Recovery

- Incident start date to closeout
 - 25% = 2.8-7.4 years
 - 50% > 8.8 years
 - 25% > 11 years

Average time to closeout: 9.4 years

Data in this analysis is aggregated by disaster number (e.g. DR-4611-LA) not by natural hazard incident. For example, even though Hurricane Ida was a single incident, it resulted in disaster declarations for 7 states. Each of these state-level declarations is represented as a data point. For PDA analysis, only PDAs that resulted in declarations for incidents 2017-2023 are included. Closeout data considers declarations that were closed between 2000-2023. Disasters declared during that period which are still open have been omitted.



GAO

Data sources

OpenFEMA Dataset: Disaster Declarations Summaries - v2

Version: 2	Last Data Refresh: 11-01-2023					
Entity Name	DisasterDeclarationsSummaries					
API Endpoint	https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries					
Update Frequency	R/PT20M					
Program URL	https://www.fema.gov/disasters/how-declared					
Category	Disaster Information					
Keywords	disaster					



LINCOLN LABORATORY MASSACHUSETTS INSTITUTE OF TECHNOLOGY

United States Government Accountability Office

Report to Congressional Requesters



OpenFEMA Dataset: Disaster Declarations Summaries - v2

Version: 2	Last Data Refresh: 11-01-2023					
Entity Name	DisasterDeclarationsSummaries					
API Endpoint	https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries					
Update Frequency	R/PT20M					
Program URL	https://www.fema.gov/disasters/how-declared					
Category	Disaster Information					
Keywords	disaster					

- 1. Download data from OpenFEMA <u>https://www.fema.gov/openfema-data-page/</u> <u>disaster-declarations-summaries-v2</u>
- 2. Select major disasters only and filter for recent incidents
- 3. Declaration data is recorded at the county level □ aggregate by DR number
- 4. Analysis
 - Use Census data to calculate total area declared for each disaster
 - Calculate PDA time as the number of days from incident start to first declaration
 - Calculate closeout time as the number of days from incident start to closeout



Analysis Approach in R

1. Download declaration data from OpenFEMA https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2

res <- GET("https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries.json")

data <- fromJSON(rawToChar(res\$content))

decs <- data\$DisasterDeclarationsSummaries

2. Format dates; calculate number of days from incident to declaration and closeout

decs\$incidentBeginDate <- as.Date(decs\$incidentBeginDate)

- decs\$incidentEndDate <- as.Date(decs\$incidentEndDate)
- decs\$declarationDate <- as.Date(decs\$declarationDate)
- decs\$pdaTime <- decs\$declarationDate decs\$incidentBeginDate

decs\$pdaTime <- as.numeric(decs\$pdaTime)

decs\$disasterCloseoutDate <- as.Date(decs\$disasterCloseoutDate)

decs\$closeoutTime <- decs\$disasterCloseoutDate - decs\$declarationDate

decs\$closeoutTime <- as.numeric(decs\$closeoutTime)

3. Select major disasters only and filter for recent incidents, then filter by IA, PA, or closeout date

DR <- decs[decs\$declarationType == "DR",]

DR_2017 <- DR[DR\$incidentBeginDate > "2017-06-01" & DR\$incidentType != "Biological" & DR\$incidentBeginDate < "2023-06-01",]

- DR_2017_IHP <- DR_2017[DR_2017\$ihProgramDeclared == TRUE.]
- DR_2017_PA <- DR_2017[DR_2017\$paProgramDeclared == TRUE.]

DR_2017_closeout <- DR{DR\$disasterCloseoutDate > "2000-06-01" & DR\$incidentType != "Biological" & DR\$disasterCloseoutDate < "2023-06-01" & DR\$closeoutTime > 0,] %>% na.omit()

4. Aggregate by DR number and append data for the shortest PDA time or closeout time recorded (declaration data is recorded at the county level)

DR_numbers <- unique(DR_2017_IHP\$disasterNumber)

for (i in 1:DR_numbers){

- len_var <- nrow(DR_2017_IHP(DR_2017_IHP\$disasterNumber=DR_numbers([i]],]) #return the longest pdaTime
- max_var <- max(DR_2017_IHP(DR_2017_IHP\$disasterNumber==DR_numbers(()));)\$pdaTime)
- min_var <- min(DR_2017_HP[DR_2017_HP\$disasterNumber==DR_numbers]](]].]\$pdaTime)
- startdatevar <- min(DR_2017_IHP[DR_2017_IHP\$disasterNumber==DR_numbers[[i]].]\$incidentBeginDate)
- type <- min(DR_2017_IHP[DR_2017_IHP\$disasterNumber==DR_numbers[[1]].]\$incidentType)
- maxPdaTime <- append(maxPdaTime, max_var)
- minPdaTime <- append(minPdaTime, min_var)
- incidentStartDateVar <- append(incidentStartDateVar, startdatevar)
- IncidentTypeVar <- append(incidentTypeVar, type)}

DR_2017_summary <- data.frame(DR_numbers, incidentStartDateVar, incidentTypeVar, decCount, maxPdaTime, minPdaTime)

5. Aggregate by incident type

for (i in disasterTypes) {

dtypes <- nrow(DR_2017_summary[DR_2017_summary\$incidentTypeVar == i,])

maxpdatimevar <- max[DR_2017_summary[DR_2017_summary\$incidentTypeVar==i,]\$maxPdaTime}

- disatertypecount <- c(disatertypecount, dtypes)
- maxpdatimecount <- c(maxpdatimecount, maxpdatime

disasterTypeCounts <- data.frame(disasterTypes, disatertypecount, maxpdatimecount)



An analysis of OpenFEMA Declaration Data: Area Declared



From June 1, 2017 to June 1, 2023, the declared area was larger than <u>9200 square miles</u> for more than half of disasters.

Declaration data: <u>https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries.json</u> County area data (2010 Census): <u>https://www.openintro.org/data/index.php?data=county_complete</u>

LINCOLN LABORATORY MASSACHUSETTS INSTITUTE OF TECHNOLOGY



Days to conduct Preliminary Damage Assessments for <u>Public Assistance</u> Declarations



50% of PA PDAs took 60 days or longer for declarations made from June 1, 2017 to June 1, 2023.

Declaration data: https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries.json



Years of Recovery: Incident start to closeout



For 75% of disasters that achieved closeout between June 1, 2000 and June 1, 2023, recovery took 7.8 years or longer.

Declaration-closeout data: https://www.fema.gov/api/open/v2/DisasterDeclarationsSummaries.json





	Katrina	Rita	Wilma	Total
Allocations	\$ 44,393	\$ 3,801	\$ 2,567	\$ 50,761
Obligations	44,393	3,801	2,567	50,761
Expenditures	\$ 42,555	\$ 3,776	\$ 2,563	\$ 48,894

October 2023 Report to Congress on the Disaster Relief Fund https://www.fema.gov/sites/default/files/documents/fema_october_2023_disaster_relief_fund.pdf

LINCOLN LABORATORY MASSACHUSETTS INSTITUTE OF TECHNOLOGY

Value drivers of AI and automation



Source: Deloitte analysis.

The Landscape

Different types of AI can be used for different government problems



Source: Deloitte analysis.

Scenarios for human-machine pairing



Source: The Deloitte Center for Government Insights.

Governments can make the most of what humans and machines can offer



- Processing huge data sets with speed and accuracy
- Working 24/7 without breaks, tiring, or getting distracted
- Scaling work up or down quickly
- Performing repetitive work such as opening emails
- Doing dangerous work such as underwater search and rescue, or bomb disposal



- Displaying empathy and humor
- Understanding context and picking up social cues
- Transferring their skills to others (teaching)
- Adapting their skills to different situations
- Demonstrating critical thinking, defining problems, and creative pursuits

Source: Deloitte analysis.

SIMPLIFIED AI LANDSCAPE



ChatGPT

• Accessible/Free

• Basic Tasks

- Writing
- Analysis
- Queries
- Brainstorming/Creative



Chat GPT - Applications

- Emergency Alerts Message Design
- The best 360-character
 Wireless Emergency Alerts will use this evidence-based
 template:
 - Source, hazard name/description, location, consequences of threat, protective action, time.



Chat GPT 3.5

E You

create a 360-character Wireless Emergency Alerts in this format: Source, hazard name/description, location, consequences of threat, protective action, time. From Public Health for a boil water order for all of Nashua, due to contamination do not drink, cook or bathe with water. Boil water for at least 1 minute. Bottled water available at city hall for pickup. more information at nashuanh.gov

ChatGPT

Source: Public Health Hazard: Boil Water Order Location: Nashua, NH Threat: Contamination - Do not drink, cook, or bathe with tap water. Action: Boil water for 1 minute before use. Bottled water available at City Hall. Time: Immediate. Visit nashuanh.gov for details.

You write it as a text message

ChatGPT

From: Public Health

Alert: Boil Water Order for Nashua, NH. Water Contaminated! Don't use tap water for drinking, cooking, or bathing. Boil for 1 min. Get bottled water at City Hall. Details: nashuanh.gov △ △ ⑦ ②



Chat GPT 4

E You

create a 360-character Wireless Emergency Alerts in this format: Source, hazard name/description, location, consequences of threat, protective action, time. From Public Health for a boil water order for all of Nashua, due to contamination do not drink, cook or bathe with water. Boil water for at least 1 minute. Bottled water available at city hall for pickup. more information at nashuanh.gov

ChatGPT

Wireless Emergency Alert: Public Health Advisory

- · Source: Public Health Department
- · Hazard: Boil Water Order
- · Location: Nashua
- . Consequence: Contaminated water; do not drink, cook, or bathe with unboiled water
- Protective Action: Boil water for at least 1 minute before use. Bottled water available at City Hall for pickup.
- . More Information: Visit nashuanh.gov
- · Time: Effective Immediately

You write it as a text message

Which response do you prefer?

Your choice will help make ChatGPT better.

Response 1

Public Health Alert for Nashua:

Due to water contamination, a Boil Water Order is in effect immediately. DO NOT drink, cook, or bathe with unboiled water. Ensure to boil water for at least 1 minute before use. Bottled water is available for pickup at City Hall. For more info, visit nashuanh.gov. Stay safe!

Response 2

Public Health Alert for Nashua: BOIL WATER ORDER in effect due to contamination. DO NOT drink, cook, or bathe with water unless boiled for 1 min. Bottled water available at City Hall. Details at nashuanh.gov

00



Future of ChatGPT (and tools like it)

- Integration into Platforms
 - Google, Microsoft
- Personalization and Contextual Adaptability
 - Learns and adapts to the human users preferences
- Multimodality
 - Understand and process multiple forms of input, such as text, images, video, and audio
- Specialized models for specific industries or domains
 - GPTs
- Faster, Cheaper, More Functionality

Google Flood Hub

- Al Model
- Pulling Open Data



Flood Hub - Future



AI Generated Damage Assessments

- Half of Disaster declared from 2017-2023 were over 9,200 square miles
- Imagery is abundant but must be reviewed for information
- Very people intensive process
- Often a sample of damages is done not comprehensive or complete
- Rapid classification of damages leads to faster recovery



Esri Al Generated Geospatial Damage Assessments

Maui Fires Damage Assessment - Data derived from Airbus imagery distributed through SkyWatch



Trends and Research in AI

Buzzwords

- Foundational models
 - Large language models
 - Vision models
 - Geospatial data (GeoAI)
- Hardware
 - GPUs and supercomputers
 - Edge computing
 - Neuromorphics
- Data analysis and creation
 - One-shot learning
 - Synthetic training data
 - Non-optical imagery data analysis (e.g. Lidar, synthetic aperture radar)

Disaster-related research topics

- Flood mapping
- Damage detection and classification
- Ocean hazard detection (tsunamis)
- Wildfire forecasting
- Estimation of human condition
- Wilderness search and rescue
- Recovery forecasting

AI+HADR Workshop: https://www.hadr.ai/home



Workshop Instructions

- 1. Within your groups pick one challenge to tackle (Katie's or your own)
- 2. Deconstruct the challenge into tasks
- 3. Identify opportunities to apply AI to the challenge
 - a. Consider human/machine interface
 - b. Consider Strategy, People, Process, Ethics, Data, Technology & Platforms
- 4. Back Brief

Considerations

- 1. Deconstruct the challenge
- 2. Where do you already use automation or AI? What works? What doesn't?
- 3. Where are there untapped opportunities for automation or AI?
- 4. How should it interface with humans?
- Strategy (Why)
 - Ambition, Alignment, Approach
- People (Who)
 - Organizational design, Talent model, Change and communications
- Process (How)
 - Measurement & funding, Delivery, Governance
- Ethics (How)
 - Transparency & explainability, Policies, Bias & integrity
- Data (With What)
 - Enterprise data strategy, Data disciplines, Security, privacy & compliance
- Technology & Platforms (With What)
 - Deployment models, Security & continuity, Architecture & tools

What did you learn?

Want to learn more?

- Learnprompting.org
- Futuretools.io
- Deloitte & McKinsey AI and Future of Work Resources

Suggested resources on Al

) (#) (Ø) N 🖓

Learnprompting.org Futuretools.io Ask Chatgpt for the list https://www.dhs.gov/date

https://www.dhs.gov/data/ Al_inventory



Deloitte & McKinsey Al and Future of Work Resources

Book: A World Without Work by Daniel Susskind

Machines have taken over...save yourselves!!!!

Ps Pr Ac 📉 👝 💬 🔄 🛄

Contact Info

Emily Martuscello, CEM Director of Emergency Management City of Nashua, NH martuscelloe@nashuanh.gov Katie Picchione Associate Staff Humanitarian Assistance and Disaster Relief Systems MIT Lincoln Laboratory katherine.picchione@II.mit.edu

Justin Kates, CEM Senior Business Continuity Advisor Wawa, Inc. justin.kates@wawa.com