Natural Hazards (2023) 116:3427–3445
https://doi.org/10.1007/s11069-023-05817-1

ORIGINAL PAPER

United States Federal Emergency Management Agency regional clustering by disaster exposure: a new paradigm for disaster response

Colton Margus[1,2] · **Attila Hertelendy**[1,3] · **Yudong Tao**[4] · **Erik Coltey**[5] · **Shu-Ching Chen**[5] · **Steven Luis**[5] · **Mei-Ling Shyu**[4] · **Gregory R. Ciottone**[1]

Received: 9 February 2022 / Accepted: 3 January 2023 / Published online: 12 January 2023

Abstract

The Federal Emergency Management Agency (FEMA) divides the United States (US) into ten standard regions to promote local partnerships and priorities. These divisions, while longstanding, do not adequately address known hazard risk as reflected in past federal disaster declarations. From FEMA's inception in 1979 until 2020, the OpenFEMA dataset reports 4127 natural disaster incidents declared by 53 distinct state-level jurisdictions, listed by disaster location, type, and year. An unsupervised spectral clustering (SC) algorithm was applied to group these jurisdictions into regions based on affinity scores assigned to each pair of jurisdictions accounting for both geographic proximity and historical disaster exposures. Reassigning jurisdictions to ten regions using the proposed SC algorithm resulted in an adjusted Rand index (ARI) of 0.43 when compared with the existing FEMA regional structure, indicating little similarity between the current FEMA regions and the clustering results. Reassigning instead into six regions substantially improved cluster quality with a maximized silhouette score of 0.42, compared to a score of 0.34 for ten regions. In clustering US jurisdictions not only by geographic proximity but also by the myriad hazards faced in relation to one another, this study demonstrates a novel method for FEMA regional allocation and design that may ultimately improve FEMA disaster specialization and response.

Keywords Federal Emergency Management Agency · Spectral clustering · Emergency management · Disaster exposure · Disaster management · Data analytics

1 Introduction

Global trends in urbanization and climate change have elevated the need for more developed disaster response systems at the national level (Garschagen and Romero-Lankao 2013; Hallegatte et al. 2013; Zhang et al. 2018). China established its Ministry of Emergency Management to coordinate disparate efforts in 2018 (Hou et al. 2019; *New*

✉ Colton Margus
cmargus@bronxcare.org

Extended author information available on the last page of the article

Authority Focuses on Emergency Response, 2018), and, since 2005, India has relied on its own National Disaster Management Authority for "timely and effective response to disaster" including twelve pre-positioned battalions based on anticipated deployment need (National Disaster Response Force, n.d.). Meanwhile, the European Union Civil Protection Mechanism is supported by a pool of response capacities "acting jointly in a spirit of solidarity" to respond swiftly against threats facing member states (Official Journal of the European Union, 2014).

While the United States (US) is well recognized for its bountiful resources and degree of economic and technological development, it has also experienced myriad catastrophes of breadth and scale. From historical disasters such as the 1900 Galveston hurricane (McElreath et al. 2017), the 1906 San Francisco earthquake (*The Californian Earthquake of 1906*, 1909), and the great Mississippi flood of 1927 (Bhowmik and Demissie 1994), to modern events including the 2011 Joplin, Missouri tornado (Houston et al. 2015), the 2017 Hurricane Maria that devastated Puerto Rico (Zorrilla 2017), and the 2018 California wildfires (Syphard and Keeley 2019), no region is exempt. All five of the main Köppen–Geiger classification climate types are found within the US (Peel et al. 2007), with disasters ranging from earthquakes to forest fires experienced from coast to coast (*East vs West Coast Earthquakes*, 2018; *Bugaboo Fire Rages in Georgia and Florida*, 2007). And yet, despite this apparent ubiquity of risk, regional exposures and local vulnerabilities vary immensely by geography.

Established in 1979, the Federal Emergency Management Agency (FEMA) is a US governmental organization tasked with coordinating federal resources in response to disasters that exceed local capabilities (Executive Order 12148, 1979). The 1988 Robert T. Stafford Disaster Relief and Emergency Assistance Act gave FEMA responsibility for leading national relief efforts in response to presidential disaster declarations (Robert 1988), and the newly established Department of Homeland Security subsumed the agency in 2003. A state governor, for example, may through the state's corresponding FEMA regional administrator request a presidential declaration for federal assistance under the National Response Framework, which in turn offers structure and policy for interagency coordination in response to the incident (*National Response Framework*, 2021). FEMA's organization into ten regions is meant to facilitate this process and corresponds to the ten Office of Management and Budget-mandated regions that have since 1974 divided US states, territories, and tribes to "improve management and economies of personnel which could result in savings among federal departments" (Office of Management and Budget, 1974). FEMA, in turn, relies on these regions to carry out its mission "to reduce the loss of life and property and protect the nation" by working with local partners to "identify and address regional priorities" in accordance with the Post-Katrina Emergency Management Reform Act (2006).

While each FEMA region is expected to prepare for 'all hazards' potentially faced (McNerney et al. 2015), a potential benefit to regionalization is the concentrating of like-exposures within geographic groupings, so as to enable targeted priorities and planning. It is not clear, however, whether this benefit is adequately realized by a regional system that was devised without relative hazard vulnerability in mind. The aim of this study is therefore twofold: first, to demonstrate one method of improved clustering of US states, districts, and territories (jurisdictions) into regions based on historical disaster exposures and, second, to contrast those proposed regional assignments with the ten FEMA regions as presently arranged.

2 Data acquisition

Records of past disaster declarations were extracted from the OpenFEMA website (Federal Emergency Management Agency, n.d.). Unique events were listed by affected jurisdiction and by incident type, such as flood or fire. Among incident types provided through this centralized government registry, 'chemical', 'dam/levee break', 'drought', 'fishing losses', 'human cause', 'terrorist', and 'toxic substances' were removed from consideration given their relative infrequency and this study's focus on natural occurrences. Incidents categorized as 'other' were also excluded from analysis. The remaining incident types were aggregated by jurisdiction and year.

All FEMA disaster declarations prior to the year 2020 for all fifty states were included in this study, as were those for the District of Columbia (DC) and formal US territories. American Samoa, Guam, and the Northern Mariana Islands were collectively grouped as a single 'Pacific territories' entity. Given their proximity, the US Virgin Islands were considered along with Puerto Rico. These decisions were based on relative population and on the logistical improbability of geographical separation into two or more distinct FEMA regions. For this study, freely associated states, such as the Marshall Islands, Palau, and Micronesia, were excluded from analysis.

3 Accounting for geography and disaster exposure

Grouping individual jurisdictions into regions based on past disaster exposure and geographic location can be considered an unsupervised clustering problem. Choosing spectral clustering (SC) for this analysis is advantageous for a few key reasons. SC does not make assumptions on the form of clusters, which can be important if clustering assignments form non-convex regions (Von Luxberg 2007). SC also accepts an affinity matrix as input (Li and Guo 2012), which, in representing all possible pairwise similarities between different features for each data point to be clustered, allows for flexibility in creating the similarity metrics between different jurisdictions for this analysis.

The first step of using SC for this analysis was to generate an affinity matrix to represent the similarity of every jurisdiction to all other jurisdictions. Such similarity metrics include the centroid distance between jurisdictions, a neighbor matrix indicating whether any two jurisdictions are neighbors, and FEMA disaster declarations across all 53 unique jurisdictions. The output was affinity matrix $A \in \{x | x \in R,\ 0 \le x \le 1\}^{53\times53}$, with each cell A_{ij} representing the affinity score of a pair of jurisdictions. Once complete, an ideal number of clusters was chosen by choosing the number of clusters k between 2 and 53 that maximizes the final clustering assignment's silhouette score, a metric of consistency within clusters (Rousseeuw 1987).

Because the final affinity matrix needs to account not only for geographic location but also for the historical disaster exposure of every possible pair of jurisdictions, computing geographic and disaster exposure distance matrices was necessary. The disaster exposure data help cluster jurisdictions based on the types of disasters they are at risk of experiencing as well as their severity. Geographic distance aids in potential logistical concerns, as using only disaster exposure distance could create regions with far-flung jurisdictions. Once merged, these distance matrices were then converted into an affinity matrix for use in SC.

3.1 Geographic distance calculation

Because of the importance of physical proximity to regional identity, jurisdictions were first characterized by their direct geographic neighbors, using the jurisdiction neighbor matrix $N \in \{0,1\}^{53\times53}$ representing a matrix of the binary neighbor relationship between two jurisdictions. For this purpose, the Hawaiian Islands, the Pacific territories, and Puerto Rico were considered along with the Alaskan exclave as neighboring their most proximate continental coastline, whether Atlantic or Pacific. For example, Maine was in this way considered to neighbor Massachusetts, New Hampshire, and Puerto Rico, consistent with FEMA Region II's current role in overseeing New York, New Jersey, and Puerto Rico.

It was also necessary to calculate the physical distance in kilometers between possible pairs of jurisdictions using the latitude and longitude of their centroids. The three Pacific territories were considered jointly, relying on the arithmetic mean of their respective exclusive economic zones. Haversine distance, which calculates the great-circle distance between two latitude and longitude points, was used as shown in Eq. (1) (Robusto 1957). In the algorithm, d represents the output distance, R is the sphere's radius, $X_{\mathrm{lat}}, X_{\mathrm{lon}}$ is the first set of latitude and longitude coordinates, and $Y_{\mathrm{lat}}, Y_{\mathrm{lon}}$ is the second set of coordinates.

$$haversine(R, X, Y) = 2R\, arcsin\sqrt{\left(\frac{Y_{\mathrm{lat}} - X_{\mathrm{lat}}}{2}\right) + cos\, cos\left(X_{\mathrm{lat}}\right) cos\, cos\left(Y_{\mathrm{lat}}\right)\left(\frac{Y_{\mathrm{lon}} - X_{\mathrm{lon}}}{2}\right)} \tag{1}$$

Once calculated using the Earth's mean radius of 6371 km (Moritz 2000), the distance was then normalized. Pairs consisting of the same jurisdiction twice were given a pairwise distance of 1, while pairs of jurisdictions 6000 km or more away from one another given a pairwise distance of 0. This is demonstrated by Eq. (2), where $H \in \{x | x \in R,\ 0 \le x \le 1\}^{53\times53}$ is a matrix of the normalized Haversine distance, and $C \in R^{53\times2}$ is a matrix of centroid latitude and longitude coordinates for each jurisdiction.

$$H_{ij} = \max\left(1 - \frac{haversine\left(6371, C_{i,*}, C_{j,*}\right)}{6000}, 0\right) \tag{2}$$

Calculating the final geographic distance consisted of computing the geometric mean between the resulting normalized Haversine distance and the previously acquired jurisdiction neighbor matrix, as shown in Eq. (3), where $G \in \{x | x \in R,\ 0 \le x \le 1\}^{53\times53}$ is the final geographic distance matrix. In other words, regions with identical geographic similarity would have a distance of 0. In contrast, areas that are either far from one another or not neighbors would have a value much closer to 1 (Fig. 1).

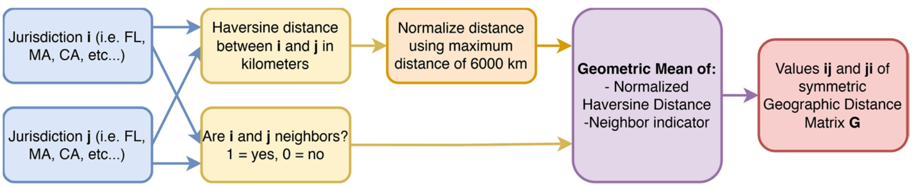


Fig. 1 Methodology diagram for creating the geographic distance matrix

$$G_{ij} = 1 - \sqrt{H_{ij} \times N_{ij}} \tag{3}$$

3.2 Jurisdiction disaster cost calculation

Disaster declaration cost per jurisdiction was used in this analysis as a proxy for disaster severity, providing a sense of economic impact and overall a more granular image of a jurisdiction's disaster declaration profile than would simply the number of a given type of disaster alone. OpenFEMA provides data on disaster declaration costs from 2007 to 2020, which was then extrapolated to the entire length of existing declaration data from 1953 to 2020.

Generating the extrapolated cost data for each jurisdiction first necessitated the creation of two intermediate datasets. The first was a dataset for every jurisdiction, demonstrating the average cost per disaster type from 2007 to 2020, in order to stay as granular as possible when extrapolating. If there were no cost data for a specific disaster type for a specific jurisdiction, then a fallback dataset was used containing the average cost of that disaster type across all jurisdictions from 2007 to 2020. Cost data on a given disaster type for a given jurisdiction were first verified to determine whether missing years could be filled in using jurisdiction-specific data or whether it would instead require using the average across all jurisdictions. Figure 2 demonstrates a block diagram of the cost data processing scheme to create a jurisdiction cost dataset from 1953 to 2020 using this limited cost data.

3.3 Disaster exposure distance calculation

With the estimated cost for each disaster type available for all years and jurisdictions, performing correlation analysis on every possible pair of jurisdictions was then possible. Such analysis can help determine relationships in disasters that appear highly correlated: for

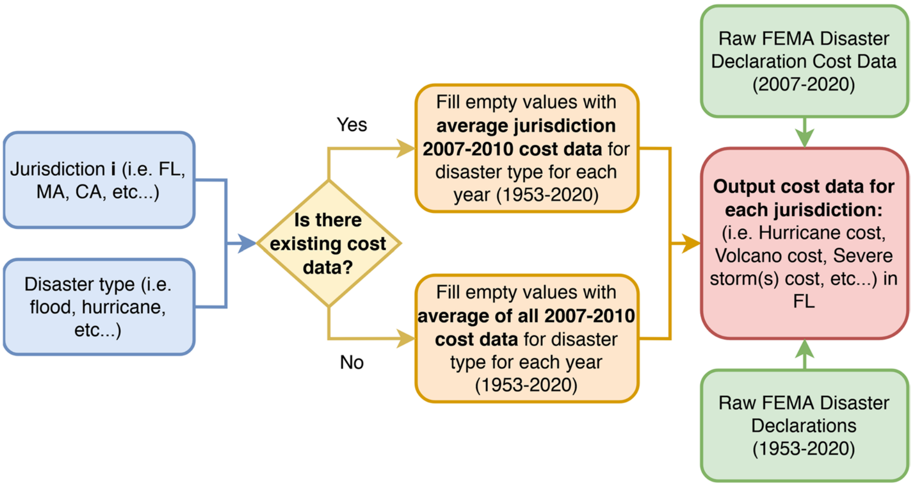


Fig. 2 Methodology diagram for creating a cost dataset by disaster type (1953–2020)

example, a hurricane in one jurisdiction occurring together with floods in a neighboring jurisdiction. The Pearson correlation coefficient was generated for every possible pair of disaster types from each pair of jurisdictions using the extrapolated cost data from 1953 to 2020. If the correlation coefficient for a particular pair of disaster type data was larger than the threshold value of 0.7, one of the correlated disaster types' data was dropped from its jurisdiction dataset. Once the datasets for the pair of jurisdictions were filtered using this method, the remaining data were then z-score standardized and thereafter aggregated using the Euclidean norm to return a final distance measure for that jurisdiction pair. Once all possible jurisdiction pairs have had their disaster exposure distance calculated, the entire matrix $DE \in \{x|x \in R,\ 0 \leq x \leq 1\}^{53\times53}$ was normalized by setting the smallest disaster exposure distance to 0 and the largest disaster exposure distance to 1. Figure 3 visualizes this process with a block diagram.

Jurisdictions with many highly correlated disaster types will have fewer standardized data to aggregate, returning a lower final Euclidean norm. In this way, the algorithm assumes that if many pairs of disaster types across the jurisdiction pair are highly correlated, it is likely that the jurisdictions have similar disaster exposure.

The final distance matrix was computed using an element-wise geometric mean of G and DE, similar to the way in which the geographic affinity matrix was calculated. This distance matrix was then converted into an affinity matrix using a variant of the Ng–Jordan–Weiss (NJW) algorithm accounting for multi-scale data (Zelnik-Manor and Perona 2004). The approach uses an individual scaling parameter, ensuring that the affinities are low across clusters and high within clusters. The output affinity matrix was then used as the input to the SC algorithm to begin generating jurisdiction clustering results.

4 Jurisdiction spectral clustering algorithm

The SC algorithm used in this analysis consists of both an embedding and k-means step to produce clustering results based on a custom affinity matrix (Von Luxburg 2007). The spectral embedding step uses Laplacian eigenmaps (Belkin and Niyogi 2003). As we already have a weighted adjacency matrix for the input graph in the form of the affinity matrix, we can directly calculate the normalized graph Laplacian using the method shown in Eq. (4), where L is the Laplacian, D is the input dimension and $A \in R^{53\times53}$ is the affinity matrix representing a symmetric matrix of jurisdiction pairs.

$$L = D^{-\frac{1}{2}}(D - A)D^{-\frac{1}{2}} \tag{4}$$

With the normalized graph Laplacian, the first k eigenvectors denoted as $u_1, \ldots, u_k$ are then calculated, with each eigenvector set as a column for the reduced embedding matrix

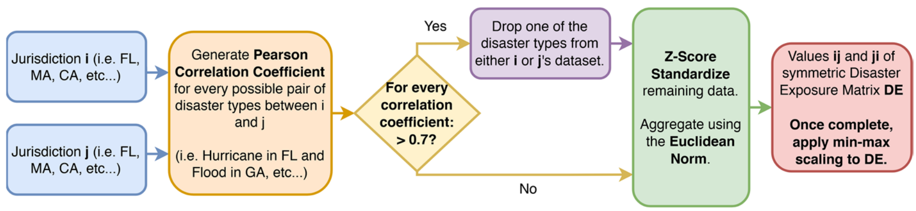


Fig. 3 Methodology diagram for creating the disaster exposure distance matrix

$E \in R^{53\times k}$. With E generated, the k-means clustering algorithm can then be used to cluster E into k unique clusters, minimizing within-cluster variance and outputting the final SC result.

5 Experimental results

Based on the OpenFEMA dataset, there have been 4198 unique FEMA disaster declarations prior to 2020. Due to their relative infrequency and artificial nature, the following declarations were excluded: 1 'chemical', 4 'dam/levee break', 6 'fishing losses', 4 'human cause', 26 'other', 2 'terrorist', and 8 'toxic substance' incidents, with 4149 (98.8%) declarations remaining. The two excluded 'terrorist' incidents involved the 2013 Boston Marathon bombing and the 2001 Al-Qaeda attacks. Twenty-six incidents reported by the US Virgin Islands were added to those of Puerto Rico, and the 14 by American Samoa, 17 by Guam, and 21 by the Northern Mariana Islands were conglomerated into a single 'Pacific territory' jurisdiction. The 22 incidents reported to FEMA by freely associated states were excluded, leaving 4127 (99.5%) disaster incidents declared by 53 distinct jurisdictions for analysis.

Disasters must meet a certain standard, albeit not fixed, to qualify for federal declaration (*Requests for emergency declarations*, 2013), yet unique incident types invariably demonstrate significant differences in community impact and scale, and the decision to grant a disaster declaration often lacks a consistent rationale across disaster types, geography, and time. Recognizing this, all past preliminary damage assessment reports available online through the FEMA digital library were obtained as portable document format (PDF) files and mined for individual and public cost estimates using Python (3.8.5). These data were then aggregated to calculate the mean total cost estimate for each incident type per state. Of the 859 past preliminary damage assessment reports available for extraction, 736 were accepted incidents (all since 2008). 657 (89.2%) of these had cost estimates available, whether individual or public.

The results in this section mainly concern the analysis of the ideal number of clusters and the resulting cluster assignments and ablation studies to help explain the effects of specific data processing techniques on the final clustering results. Such ablation studies include analysis on the choice of geographic distance metrics and the effects of using only either geographic or disaster exposure matrices.

5.1 Optimal number of cluster determination

The silhouette score metric was used to determine the optimal number of clusters based on the affinity matrix and clustering methodologies explained in Sect. 3. As shown in Eq. (5), the silhouette score is essentially the average of the silhouette coefficients of every sample in the dataset, with d_i representing the mean nearest-cluster distance and m_i representing the mean intra-cluster distance for sample i. The silhouette coefficient is bound between -1 and 1. It represents a measure of how similar a given sample, or in this case, jurisdiction, is to its cluster and dissimilar to samples in other clusters. A score close to 1 means that the sample has been assigned to the appropriate cluster, and close to -1 indicates an inappropriate clustering assignment (Rousseeuw 1987).

$$S = \frac{1}{n} \sum_{i=1}^{n} \frac{(d_i - m_i)}{\max(m_i, d_i)} \tag{5}$$

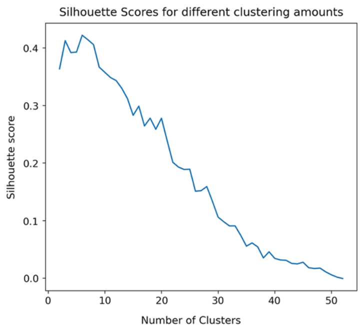
For this analysis, the silhouette score is applied to the spectral embedding matrix E, as the embedding matrix is in the correct form to calculate the silhouette score across each sample. The silhouette scores at all possible cluster numbers were then calculated, and the optimal k was chosen by selecting the number of clusters corresponding to the clustering assignment with the highest silhouette score.

Using the merged geographic and disaster exposure distance matrices and the mean cost data methodology as described, a value of $k=6$ clusters appeared to be ideal, returning a maximum silhouette score of 0.42. As can be seen from the silhouette score graph in Fig. 4a, the silhouette score peaks at six with an immediate drop off afterward, signaling a significant degradation in clustering quality as more clusters are introduced. Figure 4b contains a visualization of this result on a map of the US and its territories. The degradation in cluster quality can be qualitatively observed in the t-SNE (t-distributed stochastic neighbor embedding) plots in Fig. 5a, b, as the clusters when $k = 6$ appear much more cohesive when compared to the clusters at $k = 10$ (Maaten and Hinton 2008).

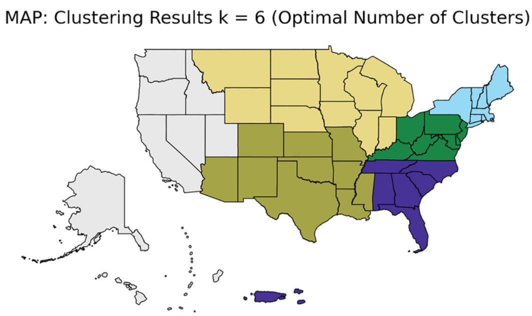
5.2 FEMA regions similarity comparison

As the existing FEMA regional assignment consists of 10 distinct regions shown in Fig. 6a, it was of interest to visualize the results using both a standard 10 clusters and the computed ideal 6 clusters, as shown in Fig. 6b, c, respectively. When directly comparing these clustering results to existing FEMA regions, they appear significantly different from the FEMA regions' current organization.

To quantitatively measure the similarity of these clustering assignments and the current FEMA regions, the adjusted Rand index (ARI) is computed, which is bounded from -1 to 1. The Rand index can be understood as the percentage of matching sample pairs across two clustering results. Simultaneously, the adjusted Rand index adjusts this score for chance, such that a score close to 0 represents relatively random labeling, as shown in Eq. (6) (Santos 2009). In this case, a higher ARI would signify that the cluster assignments between the two are similar, whereas a low ARI would signify different or random clustering assignments.

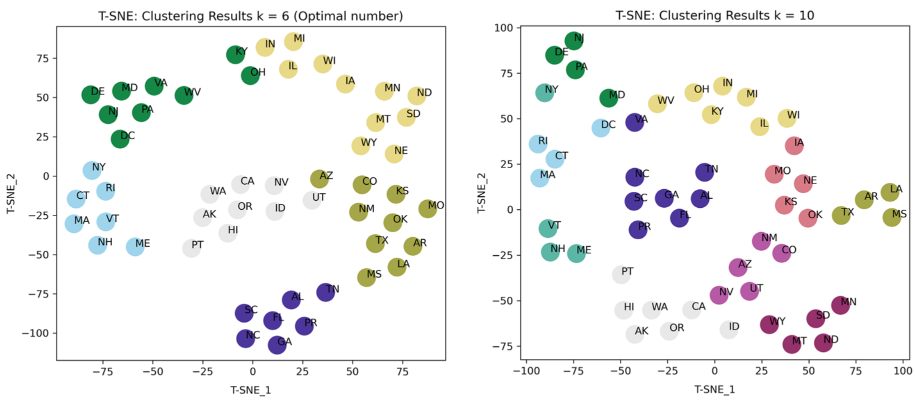


(a)



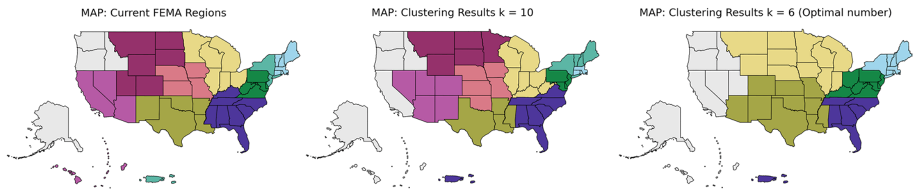
(b)

Fig. 4 Clustering results visualized by **a** silhouette scores with a different number of clusters and **b** the US region assignments for all 53 jurisdictions when $k=6$



(a) (b)

Fig. 5 T-SNE plots of the quality of clustering assignments at 6 clusters and at 10 clusters. (Perplexity = 15)



(a) (b) (c)

Fig. 6 The US jurisdiction region assignments **a** original FEMA regions, **b** clustering results with 10 clusters, and **c** the optimal clustering results with 6 clusters

$$\mathrm{ARI} = \frac{\binom{n}{2}\sum_{r=1}^{R}\sum_{c=1}^{C}\binom{t_{rc}}{2} - \left[\sum_{r=1}^{R}\binom{t_{r.}}{2}\sum_{c=1}^{C}\binom{t_{.c}}{2}\right]}{\frac{1}{2}\left[\sum_{r=1}^{R}\binom{t_{r.}}{2} + \sum_{c=1}^{C}\binom{t_{.c}}{2}\right] - \left[\sum_{r=1}^{R}\binom{t_{r.}}{2}\sum_{c=1}^{C}\binom{t_{.c}}{2}\right]} \tag{6}$$

The ARI between the 10 cluster results and the original FEMA regions is 0.43, implying that considering disaster exposure can lead to different FEMA regions' assignments. Comparing the maps in Fig. 6b, c with Fig. 6a reveals these differences.

5.3 Distance metric ablation study

As the methodology used in this analysis mainly focuses on the disaster profiles for each jurisdiction and their physical proximity to one another, ablation studies were conducted to understand the effects of individual distance matrices on final clustering results. Figure 7 demonstrates the differences in the silhouette scores when utilizing only the disaster profiles of each jurisdiction (shown in orange), only their geographic data (shown in green), or the geometric mean of both, which was used for generating the final clustering results (shown in blue).

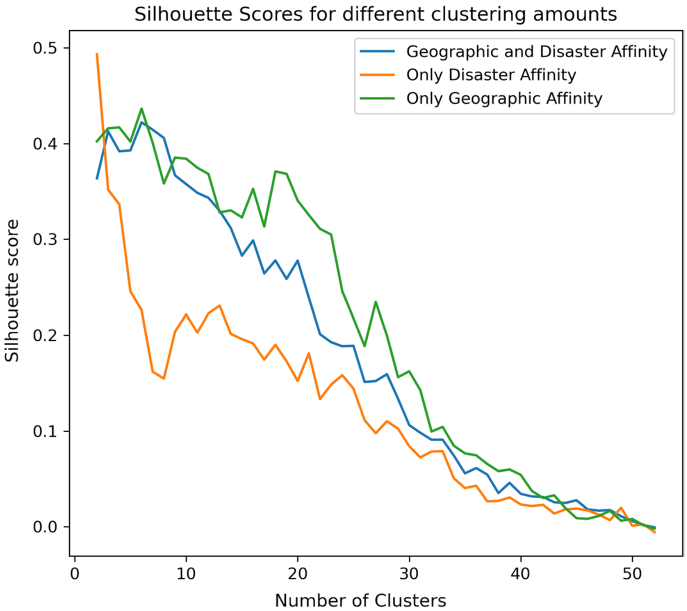


Fig. 7 Comparing the number of clusters to the silhouette scores for all possible numbers of clusters using different distance metrics

5.3.1 Disaster profile distance

The effects of variation in cluster number and distance metric can be further appreciated through the visualizations in Figs. 8, 9, 10 and 11. Figures 8, 9 focus on an ideal, silhouette-maximizing 6 clusters, while Figs. 10, 11 focus on 10 clusters consistent with the current number of FEMA regions. Moreover, while each figure (a) considers both past disaster exposure and geographic distance, each figure (b) only accounts for disaster profile while each figure (c) only accounts for geographic data. These maps are especially useful in visualizing irregularities in clustering without apparent emergence of regional shape, as seen along the coasts in Fig. 8b.

5.3.2 Geographic distance

Using only geographic distance to calculate final affinity leads to a better silhouette score at 6 clusters than when using geographic and disaster distance matrices. This can

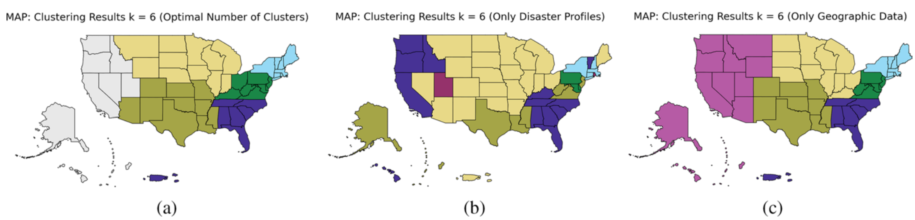


Fig. 8 The US jurisdiction region assignments at 6 clusters with different affinities

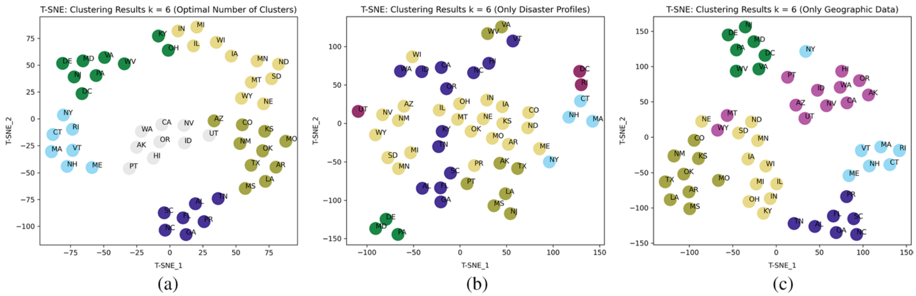


Fig. 9 T-SNE plots of the quality of clustering assignments at 6 clusters with different affinities (Perplexity = 15)

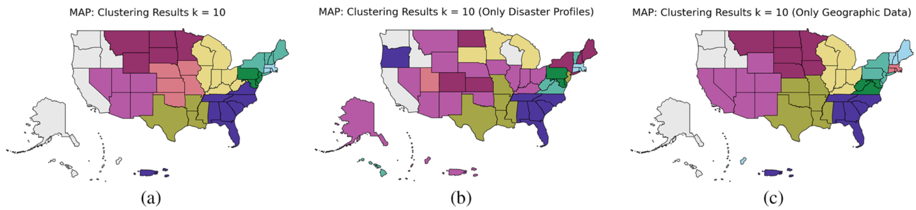


Fig. 10 The US jurisdiction region assignments at 10 clusters with different affinities

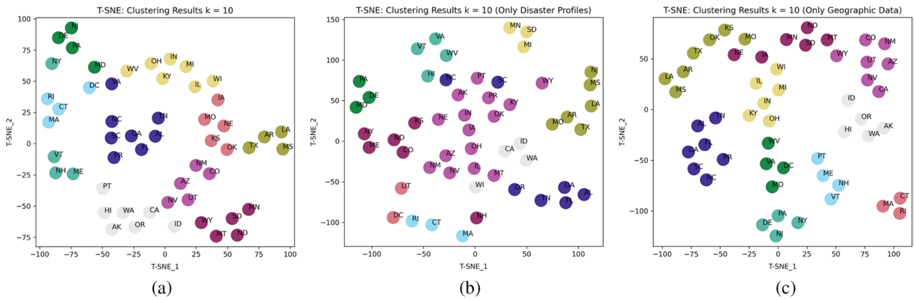


Fig. 11 T-SNE plots of the quality of clustering assignments at 10 clusters with different affinities (Perplexity = 15)

be attributed to the fact that physical distance measures are significantly easier to cluster as adjacent jurisdictions can already be considered clustered together. Adding the disaster distance matrix can significantly complicate this as correlations between disaster types could potentially span distant jurisdictions, which may just happen to have many correlated disaster types, even if the algorithm's assumption that their disaster exposure is related could be false, Figs. 8c, 9c, 10c, and 11c produce clustering into the kind of neatly partitioned regions that would be expected when using Haversine distance and neighbor information. The 10 clusters in Fig. 10c using only geographic data are also closer to the current FEMA region assignments than any other affinity method with an ARI of 0.45. This ARI score compares to 0.43 for the method employing both geographic and disaster declaration data and 0.16 when using only disaster declaration data.

5.4 Geographic data ablation study

The choice of geographic data to use for this analysis was also compared, as the final analysis used not only the actual physical distance between centroids but also an adjacency matrix demonstrating whether states were neighbors or not. Based on Fig. 12, the most stable clustering can be seen when both metrics are used together. When used separately, the best silhouette scores would only appear at 2 clusters, with any larger number of clusters leading to a significant loss in clustering quality.

Using both metrics in this analysis is especially important, as using a jurisdiction neighbor matrix allows for the analysis to overcome the shortcomings of using a singular point, the centroid, to demonstrate location. Certain jurisdictions have significantly larger surface area than others in the US, so only using centroid distance can misrepresent the actual geographic similarity between jurisdictions. Using the neighbor adjacency matrix can alleviate this by encoding information about the borders between jurisdictions that the centroid distance could not capture. However, only using neighbor information that does not include any actual geographic information about the physical location of jurisdictions will also lead to poor clustering results.

Fig. 12 Comparing the number of clusters to the silhouette scores for all possible numbers of clusters using different geographic data metrics

6 Discussion

In an effort to describe the unique consequences of catastrophic natural events and the circumstances surrounding their subsequent response, it has been said that all disasters are local, particularly in their initial phase (Ganyard 2009; Long 2018). Yet, insofar as all disasters by definition overwhelm local capabilities, there is also a need to consider disasters as being more than local, fitting into a regional or even national context. FEMA's role at the federal level has therefore evolved to augment these local efforts, in recognizing the propensity of disaster events to disrupt basic societal and governmental functions. The ten FEMA regions as they currently stand, however, do not reflect the natural distribution of hazards according to historical disaster declaration data.

This exercise in SC relies not only on physical proximity and neighboring state, but also on historical disaster exposures, and in so doing results in region assignments that draw significant contrast to the FEMA regions as currently defined. Regardless of whether six or ten regions are generated, for example, in both instances the algorithm produced a Pacific region that spanned Alaska, Hawaii, and the Pacific territories as well as the entire continental West Coast. Currently, this area is split between FEMA Regions IX and X. On the Atlantic side, the region corresponding to FEMA Region IV was recreated with notable changes: consistently excluding Mississippi and Kentucky and including Puerto Rico. FEMA Region IV administrator Gracia Szczech was quoted in September 2020 as saying, "As we enter the peak of hurricane season and continue to respond to COVID-19, we cannot let our guard down. By preparing for the hazards that are most likely to occur where you live and work, you and your family will be more resilient and better able to handle an emergency (*Don't Wait!*, 2020)." Such statements are a testament to the importance of shared regional disaster profiles, offering benefits that far exceed any concern that contemporary crises across multiple jurisdictions within a region might lead to resource competition or even depletion. Indeed, while undergoing independent review of existing disaster plans, several FEMA regional disaster plans were characterized by their "most common disasters," indicating perspective and priorities unique to that region (Richards 2012, 2015).

Such dispersed federalism implied in FEMA's role emphasizes the need for appropriately representative and responsive regional assignments (Roberts 2007). Hurricane Maria's landfall upon the southeast Puerto Rican coast in September 2017, for example, left widespread devastation (Pasch et al. 2017). With an estimated $90 billion in damage to critical infrastructure, the cyclone has since been linked with 4,645 excess deaths across the territory (Kishore et al. 2018). In the aftermath, questions emerged on the adequacy of federal planning: on implementing a pre-disaster advance contract strategy (Smith 2019), on facilitating inter-agency coordination best exemplified in the underutilization of the USNS Comfort hospital ship (Naor 2020), and on ensuring public trust despite bribery and fraud charges that have since been brought against key personnel involved in the island's disaster recovery (District of Puerto Rico, 2019). It is noteworthy that the Puerto Rican response, coordinated through FEMA Region II which also includes the US states of New York and New Jersey, ultimately could not rely upon its existing Puerto Rico hurricane annex and instead resorted to tsunami and earthquake plans that simply could not adequately address the devastation to come (Cuffari 2020). The clustering algorithm, in contrast, grouped Puerto Rico with Alabama, the Carolinas, Florida, Georgia, and Tennessee. Taking proximity and prior hurricane exposures into account may have helped with regional response to all phases of the disaster cycle, even without knowing with certainty whether structural change alone would have been of material impact.

Hurricane Maria also highlights the moral hazard of potential dependence on FEMA, not as a supplemental response but as the primary one (Long 2018; Johnston 2012). The public good of pre-disaster mitigation is in this way inherently regional. For example, not only might flooding of the Mississippi river impact multiple states at one time, but levee construction may well involve federal engagement of contractors outside a state like Louisiana (Johnston 2012). Others have demonstrated significant political motivation behind disaster declarations and their subsequent federal relief payments, showing correlation not only with a state's political importance but also with election year occurrence and even congressional subcommittee membership (Garrett and Sobel 2003). While such barriers to preparedness are the result of complex interplay between governance systems and public perception, it is plausible that a FEMA regional structure more transparently and objectively organized around shared threats might mitigate some of these effects, particularly among jurisdictions without local resilience or political clout. Cohesion and collective action in preparedness and response necessarily depend on the degree to which the interests of grouped jurisdictions converge. In US water resource management for example, prior work has demonstrated that transborder watersheds suffer jurisdictional fragmentation and corresponding watershed impairment, as defined by the United States Environmental Protection Agency (Epperly et al. 2018). In the case of FEMA, partitioning the country along shared-hazard lines might in turn better align subnational mitigation strategies, particularly if disaster types like hurricanes, which commonly impact multiple jurisdictions, are then more likely to be addressed by one federal regional office.

Recent efforts to combat coronavirus disease 2019 (COVID-19) have brought to light numerous challenges to federal and state coordination, as the first declared nationwide emergency affecting all states and territories (*COVID-19 Disaster Declarations*, 2021). With such an unprecedented and ubiquitous need, several multistate agreements emerged in the vacuum to facilitate healthcare system support and economic recovery (*Governor Murphy*, 2020; *California*, 2020). Even for an infectious disease without the geographic specificity of the natural disasters considered here, this kind of ad hoc regional pooling of effort across state lines and between government agencies demonstrates a clear willingness to rethink how disaster response can and should be regionalized.

Although FEMA currently localizes operations into distinct regions, the decision to create ten such regions, rather than fewer or more than ten, is not obvious. For example, eight regions were initially proposed at FEMA's inception but rapidly expanded to include region VII, based in Kansas City, MO, and region X, based in Bothell, WA (Office of Management and Budget, 1974). These ten regions are now used elsewhere within the federal government, for example in the Departments of Justice and Health and Human Services, as well as in agencies like the Cybersecurity and Infrastructure Security Agency (*Our Reach*, 2020; Office of Intergovernmental and External Affairs 2014, CISA regions 2022). Meanwhile, other departments have organized differently, such as the Departments of Labor and State with six and seven regions, respectively (*Regional Offices*, n.d.; *Regional Offices—Office of Foreign Missions*, n.d.). In fact, the Department of Labor's regional offices are effectively organized in such a way that the six FEMA clusters proposed here could be similarly located, if not co-located. This, along with a reduced number of administrative offices and enhanced regional cohesion, offers a potential avenue for improved efficiency and cost-saving in the long term. A 2016 Congressional Budget Office report indicated that significant budget saving might be achieved if administrative support activities required fewer personnel and locations, if direct program activities could be coordinated, and if organizational cultures and infrastructures were made compatible without sacrificing efficiency (CBO 2016). Indeed, federal strategies to reduce inter-agency fragmentation, overlap, and duplication of effort have been demonstrated across multiple areas. According to the US Government Accountability Office (GAO), federal agencies have been actively coordinating resources to address maritime infrastructure in the US Arctic, and consolidation of data centers alone across 22 federal agencies has since 2011 already led to an estimated \$5.7 billion in cost savings (GAO 2022).

While disaster management from an operational perspective may be a nascent field of research (Gupta 2016), the GAO in particular has encouraged FEMA to collect data that can facilitate decision making, cost saving, and response efforts (Irving 2007). The SC method used here illustrates one such strategy for doing so. Future work will require incorporation of logistical constraints as well as cost–benefit analysis of FEMA investments that may be employed under various regional structures. Such feasibility study of any proposed change will need to ascertain with high reliability the expected losses that can be avoided with implementation (World Bank 2014). An exercise such as this one is a preliminary attempt at re-envisioning the structural aspects of disaster risk reduction, but even in its simplicity it can serve as a template for relevant parties in rejuvenating discussion of how existing organizations might optimize mitigation and response across such disparate geography and hazard vulnerability.

7 Limitations

A jurisdiction's disaster profile was established entirely based upon frequency of prior declarations among reportable disaster types over several decades. Similarly, disaster types are often multifaceted and at times overlapping in their consequences. A 'severe storm' for example may have also spurred a 'tornado' or 'flood' and so could reasonably have been categorized by FEMA into multiple incident types. That degree of granularity is inherently lost when the categories applied are artificially treated as mutually exclusive.

Proximity was defined here as the average of a binary 'yes' or 'no' neighboring relationship between jurisdictions and the geographic distance between them. However, logistical constraints not addressed in this model, such as coordination, sourcing, and distribution, may offer an additional supply chain-oriented dimension to the concept of proximity, likely improving the feasibility and appropriateness of otherwise optimal regional groupings. In addition, this work does not address real socioeconomic inequities in how federal assistance is dispersed. Although beyond the scope of this state-level analysis, FEMA restructuring may nonetheless aim to counteract such community-level disadvantages that have been linked not only to lower overall assistance in response to a disaster but also to an impaired ability to absorb and overcome its deleterious effects (Drakes et al. 2021).

Mean cost estimates based on limited and preliminary data may be inadequate in depicting a particular disaster's ultimate magnitude, which undoubtedly also depends on morbidity, mortality, and other highly variable consequences. There are likely to be substantial differences by year and jurisdiction, and even within jurisdictions that vary considerably in both diversity and urbanization. As a result, a disaster may have significantly more human, property, or business impact yet appear less relevant to the disaster profile of an individual jurisdiction because that jurisdiction has also experienced numerous declarations of a different, perhaps less impactful kind. While this analysis helps to profile the relative frequency of various hazards, it cannot be used to draw conclusions on vulnerability, impact, or risk. FEMA relies heavily on preliminary cost estimates in formal disaster declaration, a process that is itself not fixed. This study aims not to truly collapse the multifaceted complexity of natural disasters into a single linear scale but simply to capture the degree of projected resource need that FEMA, as the responding organization, could expect. Future efforts may include more complete and granular data to better reflect strain on not only FEMA but on the affected community more broadly.

Finally, despite 67 years of disaster declaration data, 2,450 unique incidents have been recorded between January 1, 2000, and December 31, 2019, inclusive (58.4%). While this suggestion of increasingly frequent disasters can indicate either higher incidence or lower threshold for declaring, past disaster declarations do not predict future occurrences. Climate change as well as demographic and political trends may well affect how often and to what extent different states and territories experience and report disasters going forward.

8 Conclusion

This study suggests an opportunity to utilize existing disaster declaration data to organize federal emergency management operations in a way that could significantly improve disaster specialization and response. Jurisdictional differences in incident type, frequency, and impact should be considered alongside logistic constraints in developing FEMA regions that can better meet the agency's strategic objectives.

Author contributions CM, AH, YT, EC, SCC, and SL contributed to the study conception and design. The first draft was written by CM, YT, and EC. All authors commented on previous versions of the manuscript. All authors reviewed and approved the final manuscript.

Funding No funding was pursued or obtained for this research.

Declarations

Conflict of interest The authors have no potential conflicts of interest to disclose.

Human and animal rights This research did not involve human or animal participants and thus did not require informed consent.

References

Belkin M, Niyogi P (2003) Laplacian eigenmaps for dimensionality reduction and data representation. Neural Comput 15(6):1373–1396

Bhowmik NG, Demissie M (1994) The great mississippi river flood of 1993: an impetus toward sustainable floodplain management in the united states? Water Int 19(4):161–165. https://doi.org/10.1080/02508069408686224

Bugaboo Fire Rages in Georgia and Florida (2007) NASA Earth Observatory. https://earthobservatory.nasa.gov/images/7682/bugaboo-fire-rages-in-georgia-and-florida. Accessed April 12, 2021

California, Oregon & Washington Announce Western States Pact (2020) Office of Governor Gavin Newsom. https://www.gov.ca.gov/2020/04/13/california-oregon-washington-announce-western-states-pact/

CISA Regions (2022) Cybersecurity and Infrastructure Security Agency. https://www.cisa.gov/cisa-regions. Accessed Nov 3, 2022

Congressional Budget Office (CBO) (2016) Chapter 6: the budgetary implications of eliminating a cabinet department in options for reducing the deficit: 2017 to 2026. https://www.cbo.gov/sites/default/files/114th-congress-2015-2016/reports/52142-breakout-chapter6.pdf. Accessed June 22, 2022

COVID-19 Disaster Declarations (2021) Federal Emergency Management Agency. https://www.fema.gov/disaster/coronavirus/disaster-declarations. Accessed Nov 3, 2022
Cuffari, JV (2020) FEMA's Advance contract strategy for disasters in Puerto Rico. Office of Inspector General, Department of Homeland Security. https://www.oig.dhs.gov/sites/default/files/assets/2020-03/OIG-20-20-Mar20.pdf
Drakes O, Tate E, Rainey J, Brody S (2021) Social vulnerability and short-term disaster assistance in the United States. Int J Disaster Risk Reduct 53:1–10. https://doi.org/10.1016/j.ijdrr.2020.102010
"Don't Wait!—FEMA Region IV Urges Residents to Plan Now for Disasters as Part of National Preparedness Month (2020) Federal Emergency Management Agency (FEMA). https://www.fema.gov/press-release/20210318/dont-wait-fema-region-iv-urges-residents-plan-now-disasters-part-national
District of Puerto Rico, US Attorney's Office. (2019) FEMA Deputy Regional Administrator, Former President Of Cobra Acquisitions, LLC, And Another Former FEMA Employee Indicted For Conspiracy To Commit Bribery, Honest Services Wire Fraud, Disaster Fraud, Among Other Charges. US Department of Justice. https://www.justice.gov/usao-pr/pr/fema-deputy-regional-administrator-former-president-cobra-acquisitions-llc-and-another
East vs West Coast Earthquakes (2018) United States Geological Survey (USGS). https://www.usgs.gov/news/east-vs-west-coast-earthquakes. Accessed April 12, 2021
Epperly J, Witt A, Haight J, Washko S, Atwood TB, Brahney J, Brothers S, Hammill E (2018) Relationships between borders, management agencies, and the likelihood of watershed impairment. PloS one 13(9):e0204149. https://doi.org/10.1371/journal.pone.0204149
Ganyard ST (2009) All disasters are local: op-ed. The New York Times. https://www.nytimes.com/2009/05/18/opinion/18ganyard.html
Garrett TA, Sobel RS (2003) The political economy of FEMA disaster payments. Econ Inq 41(3):496–509. https://doi.org/10.1093/ei/cbg023
Garschagen M, Romero-Lankao P (2013) Exploring the relationships between urbanization trends and climate change vulnerability. Clim Change 133(1):37–52. https://doi.org/10.1007/s10584-013-0812-6
Government Accountability Office (GAO) (2022). 2022 Annual report: additional opportunities to reduce fragmentation, overlap, and duplication and achieve billions of dollars in financial benefits. https://www.gao.gov/assets/730/720470.pdf
"Governor Murphy, Governor Cuomo, Governor Lamont, Governor Wolf, Governor Carney, Governor Raimondo, Announce Multi-State Council to Get People Back to Work and Restore the Economy (2020) Official Site of the State of New Jersey. https://nj.gov/governor/news/news/562020/approved/20200413a.shtml.
Gupta S, Starr MK, Farahani RZ, Matinrad N (2016) Disaster management from a POM perspective: mapping a new domain. Prod Oper Manag 25(10):1611–1637. https://doi.org/10.1111/poms.12591
Hallegatte S, Green C, Nicholls RJ, Corfee-Morlot J (2013) Future flood losses in major coastal cities. Nat Clim Chang 3(9):802–806. https://doi.org/10.1038/nclimate1979
Hou S, Fan H, Zhao Y (2019) Practice, experience, and prospect of disaster medicine in China. Prehosp Disaster Med 34(s1):s21-22. https://doi.org/10.1017/S1049023X19000621
Houston JB, Spialek ML, Stevens J, First J, Mieseler VL, Pfefferbaum B (2015) 2011 Joplin, Missouri Tornado Experience, mental health reactions, and service utilization: cross-sectional assessments at approximately 6 months and 2.5 years post-event. PLoS Curr 26:7. https://doi.org/10.1371/currents.dis.18ca227647291525ce3415bec1406aa5
Irving, SJ (2007) Budget Issues: FEMA needs adequate data, plans, and systems to effectively manage resources for day-to-day operations highlights (No. GAO-07–139). United States Government Accountability Office (GAO), Washington https://www.gao.gov/assets/gao-07-139.pdf
Johnston JS (2012) Disasters and decentralisation. Geneva Pap Risk Insur Issues Pract 37(2):228–56. https://doi.org/10.1057/gpp.2012.13
Kishore N, Marqués D, Mahmud A, Kiang MV, Rodriguez I, Fuller A, Ebner P, Sorensen C, Racy F, Lemery J et al (2018) Mortality in puerto rico after hurricane maria. N Engl J Med 379(2):162–170. https://doi.org/10.1056/nejmsa1803972
Li X-Y, Guo L-J (2012) Constructing affinity matrix in spectral clustering based on neighbor propagation. Neurocomputing 97:125–130. https://doi.org/10.1016/j.neucom.2012.06.023
Long, B (2018) 2017 Hurricane disaster lessons. March 15, 2018. C-SPAN.org, 3:17:03 hours. https://www.c-span.org/video/?442612-1/federal-state-officials-testify-lessons-learned-2017-disasters
McElreath DH, Doss DA, Jensen C, Lackey H, Jones DW, Wigginton M, Goza R (2017) Dangers from the sea: considerations of the 1900 Galveston Hurricane. Int J Marit Hist 29(3):529–543. https://doi.org/10.1177/0843871417714138

McNerney MJ, Christopher MS, Agnes GS, Martina M, and Bill G, (2015).Improving DoD Support to FEMA's All-Hazards Plans. Santa Monica, CA: RAND Corporation. https://www.rand.org/pubs/research_reports/RR1301.html
Moritz H (2000) Geodetic reference system 1980. J Geodesy 74(1):128–133. https://doi.org/10.1007/s001900050278
Naor M, Efraim L (2020) Disaster recovery after hurricane maria in puerto rico: assessment using endsley's three-level model of situational awareness. J Bus Contin 7 Emerg Plan 13(3):278–88
National Disaster Response Force (2020) About Us | NDRF—National Disaster Response Force. http://www.ndrf.gov.in/about-us. Accessed Nov 21, 2020
National Response Framework (2021) Federal Emergency Management Agency, October 15, 2021. https://www.fema.gov/emergency-managers/national-preparedness/frameworks/response. Accessed Nov 3, 2022
Nature (1909) The Californian earthquake of 1906. Nature 80(2053):10–11. https://doi.org/10.1038/080010a0
new authority focuses on emergency response. China Daily,. http://english.www.gov.cn/state_council/ministries/2018/03/30/content_281476095337420.htm. Accessed Mar 30, 2018
Office of Intergovernmental and External Affairs (IEA) (2014) Regional offices. US department of health & human services. https://www.hhs.gov/about/agencies/iea/regional-offices/index.html
Office of Management and Budget (OMB) (1974) Circular No. A-105. Executive Office of the President. https://www.gao.gov/assets/120/119653.pdf
Official Journal of the European Union (2014) 2014/415/EU: Council Decision of 24 June 2014 on the arrangements for the implementation by the union of the solidarity clause. OJ L 192,. http://data.europa.eu/eli/dec/2014/415/oj/eng. Accessed Jan 7, 2014, p 53–58
"OpenFEMA Data Sets (2020) Federal Emergency Management Agency (FEMA). https://www.fema.gov/about/openfema/data-sets. Accessed Sep 5, 2020.
Our Reach (2020) US department of justice. https://www.justice.gov/crs/crs-our-reach
Pasch RJ, Andrew BP, and Robbie B (2017) National hurricane center tropical cyclone report: Hurricane Maria. National Hurricane Center. https://www.nhc.noaa.gov/data/tcr/AL152017_Maria.pdf
Peel MC, Finlayson BL, McMahon TA (2007) Updated world map of the Köppen-Geiger climate classification. Hydrol Earth Syst Sci 11(5):1633–1644. https://doi.org/10.5194/hess-11-1633-2007
Post-Katrina Emergency Management Reform Act of 2006 (2006) Pub. L. No. 109–295 § 503, 6 U.S.C. § 313." 2006. https://www.doi.gov/sites/doi.gov/files/uploads/Post_Katrina_Emergency_Management_Reform_Act_pdf
Regional offices (n.d.) US Department of Labor. https://www.dol.gov/agencies/wb/contact/regions. Accessed Jan 13, 2021
"Regional offices—office of foreign missions (n.d.) US department of state. https://www.state.gov/regional-offices-office-of-foreign-missions/. Accessed Jan 13, 2021
Requests for emergency declarations (2013) 44 CFR §206.35. 2013. https://www.govinfo.gov/content/pkg/CFR-2013-title44-vol1/pdf/CFR-2013-title44-vol1-sec206-35.pdf
Richards, AL (2012) Inspection of FEMA's regional offices—region IX. Office of inspector general, department of homeland security. https://www.oig.dhs.gov/sites/default/files/assets/Mgmt/2012/OIG_12-43_Feb12.pdf
Richards, AL (2015) Inspection of FEMA's Regional Offices—Region V. Office of inspector general, department of homeland security. https://www.oig.dhs.gov/assets/Mgmt/2015/OIG-15-120-Aug15.pdf
Robert T (1988) Stafford disaster relief and emergency assistance act, public law 93–288, as amended, 42 U.S.C. 5121 et seq
Roberts PS (2007) Dispersed federalism as a new regional governance for homeland security publius, publius. J Fed 38(3):416–443. https://doi.org/10.1093/publius/pjn010
Robusto CC (1957) The cosine-haversine formula. Am Math Mon 64(1):38–40
Rousseeuw Peter J (1987) Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. J Computl Appl Math 20:53–65. https://doi.org/10.1016/0377-0427(87)90125-7
Santos JM, Mark E (2009) On the use of the adjusted rand index as a metric for evaluating supervised classification. In: Alippi C, Polycarpou M, Panayiotou C, Ellinas G (eds) Artificial neural networks ICANN 2009—ICANN 2009 lecture notes in computer science. Springer, Berlin, pp 175–184. https://doi.org/10.1007/978-3-642-04277-5_18
Smith TC (2019) The case for FEMA adopting a localized advance contracting strategy: addressing major challenges & issues that hindered FEMA's 2017 Hurricane response & recover efforts. Public Contract Law Journal 49(1):193–215
Syphard AD, Keeley JE (2019) Factors associated with structure loss in the 2013–2018 California Wildfires. Fire (basel, Switzerland) 2(3):49. https://doi.org/10.3390/fire2030049

Van der Maaten L, Hinton G (2008) Visualizing data using t-SNE. J Mach Learn Res 9(11):2579–605
Von Luxburg U (2007) A tutorial on spectral clustering. Stat Comput 17(4):395–416
World Bank (2014) World development report 2014–Managing risk for development. World Bank, Washington. https://doi.org/10.1596/978-0-8213-9903-3
Zelnik-Manor L, Pietro P (2004) Self-tuning spectral clustering. In Proceedings of the 17th international conference on neural information processing systems (NIPS'04), MIT Press, Cambridge, MA, USA, p 1601–1608
Zhang W, Villarini G, Vecchi GA, Smith JA (2018) Urbanization exacerbated the rainfall and flooding caused by hurricane harvey in Houston. Nature 563(7731):384–388. https://doi.org/10.1038/s41586-018-0676-z
Zorrilla CD (2017) The view from Puerto Rico—Hurricane Maria and its aftermath. N Engl J Med 377(19):1801–1803. https://doi.org/10.1056/nejmp1713196

Authors and Affiliations

Colton Margus[1,2] · Attila Hertelendy[1,3] · Yudong Tao[4] · Erik Coltey[5] · Shu-Ching Chen[5] · Steven Luis[5] · Mei-Ling Shyu[4] · Gregory R. Ciottone[1]

Attila Hertelendy
ahertele@fiu.edu

Yudong Tao
yxt128@miami.edu

Erik Coltey
ecolt003@fiu.edu

Shu-Ching Chen
s.chen@umkc.edu

Steven Luis
luiss@cs.fiu.edu

Mei-Ling Shyu
shyu@miami.edu

Gregory R. Ciottone
gciotton@bidmc.harvard.edu

[1] Department of Emergency Medicine, Beth Israel Deaconess Medical Center, Boston, MA 02215, USA

[2] Department of Emergency Medicine, Bronxcare Health System, Bronx, NY 10457, USA

[3] Department of Information Systems and Business Analytics, Florida International University, Miami, FL 33199, USA

[4] Department of Electrical and Computer Engineering, University of Miami, Coral Gables, FL 33124, USA

[5] Data Science and Analytics Innovation Center, University of Missouri-Kansas City, Kansas City, MO 64110, USA