Data Driven Multi-Hazard Risk Visualization

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Abstract

This work presents an approach for visualizing aggregate spatial risk data for natural hazards in a way which is not restricted by fixed geographical boundaries and is intended to improve multi-risk awareness in at-risk populations. First, spatial proximity is analyzed to organize occurrences in clusters and the convex hull of each cluster is created in order to define our visualization regions. Then, each region is assigned a risk factor value which is visualized by selecting a color scheme specific to the data variation. The application of this technique is demonstrated using the state of California as a region of interest.

Introduction

Earthquakes, wildfires, hurricanes, and floods are some of the natural hazards that occur every year leaving a trail of destruction impacting communities worldwide. Natural hazards are often categorized by the location in which they occur and the severity of their impact to that location. Due to the complexity of natural hazards, visualizing their occurrences with a unified risk index is difficult. The results are often confusing to both domain professionals and the general public. In this work we present a unified risk index that is visualized in proximity-based regions that allow users to see risk visualization outside of human-constructed boundaries. Our risk index is then classified into 5 categories ranging from low-risk to high-risk, based on recommendations from National Wildfire Coordinating Group(NWCG) and UPSeis.

Across much of the literature on visualizing natural disaster risk, visualizations are often created using regions representing human-constructed boundaries, such as municipalities, counties, and states or countries [2, 3]. However, natural hazards occur without regard to anthropocentric regions - as such geographical boundaries in the context of natural hazards seems arbitrary. This work provides a more meaningful representation of region by capturing events based on their Euclidean proximity. The regions are created by computing the convex hull of clustered data points which are the centers of natural hazard occurrences. In this way we transform point-based data into regions which can be much more intuitively visualized and classified in terms of risk factors. The main focus of this work is to intuitively communicate to susceptible populations the aggregate risk without constraints related to geographical boundaries, and to provide an interface to locate a particular region of interest using maps from OpenStreetMap.

Multi-Hazard Risk Index

Data Acquisition

- Wildfire and Earthquake data from the last 10 years were chosen for the state of California.
- There were 17,894 wildfire and 12,452 earthquake (greater than 2.5 on Richter scale) occurrences in last 10 years.
- The data for wildfire and earthquake were obtained from United State Geological Survey (USGS) and Wildfire Wildland fire website.
- The latitudes and longitudes of each event were limited to 4 decimal places to capture data at street level.

Regionalization

Regionalization is an important concept in spatial analysis of data. It divides large sets of data into a number of smaller spatially contiguous related regions maintaining the homogeneous nature of the data [1].

- Our region of interest are created based on clusters obtained using the hierarchical clustering algorithm *DIANA* (DIvisive ANAlysis) [4, ch. 6].
- Convex hull of each cluster are clipped against the boundary of California to limit the domain of our work.

Intensity Classification and Risk Index Creation

Earthquake Magnitude	Area burnt(Acres)	Intensity
2.5 – 5.4	< 10	1
5.5 – 6.0	10 – 100	2
6.1 – 6.9	100 – 300	3
7.0 – 7.9	300 – 1000	4
8.0+	1000+	5

The overall risk index is computed by taking the arithmetic mean of the intensity of a natural hazard occurrence for each cluster. The obtained risk index is normalized and then is used to visualize the risk in a given region.

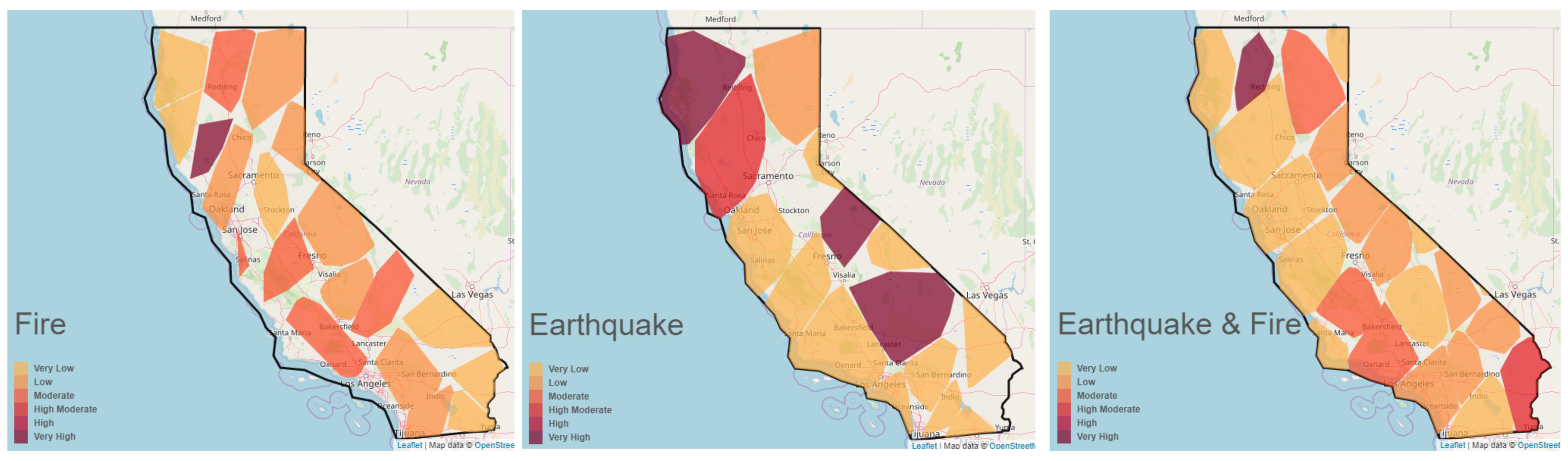

Figure 1: Risk visualization for fire (left), earthquake (middle), and aggregate risk (right).

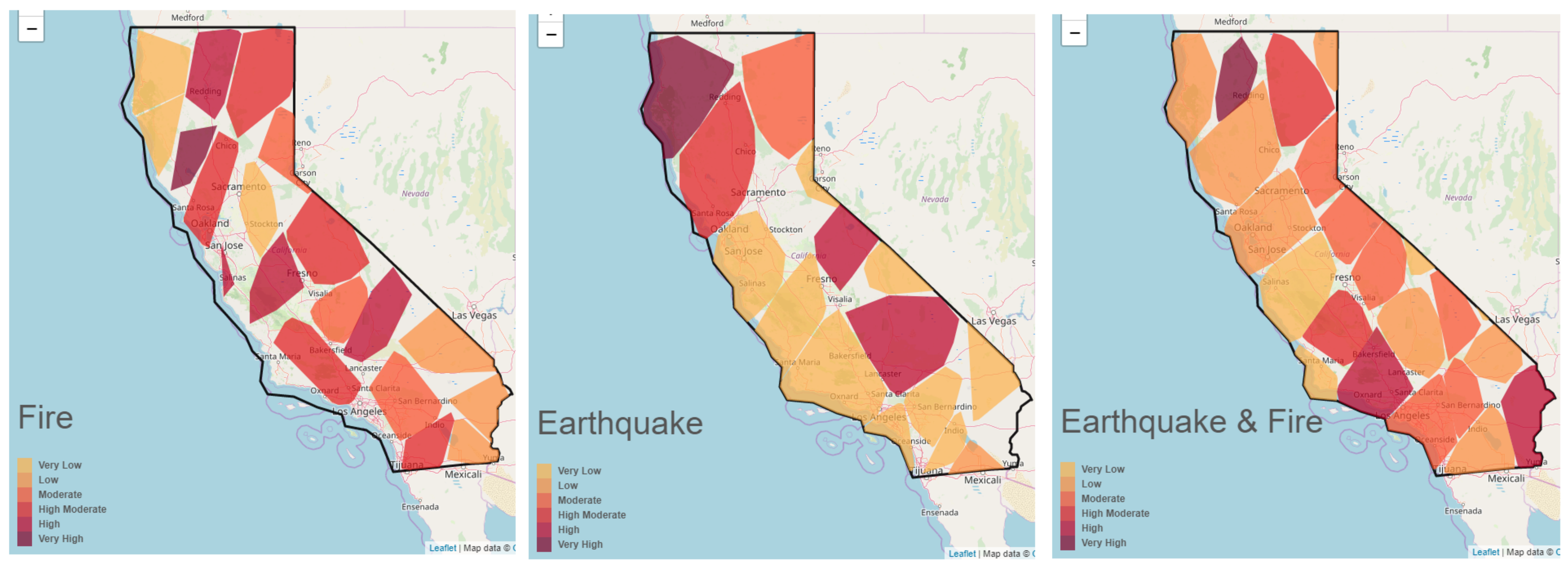

Figure 2: Risk visualization with cluster-based color scheme for fire (left), earthquake (middle), and aggregate risk (right).

Results

- This work allow users to visualize risk data related to wildfire, earthquake or the aggregate data of both wildfire and earthquake.
- Regions are visualized based on the type of risk and the variation in data.
- For non-uniform data, the algorithm chooses the cluster based color scheme.

Conclusions and Future work

This preliminary work explores several contributions:
- An approach for visualizing multi-hazard risk by regions that are not confined to human-constructed boundaries.
- The development of a unified risk factor metric.
- The introduction of an adaptive data-dependent color scheme selection.

Our approach is still in preliminary stage and we plan to explore as future work:
- The use of alternative regionalization methods such as alpha shapes or non-convex hulls, instead of the current approach of relying on simple convex hulls.
- Evaluations with user studies in order to uncover the cognitive aspects of the visualization with respect to different design choices.
- Finally, we also plan to improve the overall visualization and the additional options for the risk factor calculations.

References

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To interact with the visualization, please scan below:

(https://sharmrit.github.io/Homepage/MultiHarzardVisualization)