Predictive Modeling of Flood Susceptibility: Phase 1

UC Merced Cognitive Science
in partnership with
Universities Space Research Association
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Presentation Outline

Project Conceptualization and Framing the Problem

Understanding Risk and the Built Environment

Visualization

Modeling Challenges and Solutions

Summary

References and Appendices

Conceptualization

Progression of Project Question

“How can we visualize if it is flooding or not?”

“What factors do we need to understand to incorporate as many essential datasets as necessary to forecast and visualize flood risk?”

Our phenomena are inferred from our data
(Woodward, 2011)

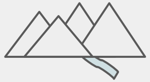
Framing the Problem

Coupled human natural systems issue

People + Place = Natural Disaster

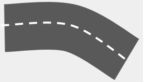
Climate Change

- Events occurring in areas not prepared or underprepared
- Larger duration, varied spread, varied intensity
  - E.g. atmospheric rivers in CA



Physical Geography and Geology

- Slope: which way is downhill?
- Features: directing water i.e. saddles in ridges, escarpments, etc
- Soil porosity/water retention
  - E.g. Less permeable clay has more run off



Humans

- Outdated or nonexistent infrastructure
- Declaring natural disasters and receiving aid based off financial damage to PUBLIC INFRASTRUCTURE at the state level (CA)
- Replacement of porous surfaces with concrete

Visualizing Confounding Factors

Red River Basin
March 2009

Riverine flooding
Snowmelt + Frozen Ground
Linear (wide) footprint
Continental Landscape
Most impacted city: Grand Forks, ND
Population: 50,000
Cost: $3.5Bn

Colorado Front Range
September 2013

Flash flooding and erosion
17” of precipitation in 48 hours
Forked footprint (2 canyons)
Mountainous landscape
Most impacted city: Lyons, CO
Population: 2,155
Cost: $4Bn

Arizona
July 2017

Seasonal monsoon + slow drainage
5.5” of precip overwhelmed city pumps
Circular/centralized footprint
Desert landscape
Most impacted city: Mesa, AZ
Population: 500,000
Cost: $18M

Images L-R: boston.com/Reuters, Denver Post, azcentral.com/Michael Chow.
Dollar values and populations approximate.

Scale Considerations

Challenges are driven by mismatches in scale, as in the case of cities being inundated with enough rain to overwhelm their pumping systems, drainage, or flood mitigation infrastructure, such as Boulder, CO in 2013.

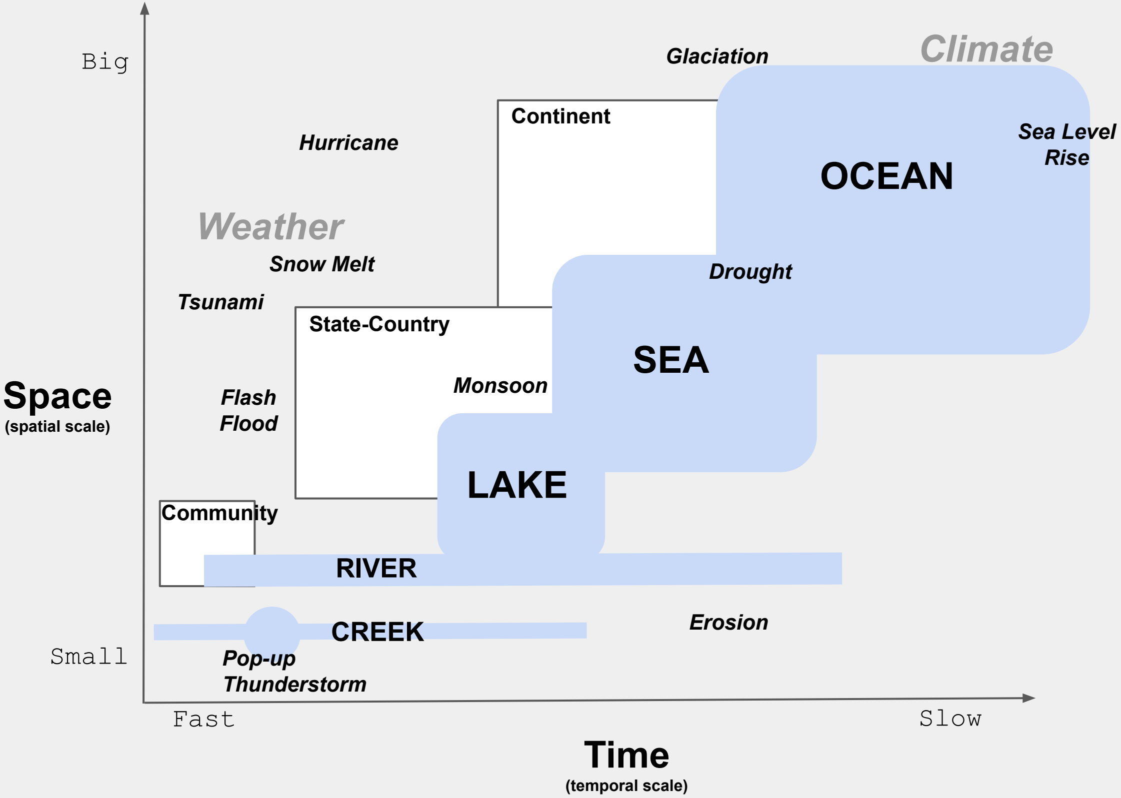


Image: University Corporation for Atmospheric Research (UCAR). Chart: M. Brown. Not to Scale.

Demographic Considerations

There are many ways to categorize users for statistical purposes

- Gender/Age/Ethnicity
- Health problems (physiological and mental)
- Location (urban vs. rural, shoreline vs. inland, elevation)
- Countries (developed vs. emerging vs. underdeveloped)
- Land tenure (owners vs. renters vs. squatters)

What are the best categories for communicating flood data?

Risk Perception

Humans are very bad at evaluating risk.

We tend to judge the probability of future events based on the past.

But the past is only one part of calculating the probability of a future event.

How do we effectively communicate the probability of a serious weather event like a flood to a population with a limited understanding of how probability works?

Computing Risk - Burningham, 2006

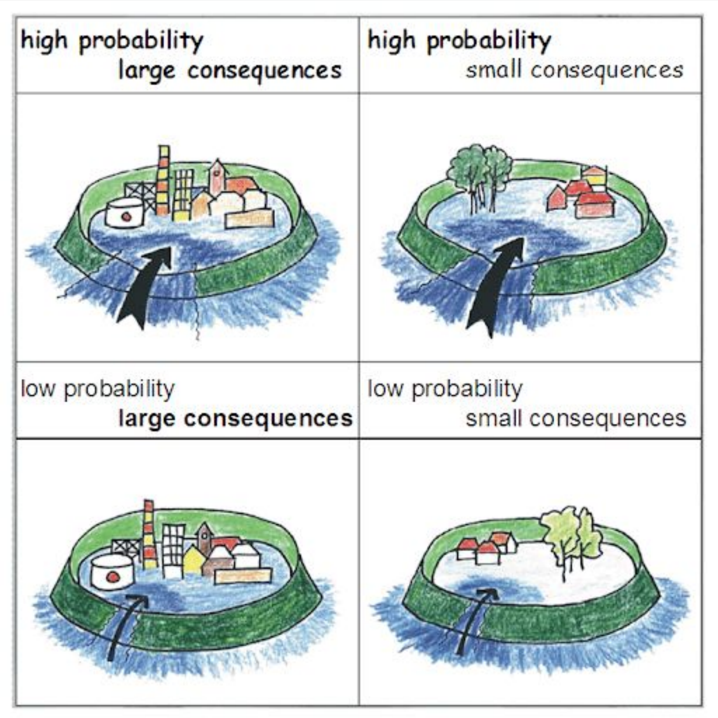
Public awareness of risk

- Awareness of living in an at-risk area
- Awareness of warning systems
- Awareness of appropriate action

Most people are unaware of risk in all 3 categories

Information is unclear and difficult to understand even when available

People aren't apathetic. They just don't have understandable information.



Computing Risk - Wachinger, 2013

Statistical risk does not significantly factor into perceived risk.

Informational factors (e.g. news) have an effect *only* in the absence of direct experience

Cultural factors are mediators for risk perception, but they are not primary causes.

Risk and Demographics - Key Takeaways

People judge their risk by prior experience first and foremost.

In the absence of experience, they turn to informational factors.

There needs to be a more standardized way of characterizing demographics and risk (Kellens 2013).

However, different people interpret the same information differently.

What’s the best way to characterize user demographics?

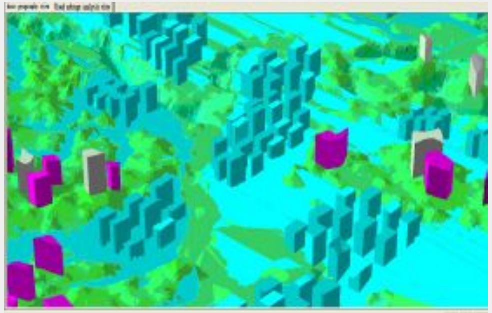
What’s the best way to present risk analyses?

Visualization

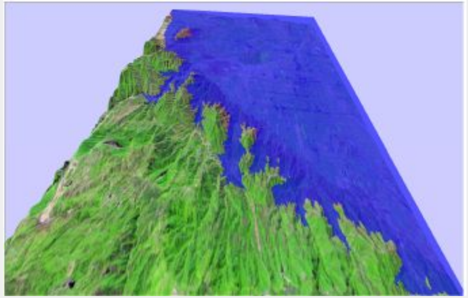
The Geospatial data can be represented mainly in two format.

- Raster
  - consists of a matrix of cells (or pixels) organized as grids where each cell contains a value representing information
  - Examples: netCDF(.nc), GeoTIFF(.tif), etc.
  - Computationally less expensive, requires more memory
- Vector
  - Consists of geometrical shapes such as points, line, polygons, etc.
  - Examples: Shapefile(.shp), GeoJSON (.json), etc.
  - Computationally expensive, requires less memory

Visualization

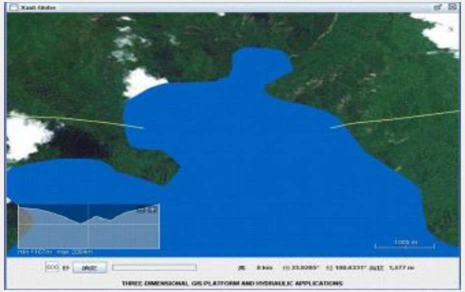


ArcEngine
Guo et al.(2009)



OpenGL
Xinxin et al.(2012)

SPH to 3D Spatio-temporal GIS application
Ye et al.(2012)



WorldWind
Jiang et al.(2010)

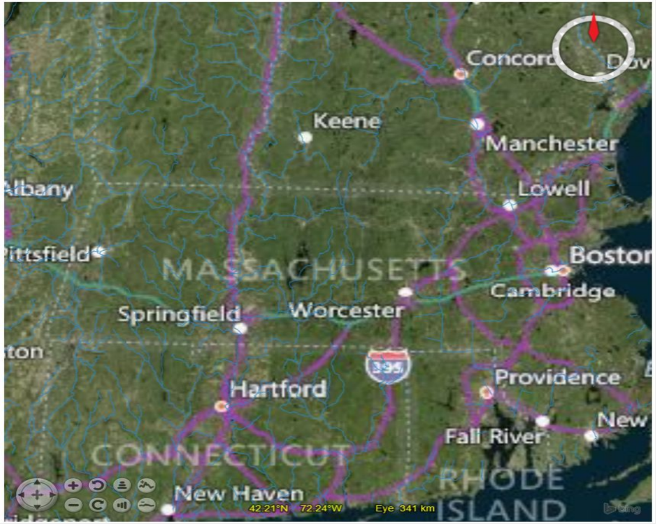
Visualization

Among many available platform, this work considered NASA's Web WorldWind and ArcGIS:

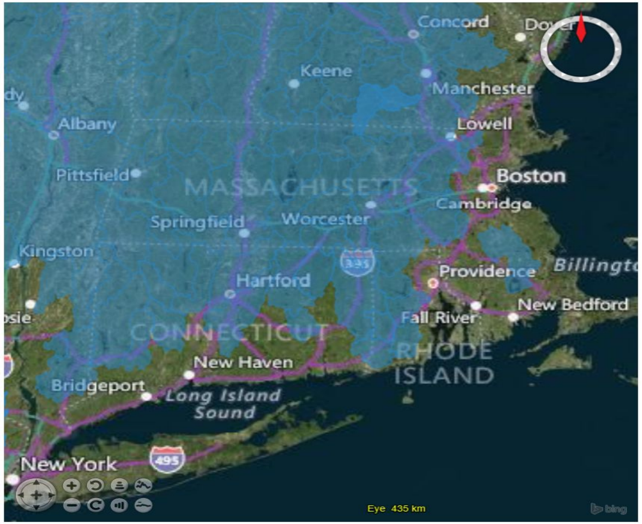
- Easy integration
- Deployable on web
- Technical support & Documentation

Visualization

Web WorldWind



Rivers



River Basins

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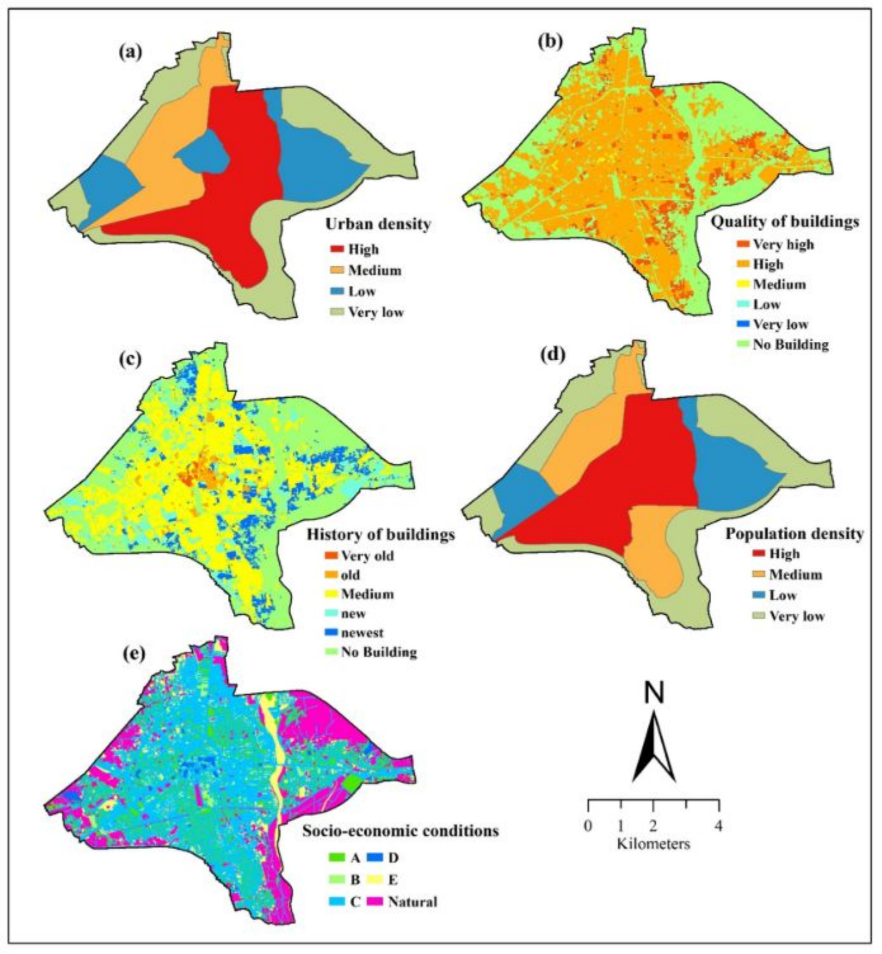
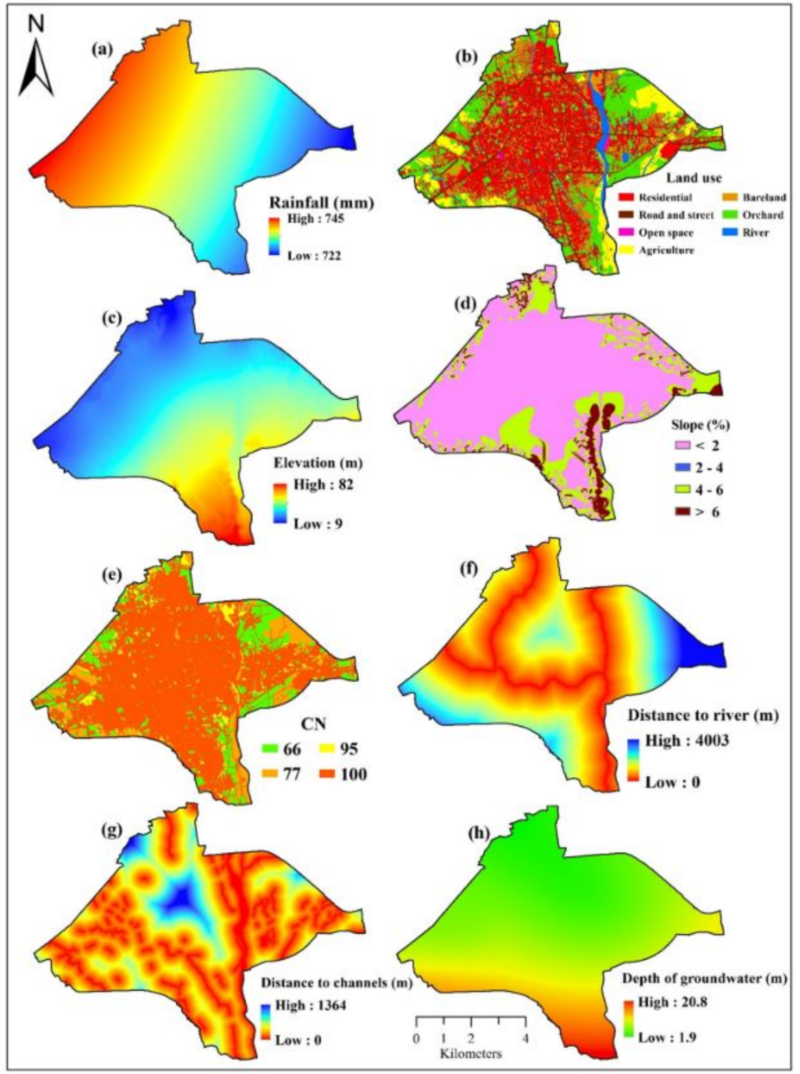




Literature Review of Modeling Floods

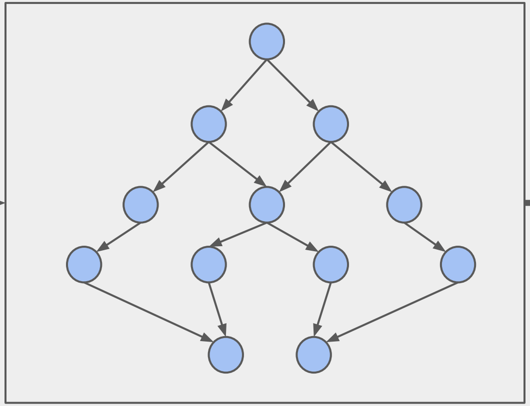
1. Khosravi, Khabat, et al. **"A comparative assessment of flood susceptibility modeling using Multi-Criteria Decision-Making Analysis and Machine Learning Methods."** Journal of hydrology 573 (2019): 311-323.
2. Darabi, Hamid, et al. **"Urban flood risk mapping using the GARP and QUEST models: A comparative study of machine learning techniques."** Journal of hydrology 569 (2019): 142-154.

$$\boxed{Risk} = Hazard \times Vulnerability$$

The probability of a flood event happening.

Input
1. Hazard
2. Vulnerability

Decision tree algorithm with Naive Bayes



Output
- 1 - flood
- 0 - non-flood

Next Steps and Recommendations

Modeling flood risk is probably one of the main challenge.

- We can start on implementing the model that has been done from the two papers from the Journal of Hydrology and apply it to a more specific area (ex. Massachusetts, USA).

- Data collection and processing of the factors important to predict flood susceptibility.
  - We have a progress summary of the data that we collected and there is a provided code along with it.
  - https://docs.google.com/document/d/1R1rTaoIgmxXAHmlYn6gbthBm-L7F_CFeP0Sm2GVzF94/edit?usp=sharing
  - https://drive.google.com/drive/folders/1MMl7ECQTzpvsS8Rk71PJWeye61AIY9DP?usp=sharing

- Constructing and evaluating the model.
  - Literature review: https://docs.google.com/document/d/1O6pkmpz4ESHgwkdV86N7IdyB6VRnUa9-tzv4_NF-gVw/edit?usp=sharing

Summary

Conceptualization

- People + Place = Natural disasters
- Spatio-temporal scale matters
- Multiple factors of flood susceptibility

Visualization

- WebWorldWind
- ArcGIS
- Problem in data file types

Risk Perception

- Humans evaluating flood risk
- Characterization of demographics and risk
- Public awareness and communication

Modeling

- Big data in multiple scales and dimensions
- Interpretive structural model
- Scalable and robust

References

Burningham, K., Fielding, J., & Thrush, D. (2008). ‘It'll never happen to me’: understanding public awareness of local flood risk. *Disasters*, *32*(2), 216-238.

Kellens, W., Terpstra, T., & De Maeyer, P. (2013). Perception and communication of flood risks: a systematic review of empirical research. Risk Analysis: An International Journal, 33(1), 24-49.

Sakas, Michael Elizabeth. “Roads And Bridges Have Been Rebuilt, But Lyons Still Struggles To Recover Community Lost In The Floods.” Colorado Public Radio. www.cpr.org,https://www.cpr.org/show-segment/roads-and-bridges-have-been-rebuilt-but-lyons-still-struggles-to-recover-community-lost-in-the-floods/.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox—implications for governance and communication of natural hazards. *Risk analysis*, *33*(6), 1049-1065.

Guo, X.C., D.G. Luo, S.H. Zou, D.J. Li and W.Q. Zheng, 2009. Developing the 3D flood model visualization system based on the arcengine. Proceeding of the WRI World Congress on Computer Science and Information Engineering, 5:352-356.

Xinxin, L., W. Wanggen, L. Li, Z. Ximin, G. Chao and Y. Xiaoqin, 2012. Realization of flood simulation visualization based on OpenGL. Proceeding of International Conference on Audio, Language and Image Processing (ICALIP, 2012), pp: 1151-1154

Ye, F.H., H.B. Wang, S. Ouyang, X.M. Tang, Z. Li et al., 2012. Spatio-temporal analysis and visualization using SPH for dam-break and flood disasters in a GIS environment. Proceeding of International Symposium on Geomatics for Integrated Water Resources Management (GIWRM, 2012), pp: 1-6

Jiang, R., J. Xie, J. Li and T. Chen, 2010. Analysis and 3D visualization of flood inundation based on WebGIS. Proceeding of 2010 International Conference on E-Business and E-Government (ICEE, 2010), pp: 1638-1641

Questions?

Appendix Slides

Web World Wind:

- API available: https://github.com/NASAWorldWind/WebWorldWind
- API Guide: https://nasaworldwind.github.io/WebWorldWind/index.html
- Code for reading .shp and .tif file available: https://drive.google.com/drive/folders/1tiRbf3mLFxatyIZTx6BHDxMCFmmmUgY0?usp=sharing
- Challenges involved in installation:
  - Choosing the correct version of Node.js
  - Finding and installing all dependencies

Summaries:

- Data: https://docs.google.com/document/d/1R1rTaoIgmxXAHmlYn6gbthBm-L7F_CFeP0Sm2GVzF94/edit?usp=sharing https://drive.google.com/drive/folders/1MMl7ECQTzpvsS8Rk71PJWeye61AIY9DP?usp=sharing
- Model Literature Review: https://docs.google.com/document/d/1O6pkmpz4ESHgwkdV86N7IdyB6VRnUa9-tzv4_NF-gVw/edit?usp=sharing