

Analysis of flood-insurance in minimizing cost to homeowner for Nashville, TN

-Raghav Sharma



Background and Motivation

Methodology

Results & Conclusion

Limitations

Additional Projects

Questions

\$2 billion
Private
property
losses

10%
Nashville
properties in
100-yr flood
plain

The Cumberland River crested downtown Nashville at 51.86ft in May 2010, the highest level recorded since the Cumberland Dam system was built in early 1960s.



- Average annualized cost to Nashville homeowners from riverine flooding.
- Impact of flood insurance in minimizing flood losses.

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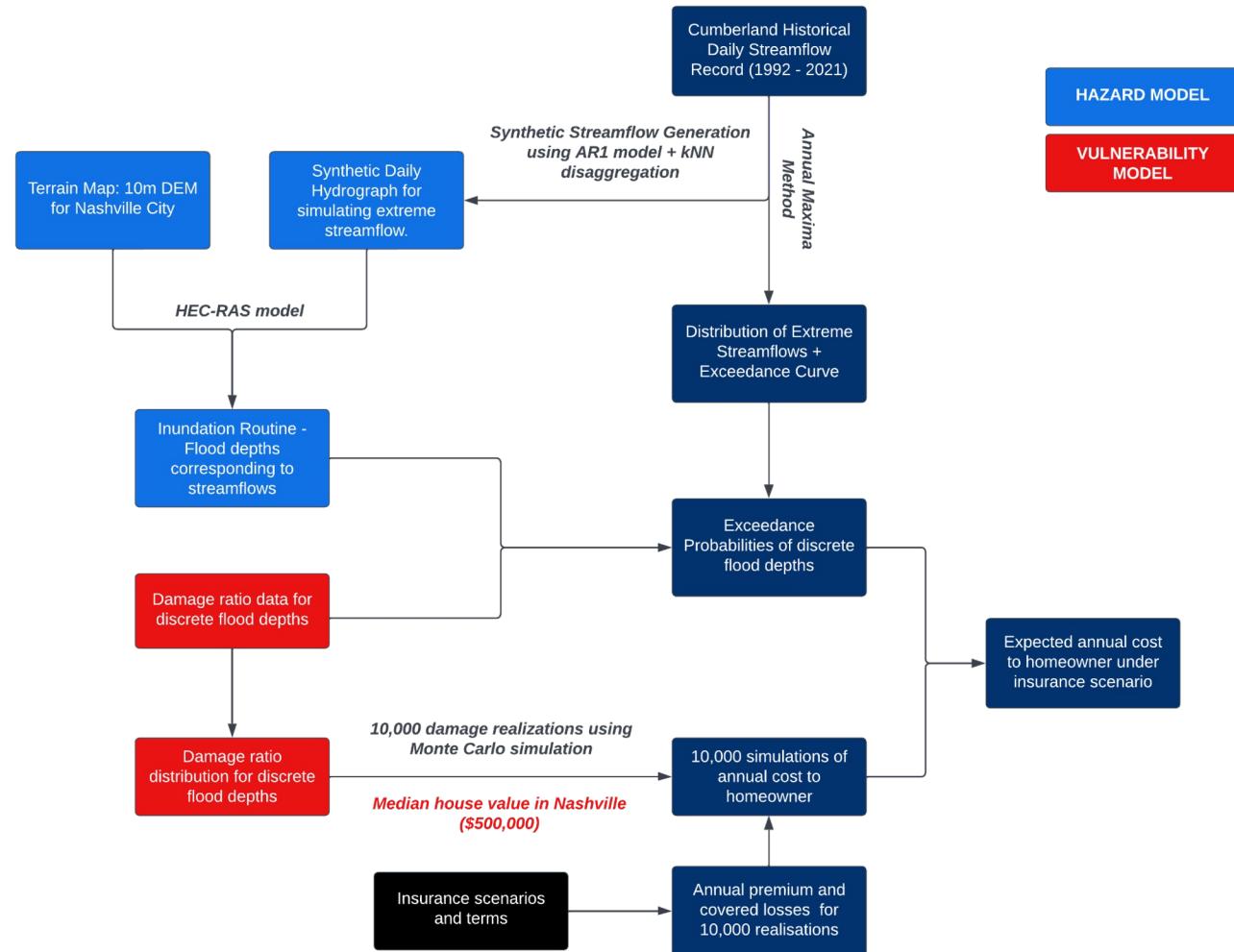
Data used

1. Cumberland Historical Streamflow Record - USGS StreamStats (Station ID: 03431500)
2. 10m DEM Nashville City - USGS
3. 100 Damage Ratios for each flood depth
4. Insurance Terms with max coverage of \$250,000:

Insurance A: \$1500 annual premium, deductible = \$1,250

Insurance B: \$1200 annual premium, deductible = \$5,000

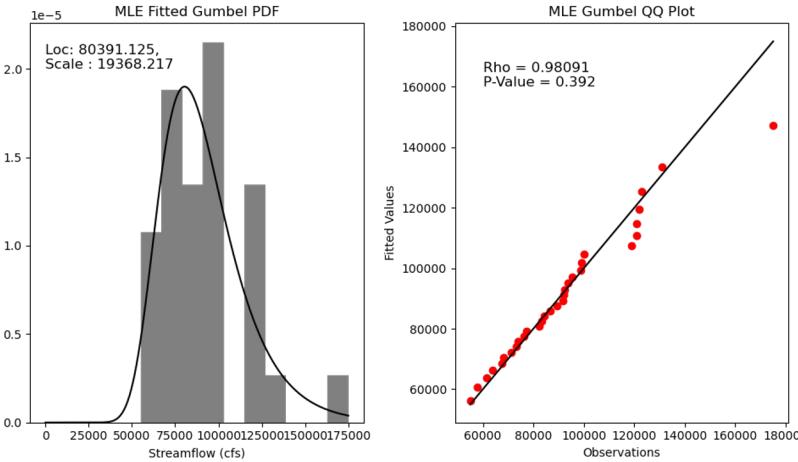
Insurance C: \$900 annual premium, deductible = \$10,000



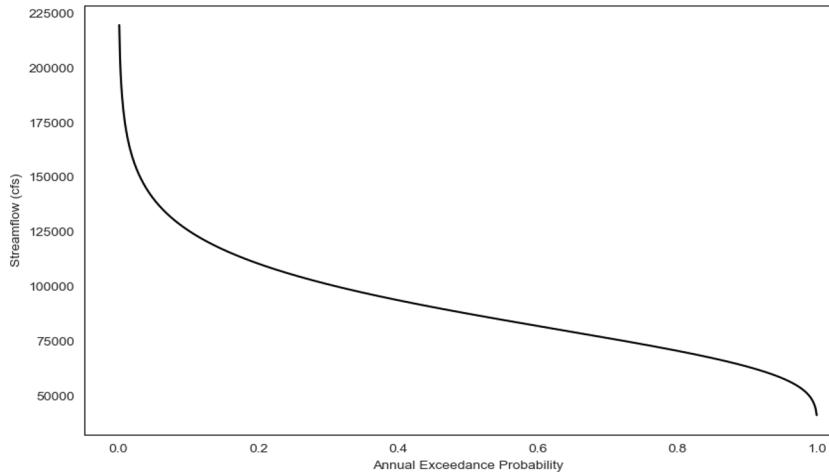
Nashville Extremes & Exceedance Curve

- Annual Maxima method for estimating extreme streamflows.
- Fit extreme value distributions to annual maxima data. Gumbel distribution gives best fit.
- Develop streamflow exceedance curve to determine exceedance probability and return periods of each streamflow.

Fitting Gumbel distribution on Annual Maxima



Streamflow Exceedance Curve



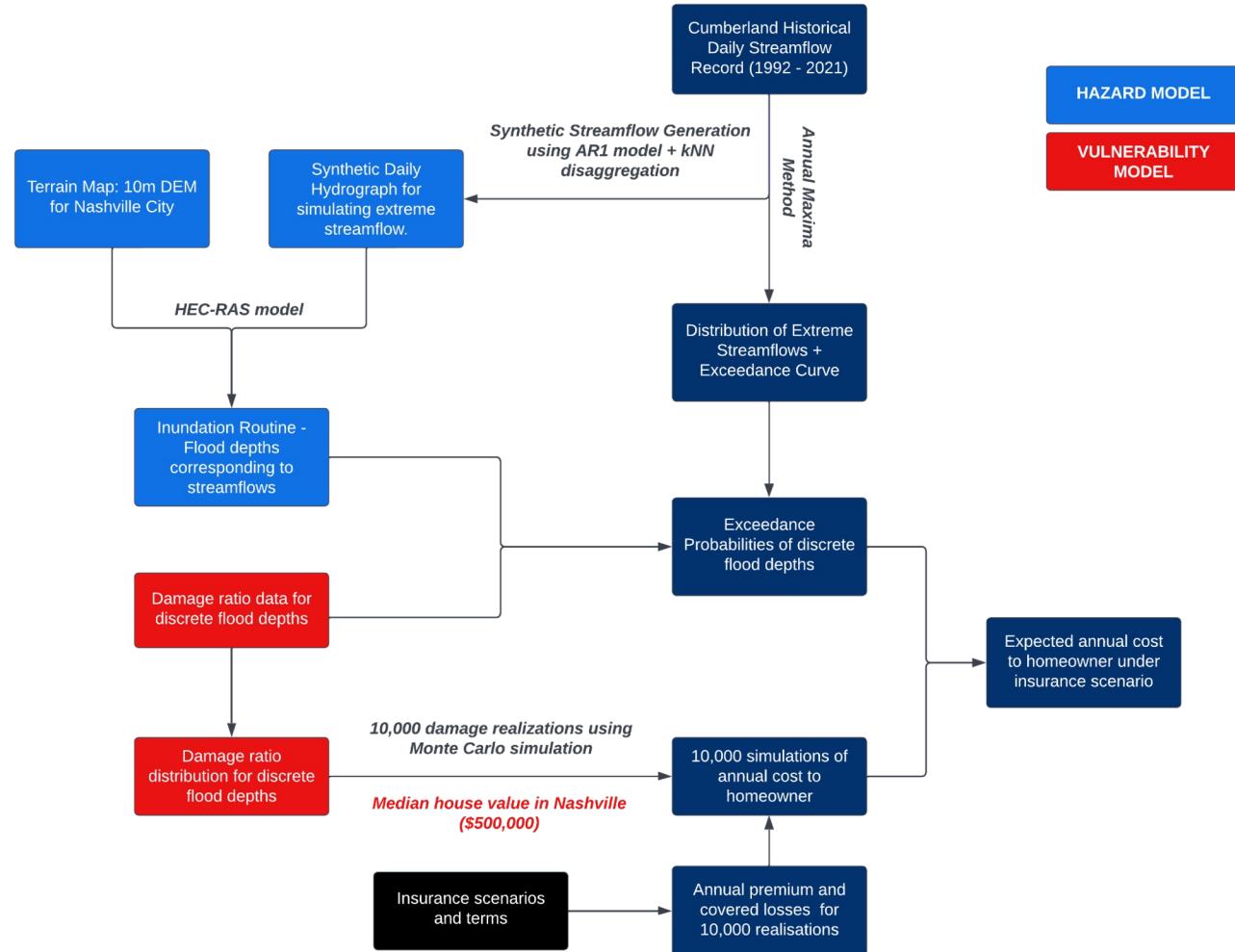
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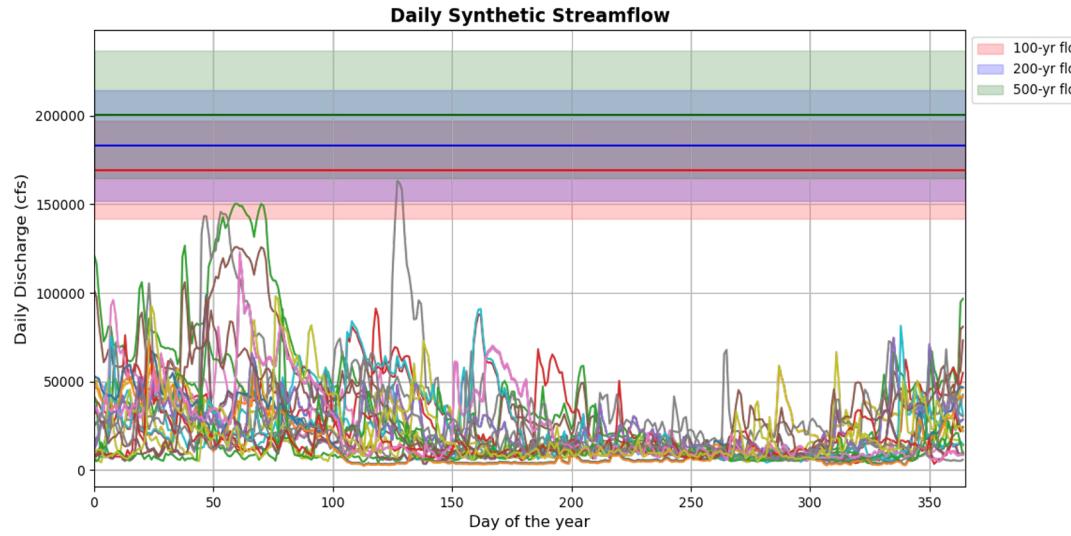
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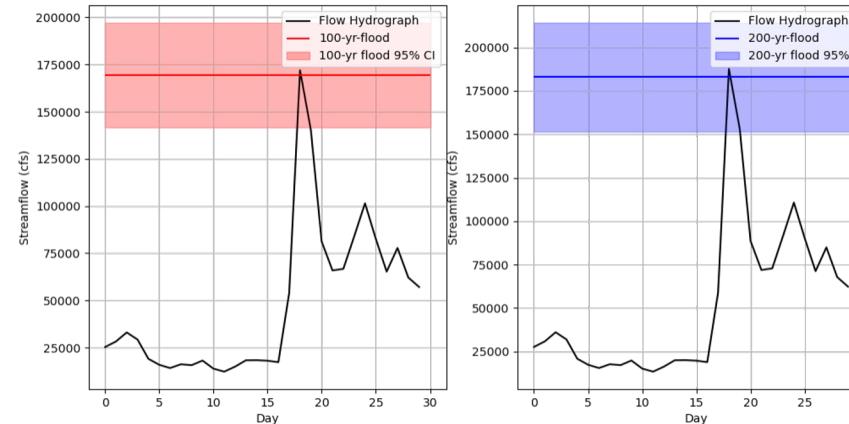
Synthetic Streamflow Generation

Generates daily streamflow series satisfying the range of reasonable future conditions and preserves statistical patterns in historical streamflow

- Sample an annual flow from AR(1) model (Q_s)
- Sample a historical year with similar flow ($Q_h \sim Q_s$) using k-nearest neighbors.
- Scale normalized streamflow from sampled year by (Q_s/Q_h)
- Select a 30-day series around largest streamflow and scale it to desired streamflow value



Example 30-day hydrograph scaled to 100 and 200-yr streamflows



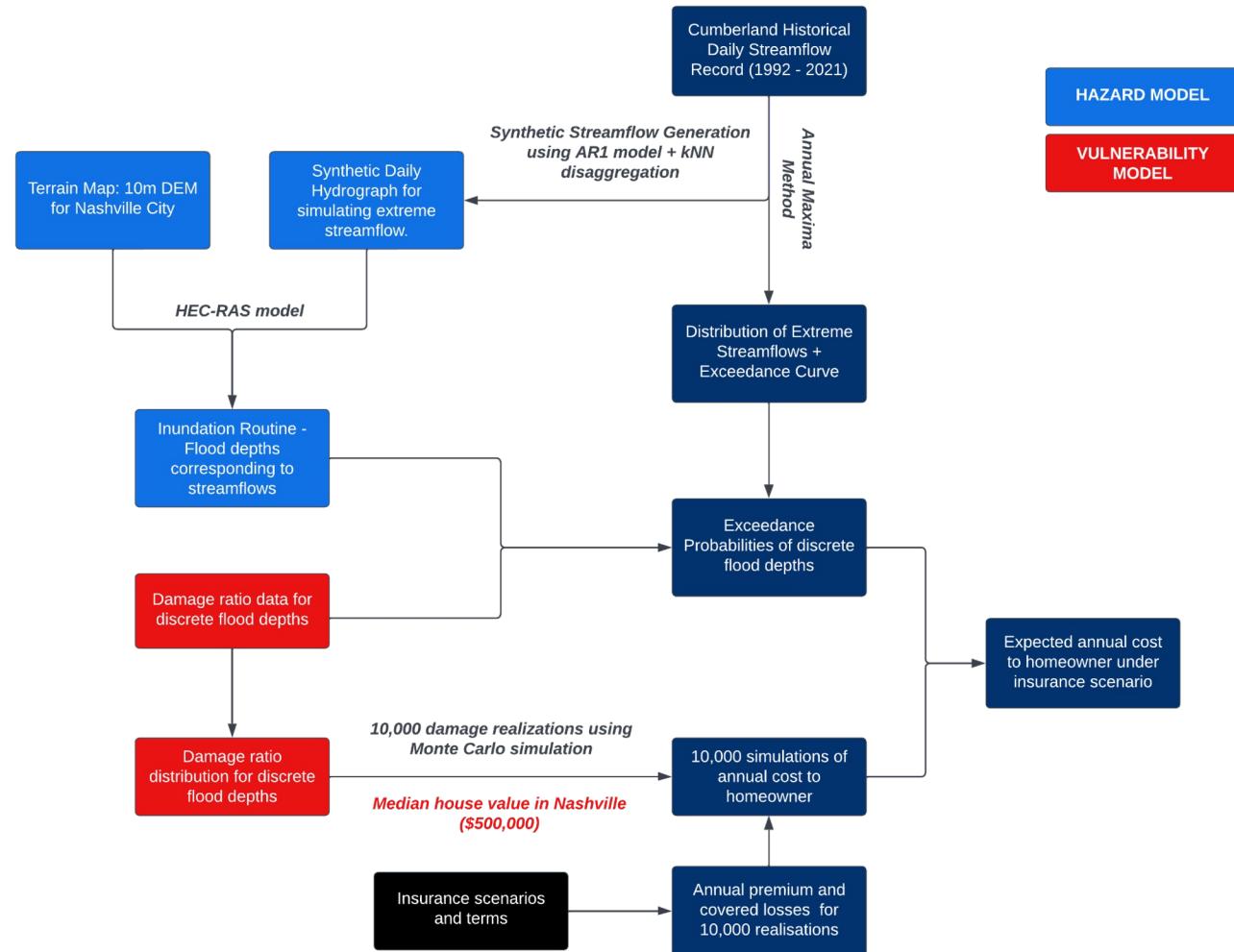
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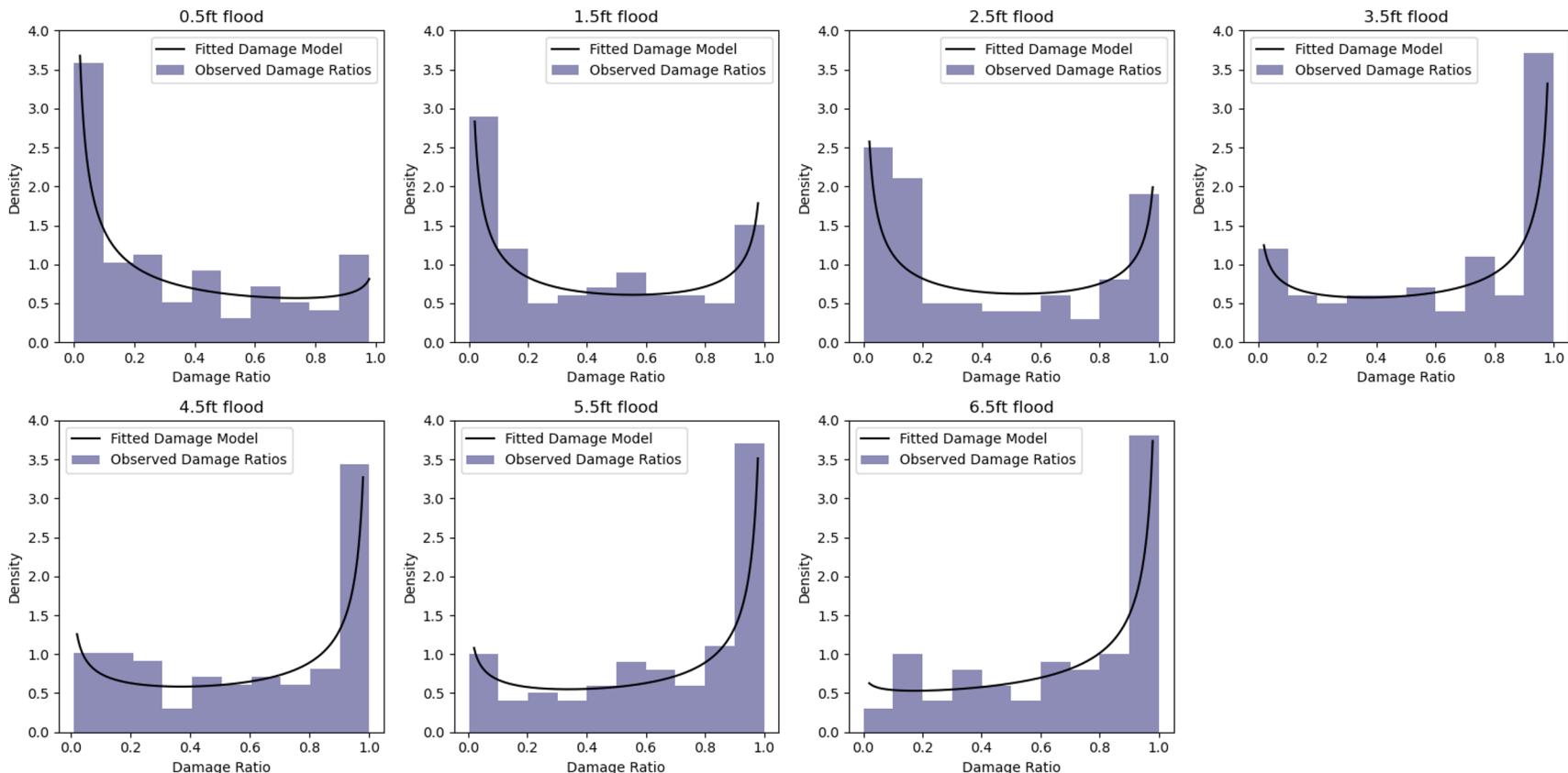
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Damage Ratio Data (Vulnerability Model)



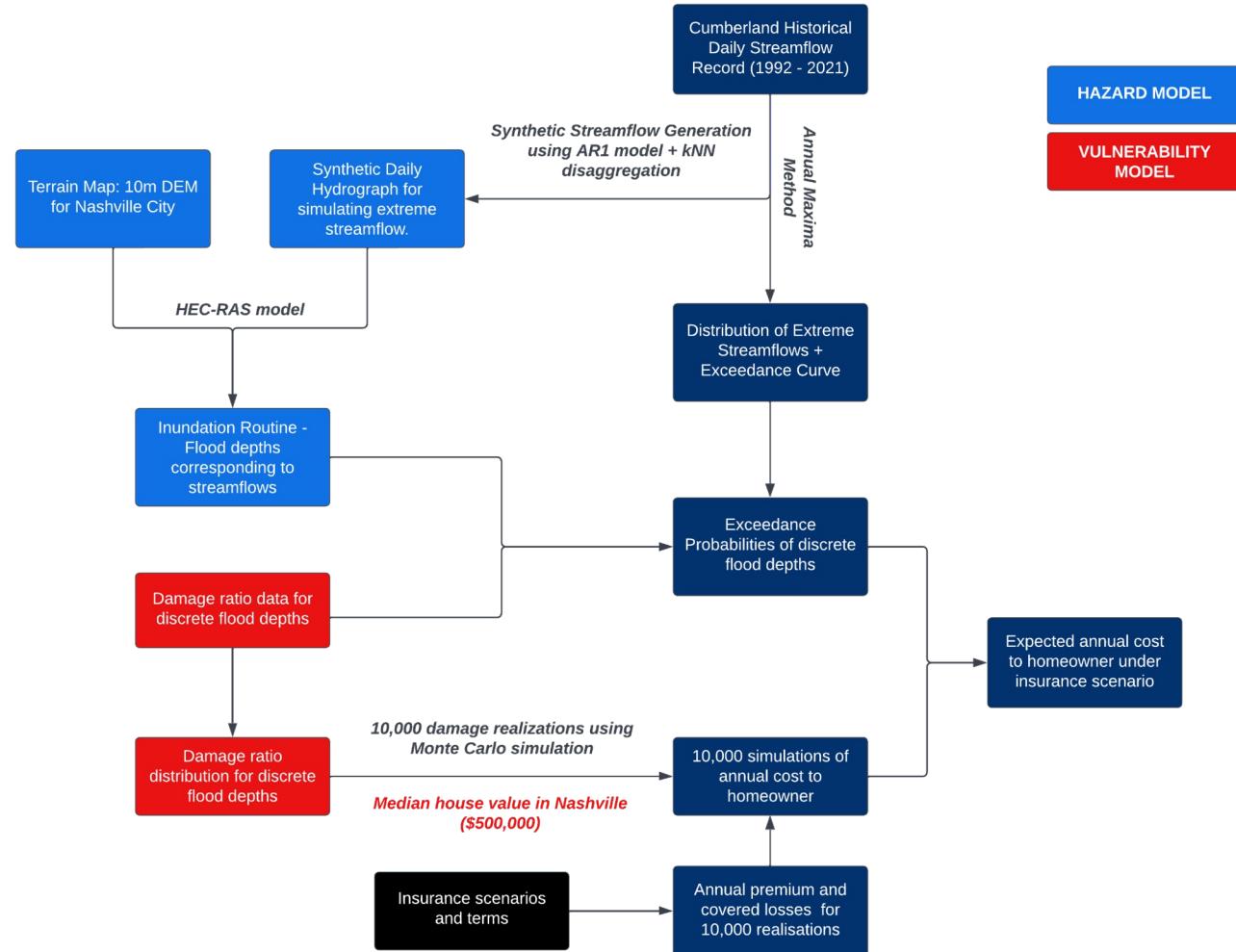
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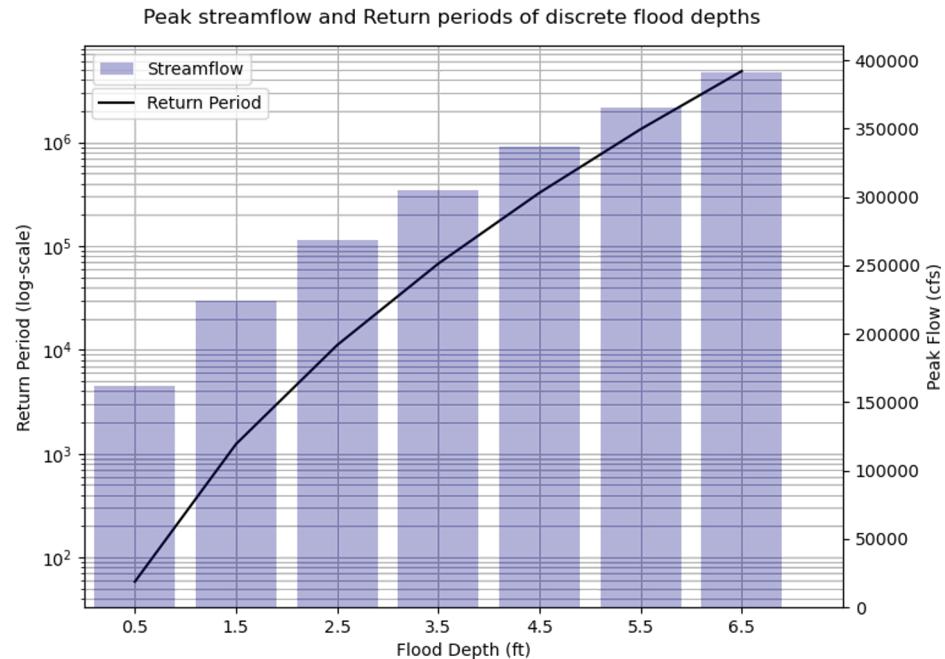
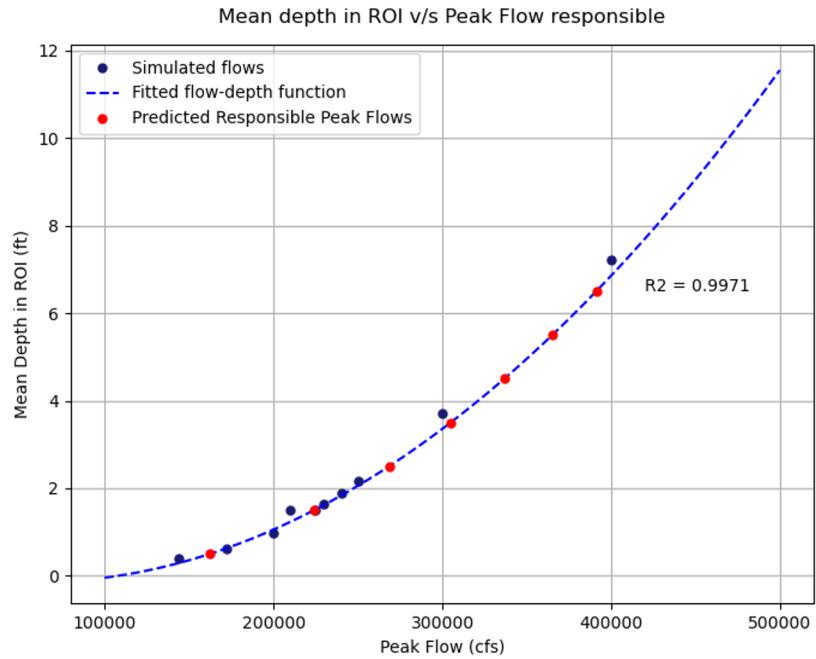
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Peak Flows and Mean Depth in ROI



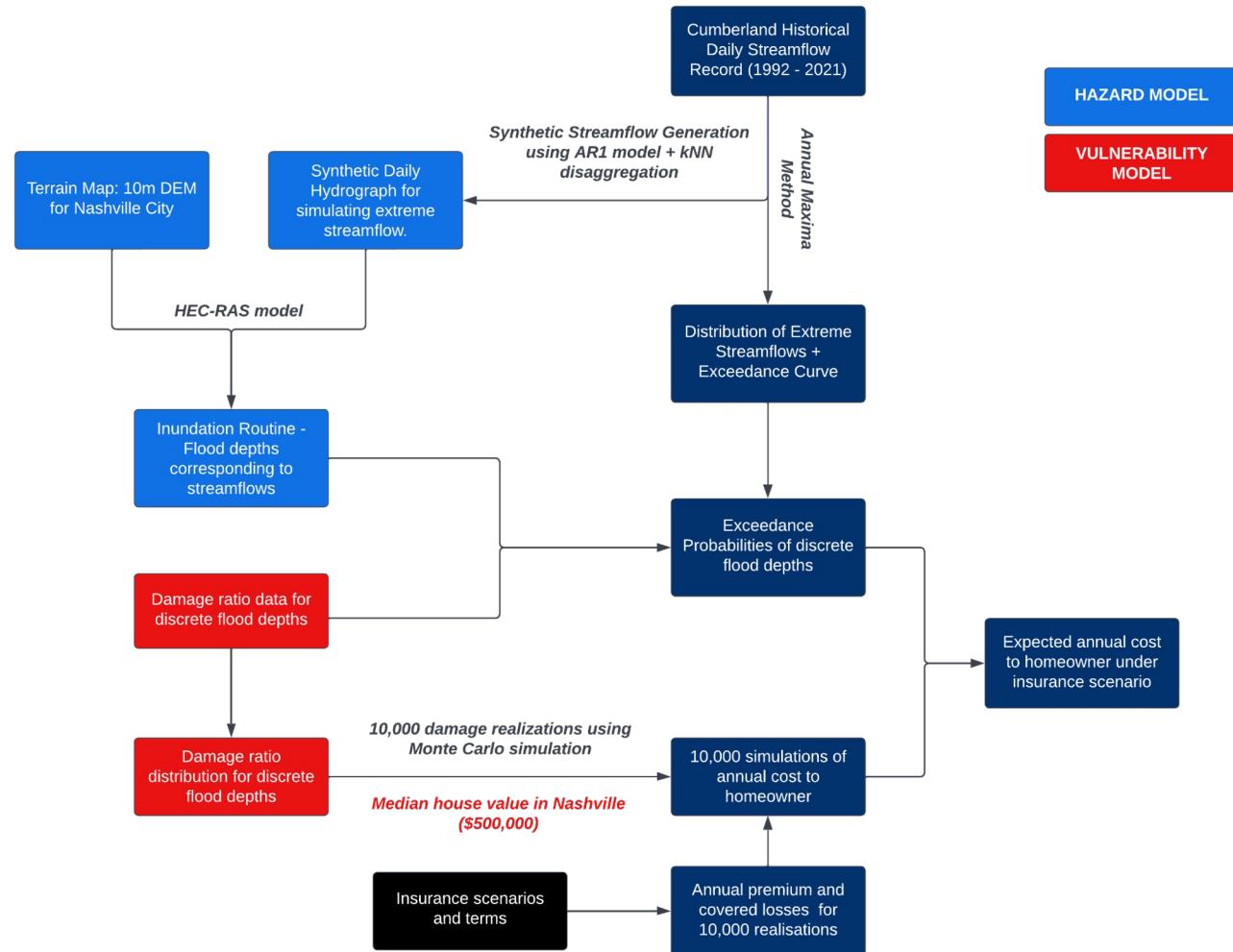
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NFIP Insurance Terms

Insurance	A	B	C
Annual Premium (\$)	1,500	1,200	900
Deductible (\$)	1,250	5,000	10,000
Max Coverage (\$)	250,000	250,000	250,000

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100-yr Flow Simulation

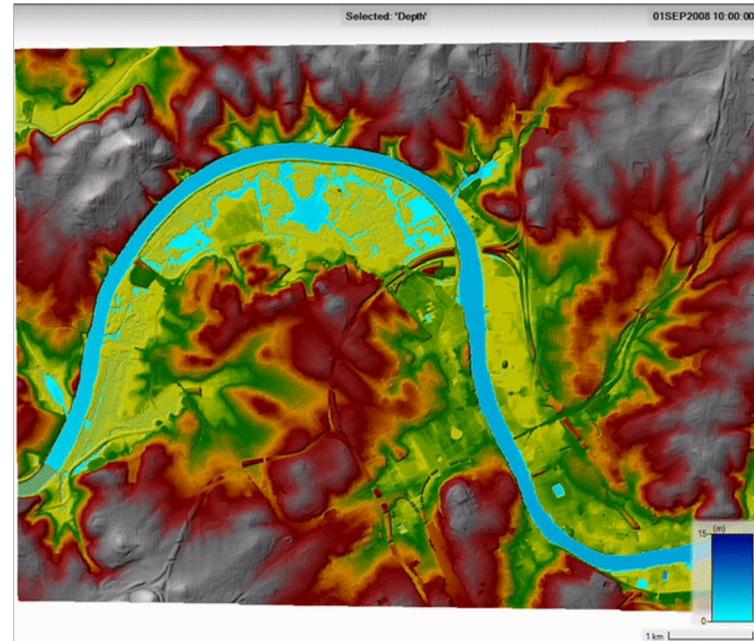
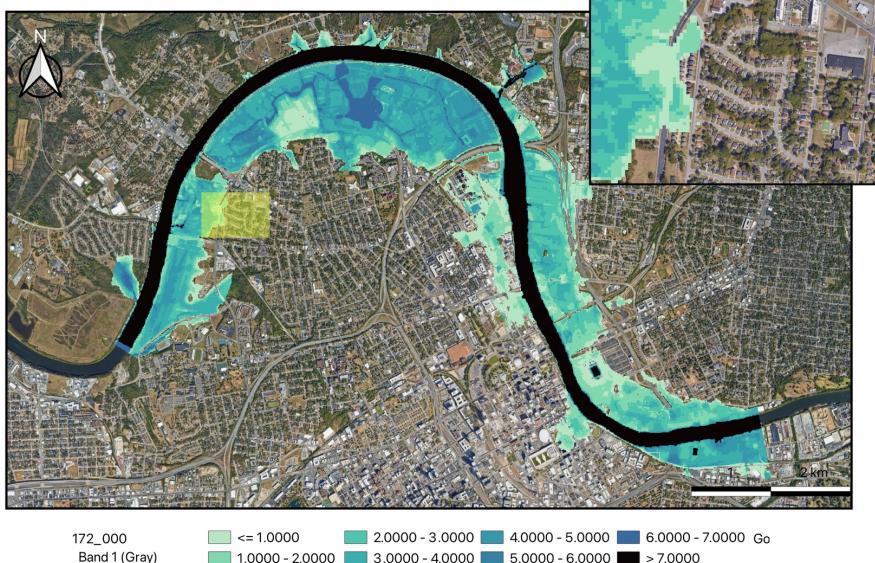


HEC-RAS 100-yr floodplain

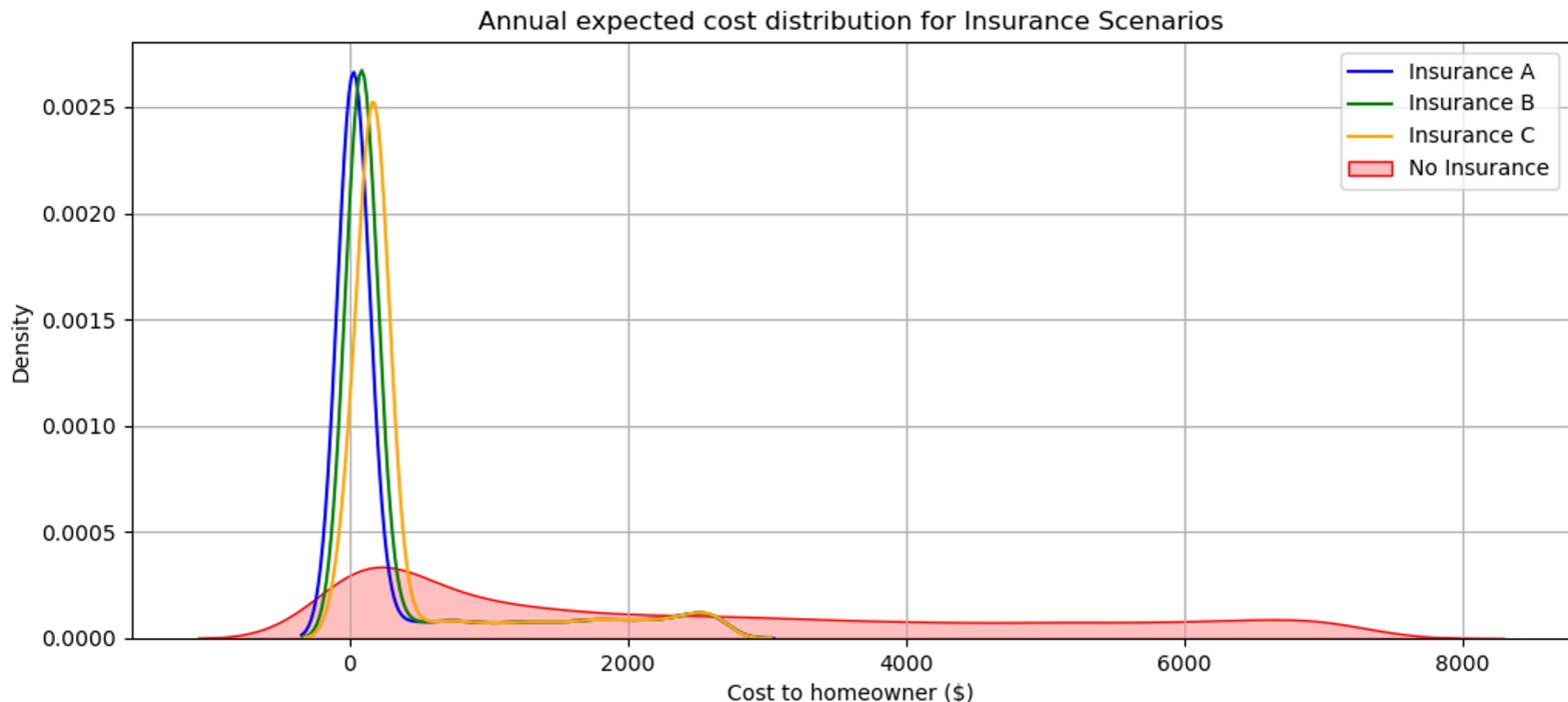


FEMA Floodmap

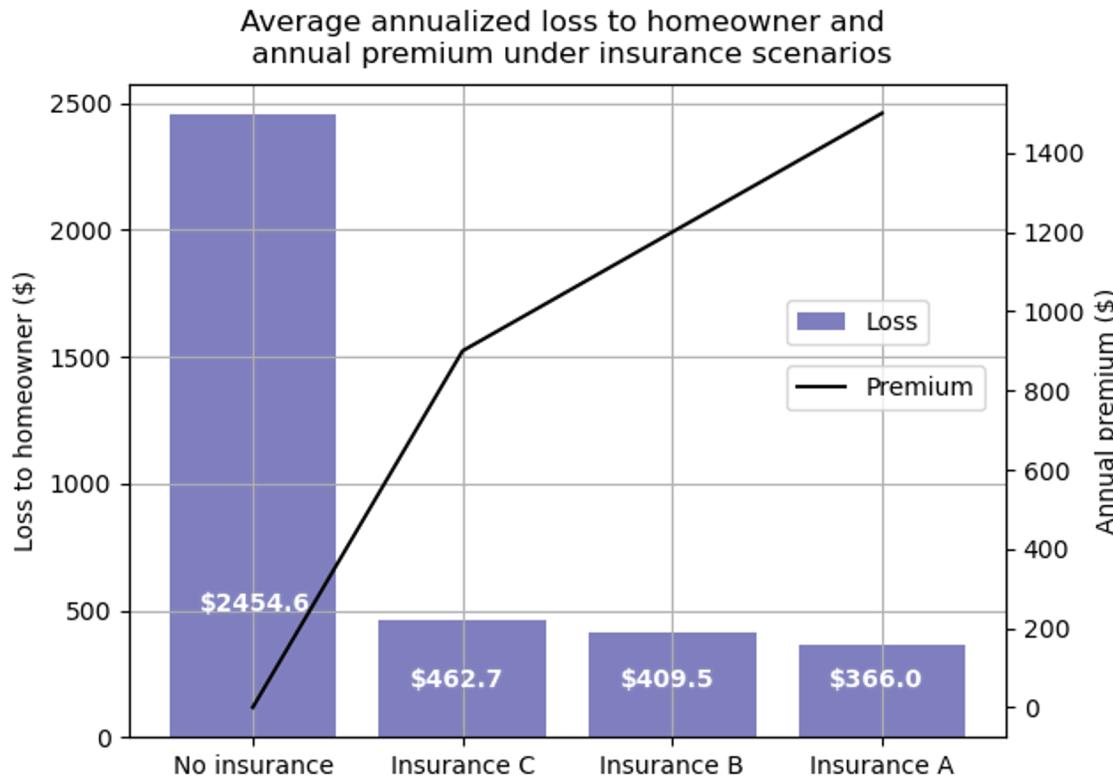
100-yr Flow Simulation



Distribution of annualized cost to homeowner



Average annualized cost to homeowner



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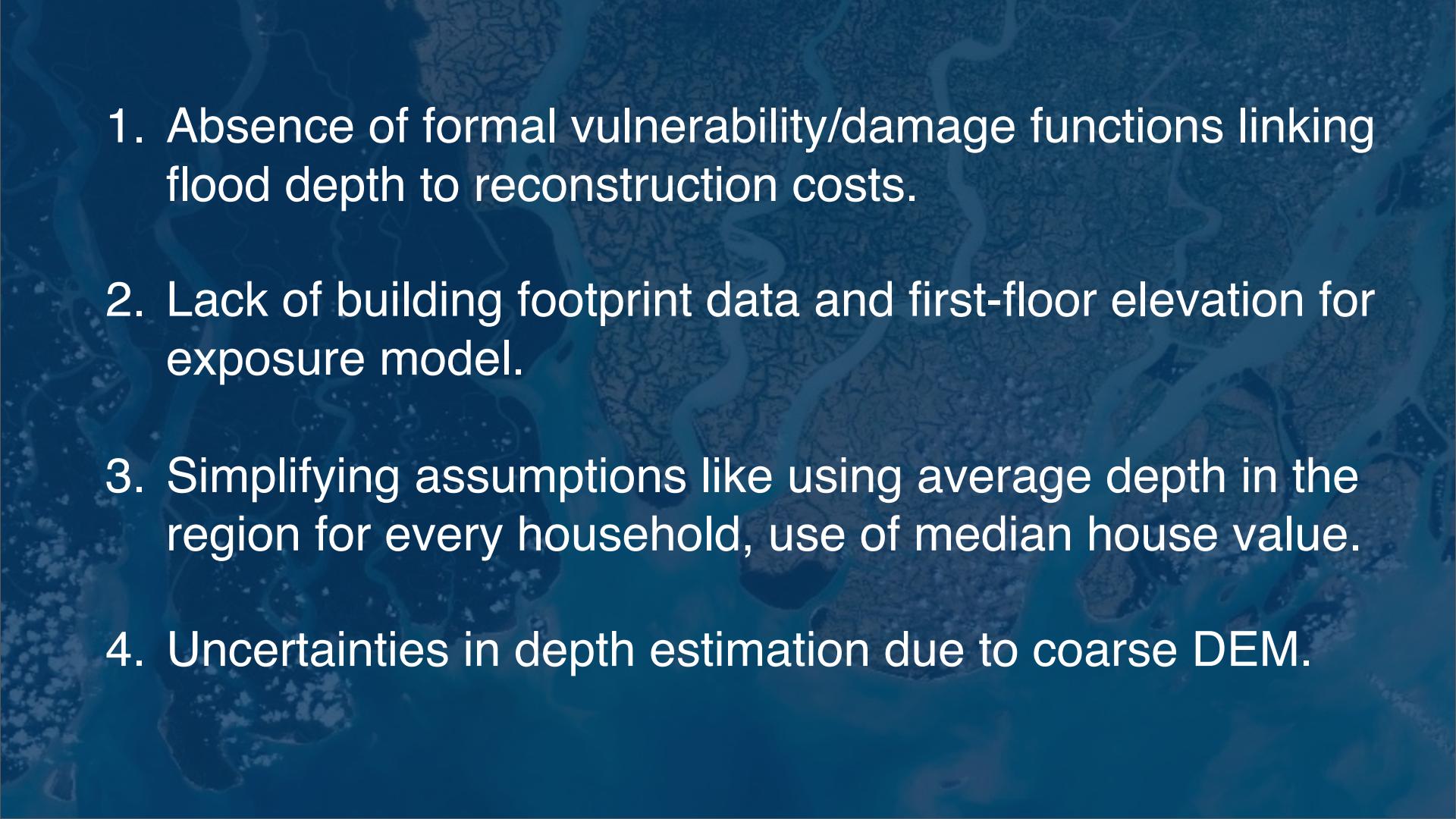
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1. Absence of formal vulnerability/damage functions linking flood depth to reconstruction costs.
 2. Lack of building footprint data and first-floor elevation for exposure model.
 3. Simplifying assumptions like using average depth in the region for every household, use of median house value.
 4. Uncertainties in depth estimation due to coarse DEM.

Acknowledgements

1. **Dr. Sarah Fletcher**, *Assistant Professor – Department of Civil and Environmental Engineering, Stanford University*: For teaching Stochastic Hydrology (Synthetic Streamflow and Hydrologic Extreme Analysis) and offering project mentorship and feedback.
2. **Dr. Jack Baker**, *Associate Dean – Faculty Affairs and Professor – Department of Civil and Environmental Engineering, Stanford University*: For providing damage ratio data and teaching Probabilistic Models in CEE (Monte Carlo Simulation).

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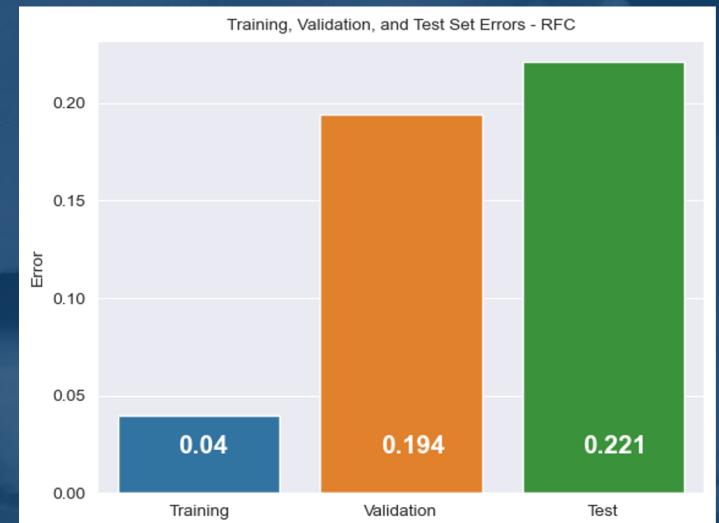
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ML model for fast flood model error prediction.

Objective: To predict errors of fast flood model given domain characteristics and use predicted error for model correction and improving accuracy.

Built a tree-ensemble model for predicting fast flood model errors for generalizing error analysis across multiple domains and topographies with 80% test set accuracy.

Predictor variables: Inland Distance, Elevation, Distance from nearest water body, Fast Flood Model Depth, and Water Level Forcing.

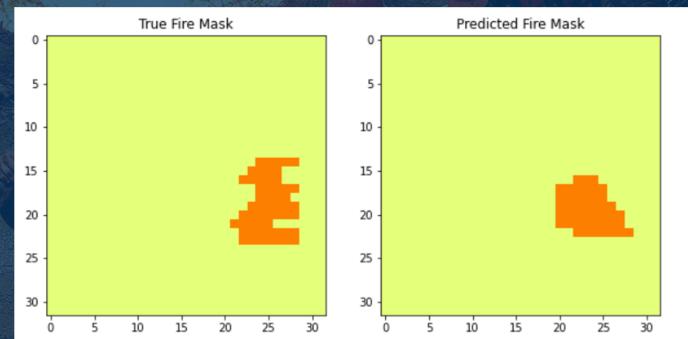
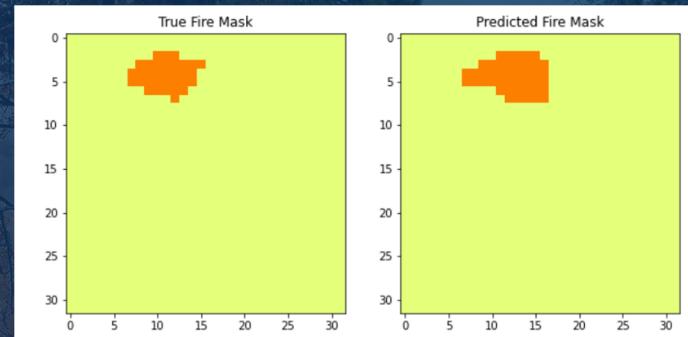


DL model for predicting next day wildfire spread

Objective: To predict next day wildfire mask given previous day fire mask and meteorological / physical features from satellite data.

Built a U-Net like CNN model with a contraction and expansion path for image segmentation into fire/no-fire regions.

Input features: Elevation, Wind Direction, Wind Velocity, Min/Max Temp, Humidity, ERC, Precip, Drought Index, Population Density, Vegetation, Previous Fire Mask



THANK YOU
Questions?