Tsunami Fragility estimates for damage quantification

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Traditional vulnerability estimates: Tsunami Fragility Functions (TFF)

- Adapted from seismic hazard analysis conventions
- Quantitative vulnerability models
- Link hazard (demand parameter) to risk (damage exceedance)
- Asset-type specific

Definitions:

Koshimura et al. 2009 Reese et al. 2011

[TFF are] measures for estimating structural damage […] to tsunami attack. [They] are expressed as the damage probability of structures with regard to the hydrodynamic features of inundation.

[TFF] give the probability of being *in or exceeding* a specific damage state (*DS*) as a function of the demand imparted to the structure by the hazard.

Brief history of TFFs

- Koshimura et al. 2009 introduce fragility functions for tsunamis
- Reese et al. 2011: multi-class TFF using GLM
- Mas et al. 2012: TFFs in areas with low data availability
- Suppasri et al. 2013: TFF for Japan, following the 2011 Great East Japan Earthquake
- De Risi et al. 2017: TFFs accounting for input uncertainty

Use-cases and limitations of TFF

- Use cases:
	- Academic discussion
	- Proposed implementation in PTRA
- Limitations:
	- Not transferrable
	- Demand parameters usually proxies for direct loads
		- \circ inundation height \rightarrow Hydrodynamic force
	- Aggregated measure
- TFF Applications for disaggregated estimates:
	- a) Adriano et al. 2014 (No ground truth)
	- b) Rehman & Cho 2016 (No ground truth)
	- c) Moya et al. 2018 (Earthquake damage)

Fig. 8. Left: An instance of a synthetic EBDS. Right: The actual EBDS from field survey.

Tsunami Fragility Functions in context

- Push for standard integrated PTHA \rightarrow PTRA workflow (AGHITAR, GTM)
- Guidelines for policy & insurance

[1] AGHITAR: **A**ccelerating **G**lobal science In **T**sunami **HA**zard and **R**isk analysis [2] GTM: **G**lobal **T**sunami **M**odel

4

Risk-informed

Decision Making

Figure courtesy of: J. Behrens et al., "Probabilistic Tsunami Hazard and Risk Analysis: A Review of Research Gaps," *Frontiers in Earth Science*, vol. 9, 2021.

Damage-to-loss

5

Disaggregated damage estimates require:

- disaggregated inputs \overline{M}
- disaggregated model □

Figure courtesy of GEM OpenQuake:

https://docs.openquake.org/vulnerability/vulnerability/vulnerabi lity_dam2loss_computing_vul.html

Adaptability and uncertainty

6

• Why are TFF **not applicable** to other areas?

- Demand parameter \rightarrow result of inundation model parameters
- Different areas \rightarrow different model parameters
- Different areas \rightarrow different structural response

• **Solutions:**

- Account for input uncertainty around model parameters and structural response
- Add parametric proxies for influencing factors [bld material, bld density, coastal distance, elevation, etc…]

Experiments 7

Random forests for fragility estimates

Param1 : Param2 :

 $Bld 1$ Bld 2 Bld 3 $1 - 1$ Bld n $- - - - -$

DS₁

! Geom

 \cdots

- \rightarrow Control for effect of latent processes
	- Directly relate physical parameters to building damage

Machine learning classification

- \rightarrow Learn disaggregated damage estimation
- \rightarrow Direct spatial output

Experimental results 9

B: Moya et al. Method C: RF Method (**Ours**)

D: Ground truth

- Tested direct TFF application methods (slide 7)
- Compare to our proposed RF method

Discussion & limitations

10

 0.02

0.82

- Results:
	- Damage learned from physical parameterization of tsunami and environment
	- Direct fragility estimates for individual buildings
- Limitations:
	- Performance scales with number of classes (more classes \rightarrow lower performance)
	- Does not account for inherent class ordering
	- Learns unexpected spatial response

Probabilistic approach – overview

Bayesian decision making toolbox:

- 1. Allows us to include more features (than TFF)
- 2. provides optimization routines, e.g. HMC, VI, etc…
- 3. Places distribution over parameters \rightarrow input uncertainty
- 4. Propagates uncertainty to the posterior distribution \rightarrow output uncertainty

HMC: Hamiltonian Monte Carlo, VI: Variational Inference

Probabilistic approach - results 12

- Generally improved results
- Relative low inundation \rightarrow Greater uncertainty(DS2)
- Hypothesis: earthquake effects are more relevant at lower inundation levels

Discussion & Limitations - cont. 13

Noto

 $1e3$

 3.5

 3.0

2.5

Edge

2.0

Edge

1.5

 1.0

 0.5

 0.0

 2.0

Pedency
Fedency
1.0

 0.5

 $0.0 -2$

 2.5^{1e2}

 $\mathbf 0$

Inundation

 Ω

Inundation

Inland misclassification correlates with "**pancake collapse** "

In areas of low inundation height, the model has high confidence but has no notion of EQ effects.

Discussion & Limitations

15

Advantages over previous methods:

- Increased performance
- Spatially consistent (learning better, more interesting trends)
- Appears to generalize **in-distribution**

Limitations:

- Out-of-distribution (Noto case) performance much lower on destroyed class:
	- 1. Hypothesis: significantly greater influence of EQ impacts
	- 2. Parameter definition require knowledge of domain (not naïve like random forest)

Takeaway message:

- 1. We developed a probabilistic method for building fragility estimation
- 2. Our method performs in-distribution (not necessarily in-domain)
- 3. Measuring the predictive uncertainty, allows:
	- Identify patterns that are not captured by the parameters (e.g. EQ impacts)
	- Inform decision makers about potential extra risk
- 4. Fits into the PTHA + PTRA framework \rightarrow disaggregated estimates