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Causality-Informed Bayesian Inference for Rapid Seismic Ground Failure and Building Damage Estimation

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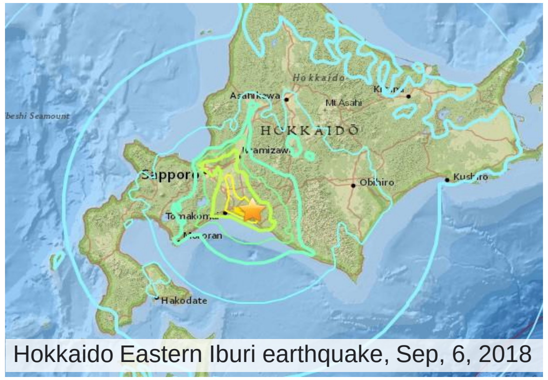
Cascading Seismic Hazards and Impacts

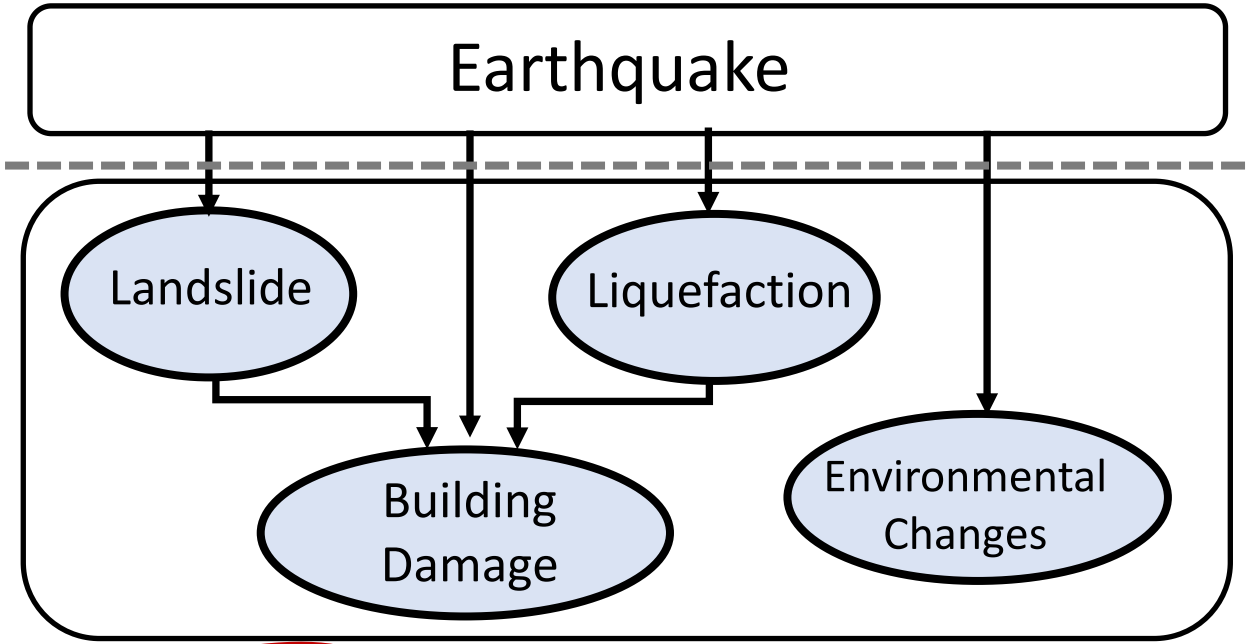
Moderate-to-large earthquakes are often followed by a series of ground failures and subsequent impacts, such as landslides, liquefaction, and building damage.

Cascading Seismic Hazards and Impacts


Hokkaido Eastern Iburi earthquake, Sep, 6, 2018

Primary Hazard

Intermediate Hazards and Impacts (Unobserved)



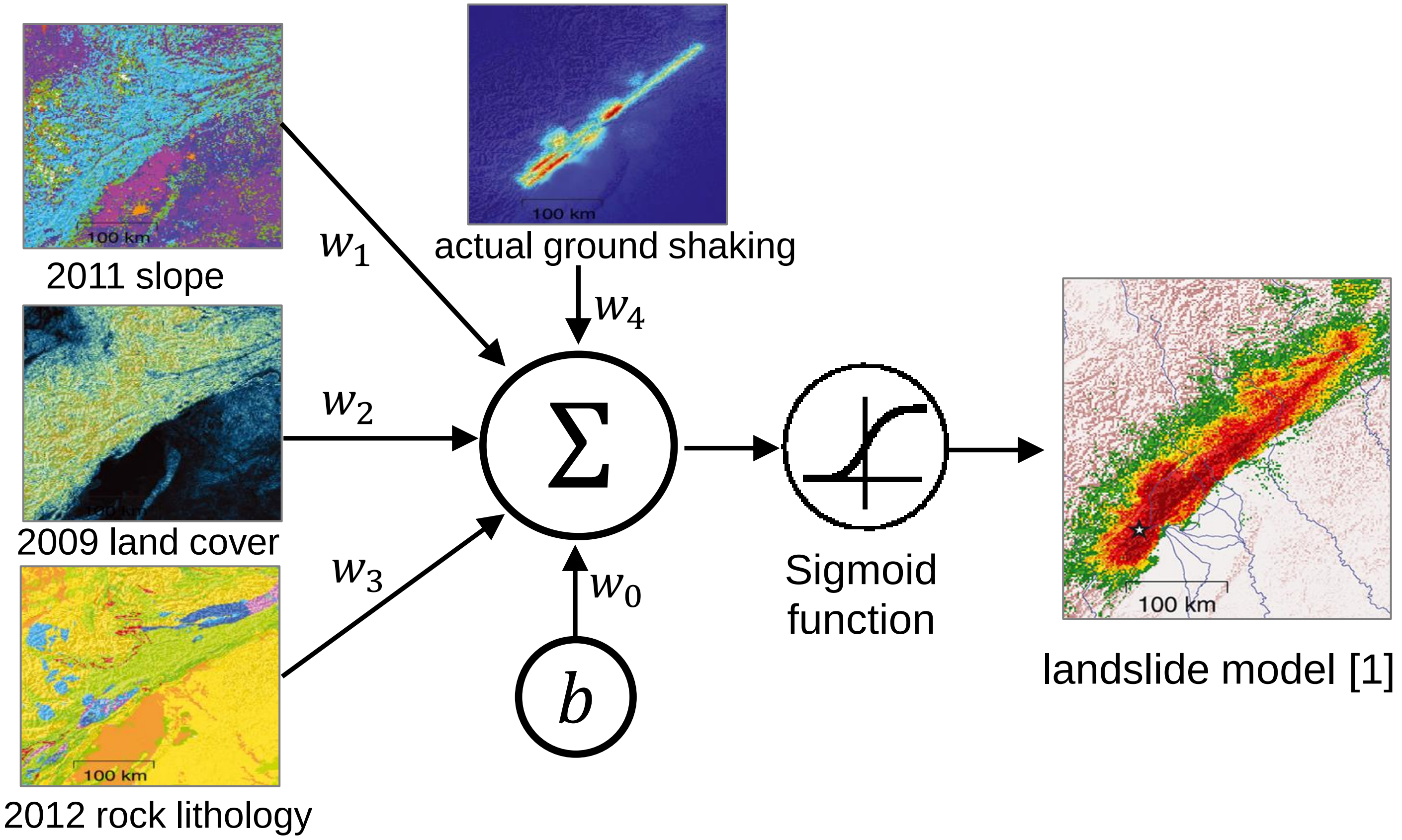
Existing Hazards and Impact Models

Most existing models focus on single type of hazard or impact

- Traditional statistical model
  - ✓ Incorporating physical features
  - ✓ Easy to implement
  - ✓ Global (event-sharing) patterns

  - ? Outdated and low-reso features
  - ? Ignoring event-specific patterns
  - ? Ignoring the interdependencies among hazards

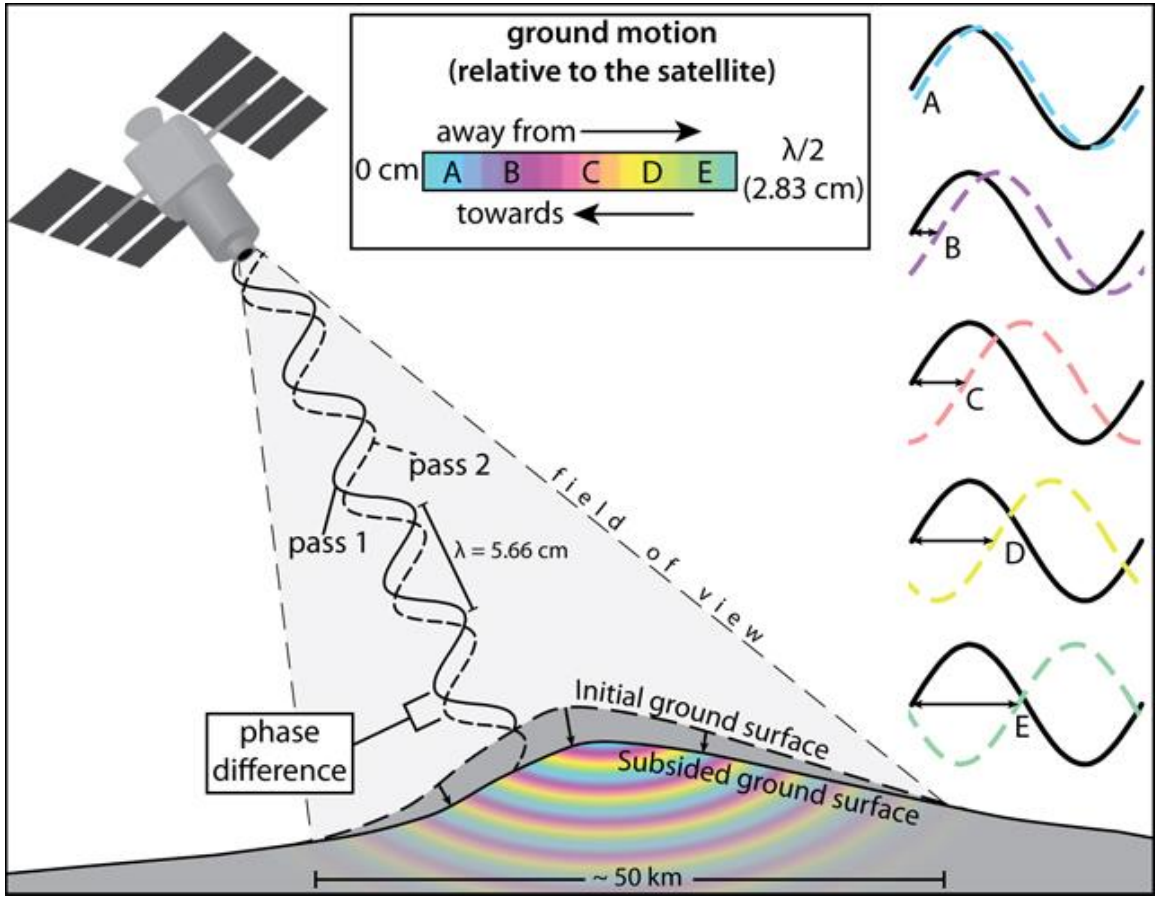
  → constrained accuracy



[1] Nowicki Jessee, M. A., Hamburger, M. W., Allstadt, K., Wald, D. J., Robeson, S. M., Tanyas, H., ... & Thompson, E. M. (2018). A global empirical model for near-real-time assessment of seismically induced landslides. *Journal of Geophysical Research: Earth Surface*, *123*(8), 1835-1859.

Existing Hazards and Impact Models

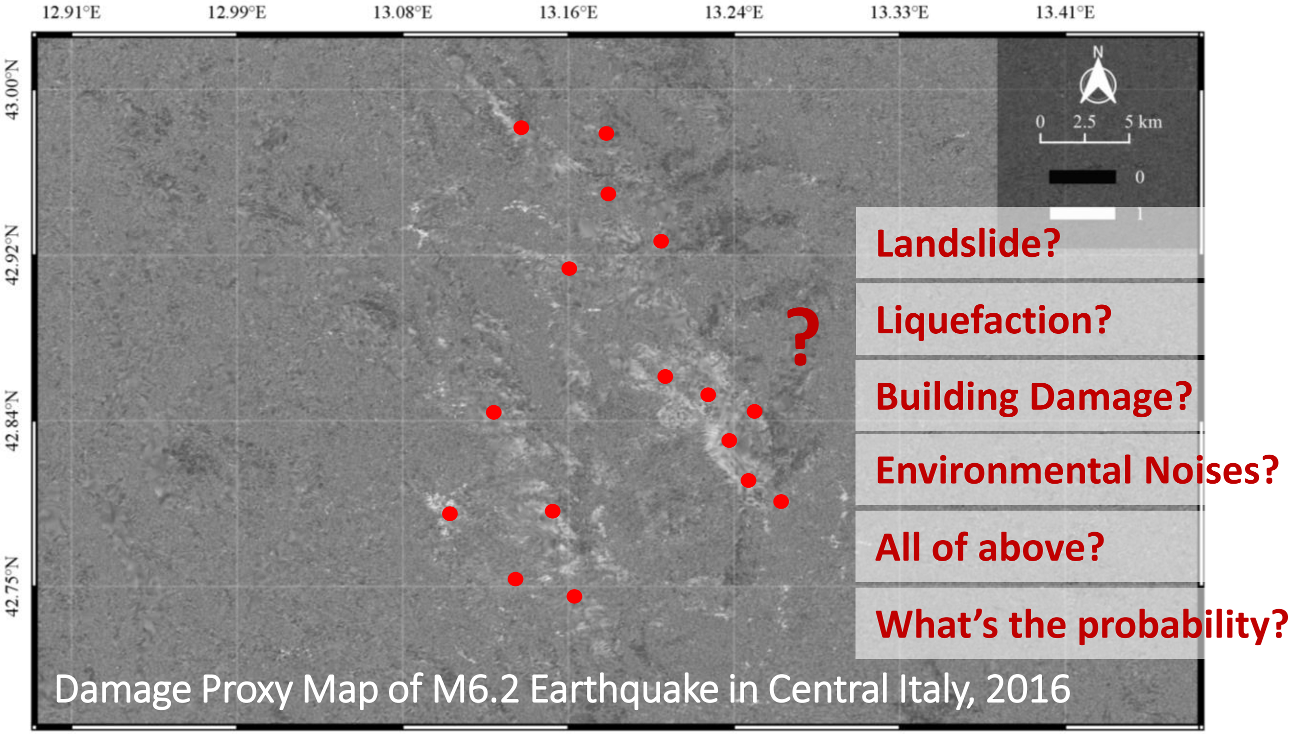
Remote sensing brings high-resolution and location-specific information



- e.g., Damage Proxy Maps based on InSAR images estimate changes of temporal coherence of satellite images before and after earthquake to indicate the ground surface changes.

Existing Hazards and Impact Models

Remote sensing brings high-resolution and location-specific information

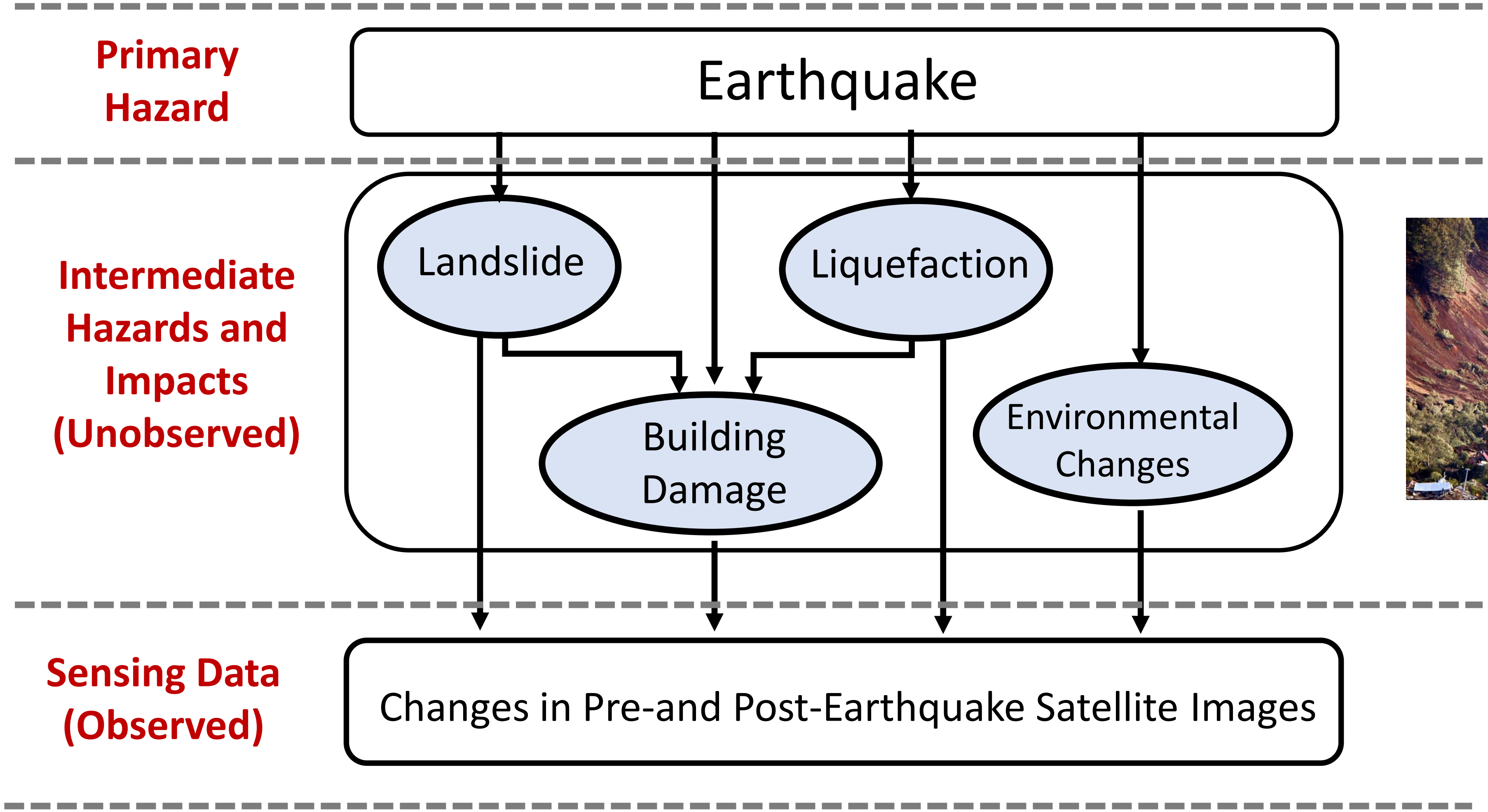


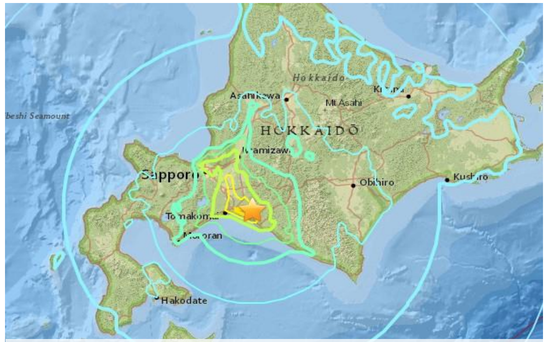
Damage Proxy Map of M6.2 Earthquake in Central Italy, 2016

- e.g., Damage Proxy Maps based on InSAR images estimate changes of temporal coherence of satellite images before and after earthquake to indicate the ground surface changes.

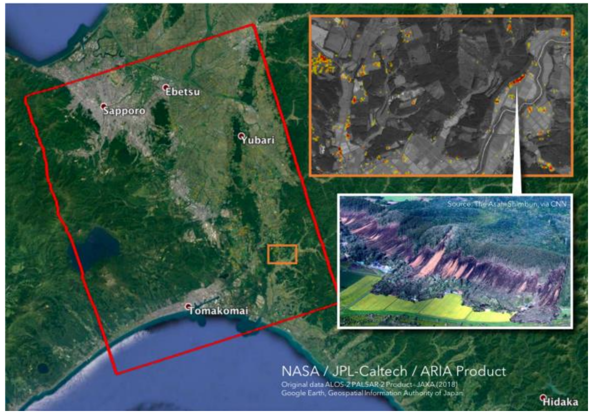
✓ High-resolution information
✓ Event-specific up-to-date field information
? Mixed signals of multiple hazards and impacts
? High environmental noises

Cascading Seismic Hazards and Impacts





Hokkaido Eastern Iburi earthquake, Sep, 6, 2018

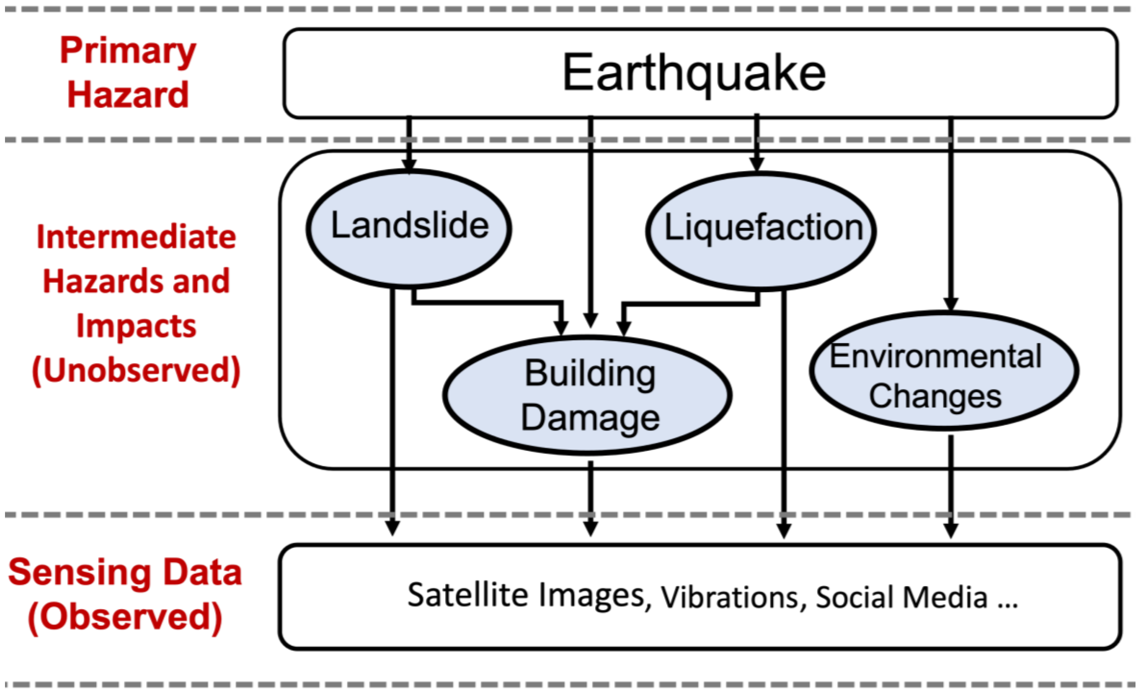


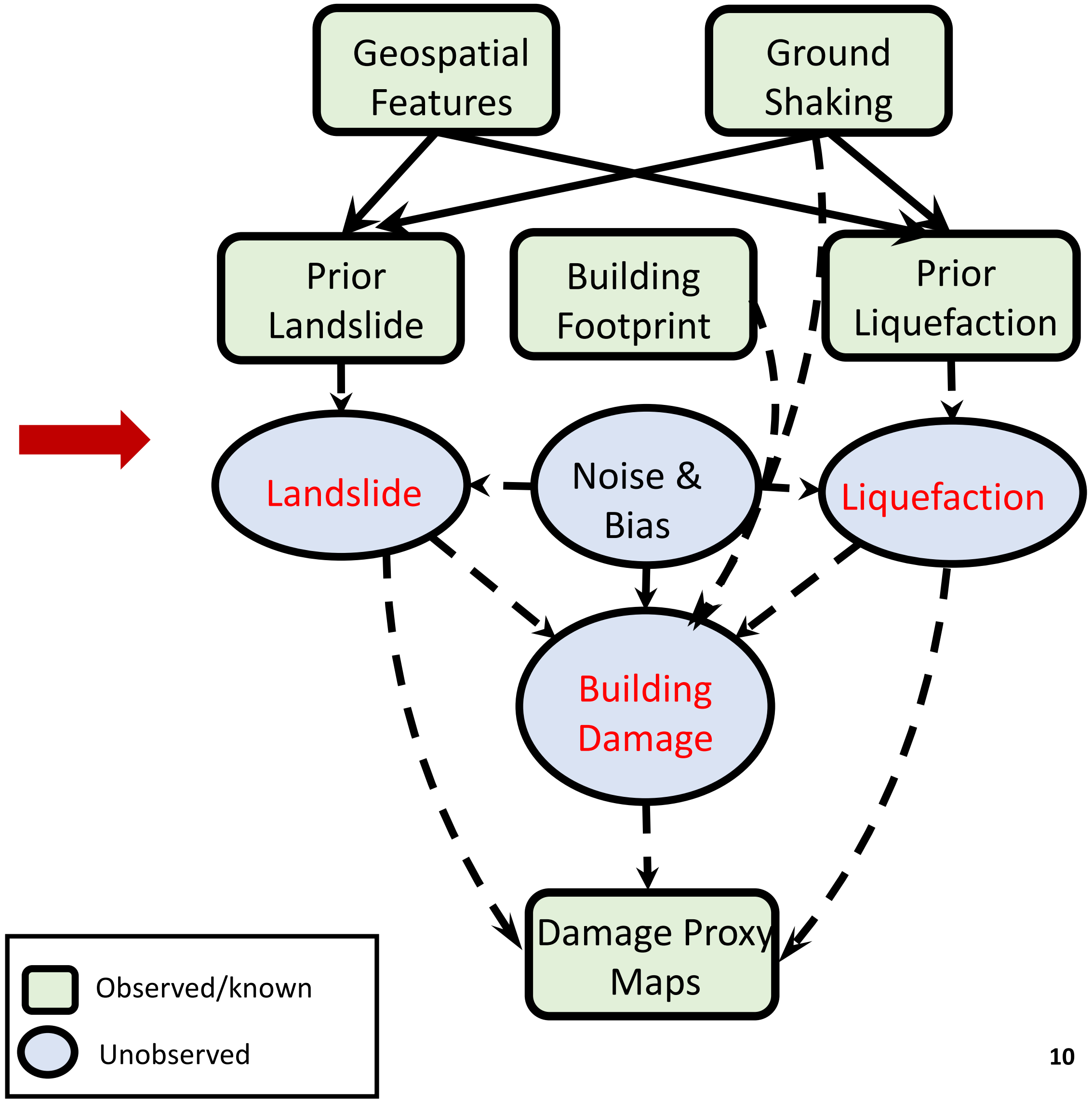
Research Objective

To effectively fuse prior geospatial models with remote sensing data for rapid and accurate **joint estimations** of **multi-hazard** and **building damage**.

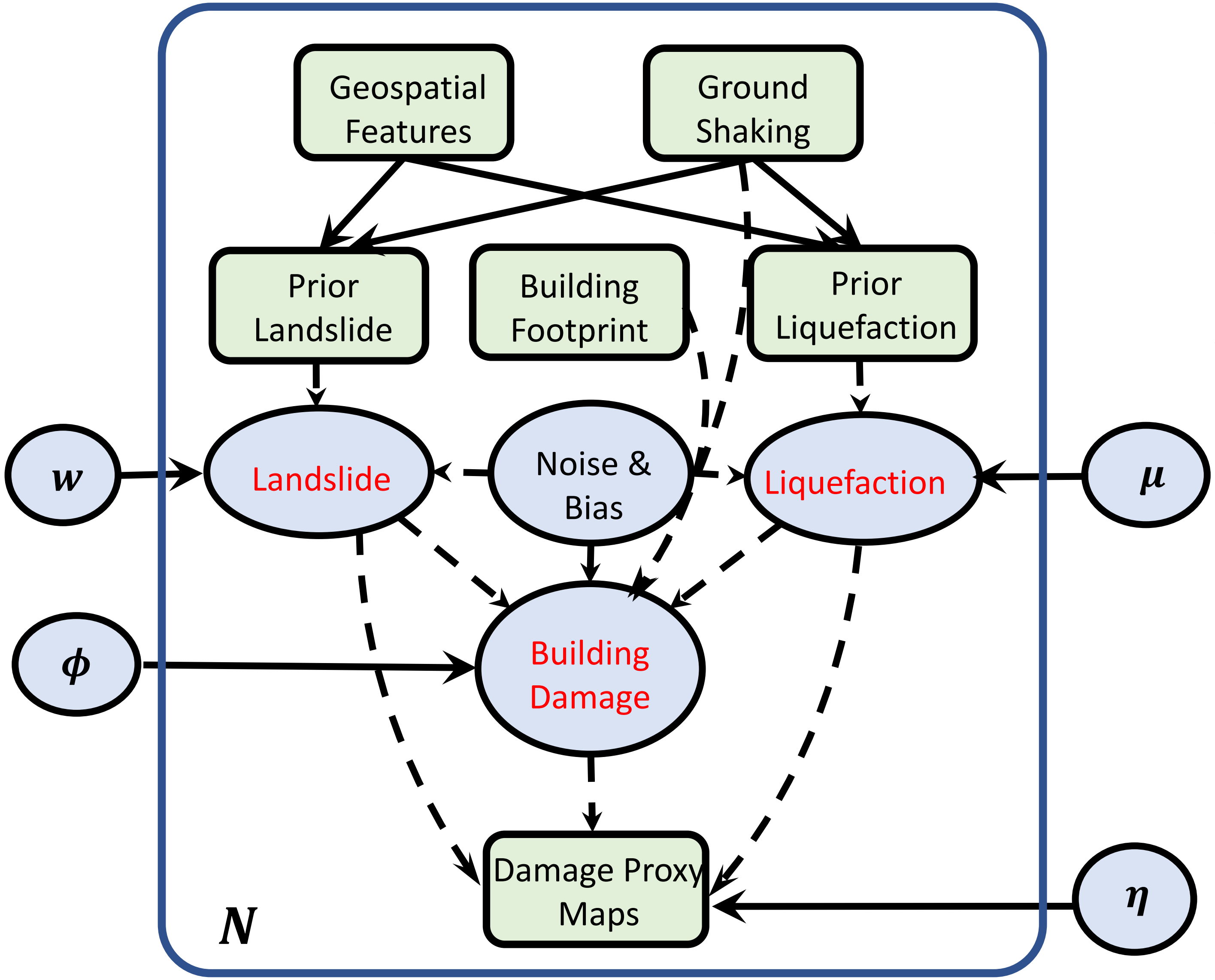
Causal graphical model to approximate complex interactions

- Conceptual interactions

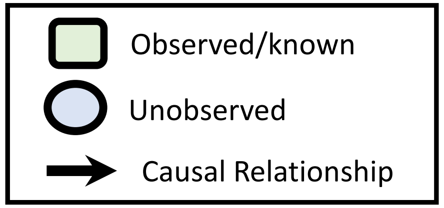




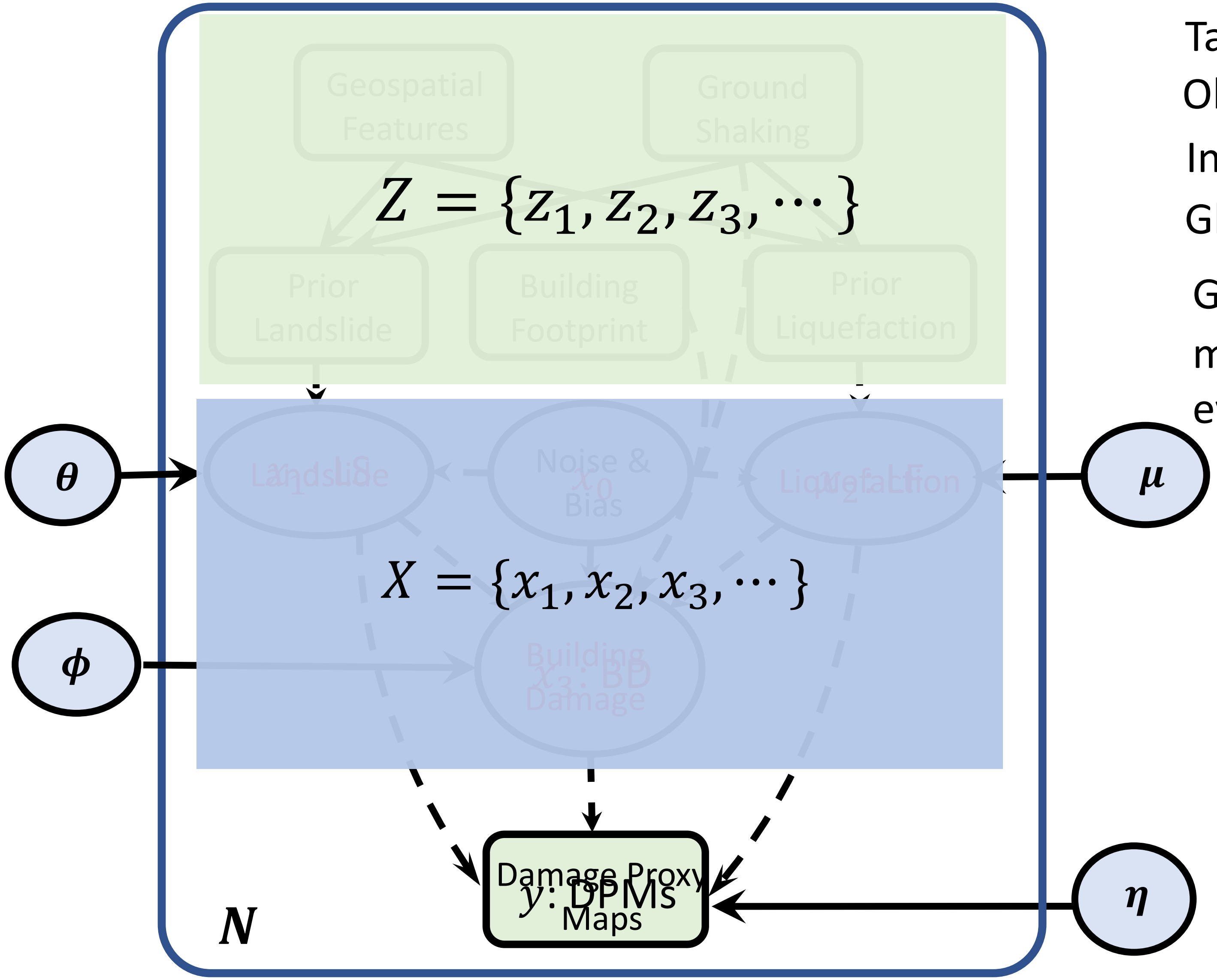
Causal graphical model to approximate complex interactions



- ✓ Flexible, interpretable, and structured representations – easy to add or delete nodes
- ✓ Better approximate the complex distribution transformation
- ✓ Fuse prior models with information from sensing observations through causal dependencies



Inference over Multi-layer Causal Bayesian Networks



Target Variables: $X = \{x_1, x_2, x_3, \cdots\}$

Observed Variables: Y

Input prior knowledge: Z

Global parameters: $W = \{\theta, \mu, \phi, \eta\}$

Goal: infer posterior probability of unobserved multi-hazards and impacts: $P(x_i^l = 1|Y, Z)$ for every location $l \in \{1, \cdots, N\}$

- ? Multi-layer unobserved variables
- ? Unknown parameters for unobserved variables
- ? Scalability to large regions
- ? No inventory is available

Inference over Multi-layer Causal Bayesian Networks

Goal: Given sensing observations Y and geospatial information Z, infer the probability of unobserved multi-hazards and impacts: $P(x_i^l = 1|y^l)$ for every location l

Potential solutions

Variational inference: Approximate the posterior $P(x_i^l = 1|y^l)$ with a family of distribution $\mathrm{q}(x_i^l = 1)$ by optimizing the marginal likelihood of observations $P(Y)$

Monte Carlo Markov Chain: Approximate $P(x_i^l = 1|y^l)$ by applying a stochastic transition operator to iteratively sample from the posterior.

(sampling process hardly converges in large networks with multiple unobserved variables)

Variational Inference over Multi-layer Causal Bayesian Networks

Goal: Given sensing observations Y and geospatial information Z, infer the probability of unobserved multi-hazards and impacts: $P(x_i^l = 1|y^l)$ for every location l

The main idea behind variational Bayes:

- Initialize the posterior estimations as Bernoulli distributions over the unobserved variables with set of variational parameters, $q(x_i^l = 1)$

- Then, we find the setting of the global parameters that makes our approximation closest to the posterior distribution.
  - This is where optimization algorithms come in.

- Then we can use with the fitted parameters in place of the posterior.
  - E.g. to investigate the posterior distribution over the hidden variables, to form predictions about future data, or find modes, etc.

Inference over Multi-layer Causal Bayesian Networks

The Evidence Lower Bound: A tight lower bound for marginal log likelihood of observed variables

$$\sum_{l\in\{1,\cdots,N\}} \log P\left(y^l\right) = \sum_{l\in\{1,\cdots,N\}} \log \int_{X^l} p\left(X^l, y^l\right)\frac{q(X^l)}{q(X^l)} = \sum_{l\in\{1,\cdots,N\}} \log \left(\mathbb{E}_q \left[\frac{p\left(X^l, y^l\right)}{q(X^l)}\right]\right)$$

$$\geq \underbrace{\sum_{l\in\{1,\cdots,N\}} \mathbb{E}_q \log p\left(X^l, y^l\right) - \mathbb{E}_q \log q\left(X^l\right)}_{\text{The Evidence Lower Bound (ELBO)}}$$

Maximizing this ELBO to maximize the log-likelihood

$$\log p(Y) = KL(q(X)||p(X|Y)) + ELBO$$

Maximizing this ELBO is equivalent to minimize the distance between $q(X)$ and true posterior distribution

Inference over Multi-layer Causal Bayesian Networks

Our objective function for maximization : ELBO in our multi-layer causal Bayesian network

$$
\begin{aligned}
\mathscr{L}(\mathbf{q},\mathbf{w}) = \sum_{l\in\mathbf{L}} \Bigg\{ & -\log y^l - \log w_{\varepsilon_y} - \frac{(\log y^l)^2 + w_{0y}^2 + \sum_{k\in\mathbf{P}(y^l)} w_{ky}^2 q_k^l}{2w_{\varepsilon_y}^2} \\
& - \frac{\sum_{\substack{i,j\in\mathbf{P}(y^l)\\ i\neq j}} w_{iy} w_{jy} q_i^l q_j^l - w_{0y}\log y^l - (\log y^l)(\sum_{k\in\mathbf{P}(y)} w_{ky} q_k^l) + w_{0y}\sum_{k\in\mathbf{P}(y^l)} w_{ky} q_k^l}{w_{\varepsilon_y}^2} \\
& - \sum_{\substack{v_i,v_j\in\{0,1\}\\ i\in\{LS,LF,BD\}\\ j\in\mathbf{P}(i)}} \log\{1+\exp[(-1)^{v_i}\cdot(w_{0i} + \sum_{j\in\mathbf{P}(i)} I(j,\alpha_i) w_{ji}) + \frac{w_{\varepsilon_i}^2}{2}]\} \prod_{k\in\{i,j\}} (q_k^l)^{v_k}(1-q_k^l)^{1-v_k} \\
& - \sum_{i\in\{LS,LF,BD\}} [q_i^l \log q_i^l + (1-q_i^l)\log(1-q_i^l)] - \frac{\prod_{i\in\mathbf{P}(u^l)} q_i^l}{2\sigma^2} \Bigg\},
\end{aligned}
$$

Maximizing this ELBO by
optimizing (1) posterior approximation q(X) and (2) the global weight parameters W

Stochastic Variational Inference Algorithm Design

Classical VI is inefficient: Need to crunch through the full dataset to update variational parameters

Can’t handle massive data

1. Local pruning → remove inactive nodes for some locations
2. Stochastic variational inference → update the model with mini-batched data
3. L-1 regularization to global causal coefficients→ constrain the information from prior model or from DPMs

Algorithms for Joint Inference of Posterior and Causal Coefficients

Causal dependency assumption

- DPM vs Damage (LS, LF, BD): log-linear; Between Damage (LS, LF, BD): logit-linear

Expectation-Maximization for optimizing the ELBO

- In each iteration, we first randomly sample a mini-batch of locations from the given map.
- Construct local model through local pruning strategy.
- In the expectation step, update the posterior estimates.

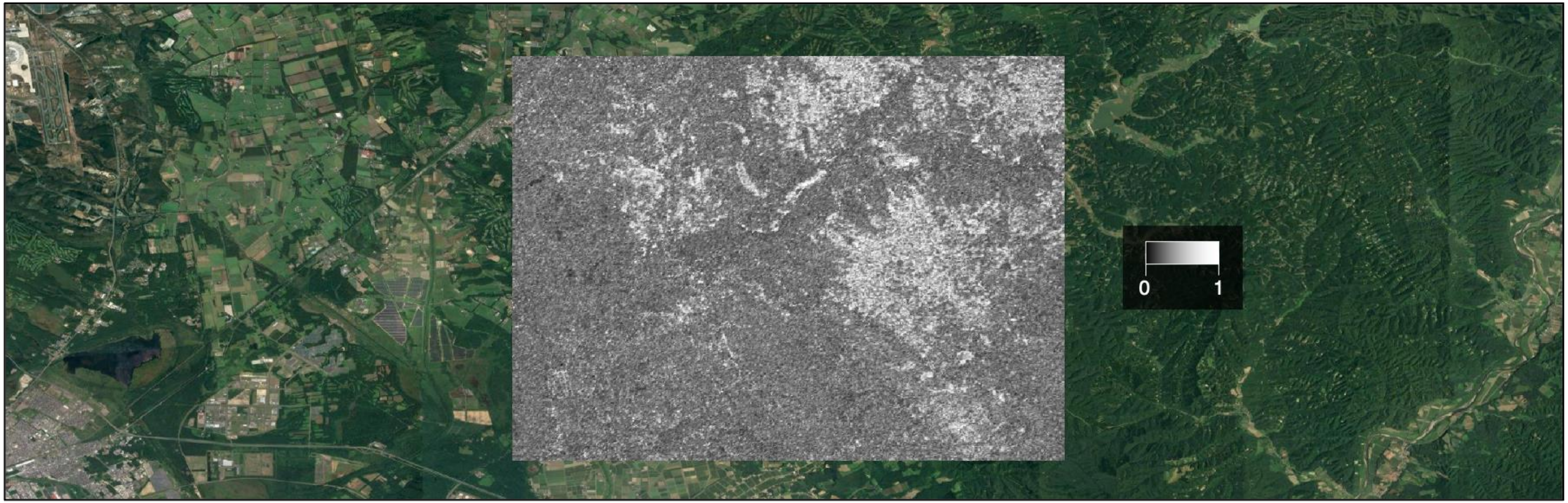
$$q_i^l = \frac{1}{1+\exp(-T(q^l_{\mathbf{P}(i)}, q_{\mathscr{S}(i^l,\mathscr{C}(i^l))}, q_{\mathscr{C}(i^l)}, y^l, u^l))}$$

- In the maximization step, we conducted stochastic gradient updates to estimate the optimal weights using a mini-batch of data randomly sampled from different locations.

$$w^{(t+1)} = w^{(t)} + \rho \mathscr{A} \nabla \mathscr{L}^{(t)}(w)$$

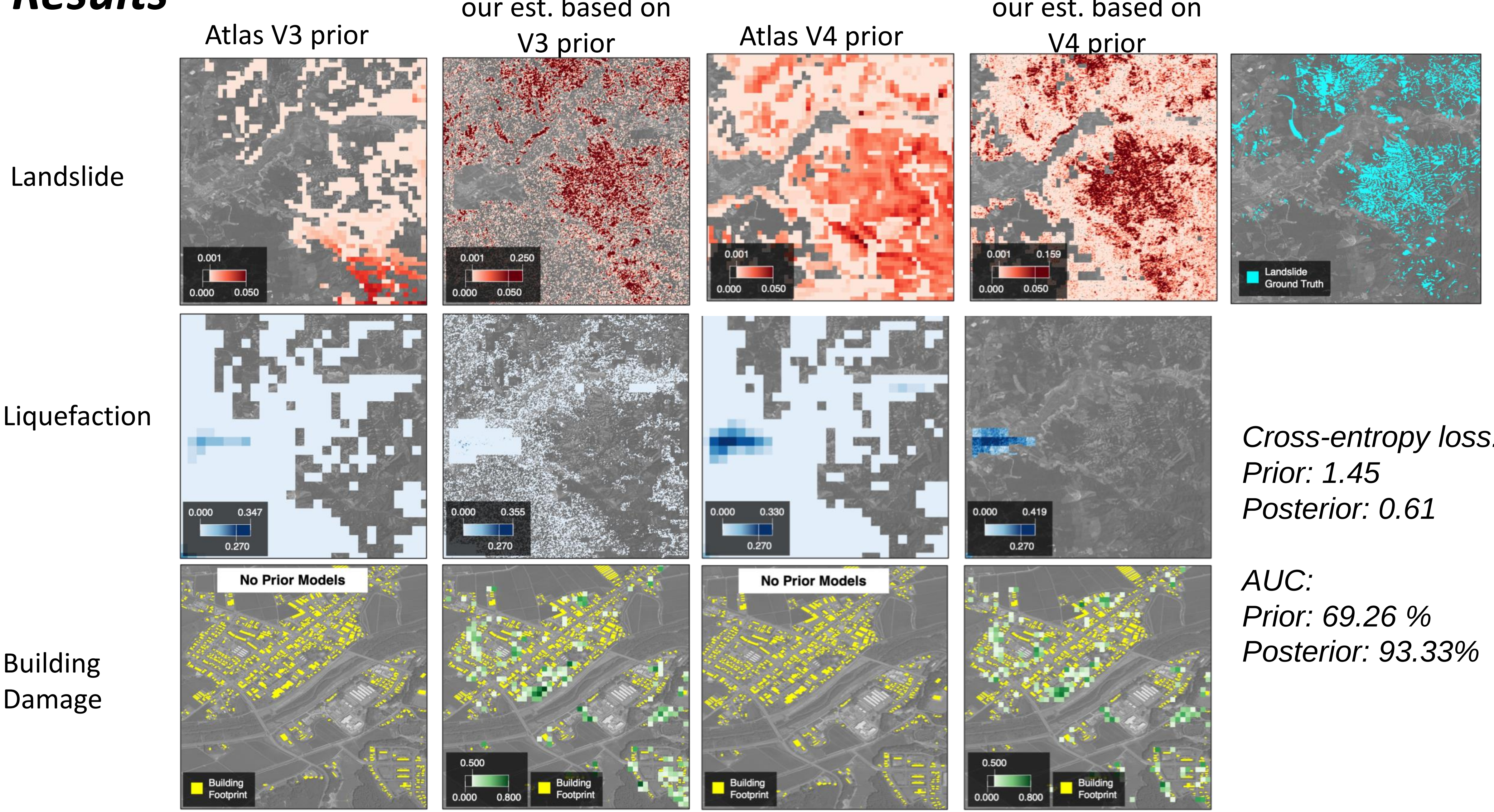
Results

The 2018 Hokkaido, Japan Earthquake occurred on September 6, 2018, at 3:08 am (JST)



DPM3: 30m resolution, covered the towns of Atsuma and Abira, generated by ARIA team using the SAR images from the ALOS-2 satellites of the Japan Aerospace Exploration Agency

Results



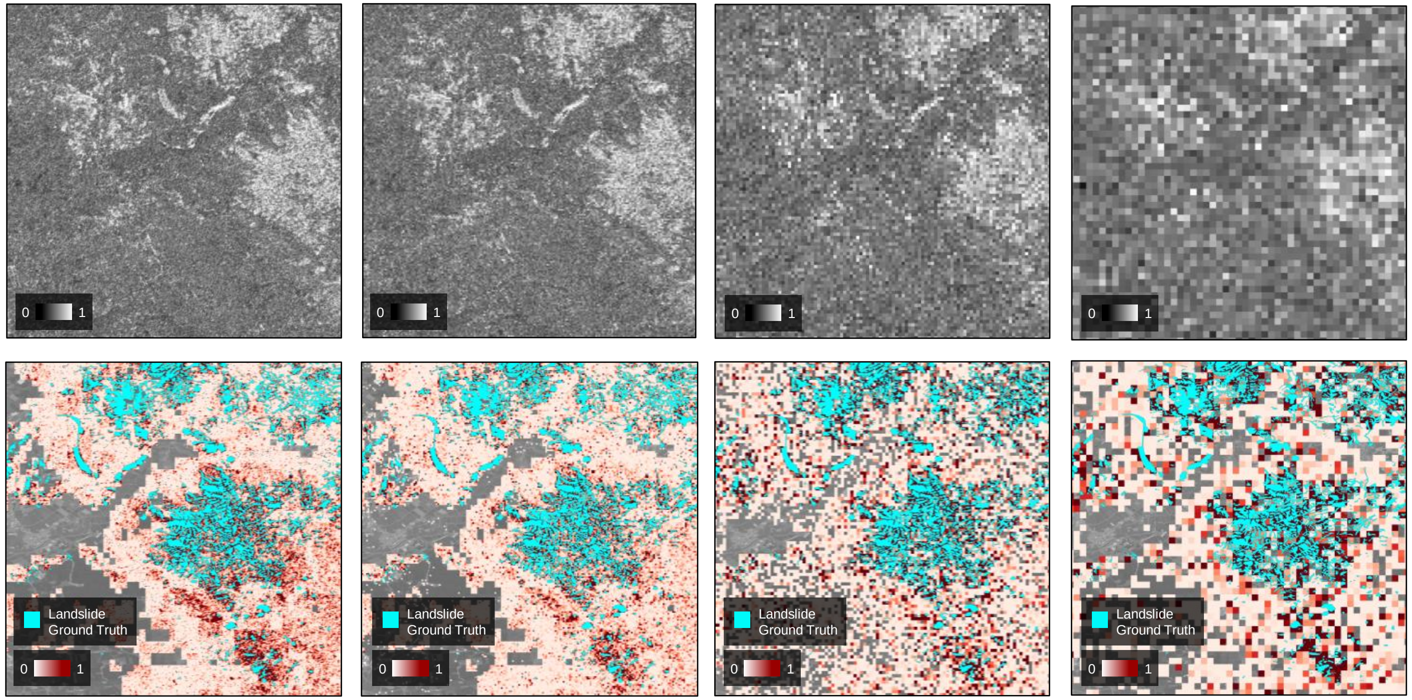
Cross-entropy loss:
Prior: 1.45
Posterior: 0.61

AUC:
Prior: 69.26 %
Posterior: 93.33%

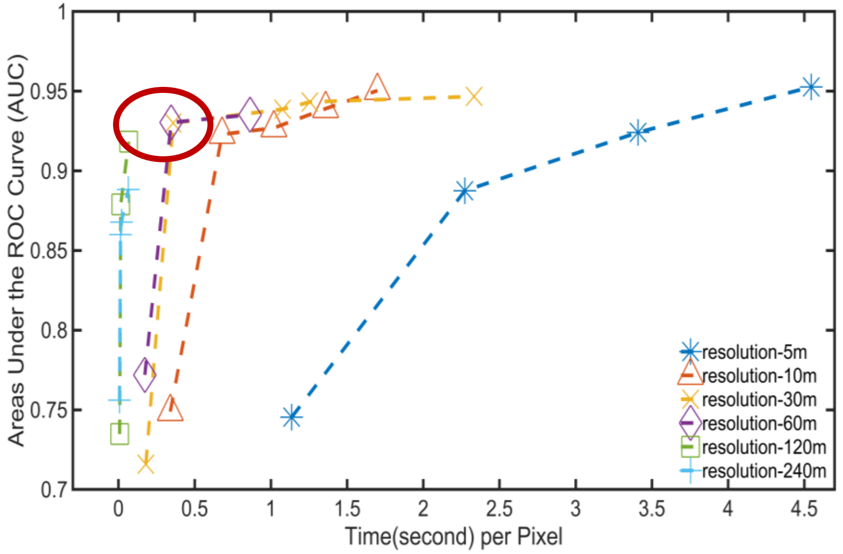
Results

The 2018 Hokkaido, Japan Earthquake occurred on September 6, 2018, at 3:08 am (JST)

	Resolution 30m	Resolution 60m	Resolution 120m	Resolution 240m
DPM				
Landslide				

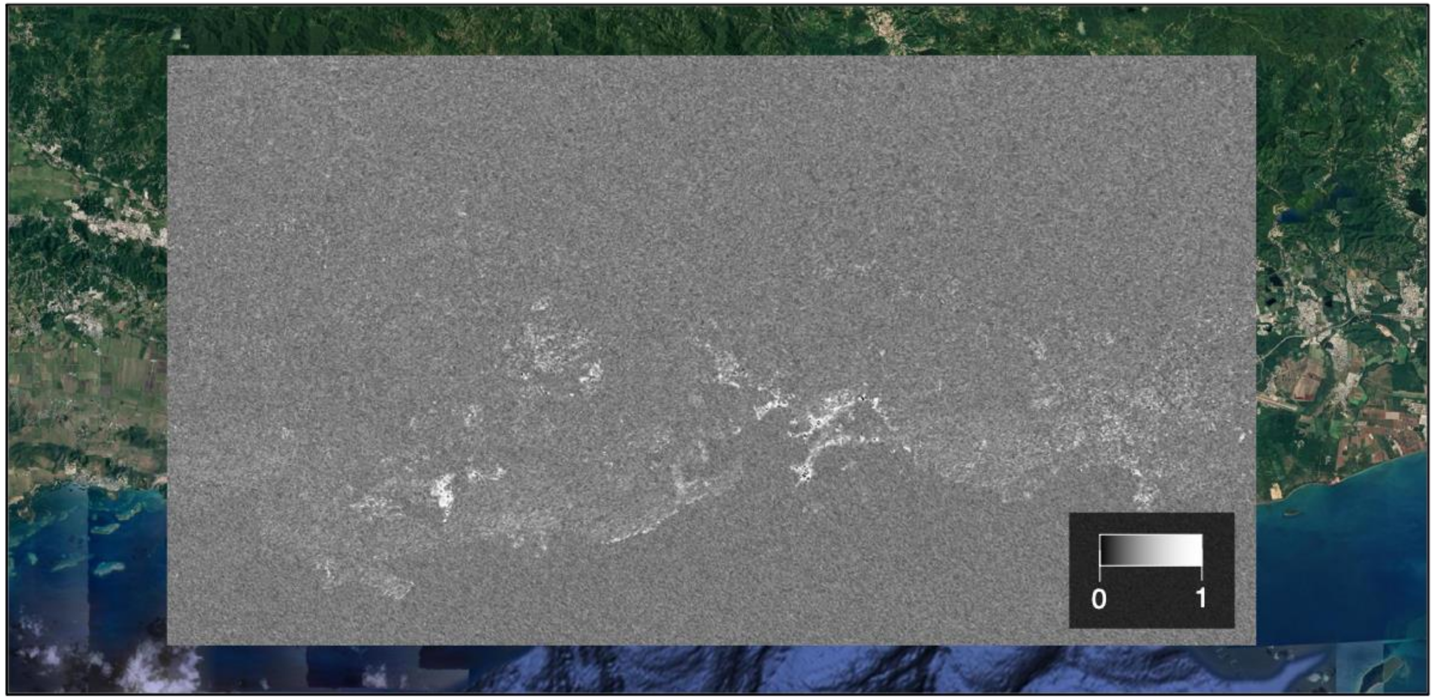


Posterior AUC	93.33%	93.04%	91.84%	88.83%



Prior AUC: 69.26 %

Results



DPM2: 30m resolution, covered the towns of Atsuma and Abira, generated by ARIA team using the SAR images from the Copernicus Sentinel-1 satellites of the European Space Agency

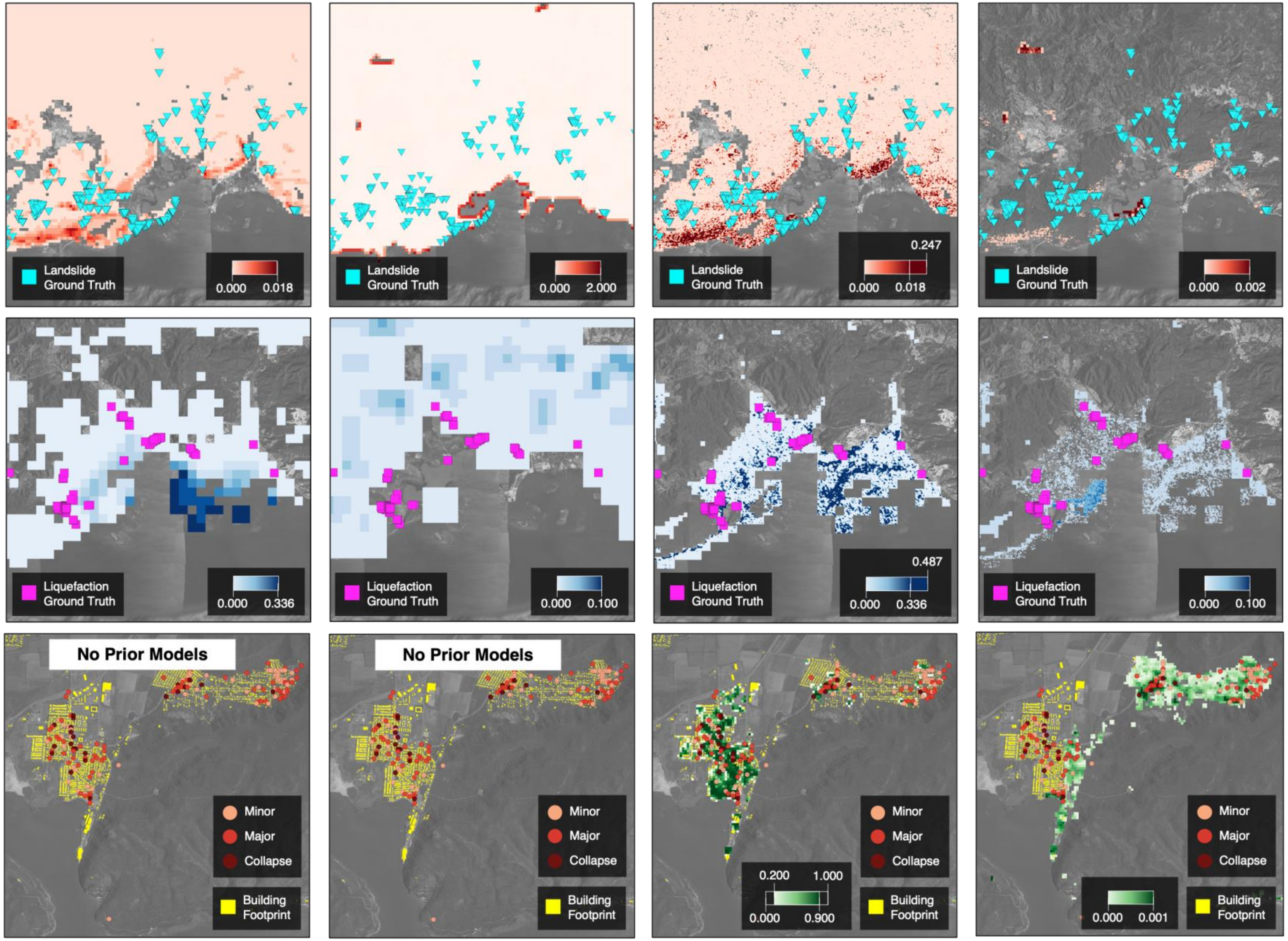
Results

Prior | Uncertainty with prior | Our model | Uncertainty with our model

Landslide

Liquefaction

Building Damage



Cross-entropy loss:
Prior: 0.0238
Posterior: 0.0175

AUC:
Prior: 90.36 %
Posterior: 90.83%

Cross-entropy loss:
Prior: 0.0301
Posterior: 0.0095

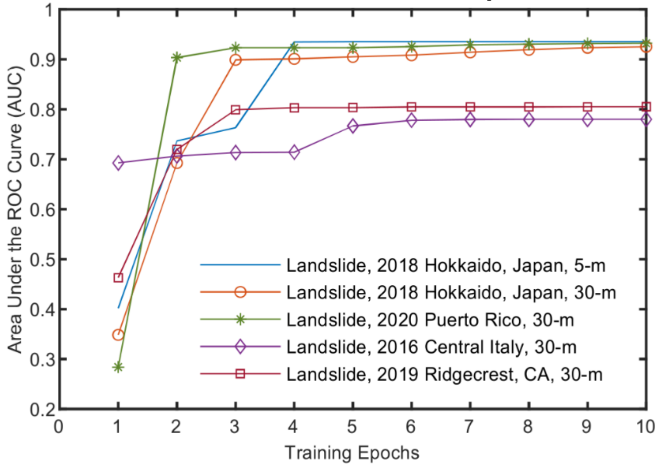
AUC:
Prior: 82.87 %
Posterior: 90.49%

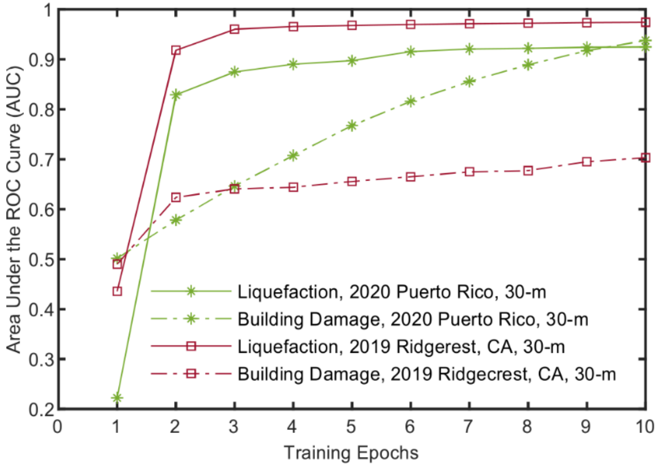
Binary-class AUC:
Prior: 69.50 %
Posterior: 92.36%

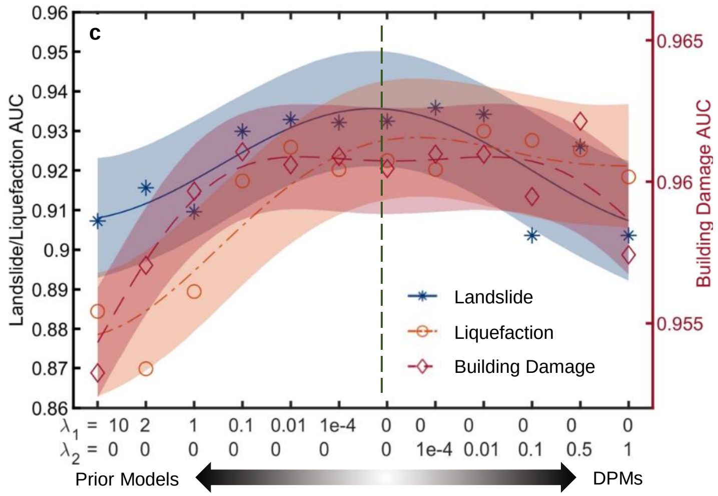
Results

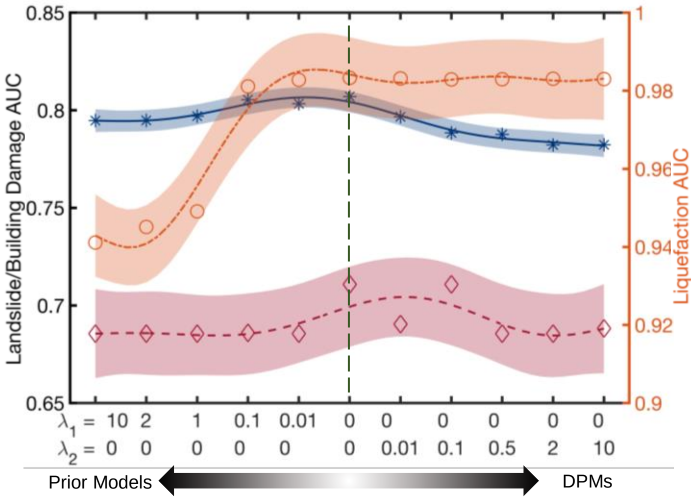
Advantages of the algorithm:

- converging fast
- flexible to control the information input from prior models and DPMs









Conclusions

- Jointly modeling seismic multi-hazards and impacts based on their causal dependencies helps to better understand the mixed signals in sensing images
- A new stochastic variational inference algorithm is derived to infer over large-scale seismic zone efficiently and effectively
- Damage proxy maps provide event-specific high-resolution information about multiple hazards and building damage and can be integrated with event-sharing geospatial models

Acknowledgement

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- Email to Susu.Xu@stonybrook.edu if any questions.

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USGS

[1] Xu, S., Dimasaka, J., Wald, D. J., & Noh, H. Y. (2022). Bayesian Updating of Seismic Ground Failure Estimates via Causal Graphical Models and Satellite Imagery. The 17th World Conference on Earthquake Engineering, Japan.
[2] Xu, S., Dimasaka, J., Wald, D., Noh, H. Y., Seismic Multi-hazard Estimation via Causal Inference from Satellite Imagery, under major revision at Nature Communications