PREDICTING TSUNAMI INUNDATION AND IMPACTS USING OFFSHORE WAVE DATA AND ML FOR RAPID ASSESSMENT

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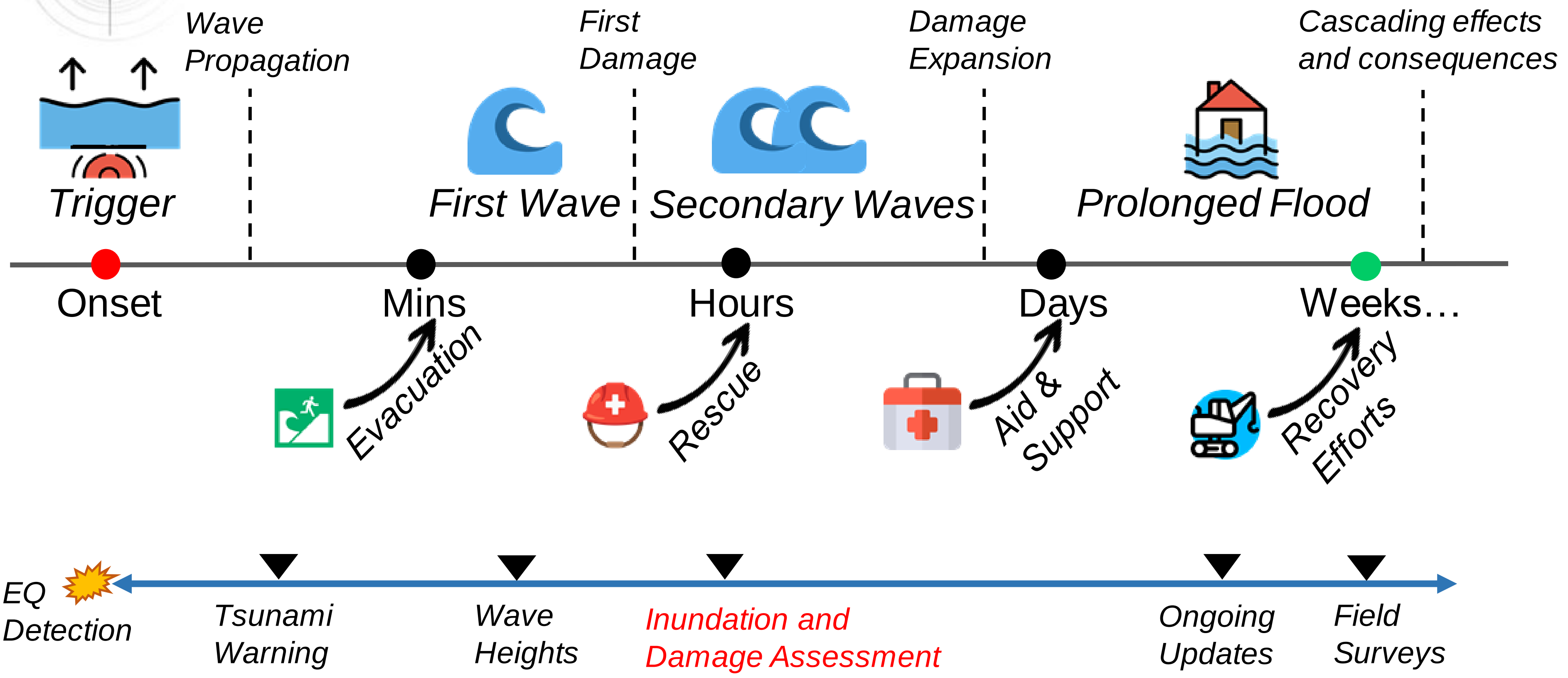
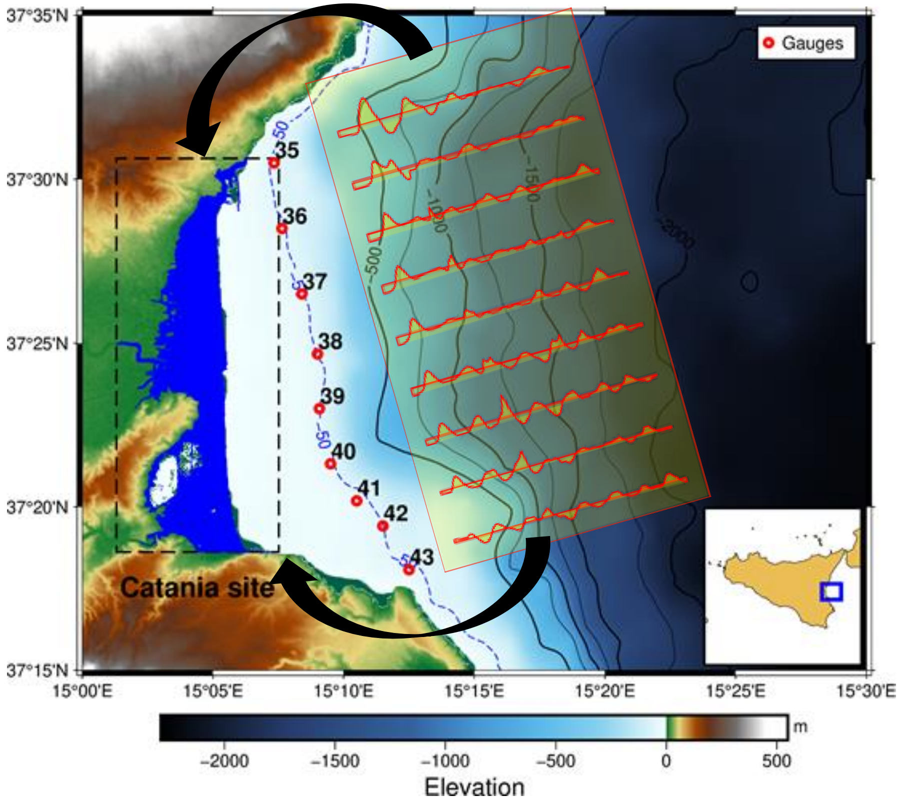
IUSS Scuola Universitaria Superiore Pavia
GEM GLOBAL EARTHQUAKE MODEL working together to assess risk
NGI
ISTITUTO NAZIONALE DI GEOFISICA E VULCANOLOGIA
Australian Government
Geoscience Australia



Tsunami Disaster Management Timeline

Rapid Inundation and Damage Assessment:

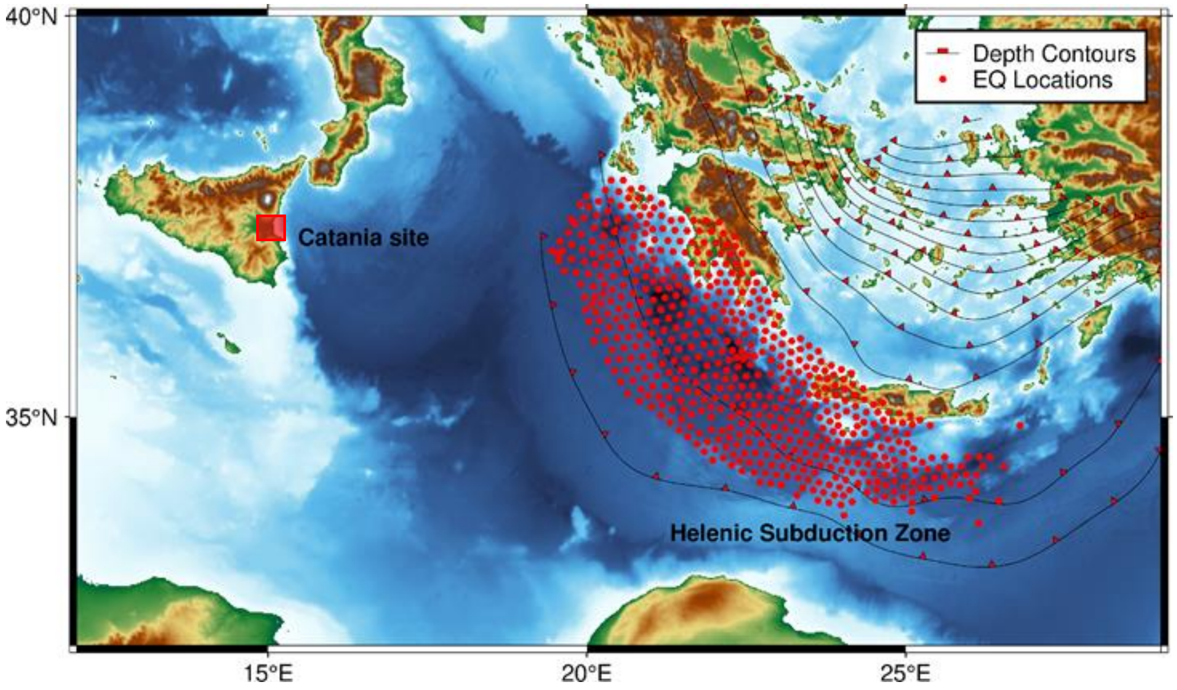
- Urgent Computing
- Remote Sensing
- Machine Learning
  - Inputs from ocean sensors or low fidelity propagation models
  - High resolution inundation for urban environment
  - Damage assessed as a downstream task



Resolving the information gap in crisis

Simulated by INGV, NGI and Uni Malaga

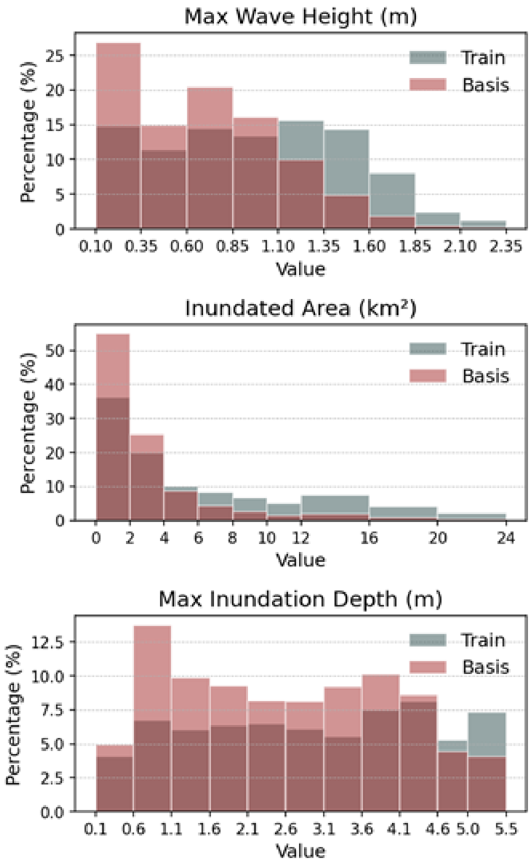
- NEAMTHM18 Tsunami Hazard Model (Basili et al., 2021)
- 23,086 Events for HSZ
- Stochastic heterogeneous slip (M_w 6.8-9.02)
- High resolution inundation(10m)
- 4 hrs of simulations using Tsunami-HySEA



Region, setting and tsunami simulation data

- Train at reasonable size of data without overfit, events above 0.1 m
- Quality over quantity!
  - Emphasis on input and output range, 2655 events(75:25)
- Extensive evaluation with remaining events
  - 20430 events, wide range of locations and magnitude

Data in training and testing

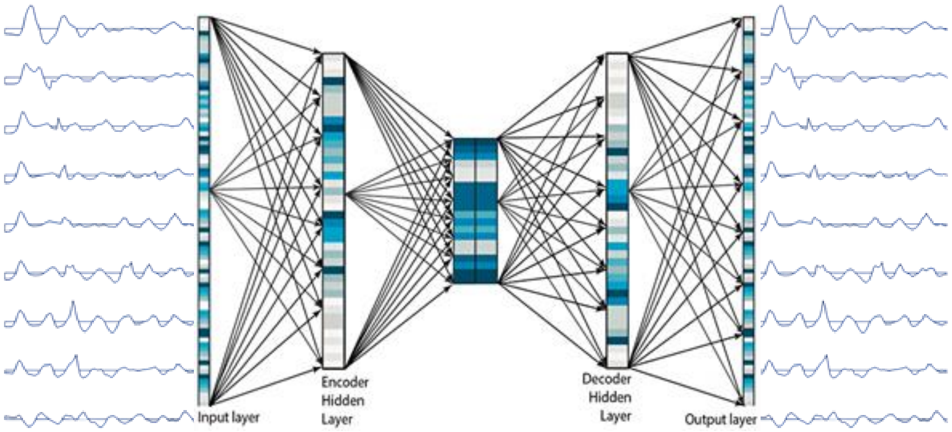


Known input variability

Unknown output variability

Stage 1. **Pretraining** – train neural networks with random weights with as much data as you have.

- Offshore Waveforms
    - 9 site(50m isobath)
    - 4 hours(480 times)
    - 1D CNN layers

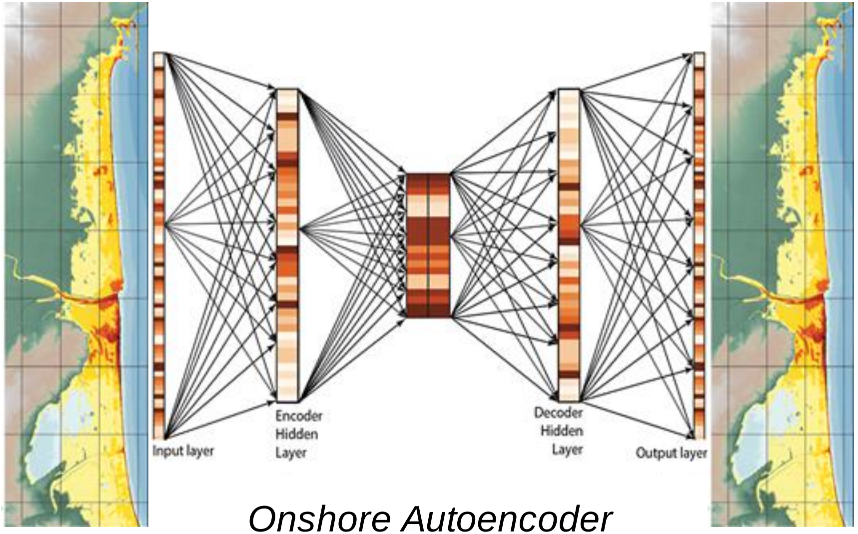


Offshore Autoencoder

What kind of machine learning? Encoder-Decoder trained with a pretraining and finetuning approach.

Stage 1. **Pretraining** – train neural networks with random weights with as much data as you have.

- Onshore Inundation
  - 416,318 locations
  - 10m resolution
  - MLP layers (fully connected)

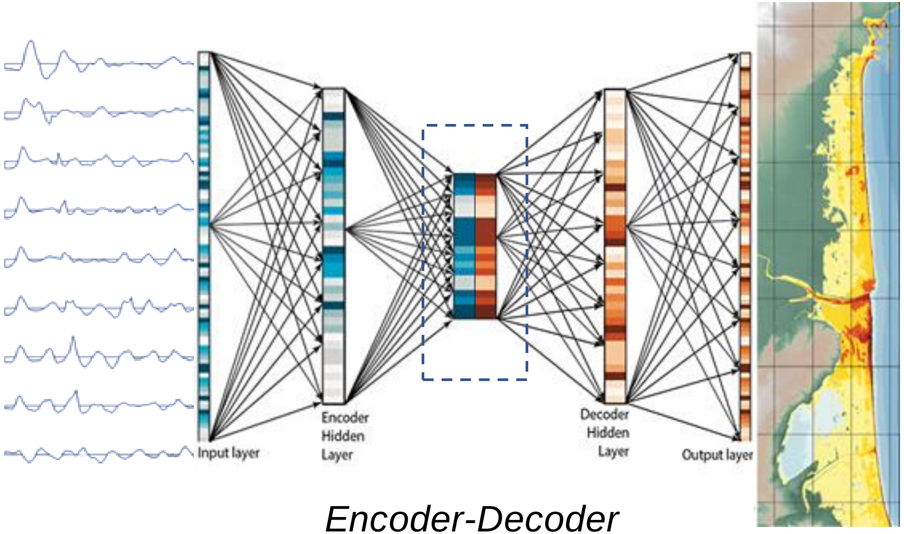


Onshore Autoencoder

What kind of machine learning? Encoder-Decoder trained with a pretraining and finetuning approach.

Stage 1. **Pretraining** – train neural networks with <u>random</u> weights with as much data as you have.

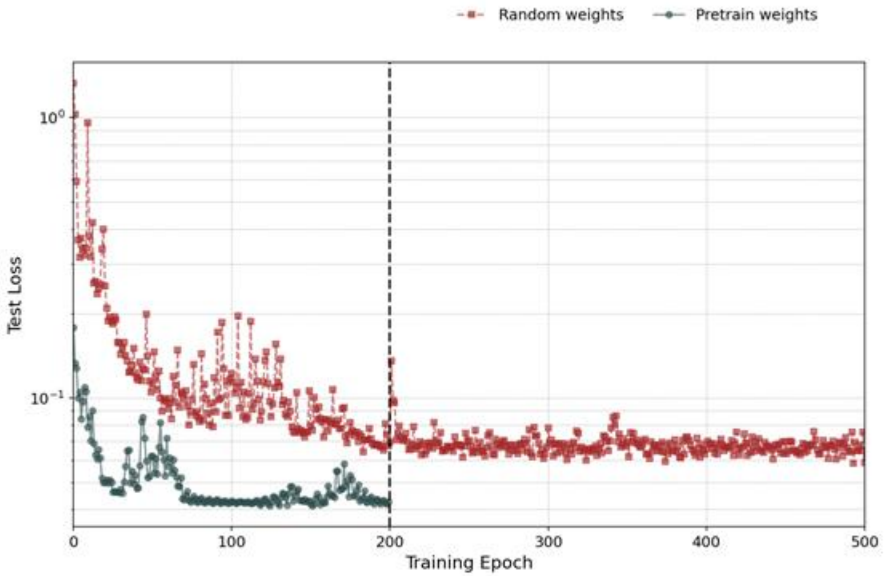
Stage 2. **Coupling layers and fine-tuning** – train neural network with <u>pretrained</u> weights with less data



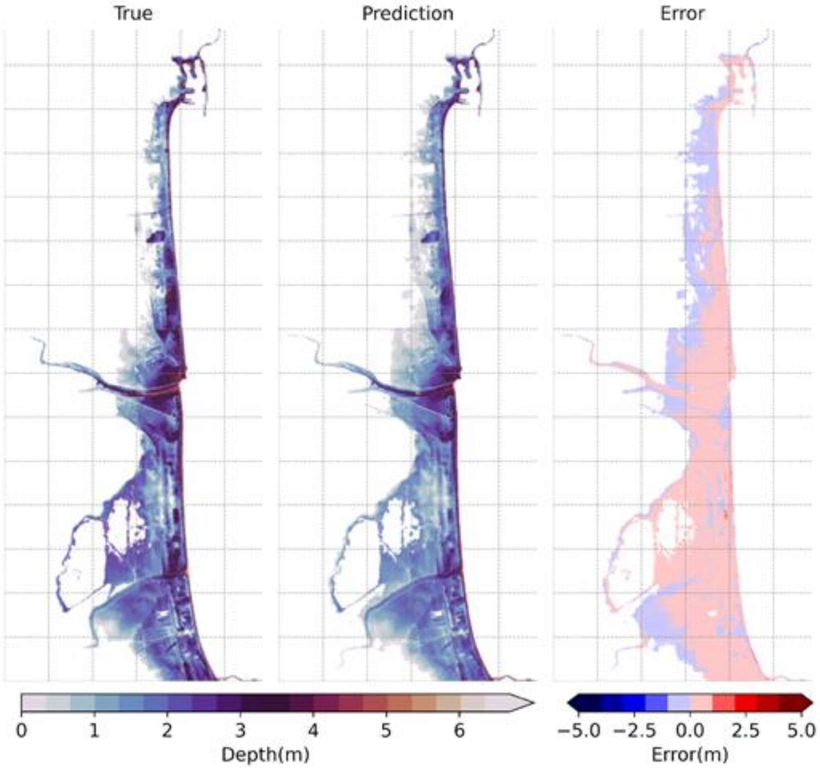
Encoder-Decoder

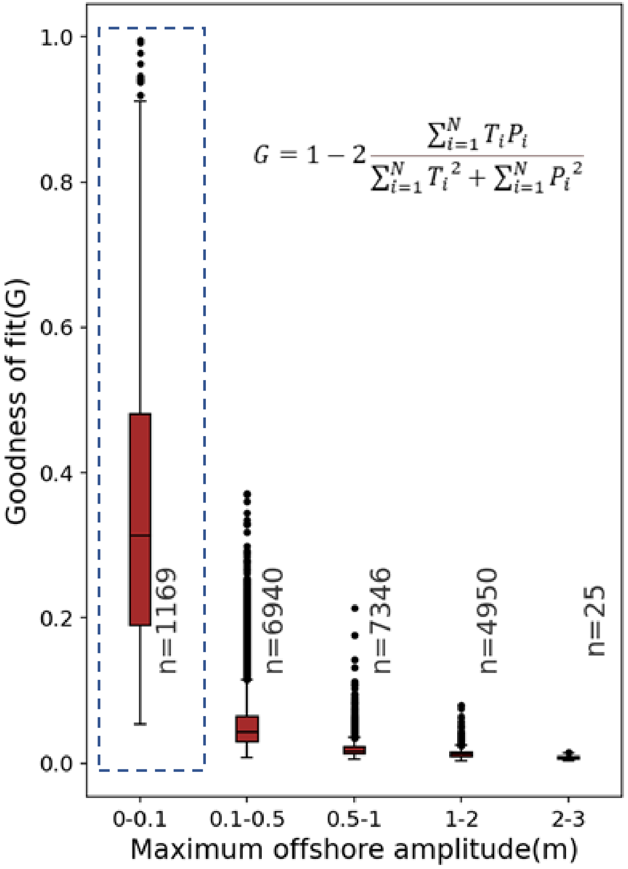
What kind of machine learning? Encoder-Decoder trained with a pretraining and finetuning approach.

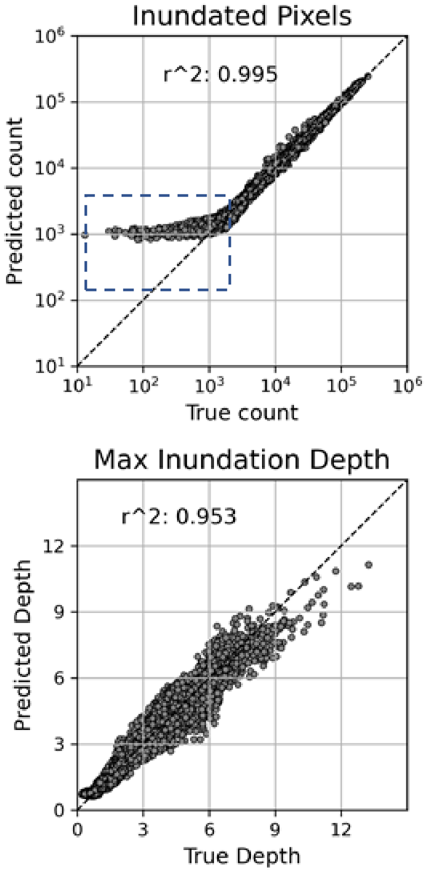
- Efficient use of available data.
- Converges at a lower minima.
- Faster and more stable training.
- Evaluate intermediate results for better config of architecture.
- Supplement other datasets in pretraining stage



Test Epoch Loss during training

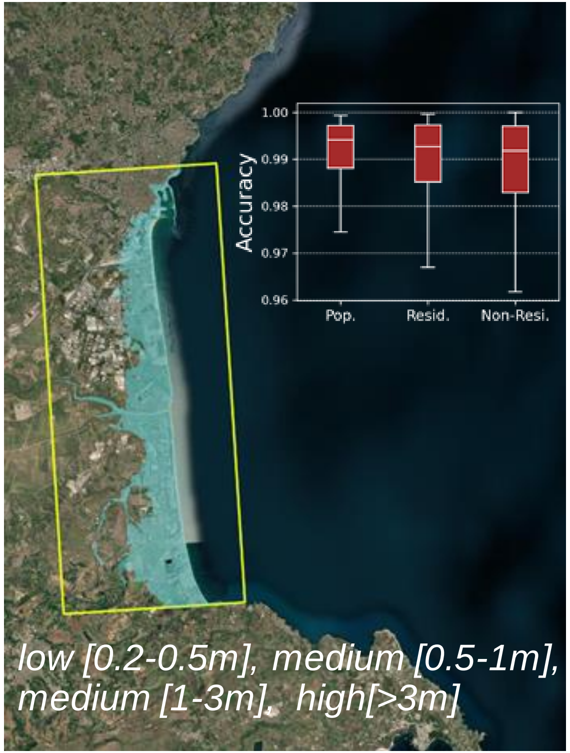




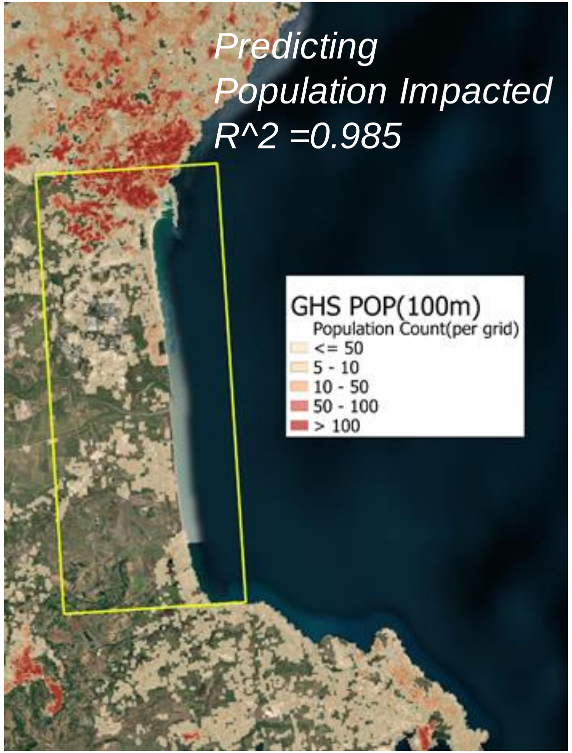


How good are machine learning surrogates for inundation prediction?

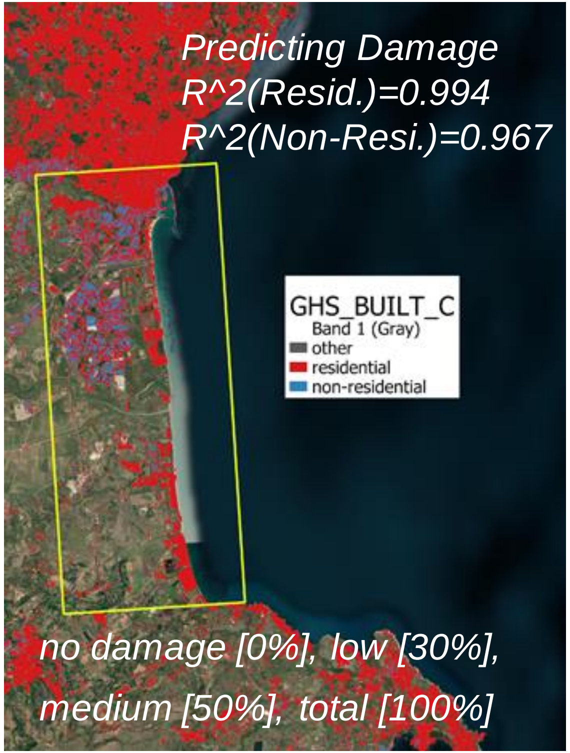
Area at Risk



Population



Settlement



Damage Assessment - Population and settlements at risk ?

Main conclusions and open challenges

1. A complementary method to fill the much needed information gap - predict rapid inundation estimates
2. Real life is more complex - more source and mechanisms
3. Benchmarking and open datasets
4. Uncertaininity of the ML model(stochastic) and training data(synthetic, limited in size and coverage)

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Last slide ☺