18th WORLD CONFERENCE ON EARTHQUAKE ENGINEERING
WCEE2024
MILAN

MILAN, ITALY
30TH JUNE - 5TH JULY 2024
www.wcee2024.it

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

Naveen Ragu Ramalingam[1], Anirudh Rao[2], Erlend Briseid Storrøsten[3] , Kendra Johnson[2], Gareth Davies[4], Alice Abbate[5], Finn Løvholt[2], Stefano Lorito[5], Marco Pagani[2], and Mario Martina[1]

[1] **PhD Candidate at University School for Advanced Studies (IUSS Pavia), Pavia, Italy**
[2] Global Earthquake Model Foundation, Pavia, Italy
[3] Norwegian Geotechnical Institute, Oslo, Norway
[4] Geoscience Australia, Canberra, Australia
[5] Istituto Nazionale di Geofisica e Vulcanologia, Rome, Italy

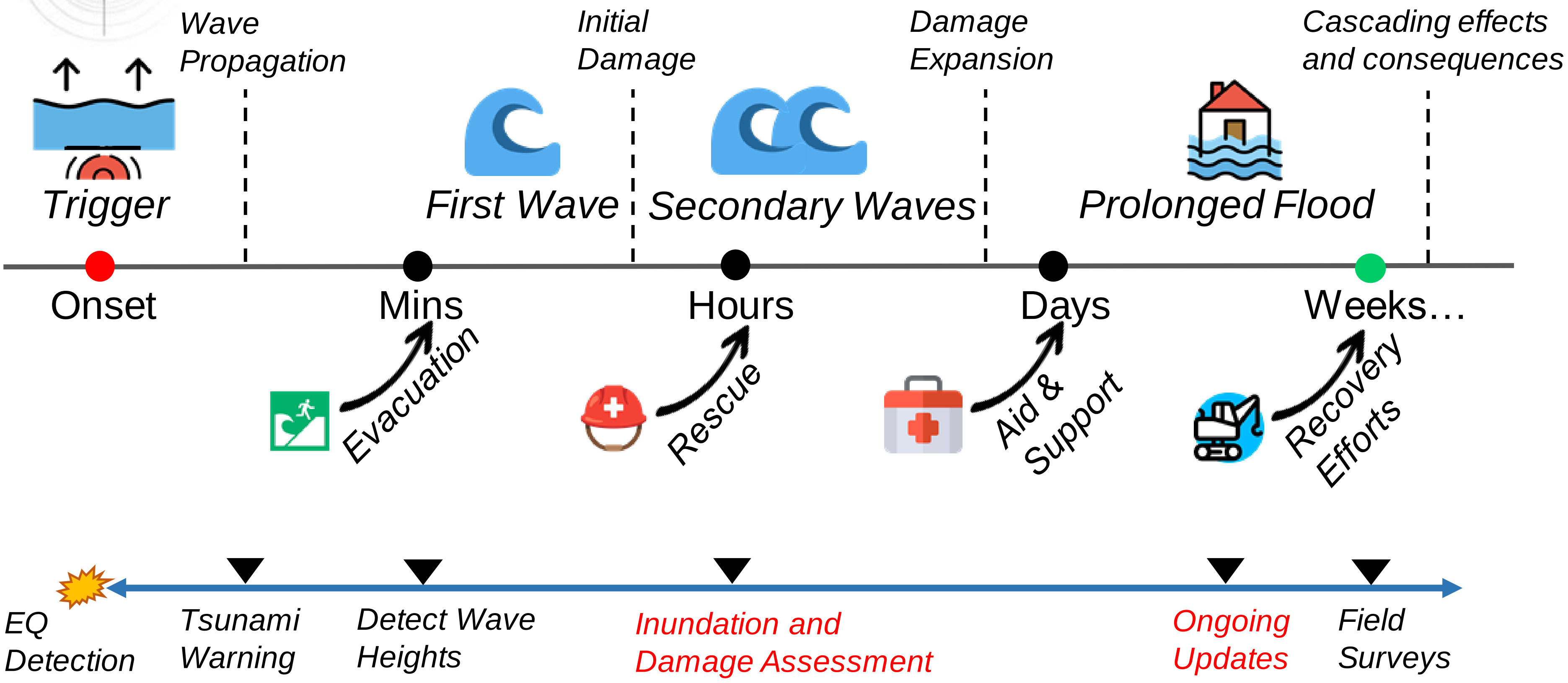
IUSS Scuola Universitaria Superiore Pavia

GEM GLOBAL EARTHQUAKE MODEL working together to assess risk

NGI

ISTITUTO NAZIONALE DI GEOFISICA E VULCANOLOGIA

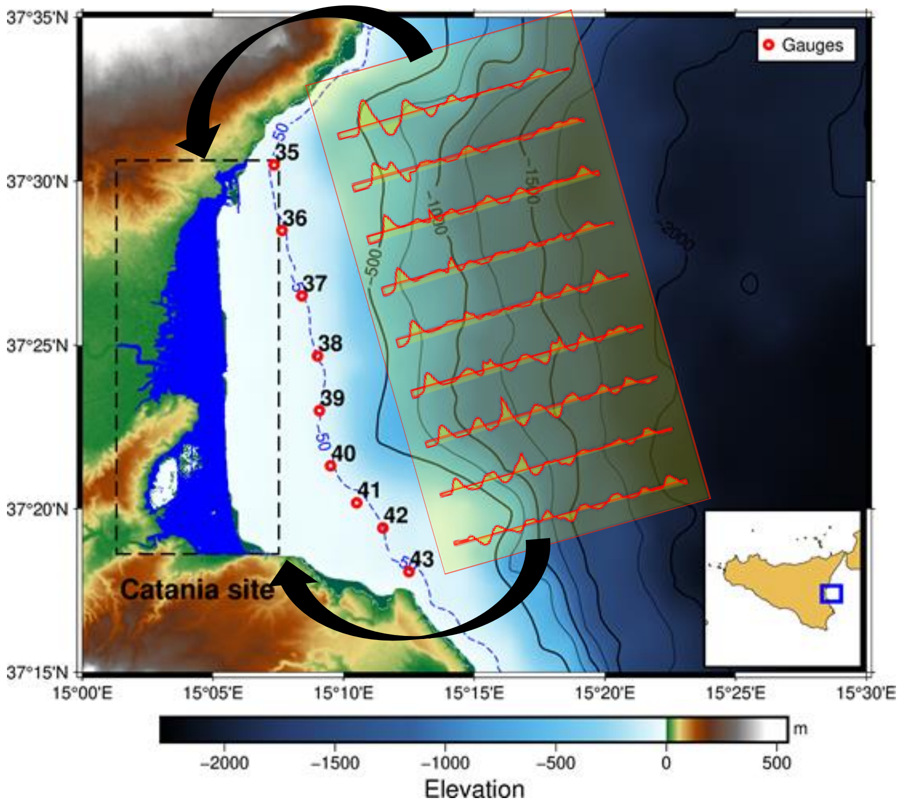
Australian Government
Geoscience Australia



Tsunami Disaster Management Timeline

Rapid Inundation and Damage Assessment:

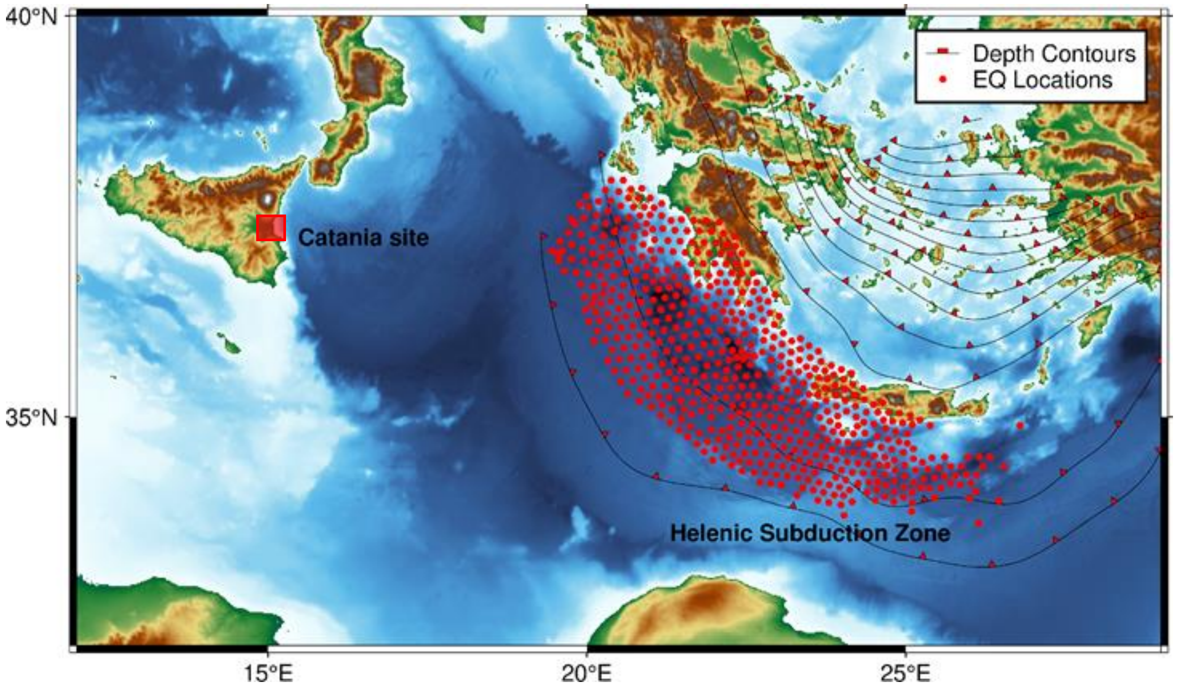
- Urgent Computing
- Remote Sensing
- Machine Learning
    - Inputs from ocean sensors or low fidelity propagation models
    - High resolution inundation for urban environment
    - Damage assessed as a downstream task



Resolving the information gap in crisis

- NEAMTHM18 Tsunami Hazard Model (Basili et al., 2021)
- 23,086 Events for HSZ
- Stochastic heterogeneous slip (M_w 6.8-9.02)
- 4 hrs of simulations using Tsunami-HySEA(Gibbons et al., 2020)
- High res. inundation(10m) at Catania

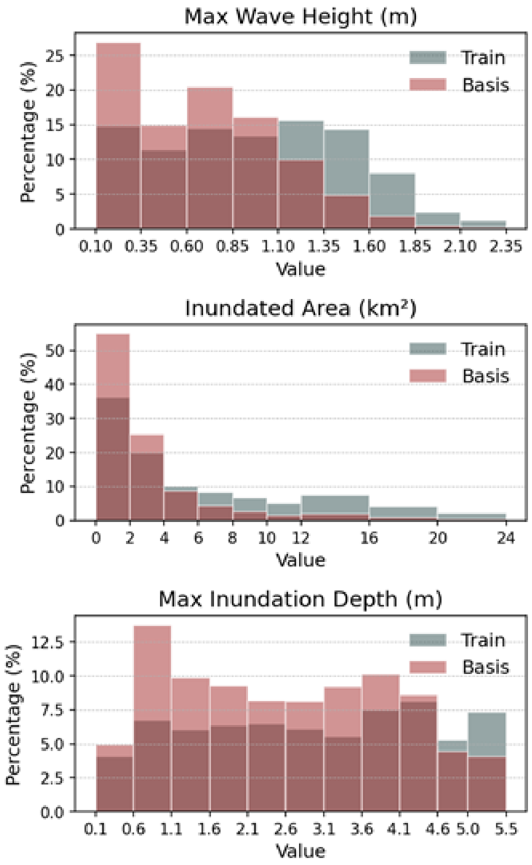
Simulated by INGV, NGI and Uni Malaga



Region, setting and tsunami simulation data

- Train at reasonable size of data without overfit, events above 10 cm
- 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

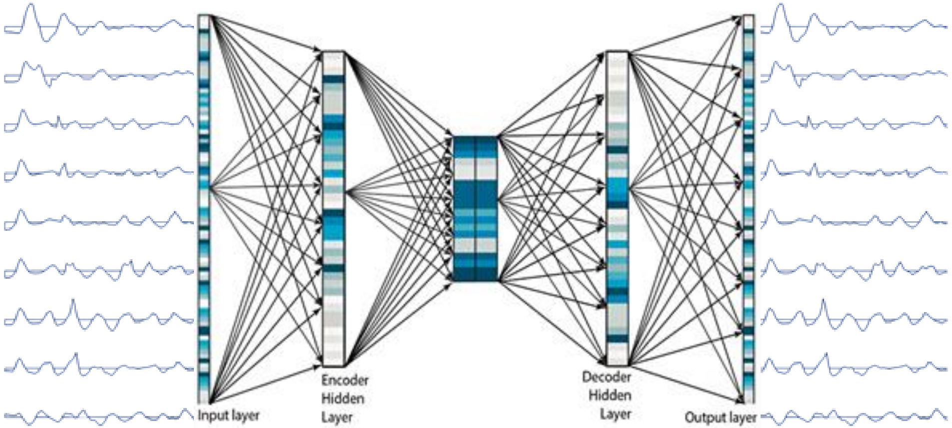


Known input variability

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

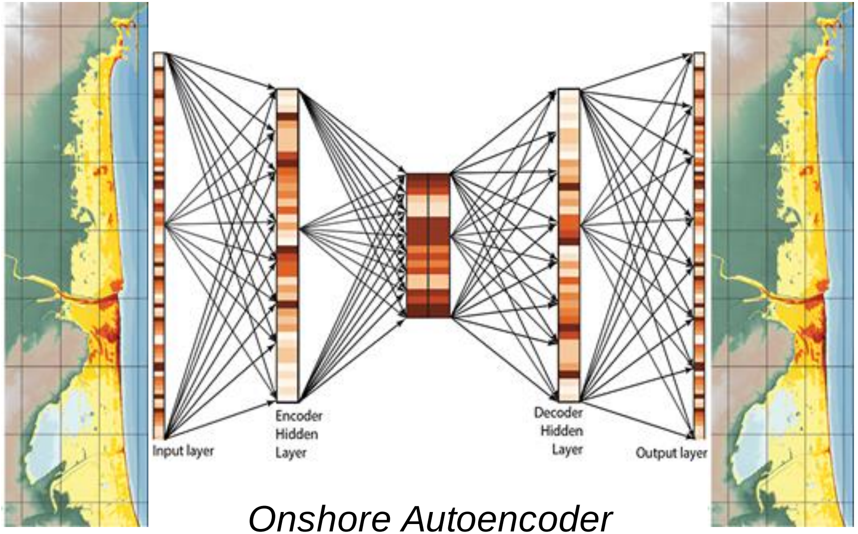


Offshore Autoencoder

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

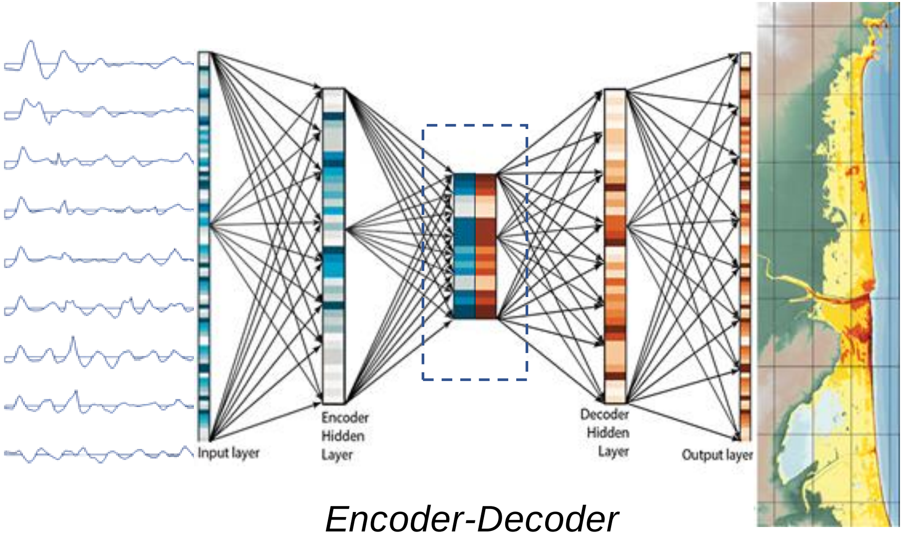


Onshore Autoencoder

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.

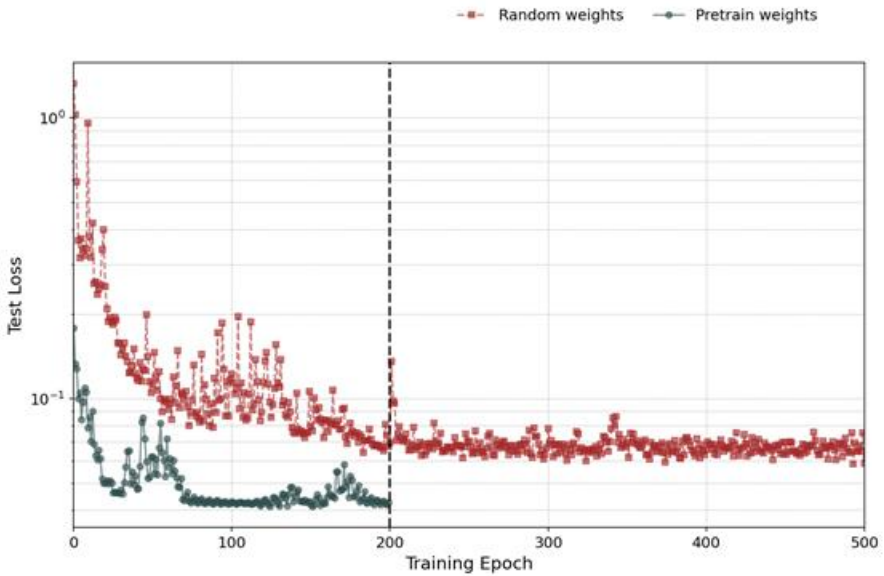
Stage 2. **Coupling layers and fine-tuning** – train neural network with pretrained weights with less data



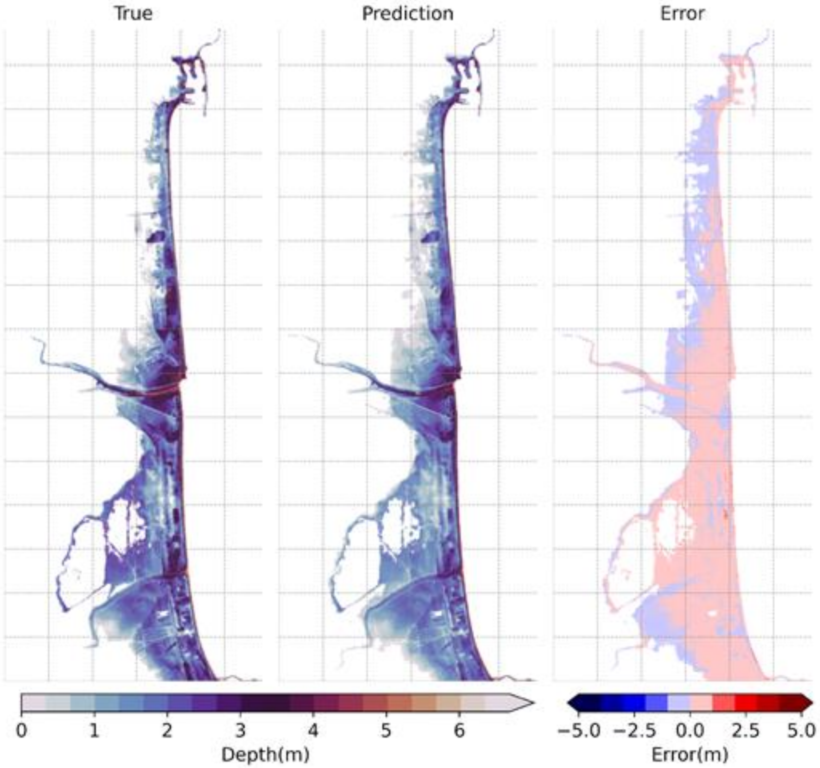
Encoder-Decoder

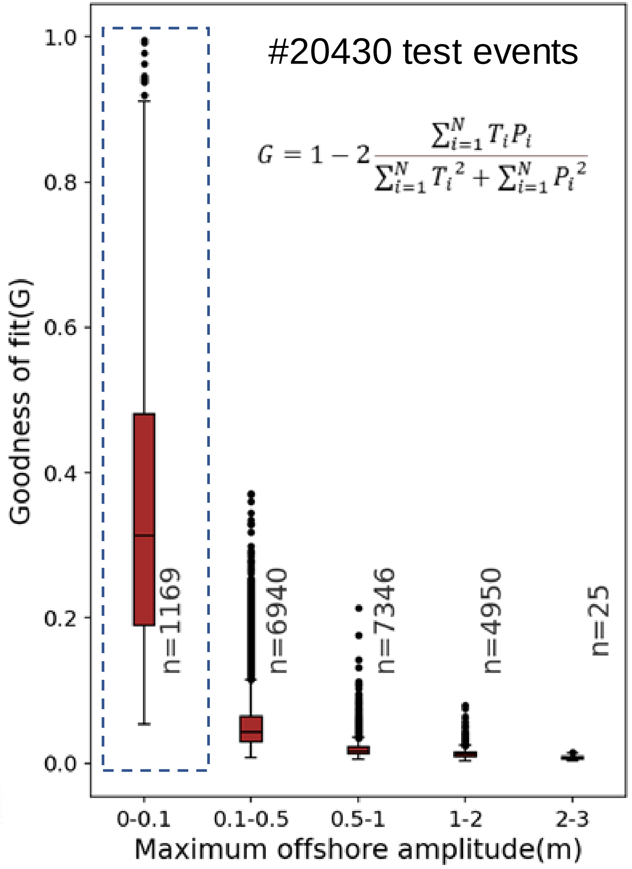
What kind of machine learning? Encoder-Decoder trained with a pretraining and finetuning approach.

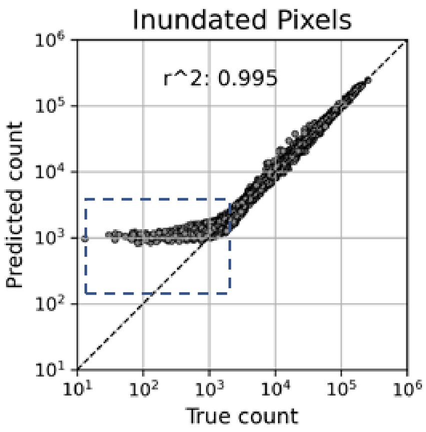
- Efficient use of available data.
- Converges at a lower minima.
- Faster and more stable training.
- Evaluate intermediate results for better config of architecture.
- Supplement other datasets in pretraining stage

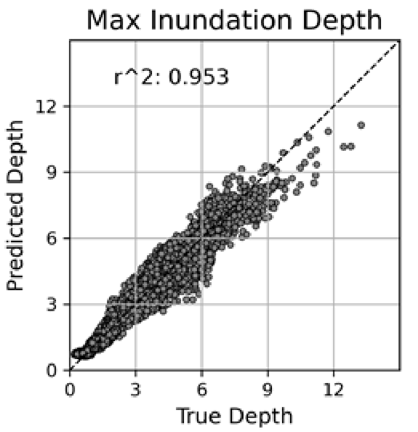


Test Epoch Loss during training



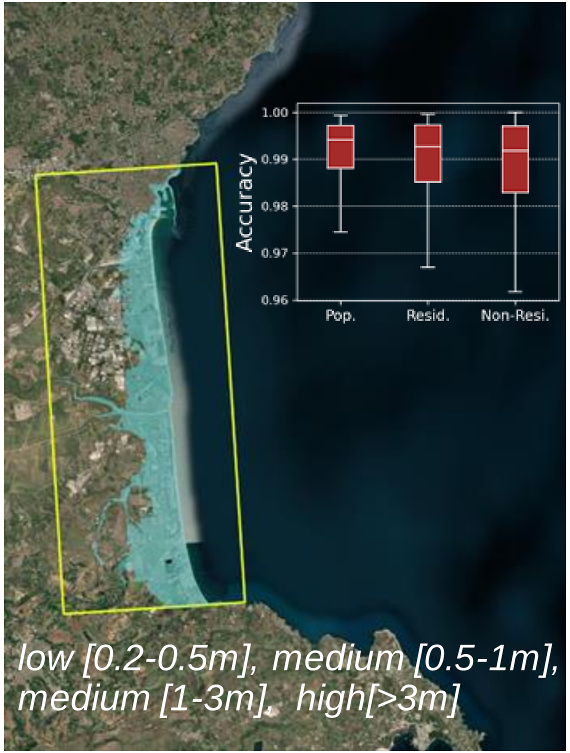


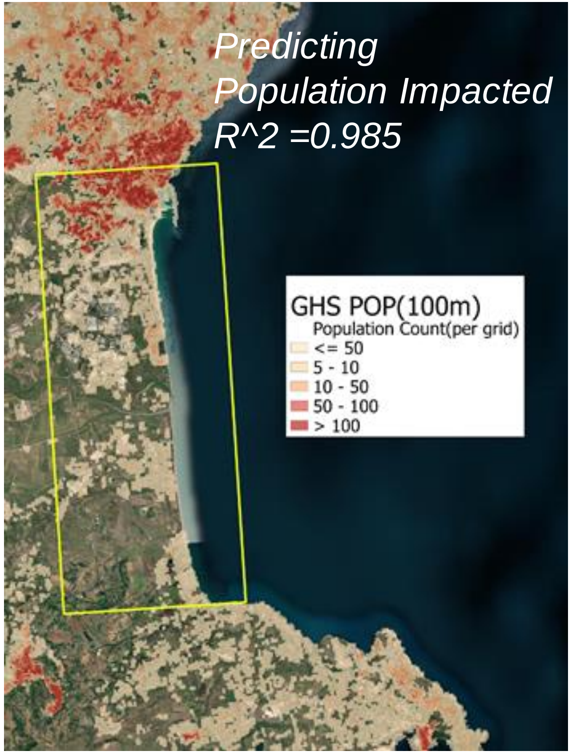


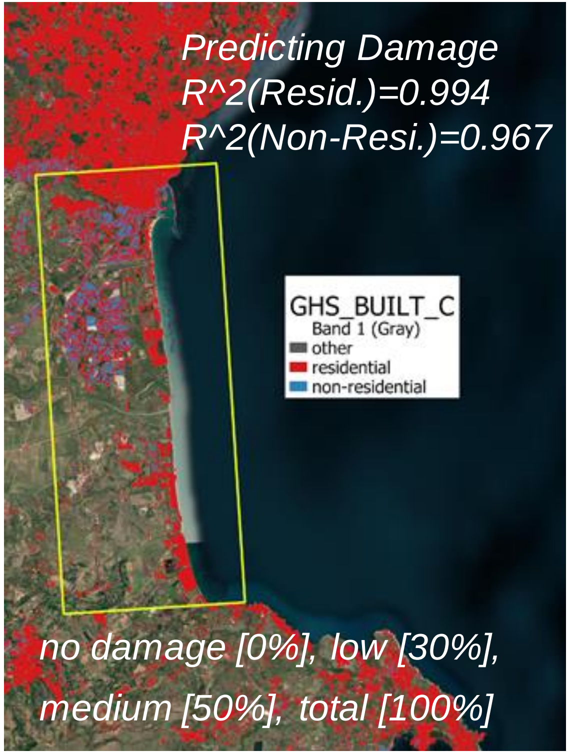


How good are machine learning surrogates for inundation prediction?

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, secondary effects – tides, deformation
3. Benchmarking and open datasets
4. Uncertainty of the ML model(stochastic) and training data(synthetic, limited in size and coverage)

naveenragur.github.io

Last slide ☺