MACHINE-LEARNING BASED ESTIMATOR FOR GROUND SHAKING MAPS

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SUMMARY

The Machine Learning Estimator for Ground Shaking Maps (MLESmap) harnesses the **predictive capabilities of Machine Learning (ML) algorithms, utilizing high-quality physics-based hypothetical seismic scenarios.**

Conceived as a novel urgent computing tool for earthquakes. MLESmap provides post-earthquake ground intensity measures (such as PSA, RotD50), generating shaking maps for a fast and reliable assessment of affected areas.

MOTIVATION

Empirical ground motion models (GMPEs) are the traditional solution to fast estimations of intensity measures (IMs) that circumvent the use of physics-based approaches. **GMPEs** proposed in a range of model functional forms, give mean and variability values for IMs (e.g., peak ground acceleration (PGA) or pseudo-spectral acceleration (PSA)) as functions of seismic observations (e.g., earthquake magnitude or site-to-source distance). **However, the sparsity of catalogs and datasets, together with regional differences and large variability in the characteristics of large earthquakes, compromise their predictive capacity.**
Given these limitations, a functional earthquake analysis demands research on complementary strategies that retain the evaluation speed of empirical GMPEs while providing physics-based precision. **We propose a Machine Learning (ML) methodology that combines the best of both approaches, capturing physical information from well-curated simulations (directivity, topography, site effects) with times-to-solution analogous to empirical GMPEs, helping to produce the next generation of shaking maps.**

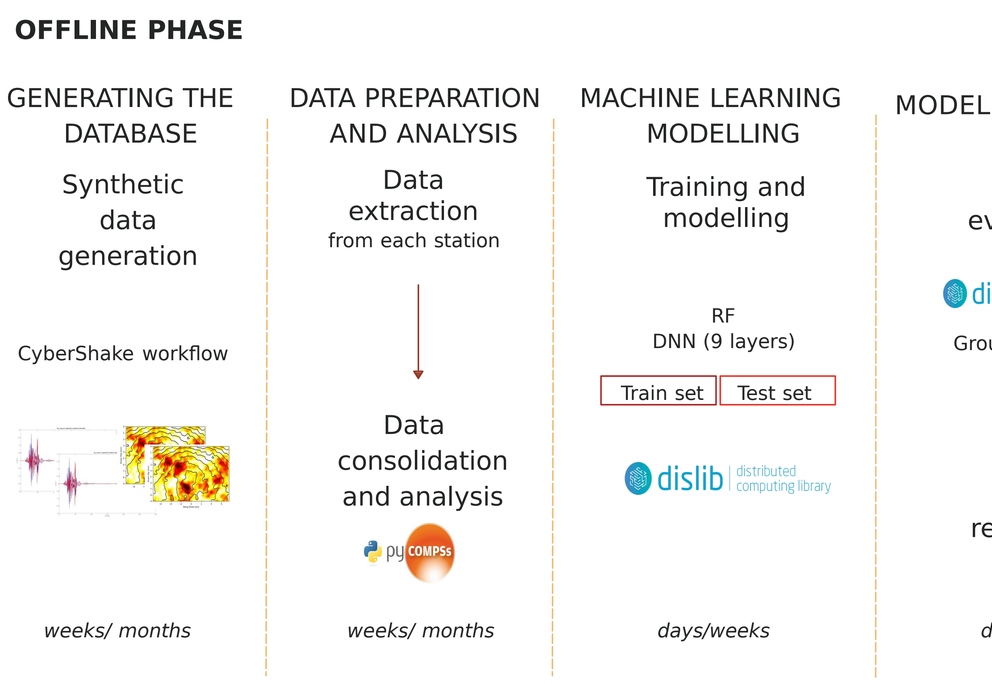
METHODOLOGY

- MLESmap Workflow -

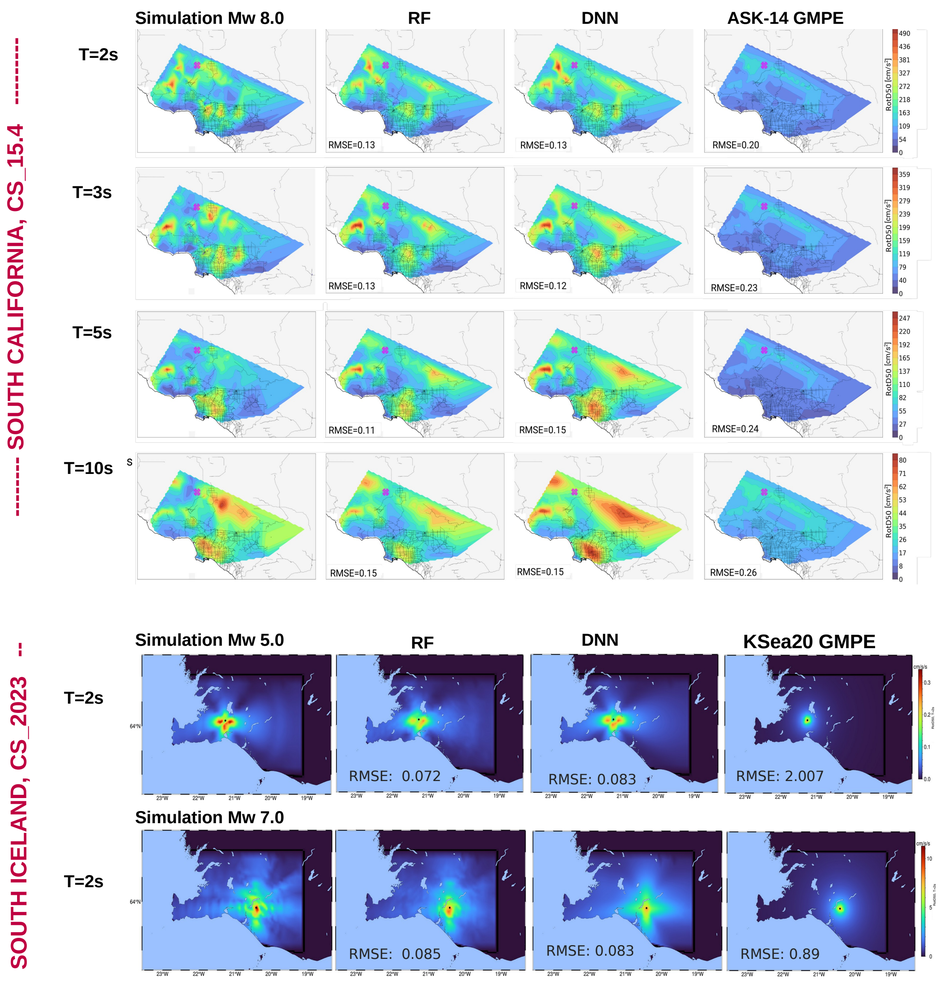
The MLESmap workflow can be described in two phases:

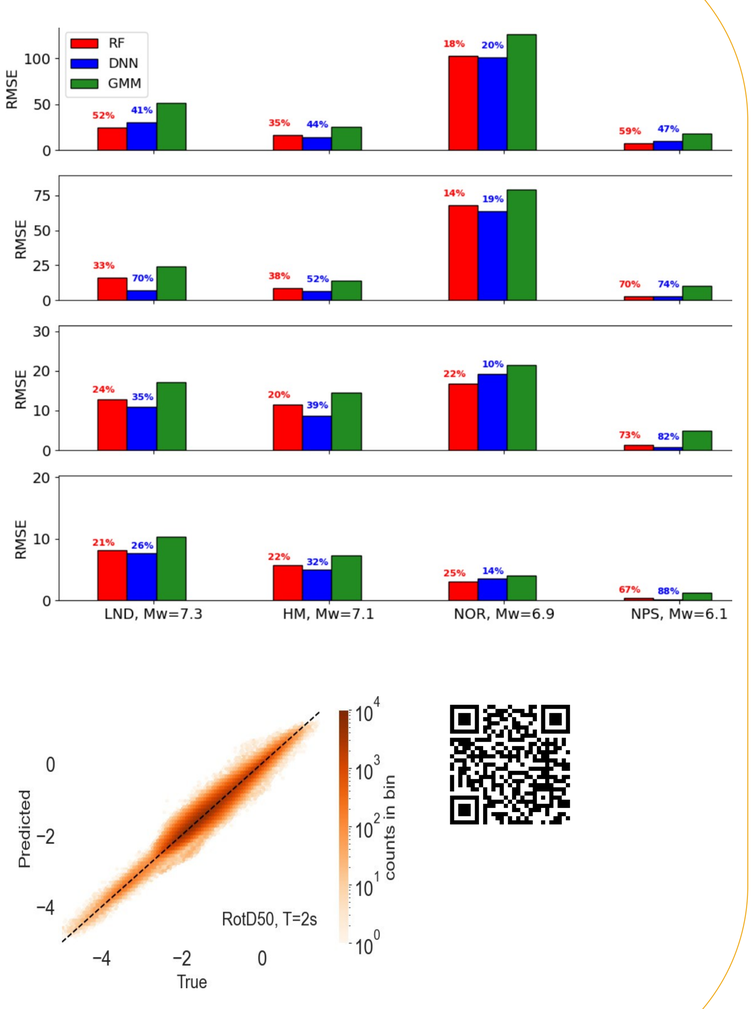
Offline:
- Generating synthetic data set
- Preparing data, extracting the used input variables for modeling
- ML modeling using regression algorithms (Neural network and ensemble trees)
- Validating accuracy against unseen simulations from ground stations, and GMMs

Online:
- Fast generating inferences using the ML models from a model repository.



RESULTS





FUTURE WORK

- Testing MLESmap in a high-frequency dataset.
- Optimizing the receiver spatial configuration for quality and performance.
- Generalizing the learning process over different regions (heterogeneous and homogeneous regions).
- Exploiting the transfer learning at low-frequencies over to high-frequencies.
- Generating a suitable dataset, including extreme events (high-magnitude earthquakes).
- Exploring multi-target inference strategies.
- Expand to new regions: New Zealand, South Spain, México.

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