Preliminary steps on AI-based active deformation processes classification and time series forecasting

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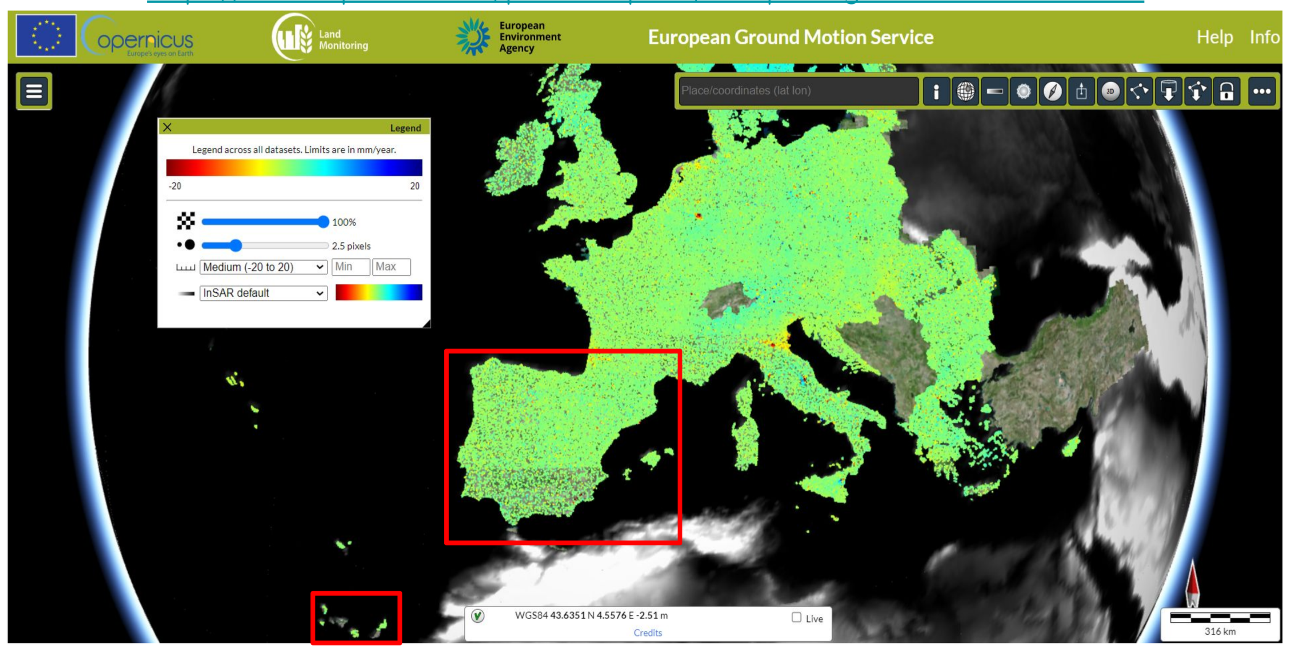
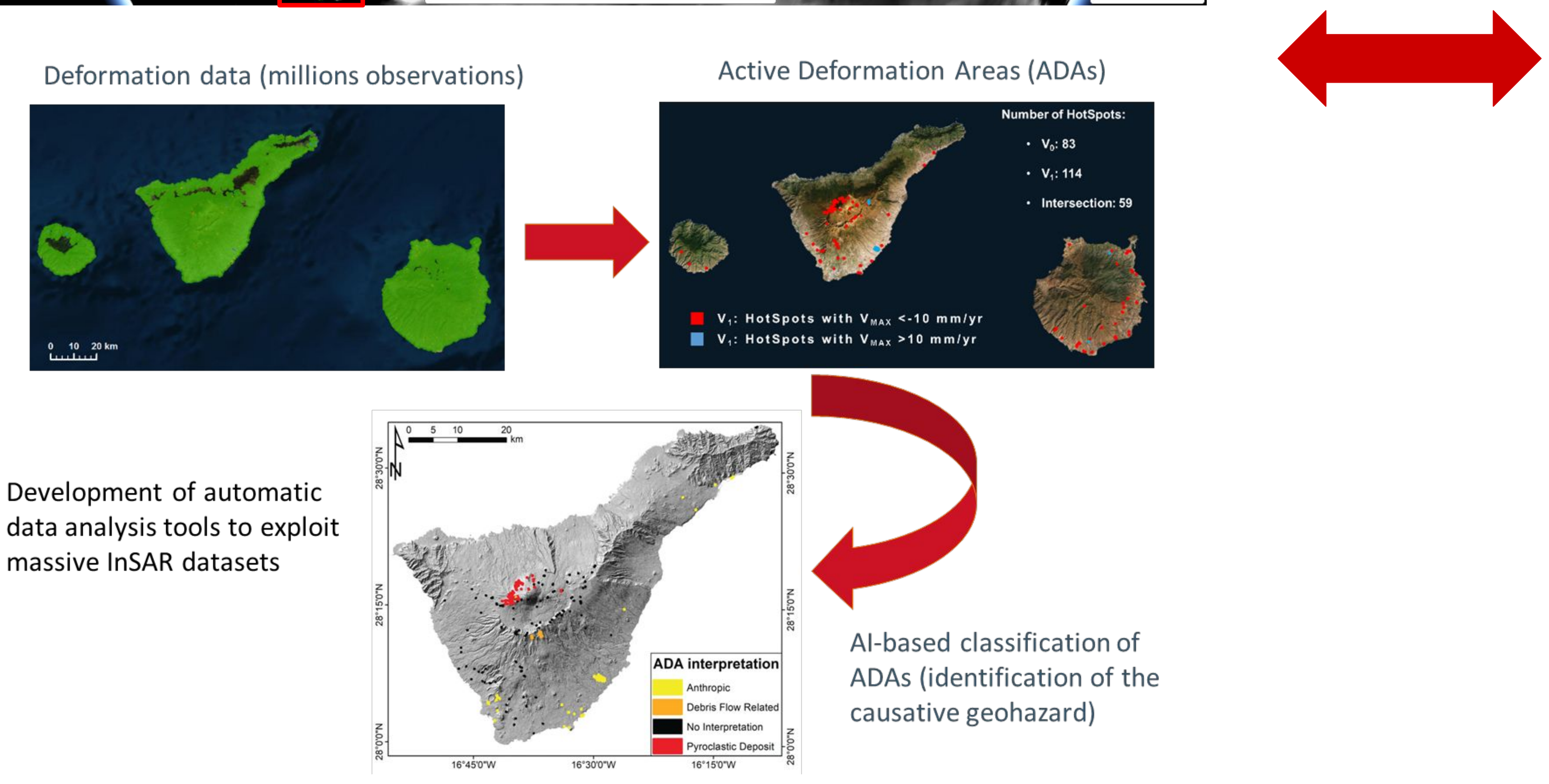
DInSAR ground deformation data (EGMS)

https://land.copernicus.eu/pan-european/european-ground-motion-service





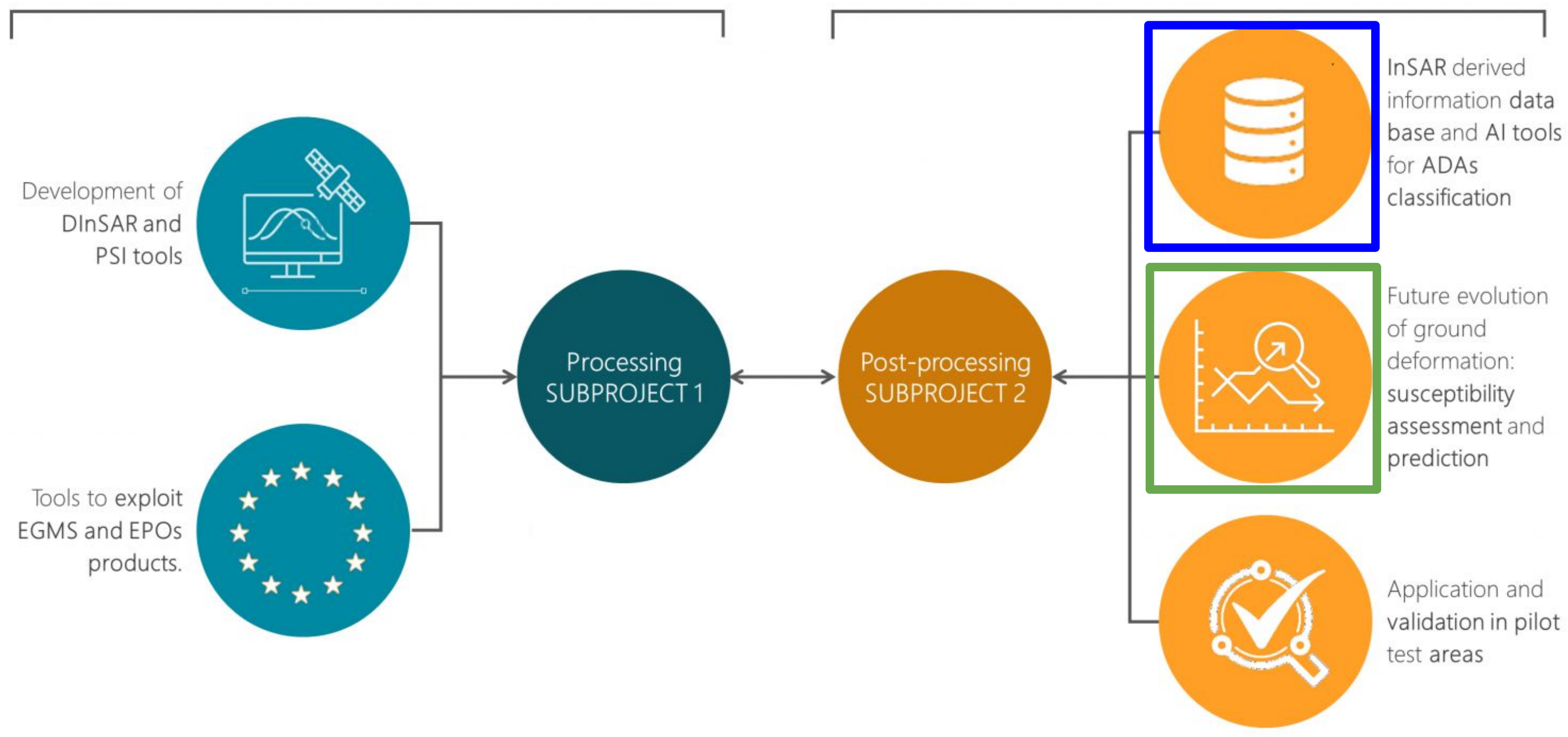
Project outline

The SARAI project ("Towards a smart exploitation of land displacement data for the prevention and mitigation of geological-geotechnical risks") aims to improve the exploitation capabilities of radar-based remote sensing techniques from Sentinel-1 missions to measure and monitor land deformation: Differential Interferometric Synthetic Aperture Radar (DInSAR) and Persistent Scatterer Interferometry (PSI). The main products of DInSAR and PSI are the ground motion velocity and time series of deformation. The goal is to improve the geohazard risk management capabilities (land subsidence, landslides, slope instability, settlements, etc.) To facilitate the use of these data and create tools for non-expert users, we propose to create AI-based products that allow the automatic analysis of large InSAR data sets to:

1. Identify the deformation signals and separate them from the noise.
2. Classify these signals according to the natural or anthropic causative phenomenon.
3. Estimate the areas most susceptible to experiencing ground movements in the future.
4. Predict the temporal evolution of ground deformation.

SARAI

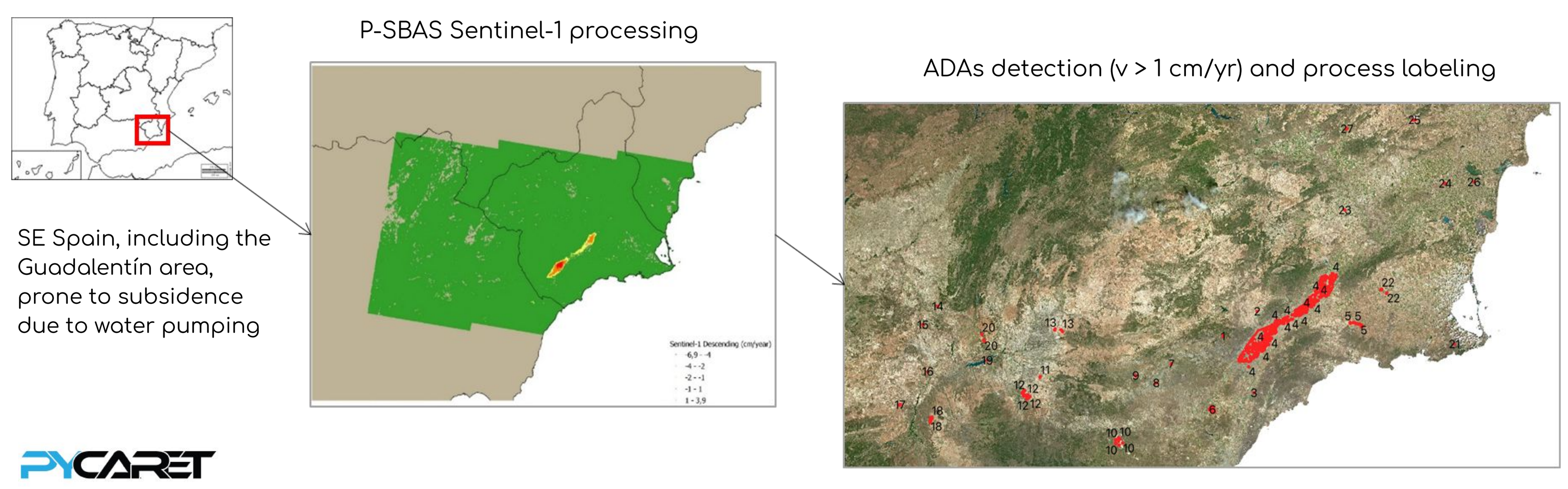
https://webwp.igme.es/sarai/index.php/en/home/



First steps

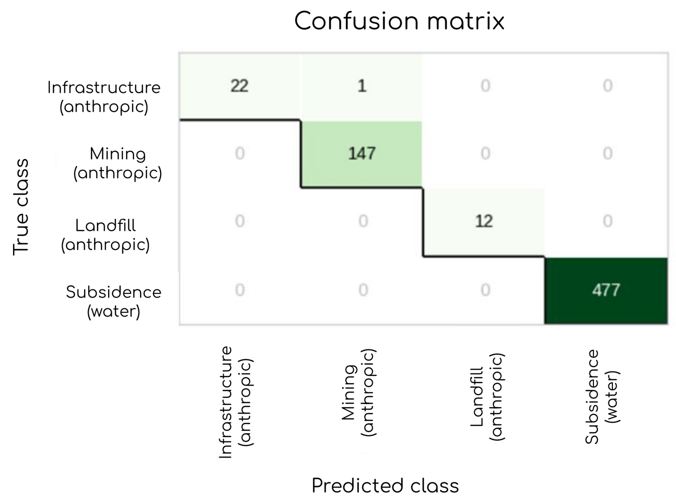
- Building a database with:
  - Previous InSAR geohazards processing results: (mean deformation velocity and time series.
  - Inventories of phenomena: landslides, subsidence, mining-induced motions.
  - Environmental covariates potentially related to ground deformation: geology/lithology, slope, land cover, distance to infrastructures, rainfall, soil water index, groundwater level, etc.
- Use database to train ML classifiers of ADAs.
- Test approaches for PSI time series forecasting:
  - Classic time series models: ARMA, Prophet.
  - ML & DL models: Random Forest, NeuralProphet, CNN, LSTM, etc.

ADAs classification

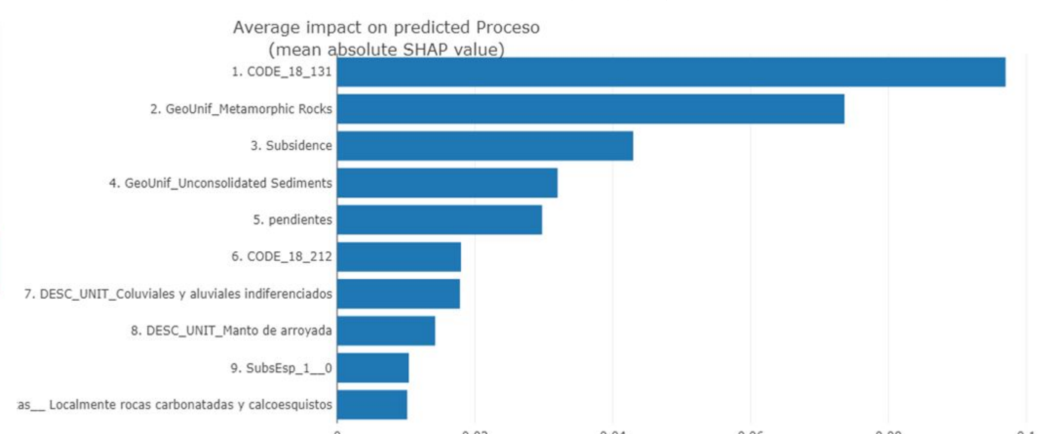


PYCARET
Best ML algorithm:
Extremely Randomized Trees (AUC > 0.99)

Confusion matrix



Explainable AI: SHAP (SHapley Additive exPlanations)

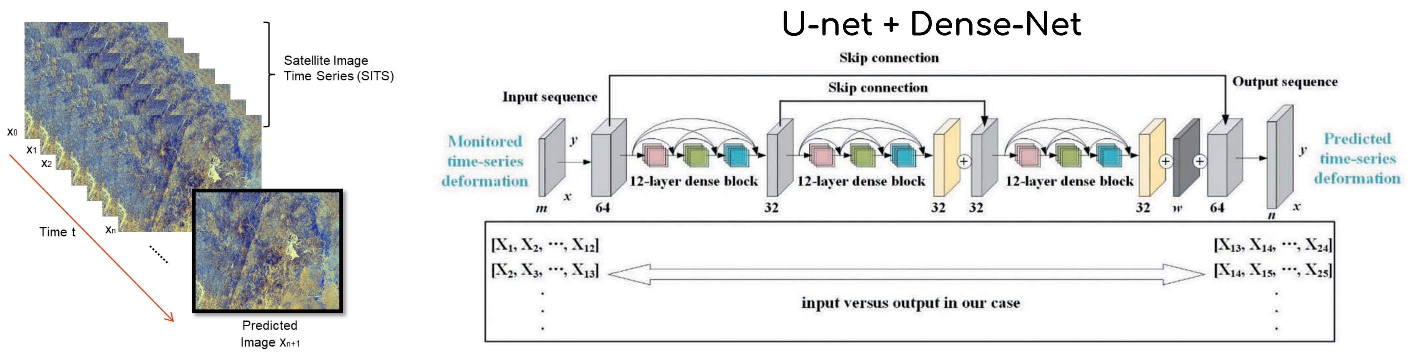


Forthcoming steps

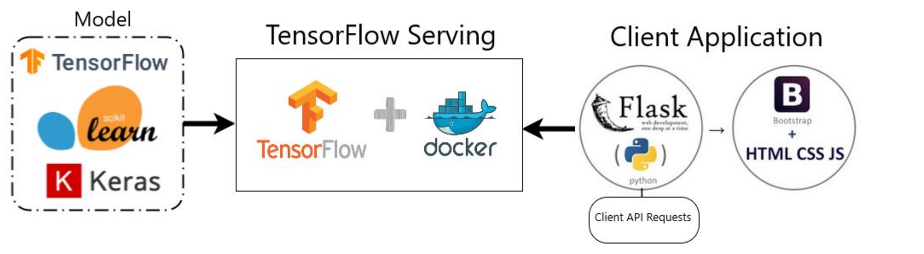
- Enlarge the database and retrain ML classifier: both more InSAR data in other locations and more spatiotemporal covariates (++ rows, ++ columns)
- Assess performance of ML classifiers against custom tools (ADATools)
- Apply ML classifier to EGMS products in Spain Spain (catalogues/inventories of covariates ready) -> to feed up the database
- Susceptibility mapping based on ADAs classification results (probability thresholds?)
- Time series clustering to make time series forcasting scalable (> 10^6 PSI points)
- Test new DL architectures (CNN, ConvLSTM) for PSI time series forcasting (e.g., 2D Satellite Image Time Series-SITS)
- Building useful training datasets for SITS prediction (e.g., data augmentation).
- MOST IMPORTANT: Generalizing, reusing, scaling (cloud, own servers, ...) and deploying (APIs, apps, web services, ...) geohazards classification and forecasting solutions

2D ground deformation time series forecasting with DL

U-net + Dense-Net



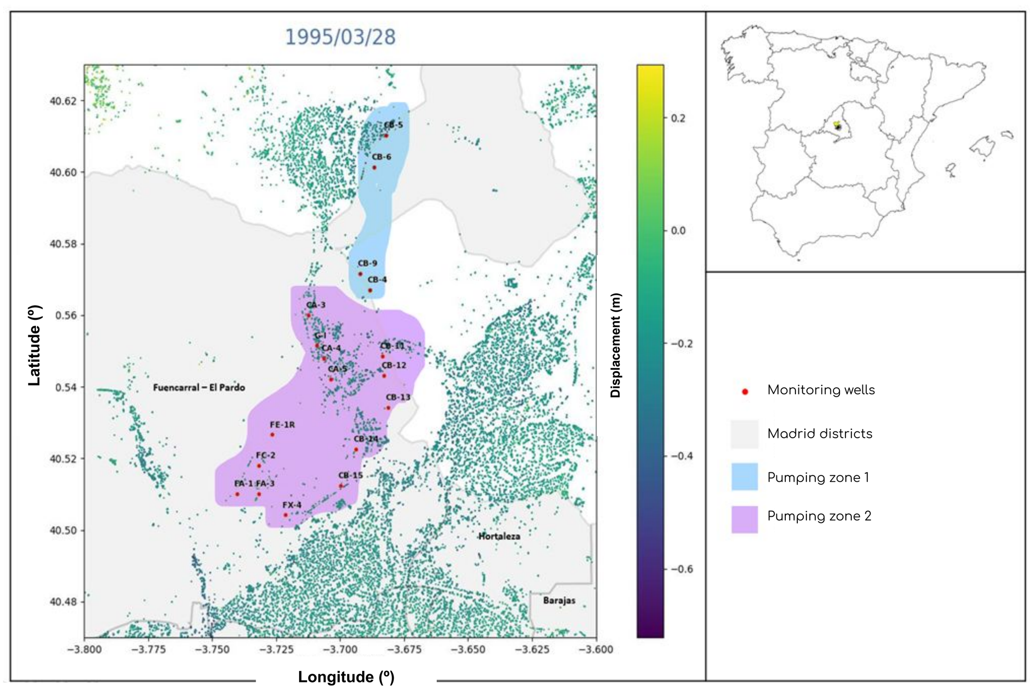
AI solutions deployment: web service & apps



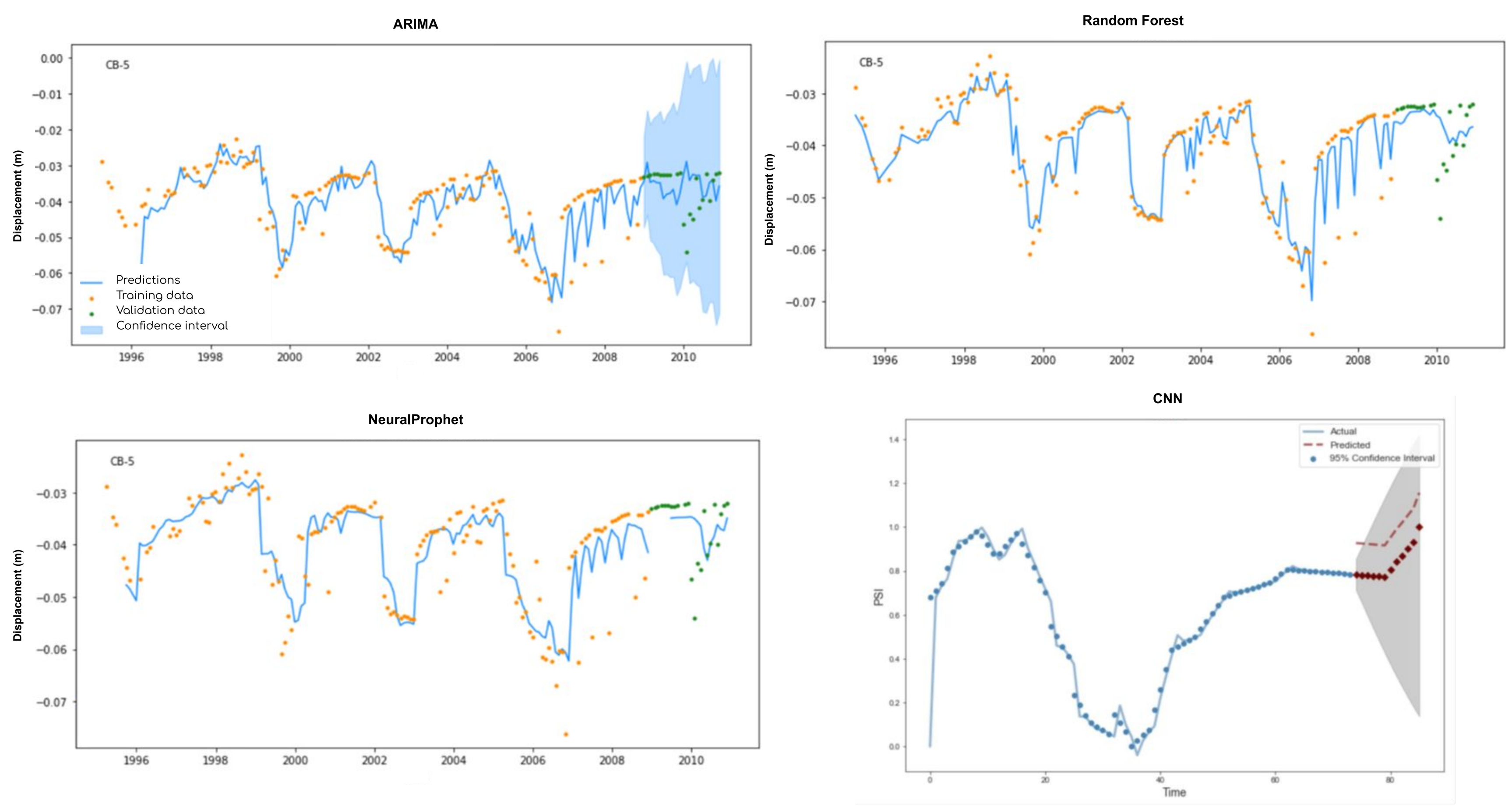
1D ground deformation time series forecasting

Madrid detrital aquifer:

- Used as backup water supply during drought emergencies.
- Ground deformation time series follow extraction/recovery cycles.
- Two periods: 1992-2000 (ERS) and 1993-2010 (ENVISAT)



learn
Keras



	Mean RMSE (m)	Mean MAE (m)	MeanMAPE (%)
ARIMA	0.009	0.007	0.566
Prophet	0.006	0.005	0.445
Random Forest	0.005	0.003	0.271
NeuralProphet (AR-Net & FFNN)	0.007	0.004	0.423
16 1D CNN$_{(2,2,64)}$	0.025	0.020	-

Final remarks

- Preliminary tests show that ADAs can be successfully classified with ML tree esemble methods. Let's see when InSAR database increases..
- Based on previous experience and literature, we expect promising results in 1D and 2D PS time series forecasting, using ML time-series models (e.g., Random Forest, NeuralProphet) and DL (CNNs, ConvLSTM, ...)
- Open issues: how to deal with SITS-DL preprocessing, training, scaling and deployment.
- Ideas and/or suggestions are highly welcome.

Funding

The SARAI project is funded by the Ministry of Science and Innovation of Spain (MCIN/AEI/10.13039/501100011033, PID2020-116540RB-C22)

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