Towards assessing the link between slow slip and seismicity with a Deep Learning approach

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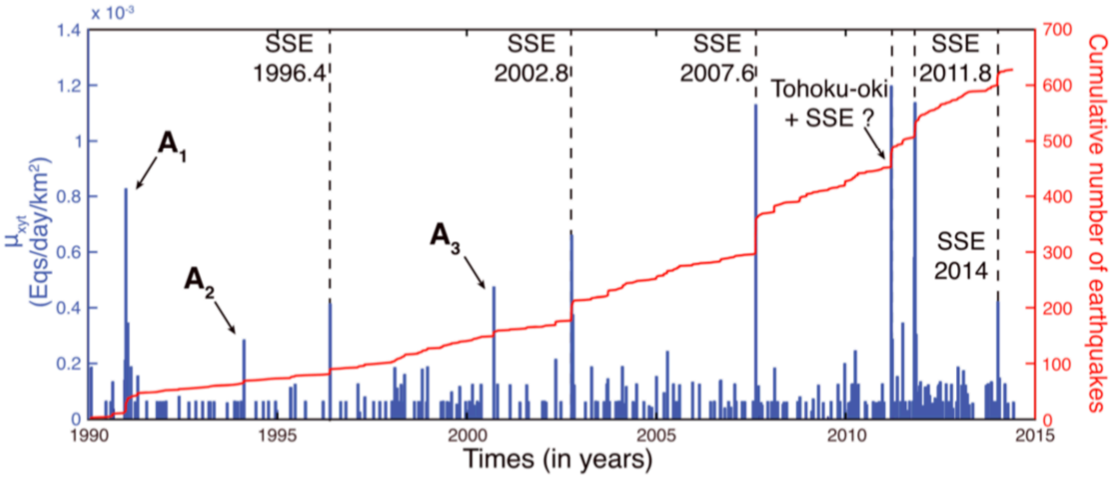
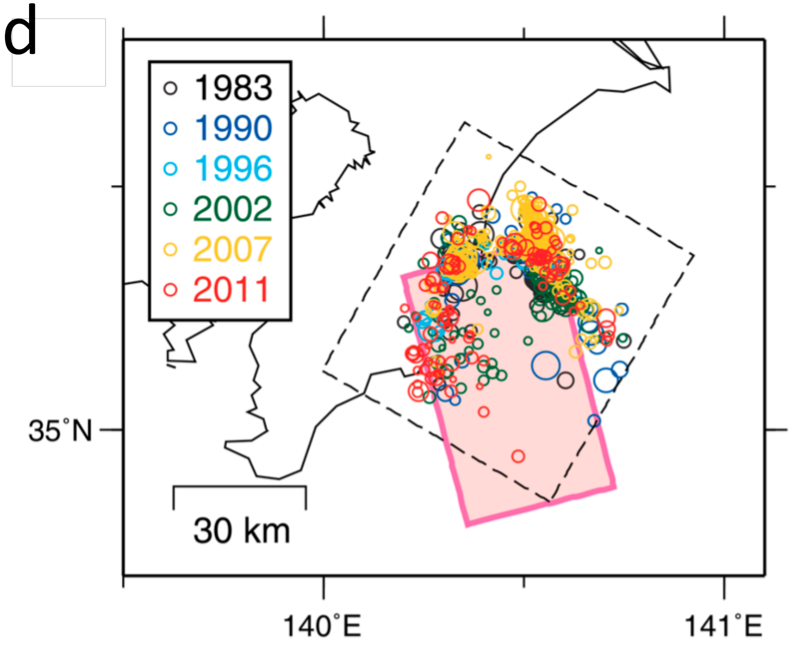
Context and objective of the work

- Slow Slip Events occur below Boso Peninsula (Japan)
- Goal: analyse the link between regular seismicity and surface deformation, using Machine Learning



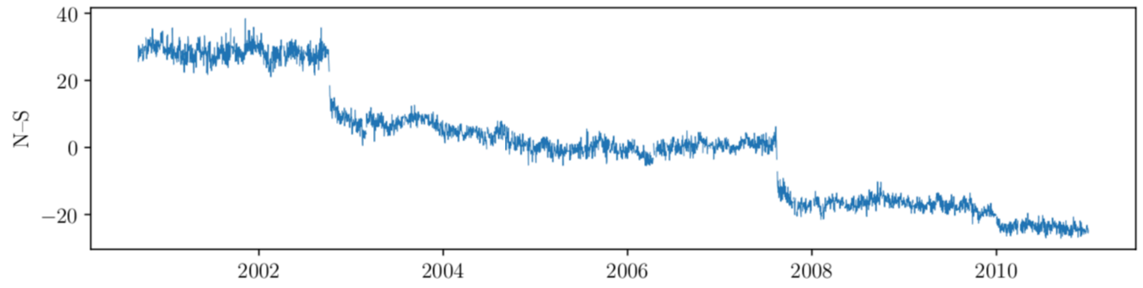
Time series of the background seismicity in Boso peninsula (Reverso et al., 2016)



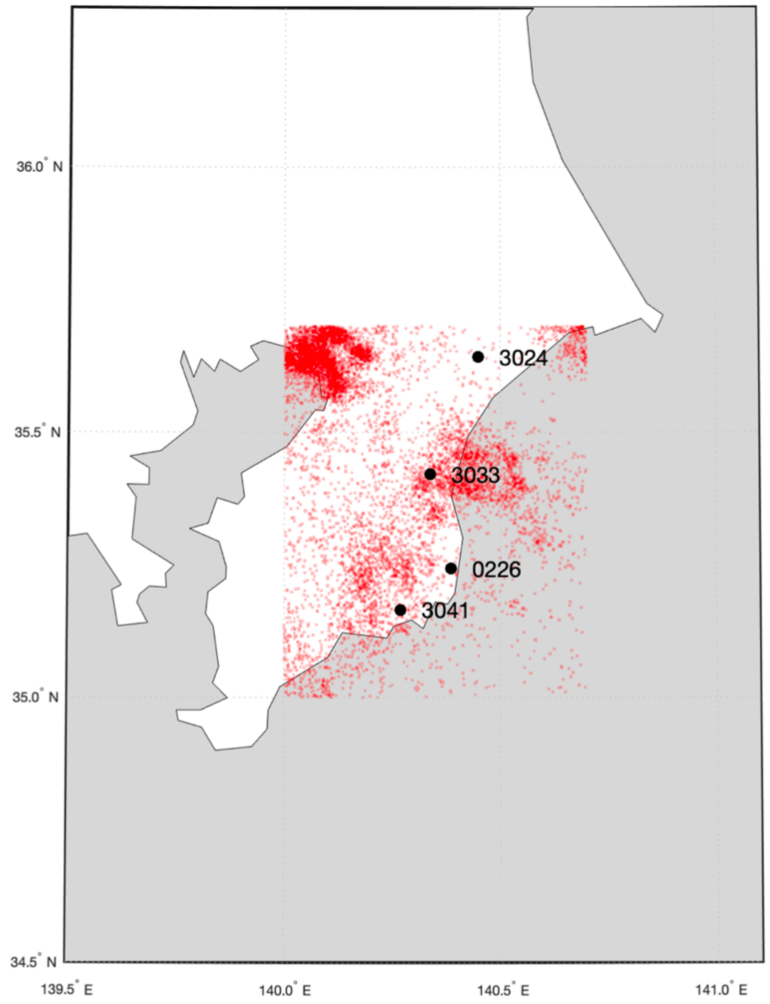
Slow Slip Events and associated earthquakes offshore Boso (Hirose et al., 2012)

Employed data

- Seismic catalogue (from JMA)
- Displacement time series (from GNSS)



N-S daily displacement time series (station 3033).



Seismicity catalogue used here (red dots). Black dots locate the four GNSS stations considered in this study

Proposed method

- Different approaches tested
  - Random Forest Regression (RF) (e.g. Rouet-Leduc et.al, 2019)
  - Deep Learning : Dual–Stage Attention–based Recurrent Neural Network (DA-RNN) (Qin et al., 2017) (with LSTM encoder – decoder structure)
- Features:
  - daily #eqs, cumulative #eqs, denoised eq. rate, modeled displacement
  - Epicenters within a given distance from the GPS station (20 km shown here)

- Train and validation: years 2000 – 2007 (about 2600 samples)
- Testing: years 2007 – 1010 (about 1100 samples)

Experimental results

- The displacement is modeled as a function of past seismicity and displacements. An extra parameter Δt [days] is required, as positions at close time steps are highly correlated each other, making the model unsensitive to the input features.

$$d(t) = f\big(\varepsilon(t), \varepsilon(t-1), \dots, \varepsilon(t-T), d(t \boldsymbol{- \Delta t}), \dots, d(t - T \boldsymbol{- \Delta t})\big)$$

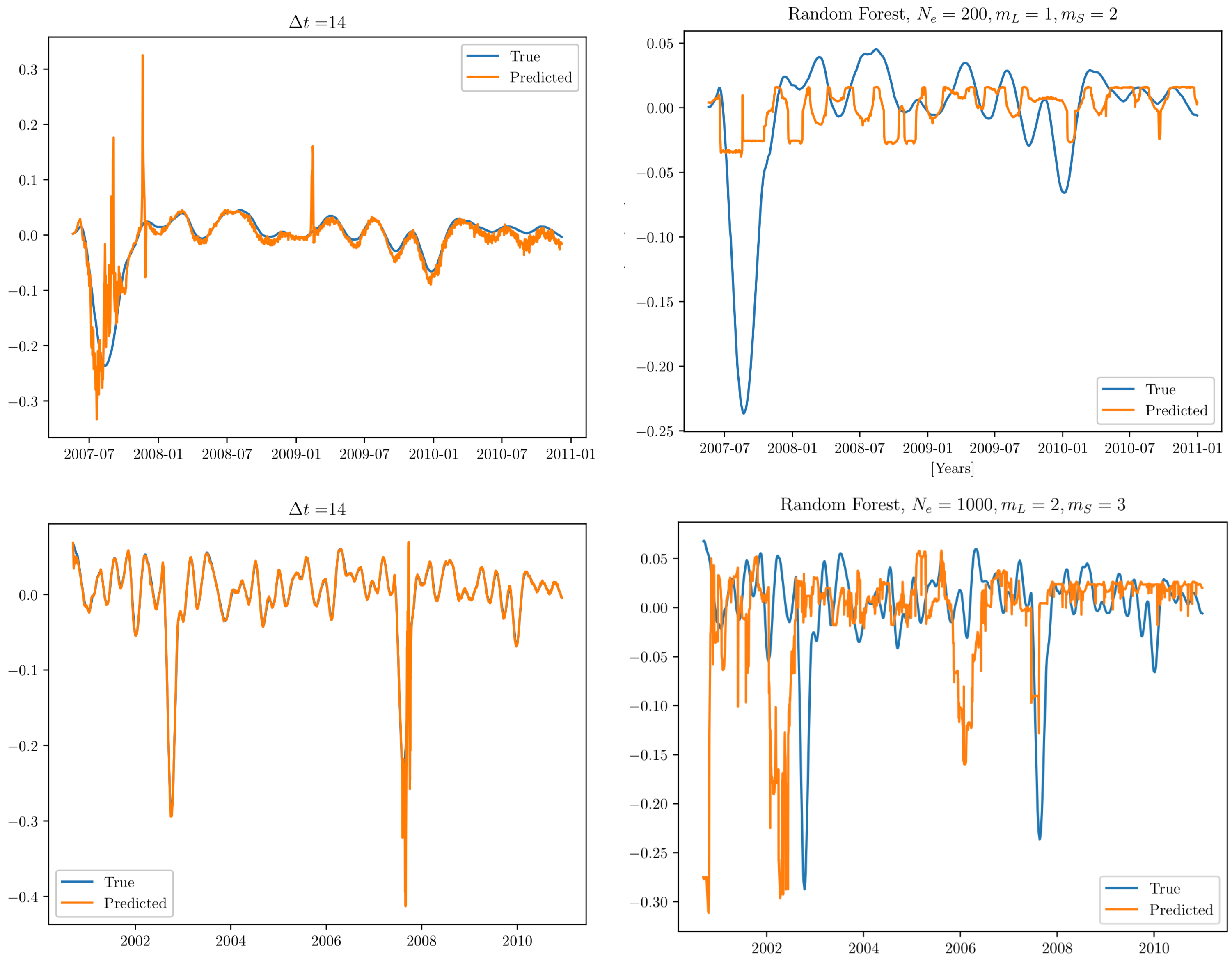
- Two experiments are shown
  - Analysis on station 3033, with feature extracted by selecting epicenter at a distance of 20 km apart the station
  - Features are extracted for stations 3024, 3033, 0226, 3041 (20 km distance). The model is trained sequentially on the whole period of interest (2000-2010) using data from stations 3024, 0226, 3041 and tested on station 3033 on the period 2000-2010.

Comparison between DA-RNN and RF

DA-RNN with $\Delta t = 14$ days

Single-station vs multi-station approach (rows) for DA-RNN and RF (columns)

- RF trained on multistations reproduces the first order time series variability, but fails to predict the exact timing and amplitude of SSEs: the link between slow slip and *regular* seismicity is not linear.
- DA-RNN fits the time series better but needs to be used with caution.



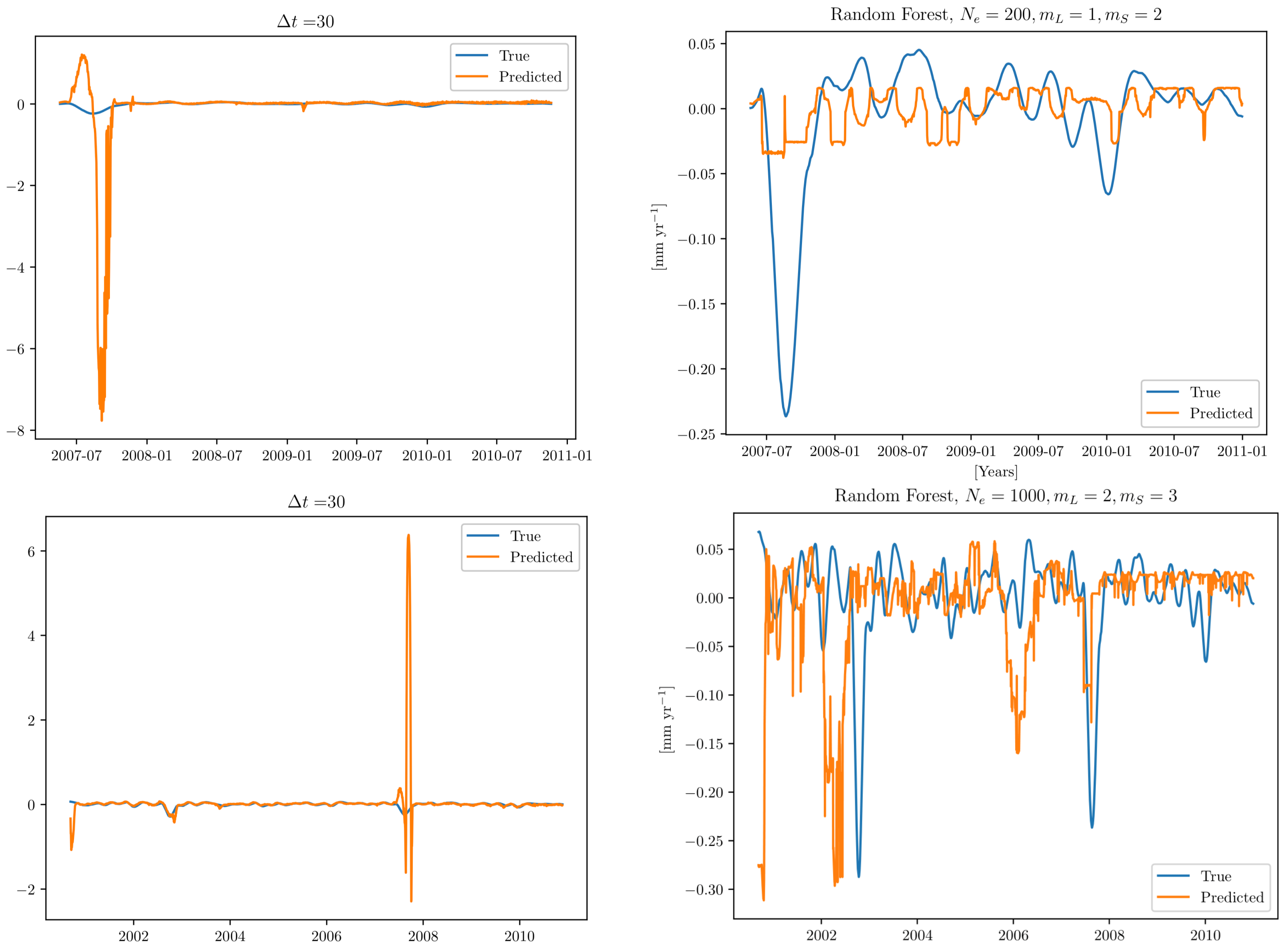
Comparison between DA-RNN and RF

DA-RNN with $\Delta t = 30$ days

Single-station vs multi-station approach (rows) for DA-RNN and RF (columns)

- RF trained on multistations reproduces the first order time series variability, but fails to predict the exact timing and amplitude of SSEs: the link between slow slip and *regular* seismicity is not linear.

- DA-RNN fits the time series better but needs to be used with caution.

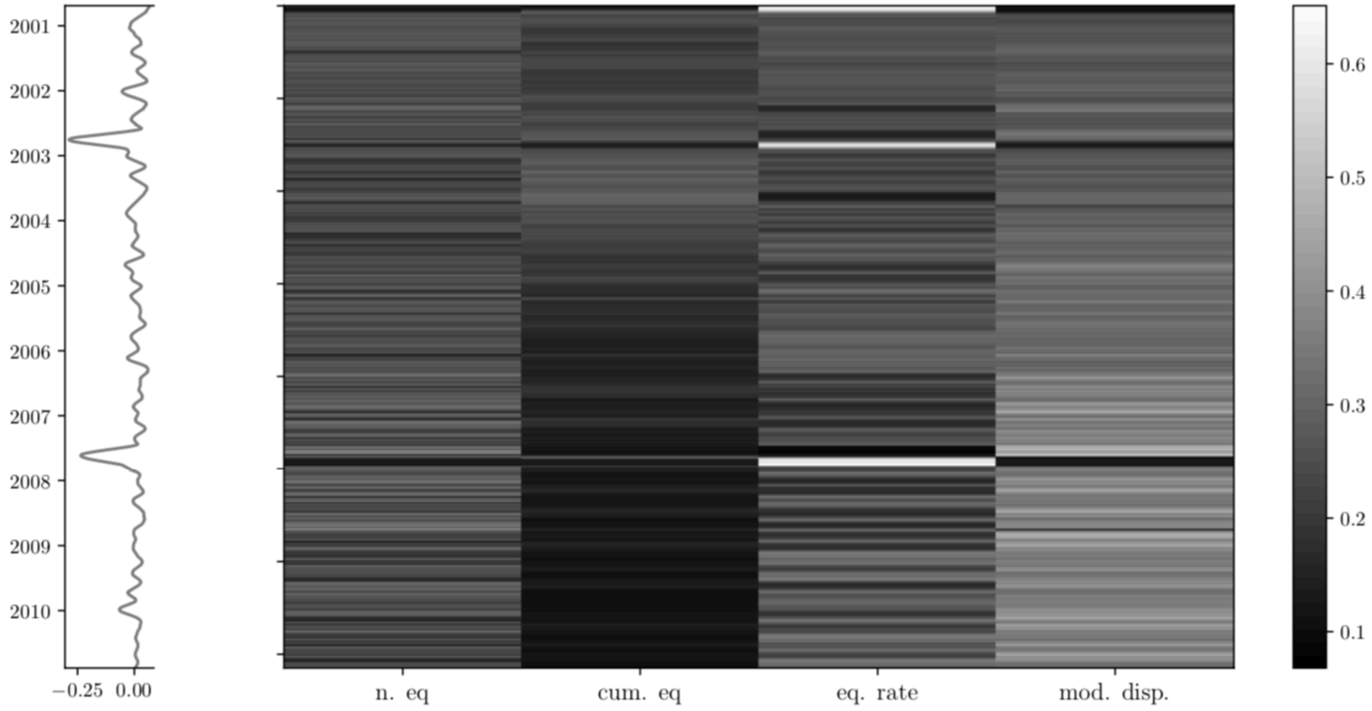


Information extracted from the attention matrix

- *attention matrix* : shows the significance of the *i*-th feature (columns) at the *t*-th time step (rows). It is obtained from DA-RNN. The expected output (displacement rate) is plotted for helping in the visualization.

Key features:

- eq. rate *during* the Slow Slip Event (SSE)
- modeled displacement *between* SSEs



Attention matrix with multistation approach ($\Delta t = 30$ days)

Attention matrix: potentially gives precious information about relevant parameters on a given phenomenon.

Conclusions and perspectives

- The experiments prove that the response of seismicity to slow slip is non-linear
- The DA-RNN approach provides potential insights into the physics of the problem, through the attention matrix
- The problem complexity pushes towards the adoption of more features and more stations

Cited literature

H. Hirose et al. “Recurrent slow slip event likely hastened by the 2011 Tohoku earthquake”. In: Proceedings of the National Academy of Sciences 109.38 (2012), pp. 15157–15161.

Y. Qin et al. “A dual-stage attention-based recurrent neural network for time series prediction”. In: arXiv preprint arXiv:1704.02971 (2017).

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B. Rouet-Leduc, C. Hulbert, and P. A. Johnson. “Con- tinuous chatter of the Cascadia subduction zone revealed by machine learning”. In: Nature Geoscience 12.1 (2019), pp. 75–79.