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National Institute
of Oceanography
and Applied
Geophysics



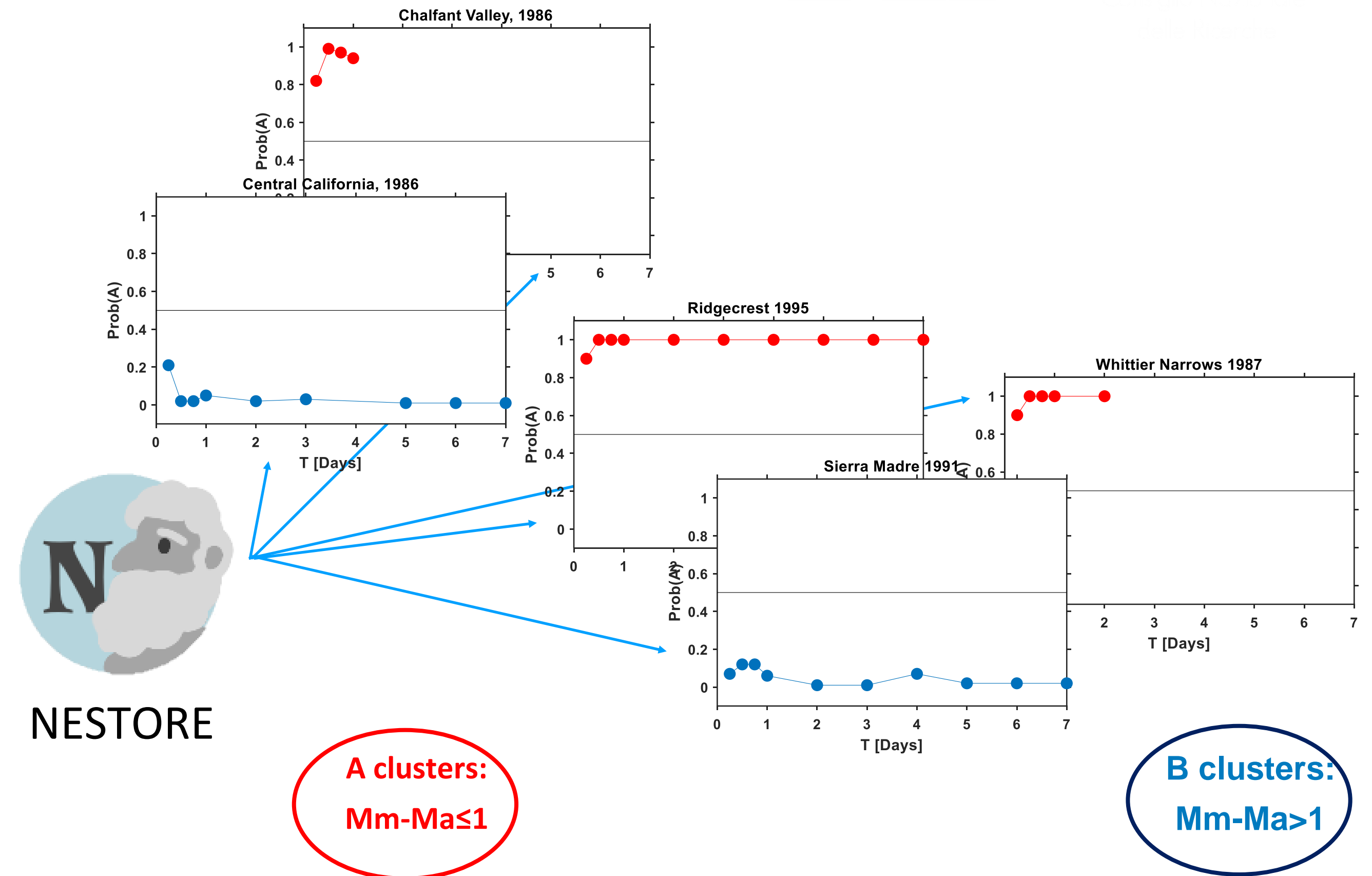
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Di Geofisica e Vulcanologia

An optimized online version of NESTORE software package for the forecasting of strong aftershocks: an application to Italian clusters

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- **NESTORE** – (*NE*xt *STr*OnG *Re*lated *E*arthquake) is an algorithm based on **machine learning** approach
- It divides the clusters into **two classes** based on the difference in magnitude D_m between the **o-mainshock** (the first large shock e.g. $M > 4$) and the strongest following earthquake
(Type A: $D_m \leq 1$ Type B: $D_m > 1$)
- NESTORE goal is type **A clusters** **probabilistic forecasting** based on **features extracted** from seismic catalogues in the first hours/days after the o-mainshock



NESTOREv1.0 Features



NUMBER AND SPATIAL DISTRIBUTION OF EVENTS

$$N_2(i) = \sum_i n_i \quad \text{if } m_i > M_m - 2$$

$$Z(i) = \frac{\text{mean}(10^{0.69m_i-3.22})}{\text{mean}(r_{ij})}$$

SOURCE AREA TREND

$$S(i) = \sum_i 10^{(m_i - M_m)}$$

$$SLCum(i) = \sum_i \text{abs}[S(t_i) - S(t_{i-1})] \frac{i \cdot dt}{(i-1) \cdot dt}$$

$$SLCum2(i) = \sum_i \text{abs}[S([s_1 + (i-1) \cdot dt, s_1 + i \cdot dt]) - S([s_1 + (i-1) \cdot dt, s_1 + (i-1) \cdot dt + d\tau]) \frac{dt}{d\tau}]$$

ENERGY AND MAGNITUDE TREND

$$Q(i) = \frac{\sum_i E_i}{E_m}$$

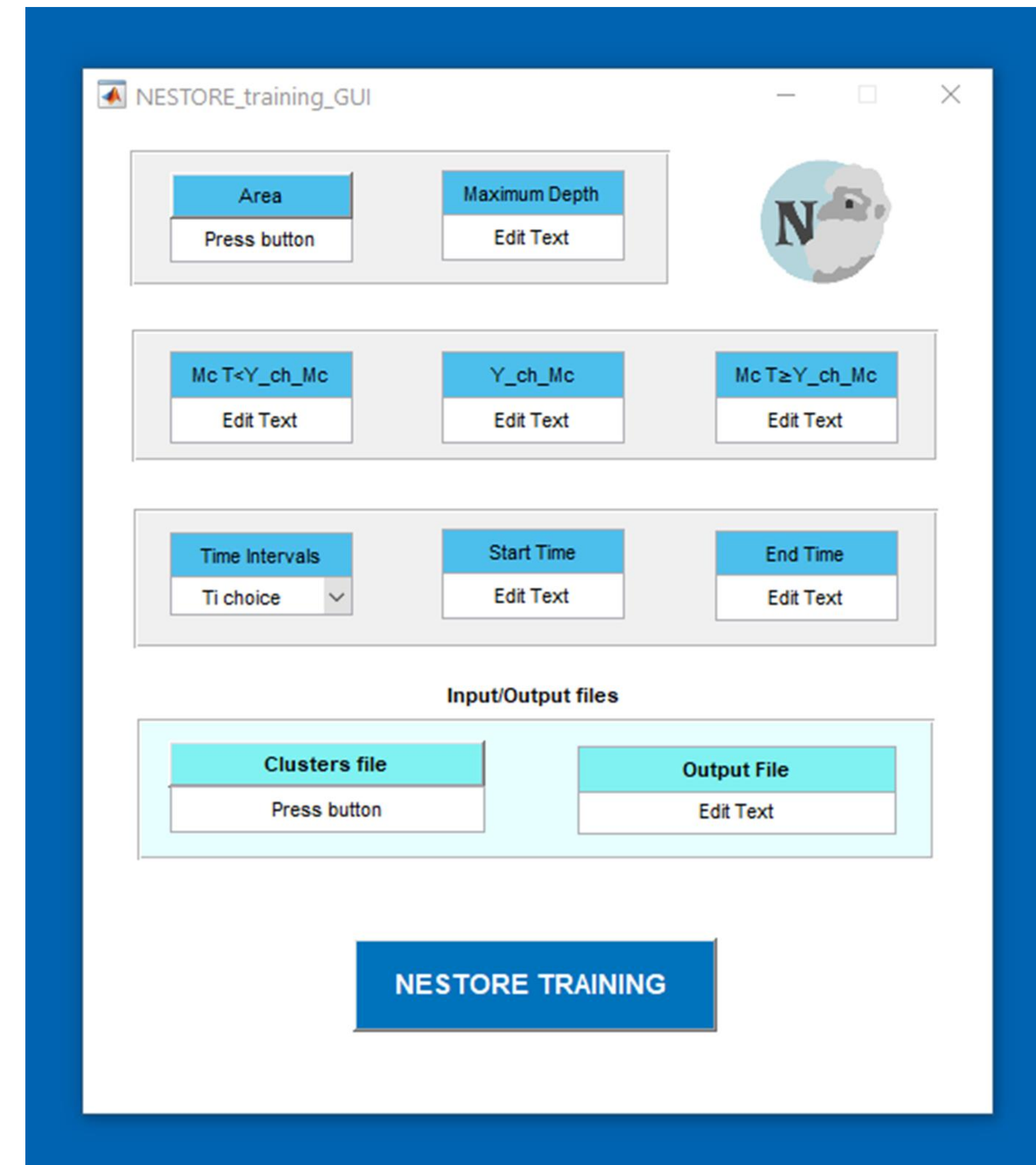
$$QLCum(i) = \sum_i \text{abs}[Q(t_i) - Q(t_{i-1})] \frac{i \cdot dt}{(i-1) \cdot dt}$$

$$V_m(i) = \sum_i |m_i - m_{i-1}|$$

$$QLCum2(i) = \sum_i \text{abs}[Q([s_1 + (i-1) \cdot dt, s_1 + i \cdot dt]) - Q([s_1 + (i-1) \cdot dt, s_1 + (i-1) \cdot dt + d\tau]) \frac{dt}{d\tau}]$$

NESTOREv1.0 modules

- **NESTOREv1.0** software package consists of four main parts:
 - **cluster identification module**
 - **training module**
 - **testing module**
 - **NRT classification (1 cluster)**
- All modules can be launched separately by **command line**, a dedicated user interface (**GUI**) is being developed too

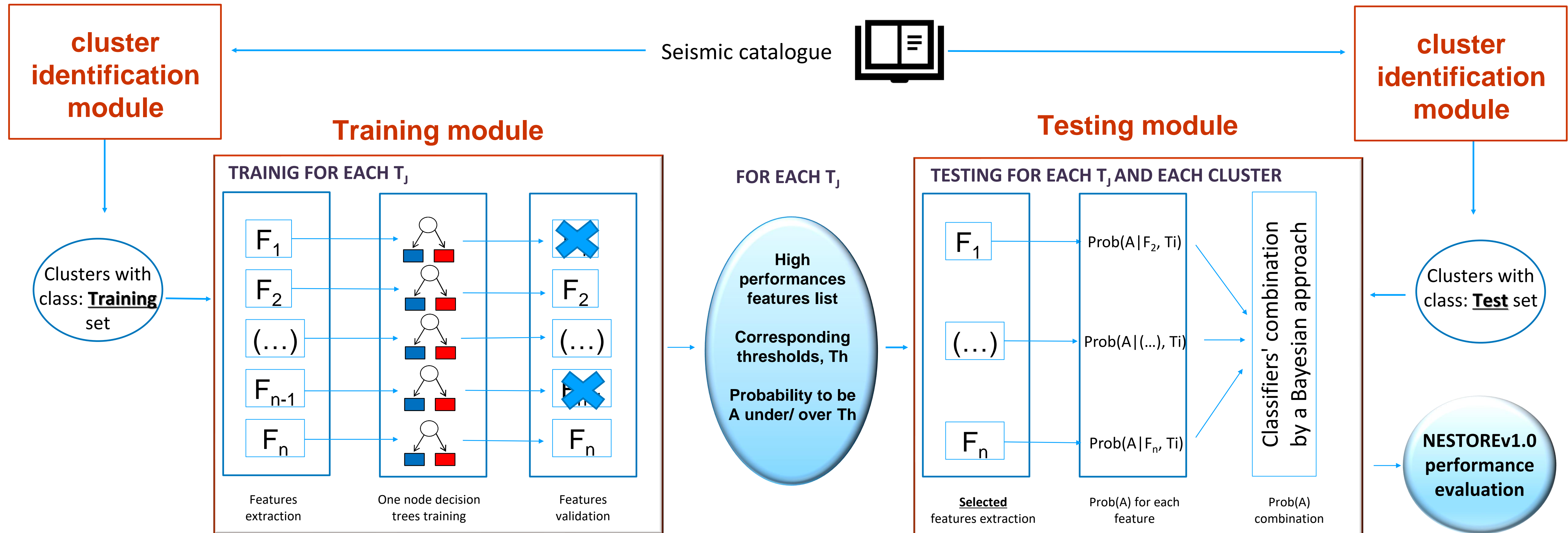


AVAILABLE ONLINE IN THE NEXT FEW MONTHS

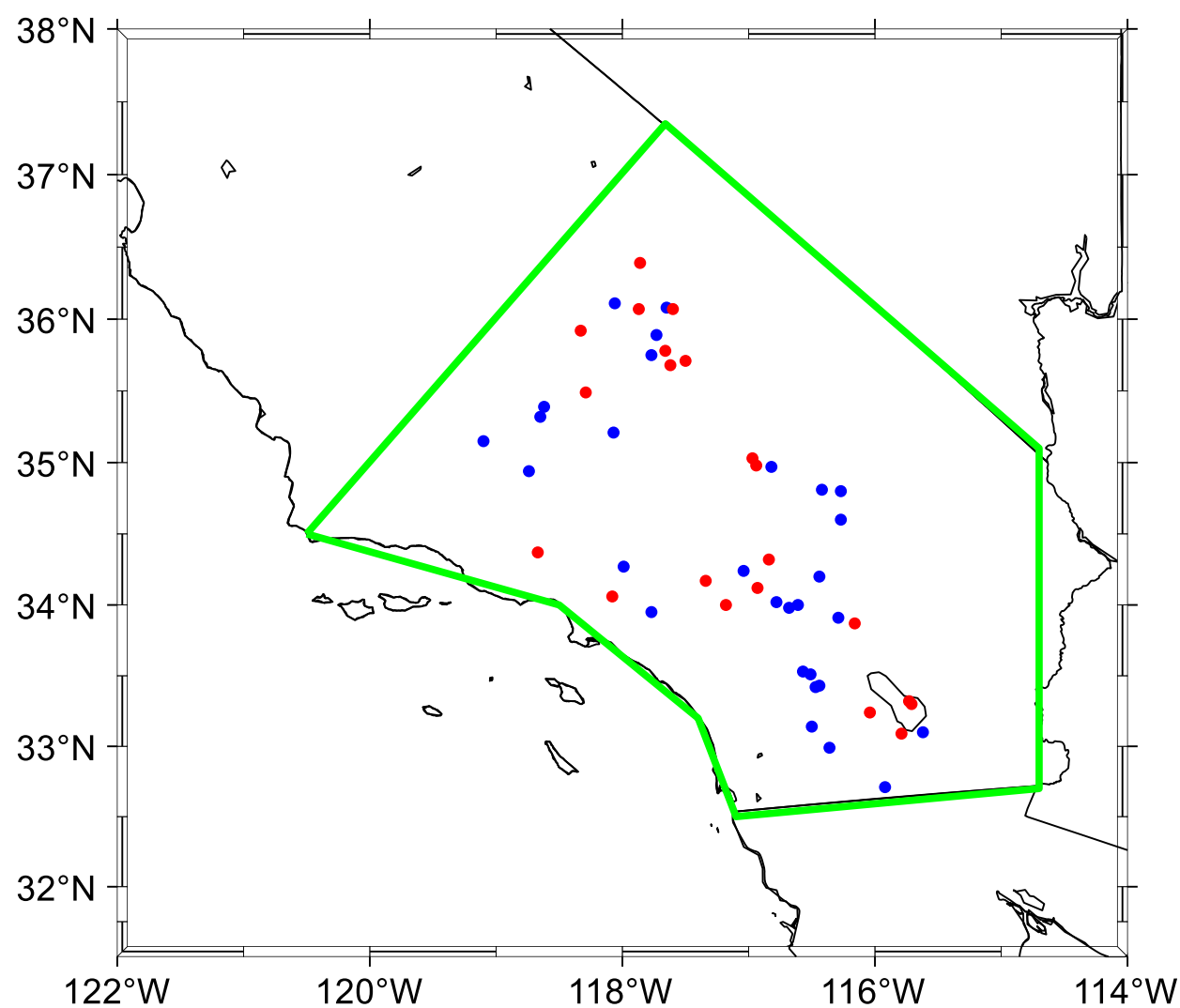


NESTOREv1.0 – TRAINING and TESTING

- NESTOREv1.0 analyses the seismic data at increasing time intervals $T=[0.25,0.5,0.75,1,2,\dots,7]$ days (T_i) after the mainshock.
- After the training NESTORE can supply the probability to have an A cluster at time intervals T_i for new clusters



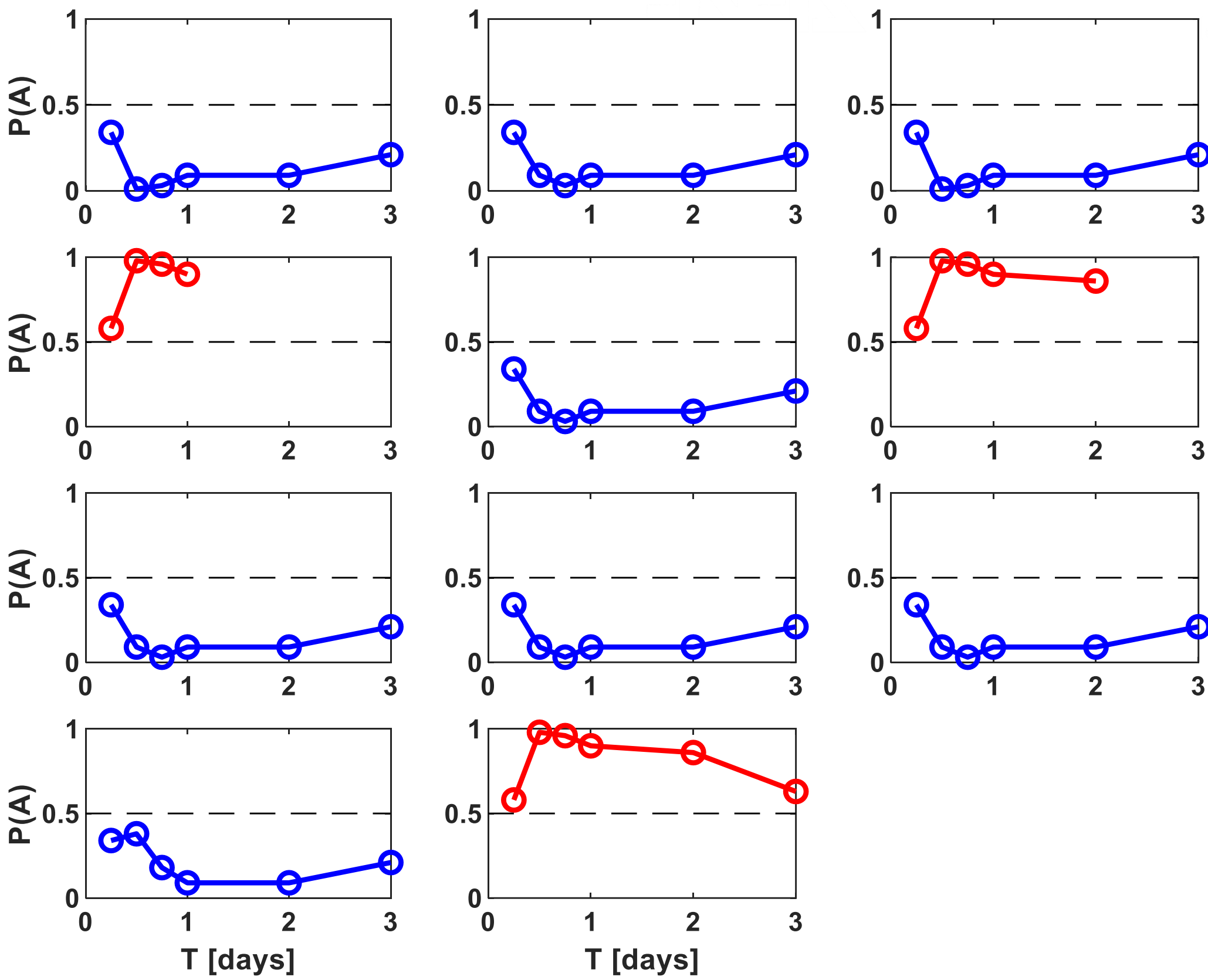
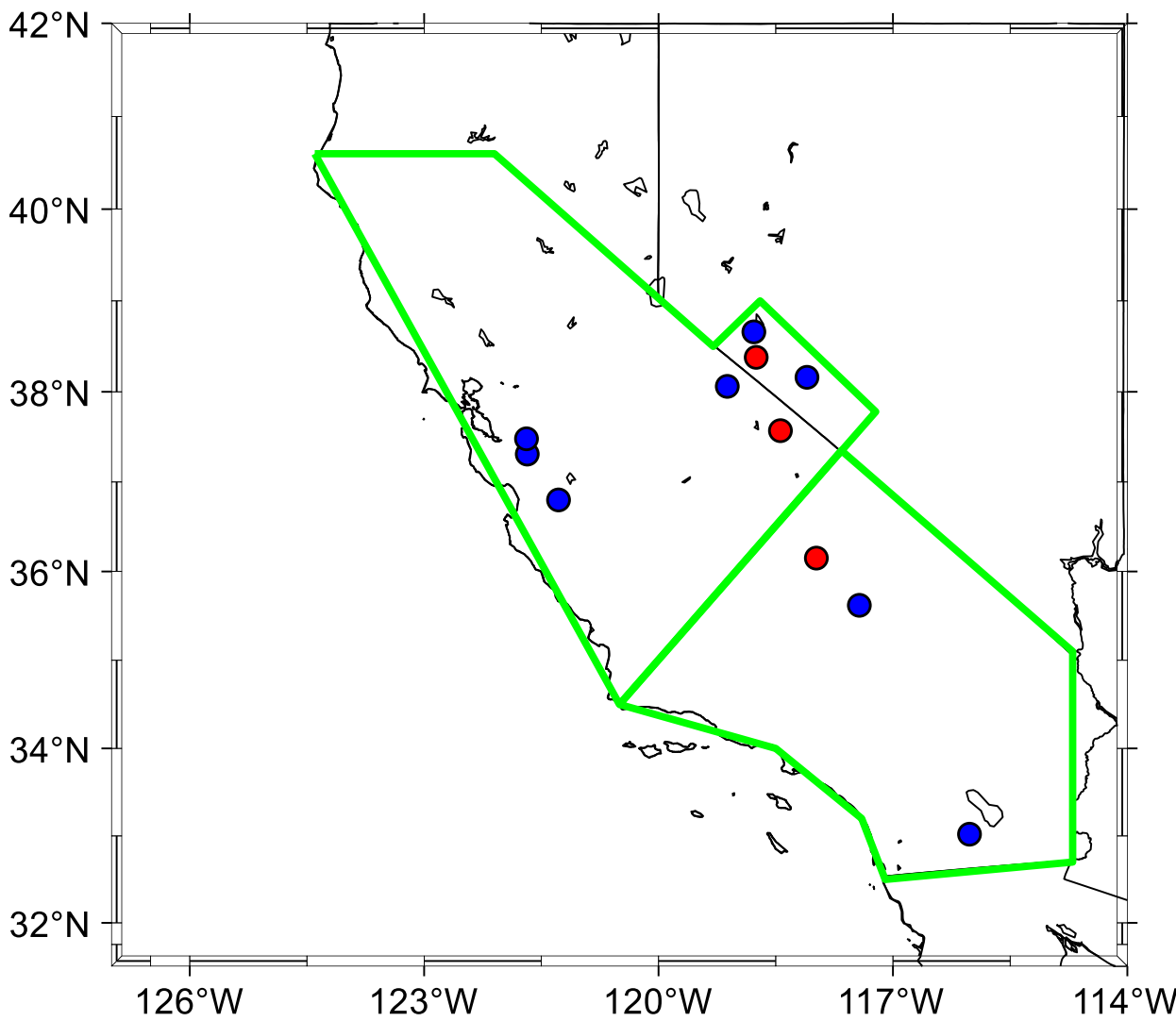
Training and testing NESTORE v1.0 in California



Dots: clusters mainshock location (50 clusters); red: type A clusters; blue: type B clusters.

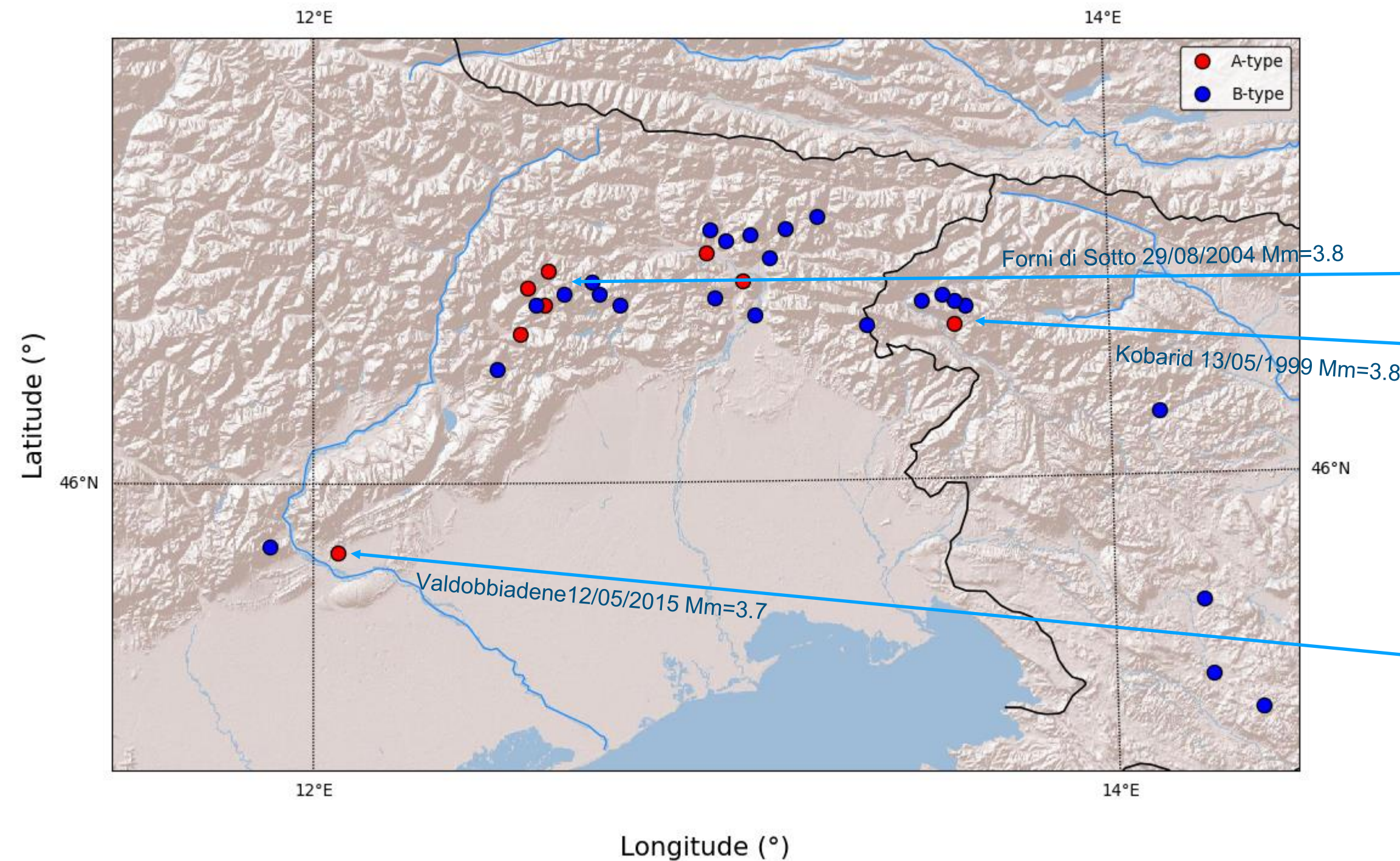
Training set:
SCSN [1981, 2020)
50 clusters

Test set:
(ComCat) [1981, 2021] +
SCSN [2020, 2021]
11 clusters



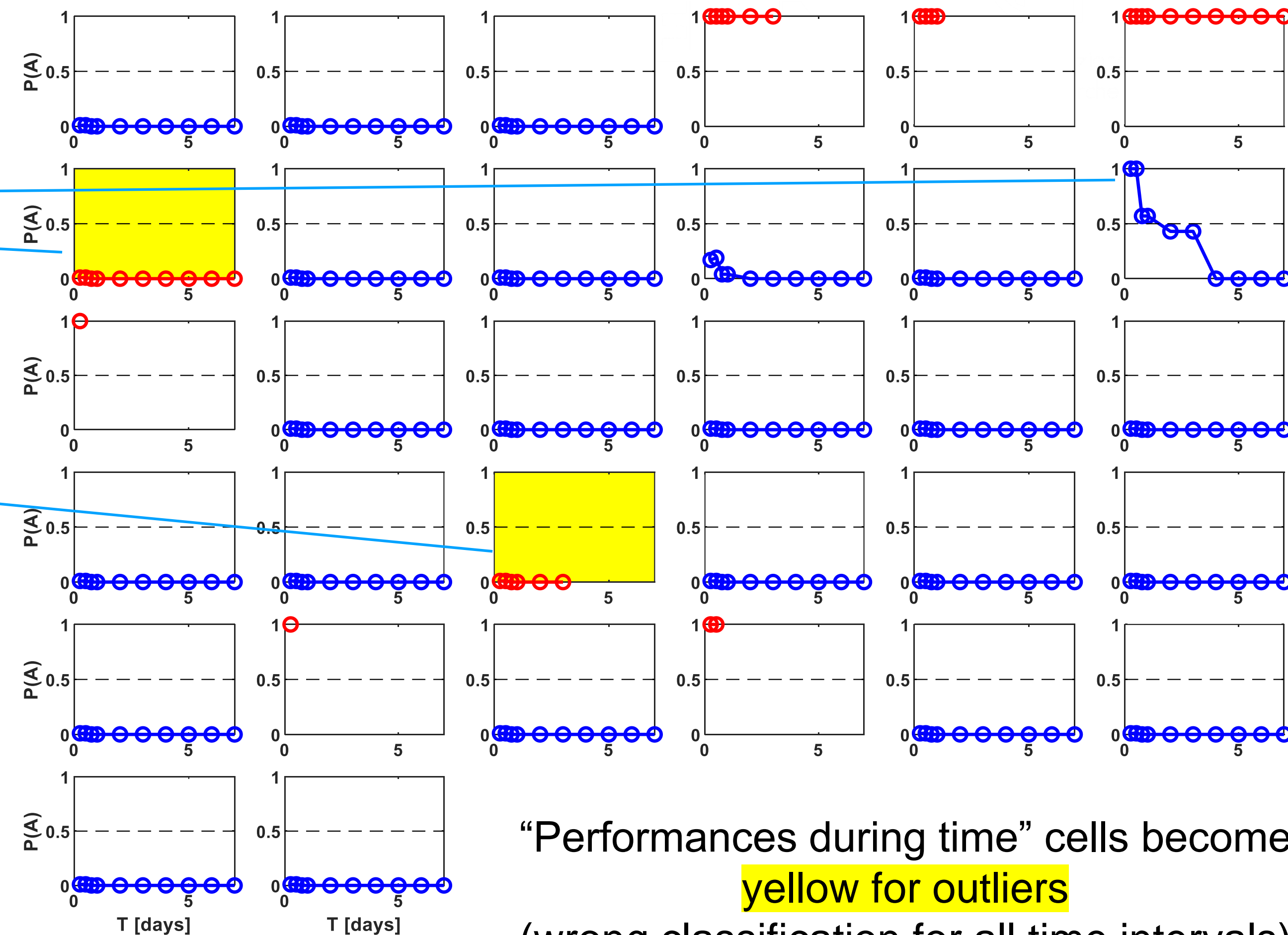
Performances during time

Self-test on NE Italy - Western Slovenia



Training AND testing: OGS catalogue [1977, 2021]
32 clusters

Dots: clusters mainshock location (50 clusters); red: type A clusters; blue: type B clusters.

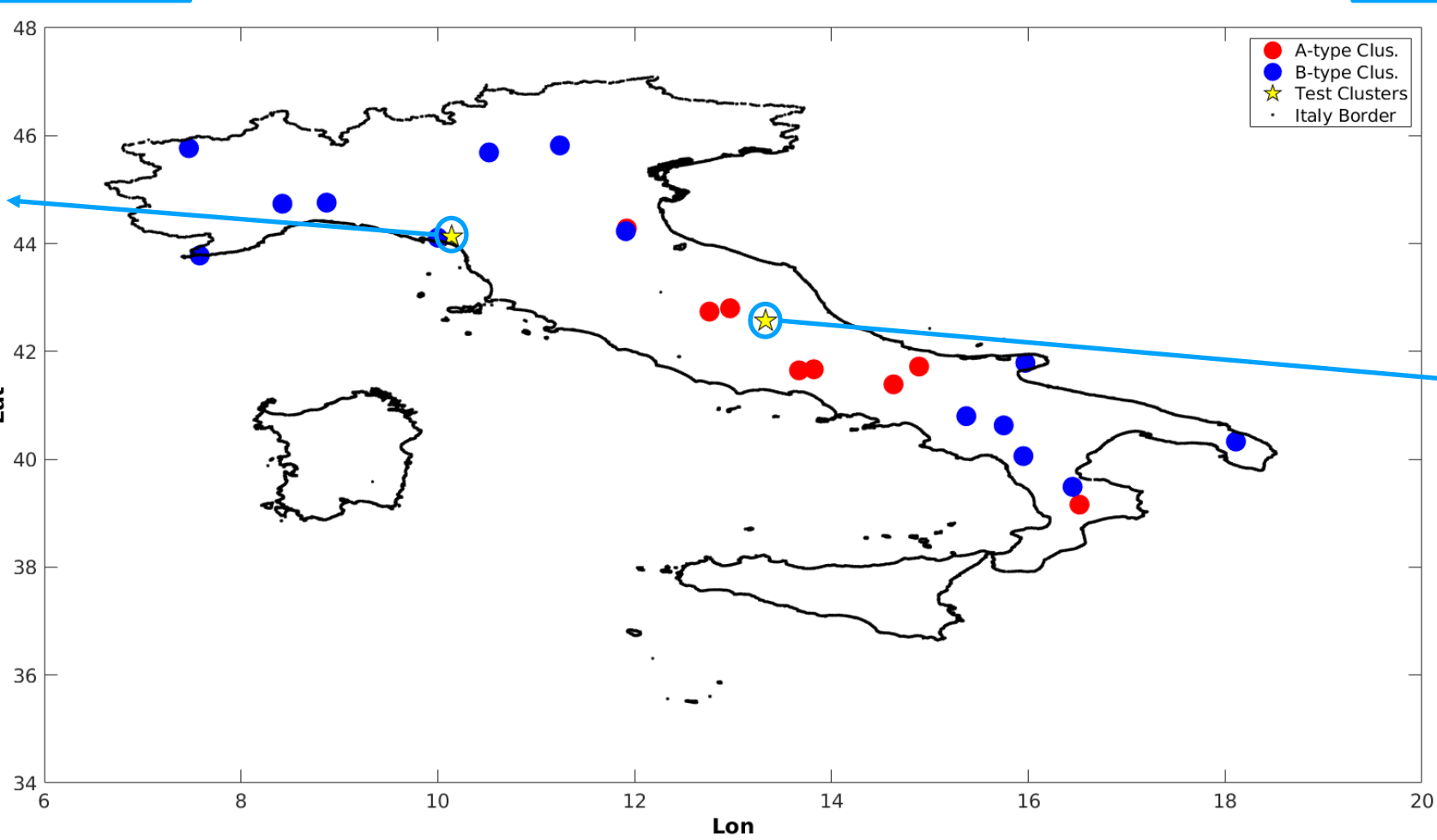
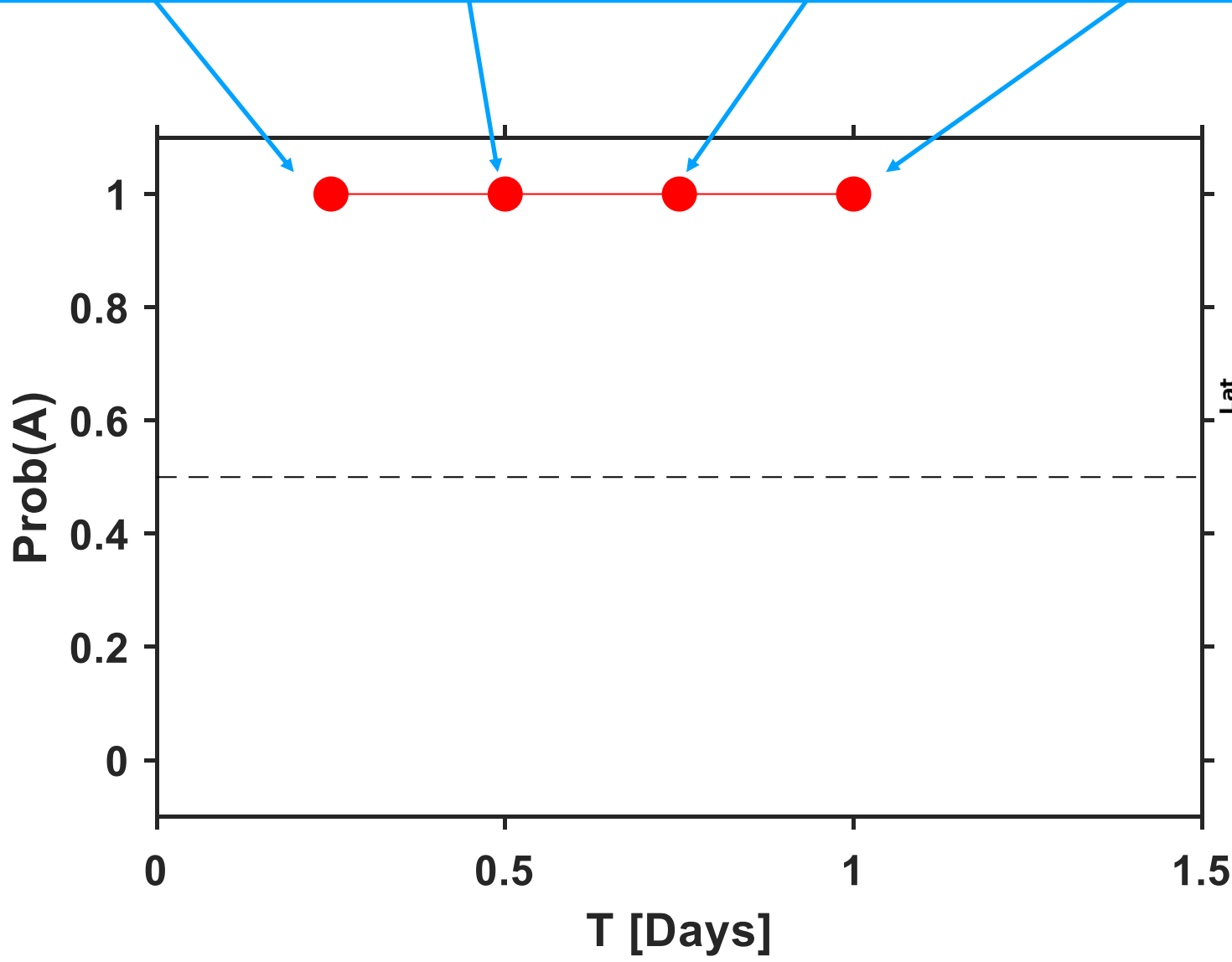
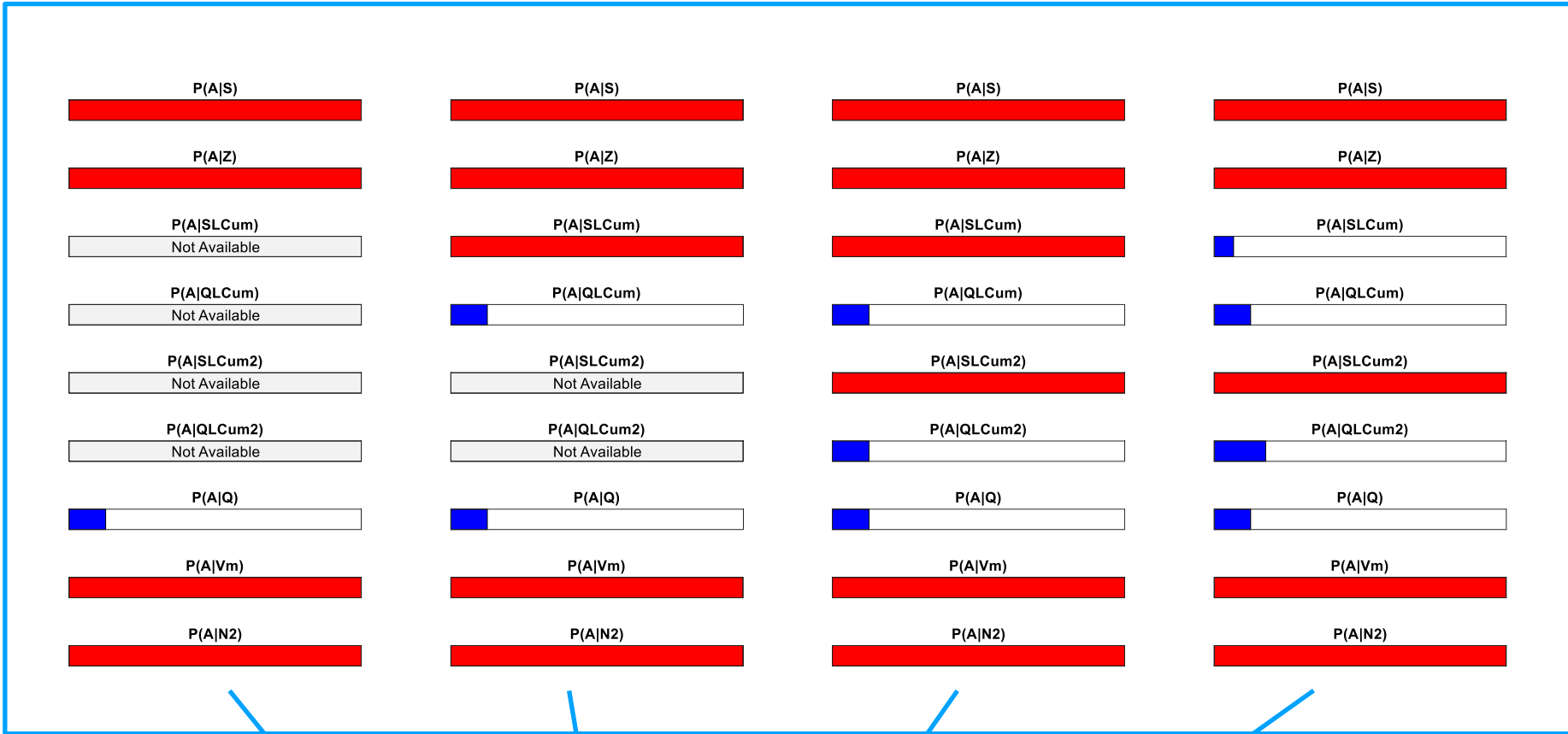
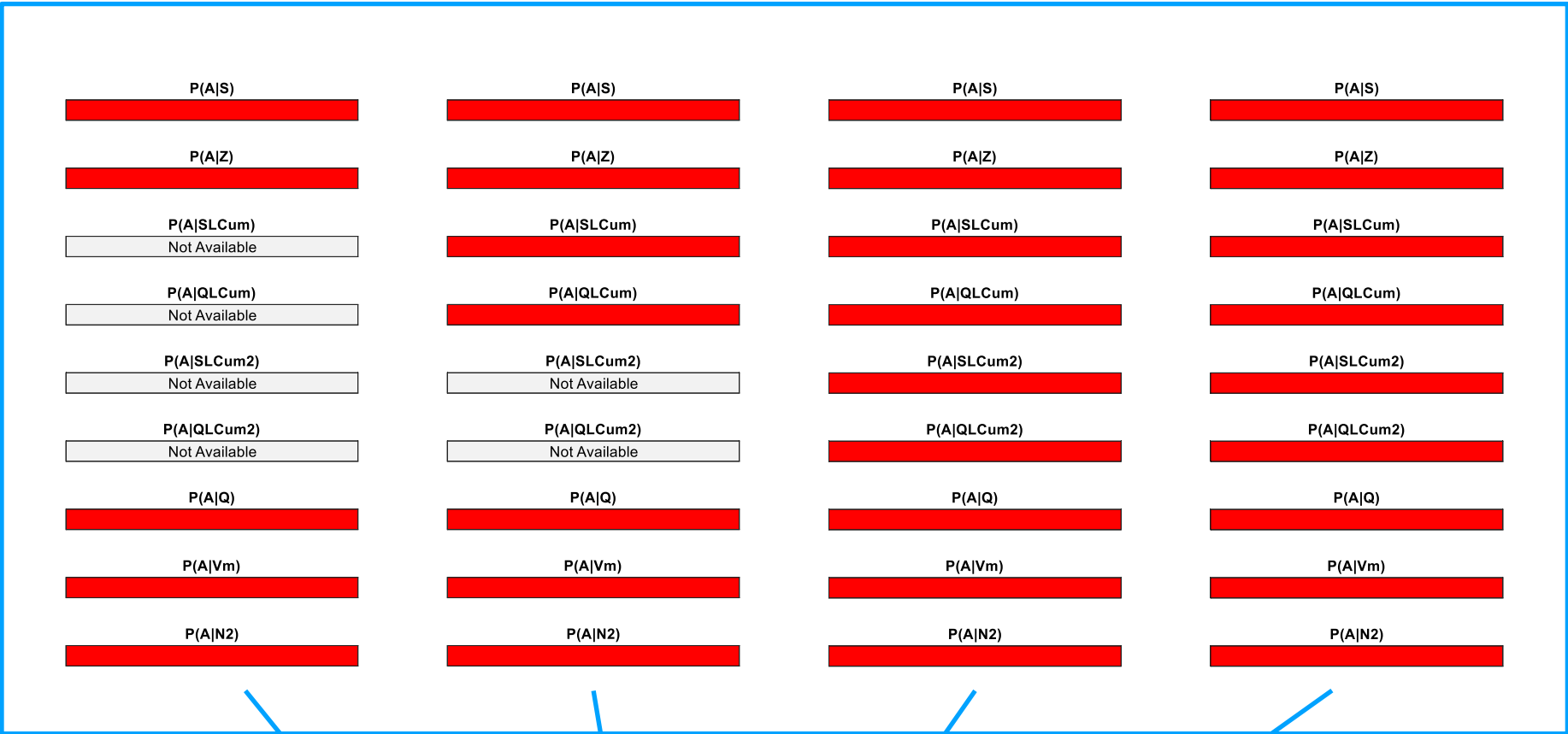


“Performances during time” cells become
yellow for outliers
(wrong classification for all time intervals)

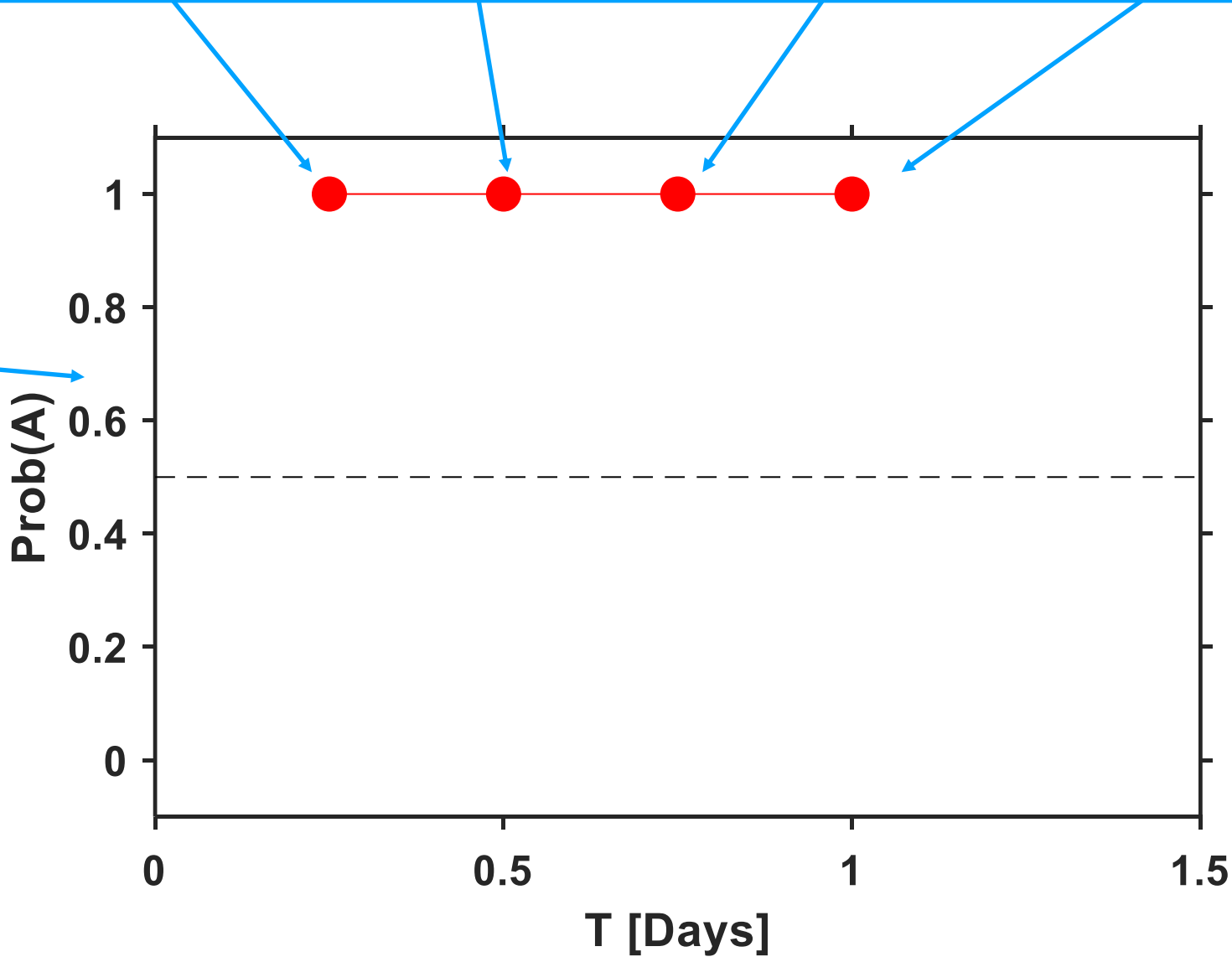
NRT classification Italy

June 21, 2013

July 22, 2017



Training set:
Lolli & Gasperini catalogue [1980-2004) + ISIDe
[2005-2009]





For further details

- Gentili S. and Di Giovambattista R. (2017). Pattern recognition approach to the subsequent event of damaging earthquakes in Italy. Physics of the Earth and Planetary Interiors, 266, 1-17.
https://www.researchgate.net/publication/314126252_Pattern_recognition_approach_to_the_subsequent_event_of_damaging_earthquakes_in_Italy
- Gentili S. and Di Giovambattista R. (2020). Forecasting strong aftershocks in earthquake clusters from northeastern Italy and western Slovenia. Physics of the Earth and Planetary Interiors, 303, 106483. <https://arxiv.org/ftp/arxiv/papers/2005/2005.02779.pdf>
- Gentili S. and Di Giovambattista R. (2022). Forecasting strong subsequent earthquakes in California clusters by machine learning. Physics of the Earth and Planetary Interiors, 327, 106879. <https://www.sciencedirect.com/science/article/pii/S0031920122000401>

Confusion matrix



		<u>True class</u>	
		p	n
<u>Hp</u> <u>class</u>	Y	TP	FP
	N	FN	TN
totals		P	N

$$Recall = TPR = \frac{TP}{P}$$

$$Precision = \frac{TP}{Y}$$

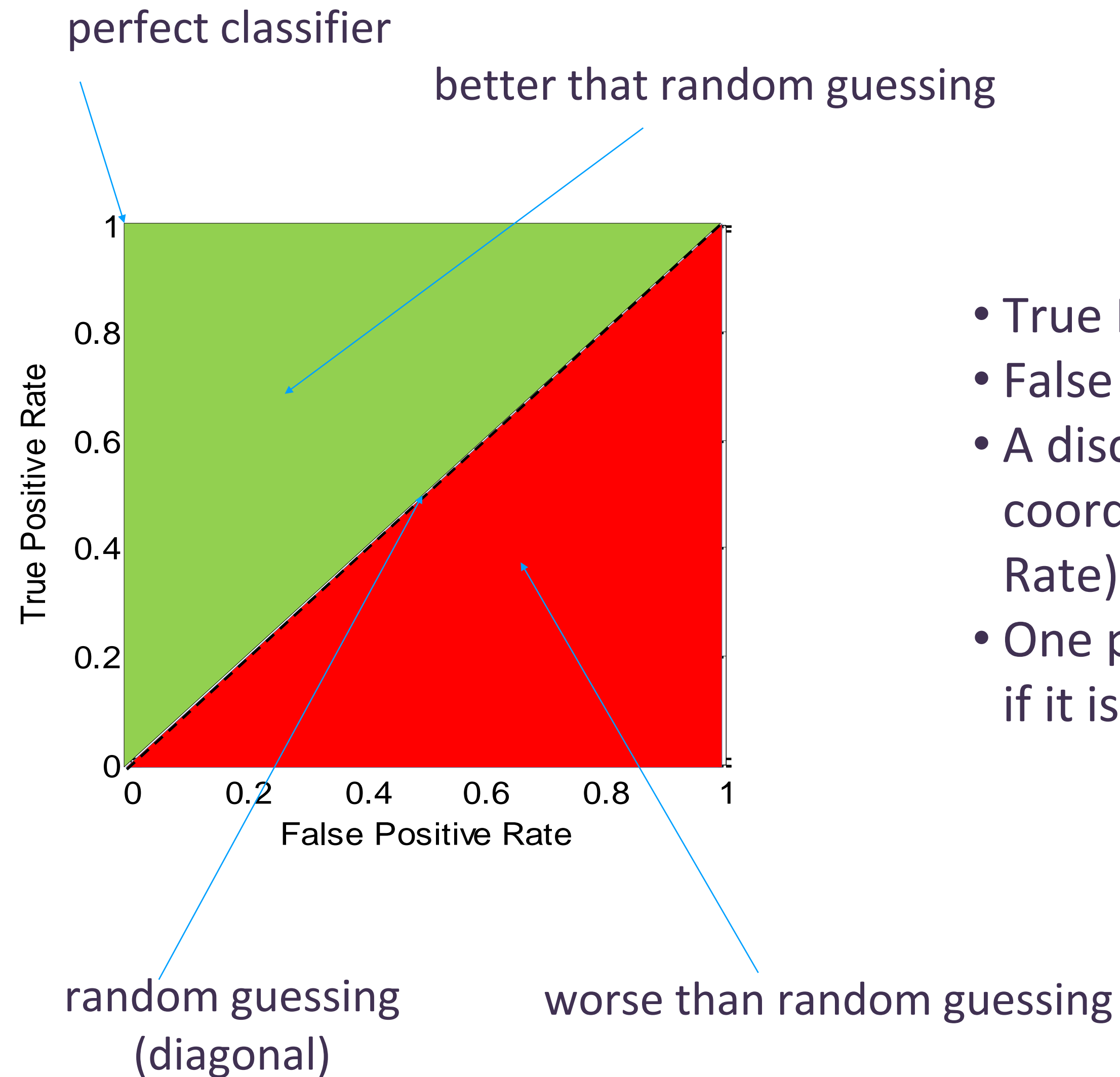
$$Accuracy = \frac{TP + TN}{P + N}$$

$$FPR = \frac{FP}{N}$$

Confusion matrix

$$Informedness = TPR - FPR$$

ROC



- True Positive Rate= True(A) / All(A)
- False Positive Rate= False(B)/ All(B)
- A discrete classifier produces a point of coordinates (False Positive Rate, True Positive Rate) in the ROC graph.
- One point in ROC space is better than another if it is closer to the point (0,1)

Classifiers combination

- For **each** T_j , only the **feature selected** during the training set are extracted
- The thresholds are compared with the value of the feature to estimate the probability p_i that the cluster is A for each feature
- The values of p_i are combined by using a **Bayesian approach**

$$P(A|D_1 \dots D_N) = \frac{[N(B)]^{N-1} \prod_{n=1}^N p_n}{[N(B)]^{N-1} \prod_{n=1}^N p_n + [N(A)]^{N-1} \prod_{n=1}^N (1 - p_n)}$$