RETROSPECTIVE OPERATIONAL AFTERSHOCK FORECASTING FOR L'AQUILA 2009 AND AMATRICE 2016 SEISMIC SEQUENCES IN CENTRAL ITALY

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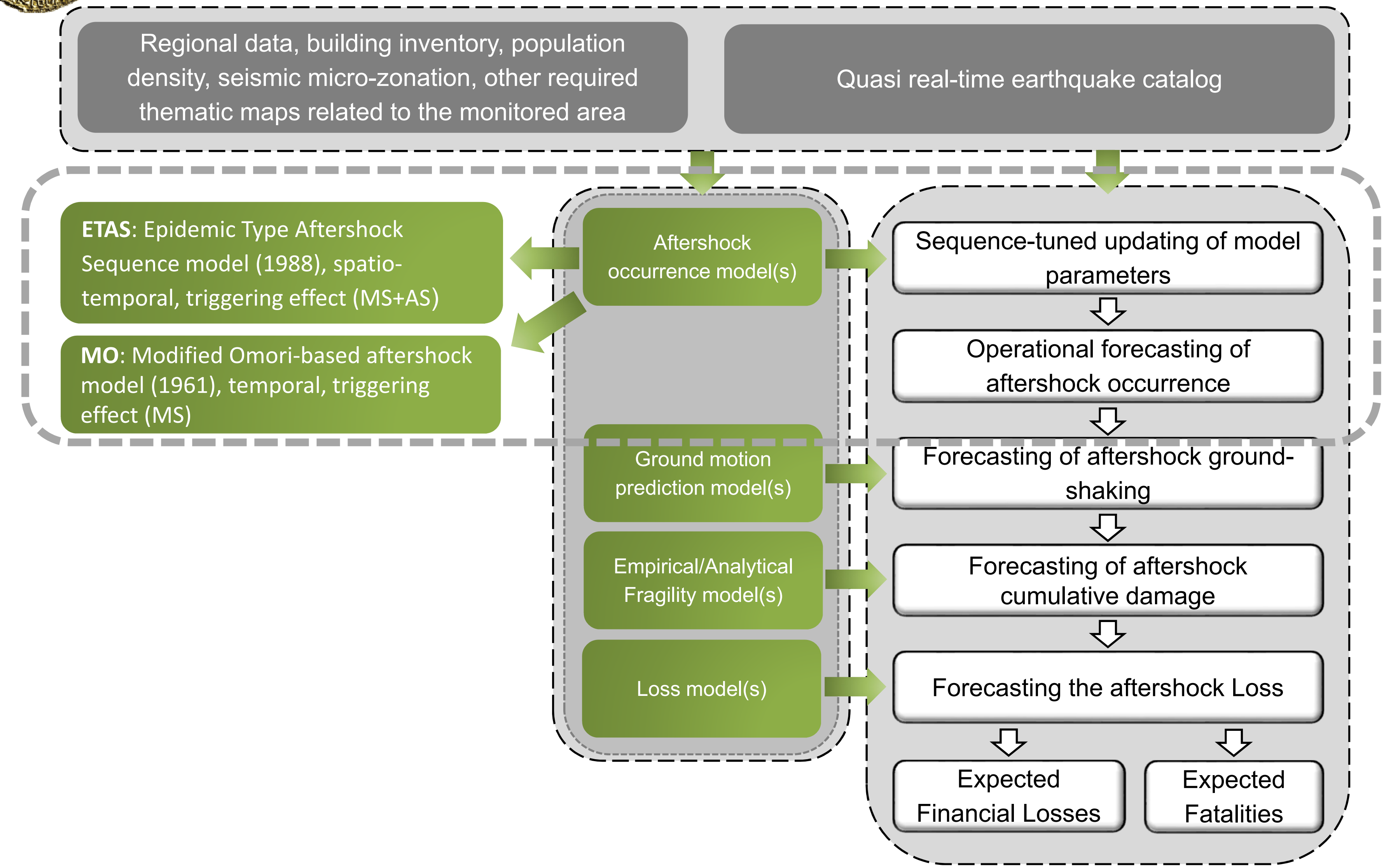
In the presence of aftershock events in an ongoing seismic sequence, numerous emergency decisions must be made; for instance,

- Which are the critical infrastructure that need to be shut down and how long?
- Will the strategic buildings, structures and infrastructures stay fully operational (or they may become vulnerable during the ongoing sequence)?
- Which are the buildings that need to be evacuated?
- Can the buildings withstand the cumulative damage due to triggered events?
- Can the rescue Team enter the damaged buildings for emergency and rescue operations?
- When can people re-enter into their houses?

Traditionally, such decisions were made based on visual inspections, best judgment, and past disaster experiences. However, decision-makers can benefit enormously from **scientific advisories in terms of early forecasts** which can provide **supports for post-earthquake management during an ongoing seismic sequence**.

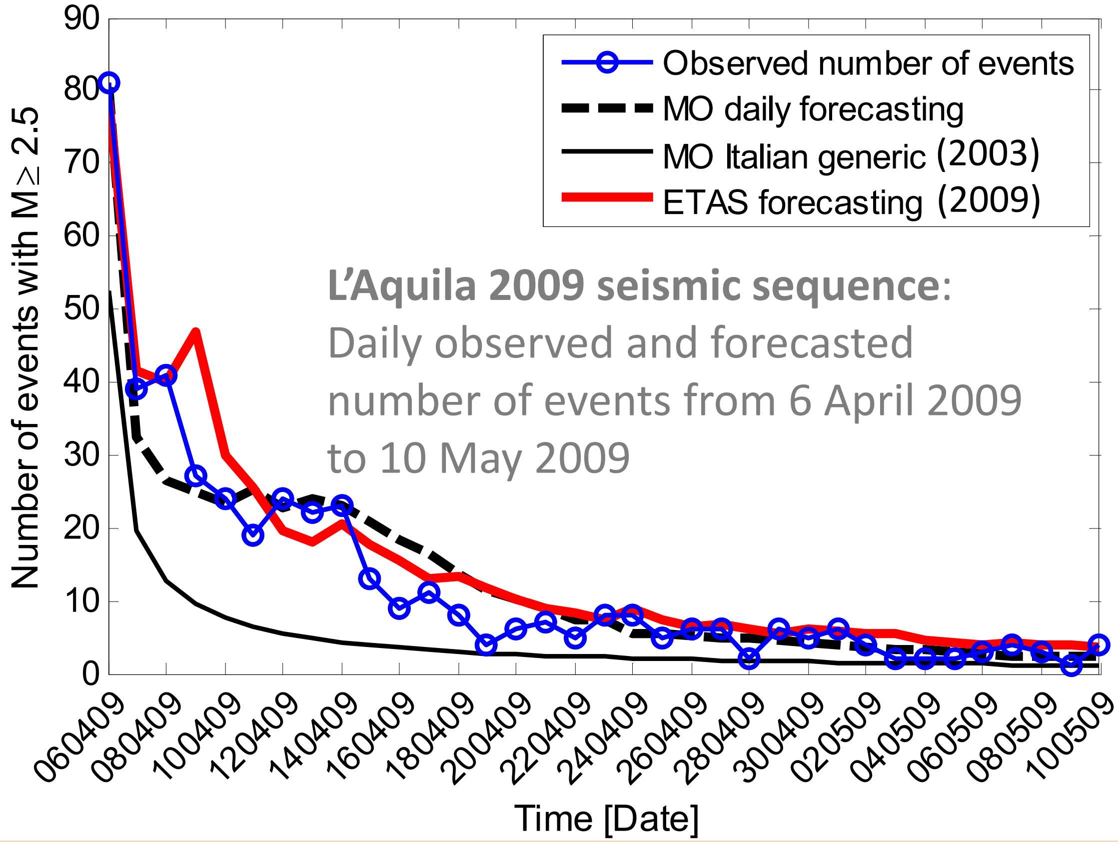


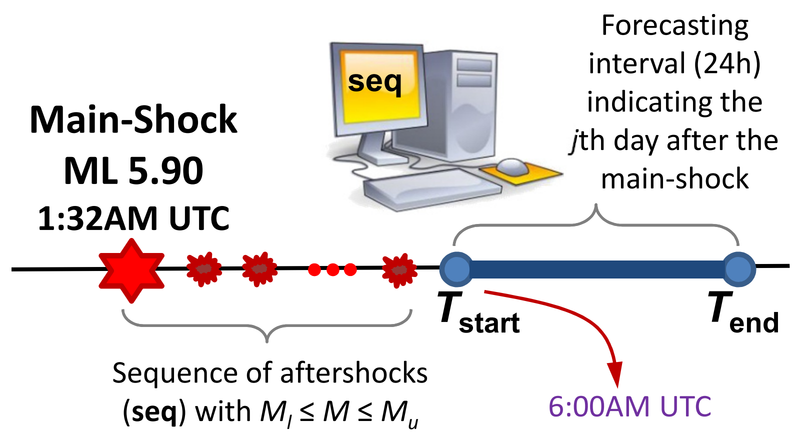
OPERATIONAL AFTERSHOCK (SHORT-TERM) RISK FORECASTING: particularly crucial as a support for rapid decision-making in the presence of an ongoing seismic sequence.

Proposed MO-based Model (spatio-temporal)

$$\lambda_{\text{MO-based}}\left(t,x,y,m\,|\,\mathbf{seq}\right)=p_{\text{MO-based}}\left(x,y\,|\,\mathbf{seq}\right)\lambda_{\text{MO}}\left(t,m\,|\,\mathbf{seq}\right)$$

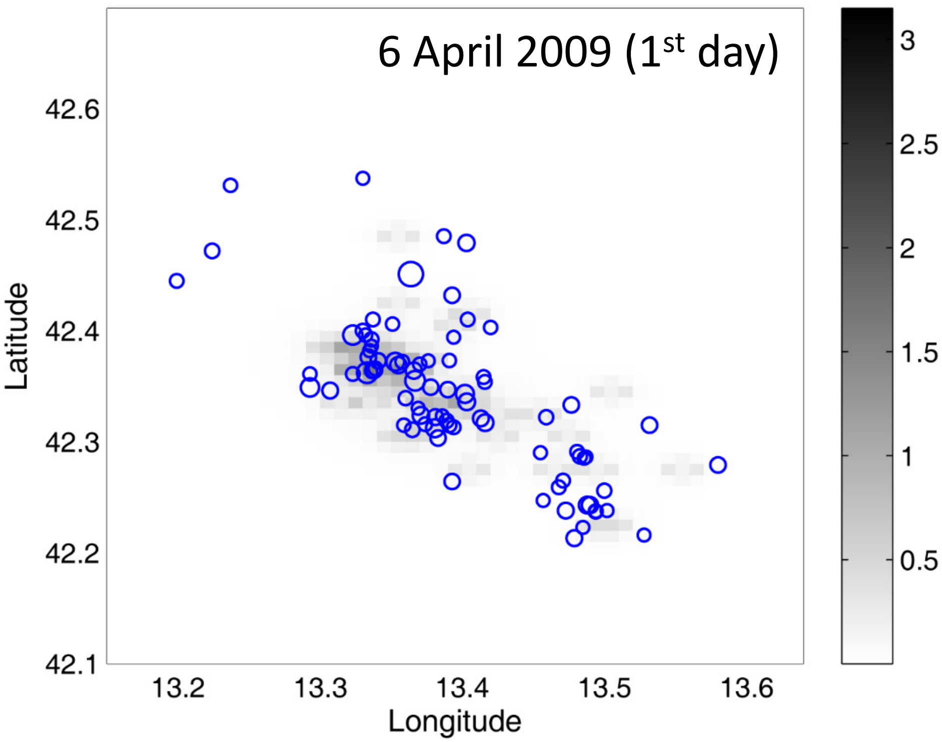
- $\lambda_{\text{MO-based}}$: Spatio-temporal rate of the proposed MO-based model
- $p_{\text{MO-based}}$: Spatial seismicity pattern
- λ_{MO}: MO-model (with temporal decay) Bayesian Updating of MO parameters

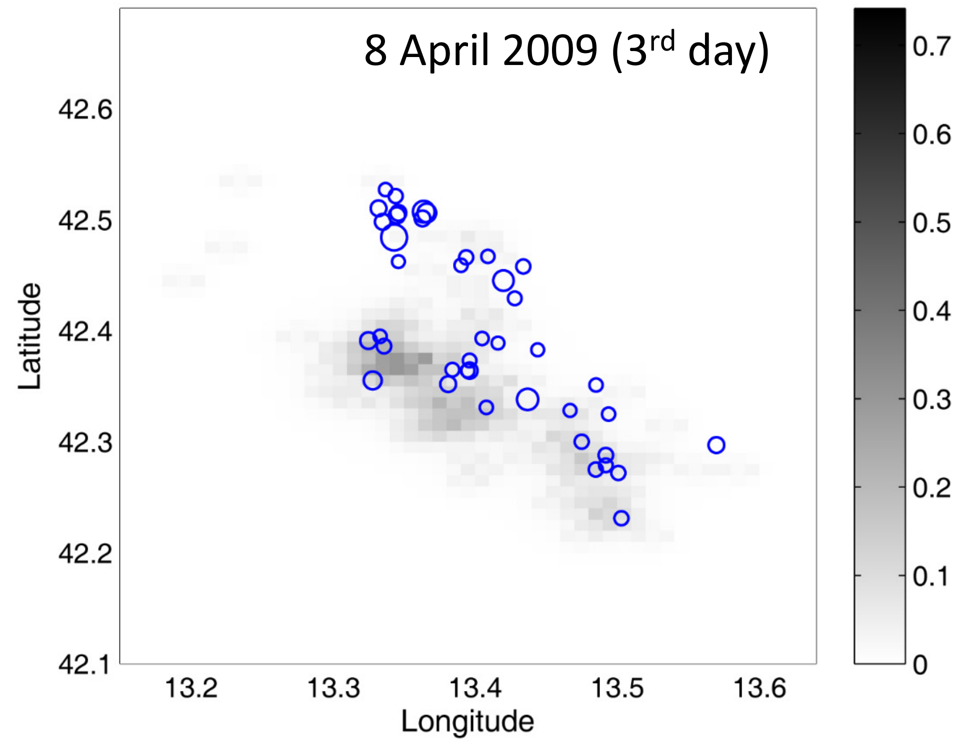




Ebrahimian H., Jalayer F., Asprone D., Lombardi A.M., Marzocchi W., Prota A., Manfredi G. (2014). Adaptive daily forecasting of seismic aftershock hazard. *Bulletin of Seismological Society of America*, 104 (1): 145-161.

Forecasted spatial distribution of seismicity based on **MO-based model** and the observed events





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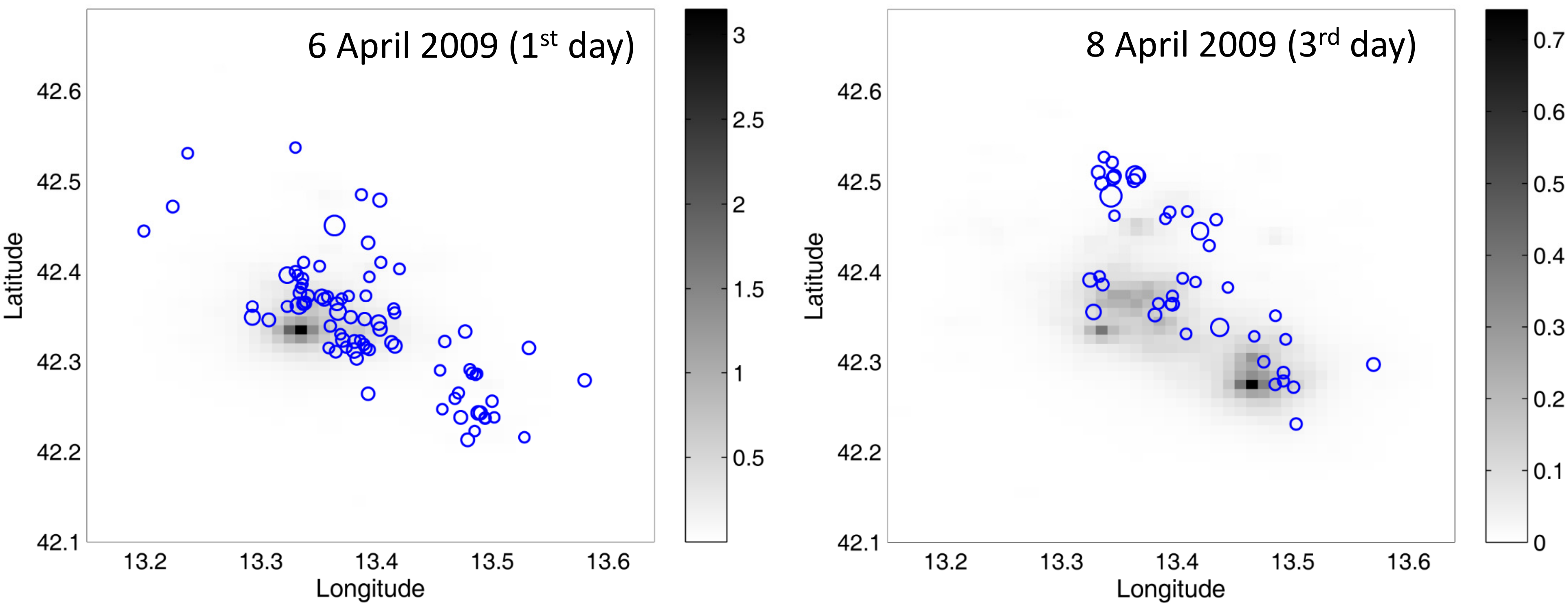
Forecasted spatial distribution of seismicity based on **ETAS model** and the observed events



According to a Bayesian Model Class Selection, we quantitatively compare the forecasted seismicity rates provided by both models: the MO-based model performs much better than ETAS in the first two days elapsed after the MS. However, for the 3rd and 4th days, ETAS seems to perform better than the MO-based model

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$$N\left(x,y,m\,\middle|\,\mathbf{seq},M_l\right)=N_b\left(x,y,m\,\middle|\,M_l\right)+\int_{T_{start}}^{T_{end}}\lambda\left(t,x,y,m\,\middle|\,\mathbf{seq},M_l\right)\mathrm{d}t$$

Average number of events in the spatial cell unit (x,y) with $M\geq m$ in the forecasting interval $[T_{start},T_{end}]$, given the observation history **seq** in the interval $[T_o\,,\,T_{start})$ and the lower cut-off magnitude M_l

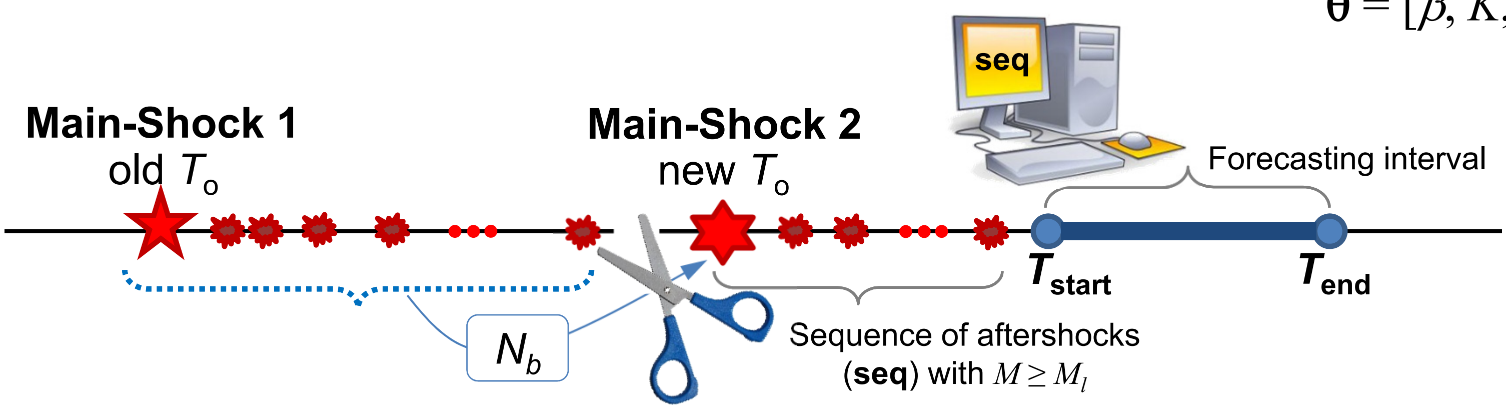
Background seismicity

The rate of occurrence of events with $M\geq m$ in the cell unit (x,y) in interval $[T_{start},T_{end}]$ at time t elapsed after the main event (at time T_o)

$$\lambda_{\text{ETAS}}\left(t,x,y,m\,\middle|\,\boldsymbol{\theta},\mathbf{seq}_t,M_l\right)=e^{-\beta(m-M_l)}\sum_{t_j<t}K\,e^{\beta(M_j-M_l)}\cdot\frac{K_t}{\left(t-t_j+c\right)^p}\cdot\frac{K_R}{\left(r_j^2+d^2\right)^q}$$

$\boldsymbol{\theta}$ = The vector of model parameters

$$\boldsymbol{\theta}=[\beta,K,K_t,K_R,c,p,d,q]$$



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- The Epidemic Type Aftershock Sequence (ETAS) model has **8 model parameters (θ)**.

- The forecasting is ***"robust"*** because it considers both:
  - the uncertainty in the model parameters due to the events occurred before the forecasting interval $[T_o, T_{start})$
  - the uncertainty in the sequence of events that are going to happen during the forecasting interval $[T_{start}, T_{end}]$

- **Robust Operational forecasting** of seismicity is performed by exploiting the link between **Bayesian inference and Markov Chain Monte Carlo (MCMC) Simulation**. After an initial transition time (in the order of few hours to accumulate enough events for updating θ), the model quickly tunes into the sequence and provides forecasting.

- Apart from being quite efficient (**low computational cost on a normal PC**), the model updating and forecasting procedure is carried on **without human interference and use of expert judgement**.

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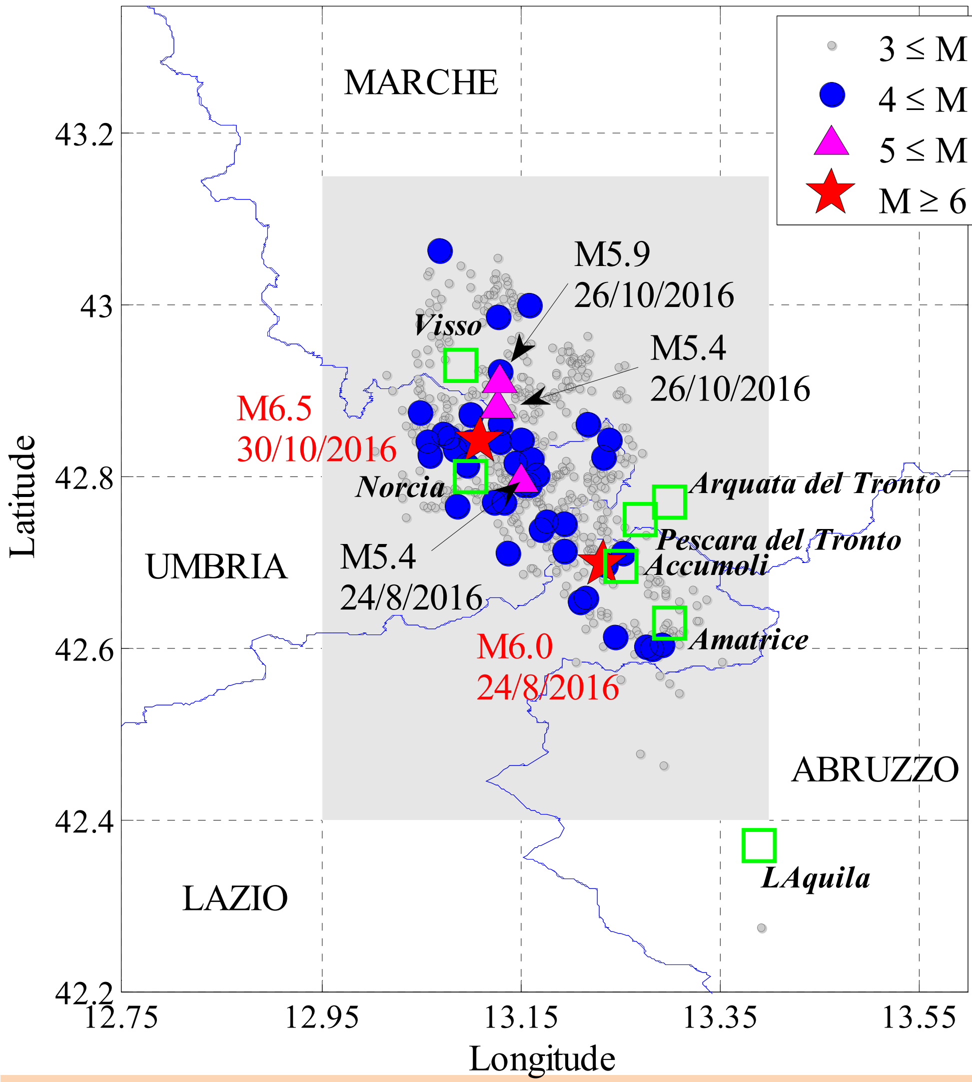
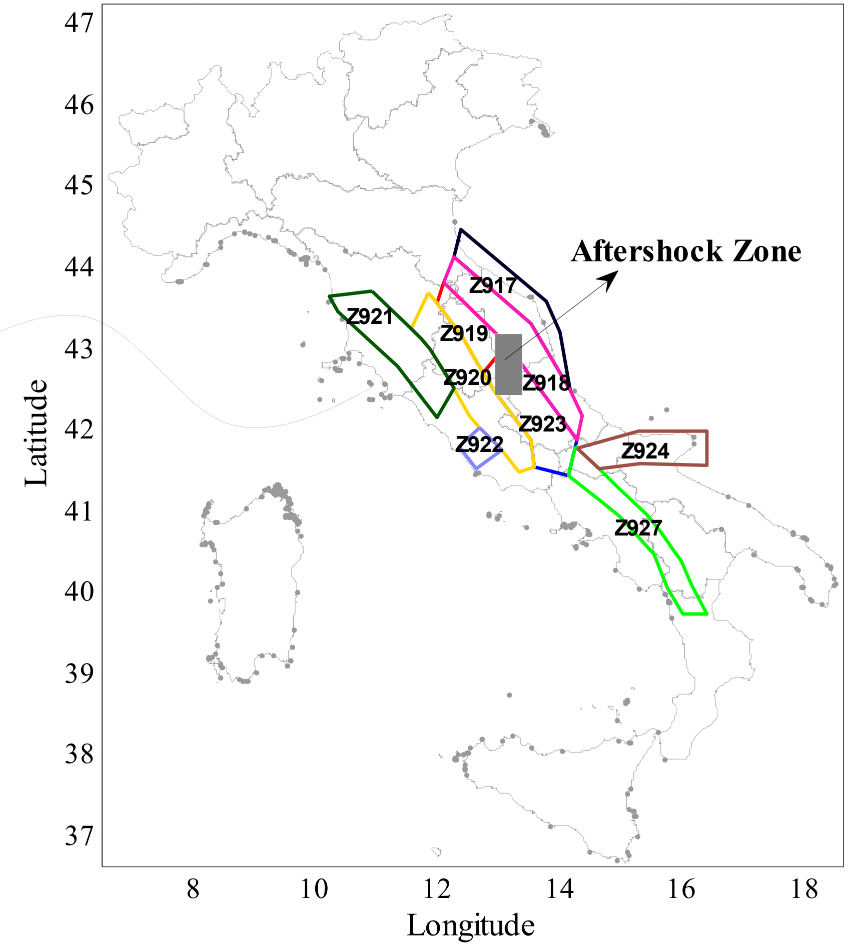
Seismic Sequence from 08/24/2016 up to 11/02/2016





Central Italy (Amatrice) seismic sequence 2016

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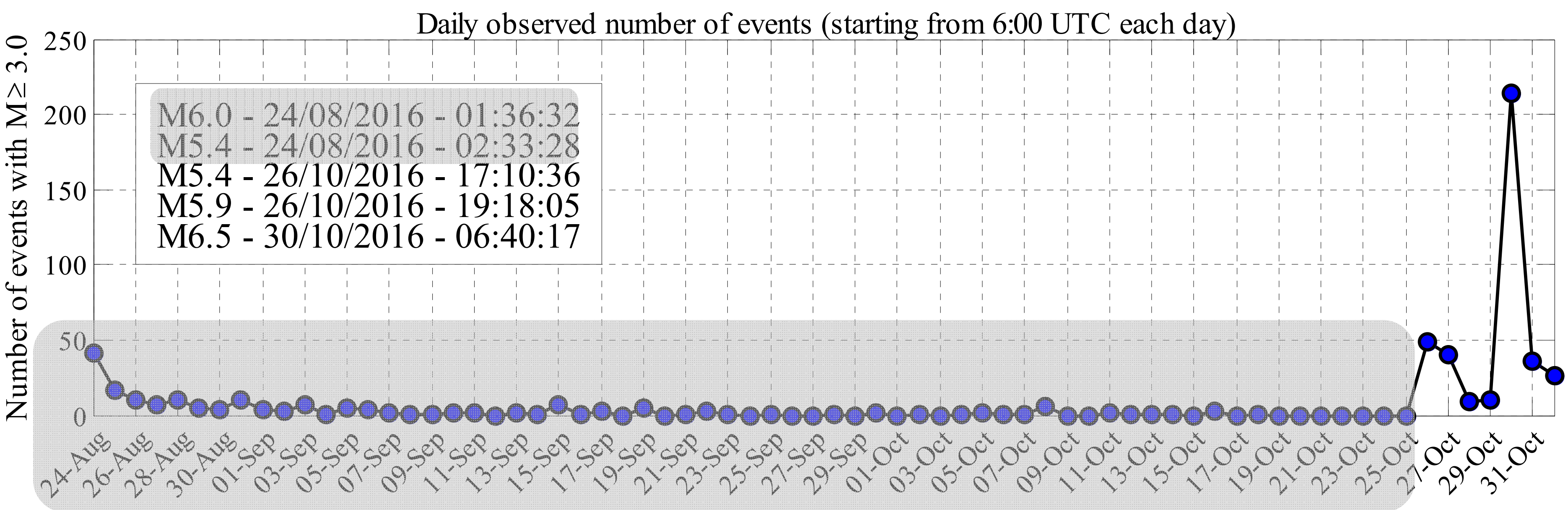

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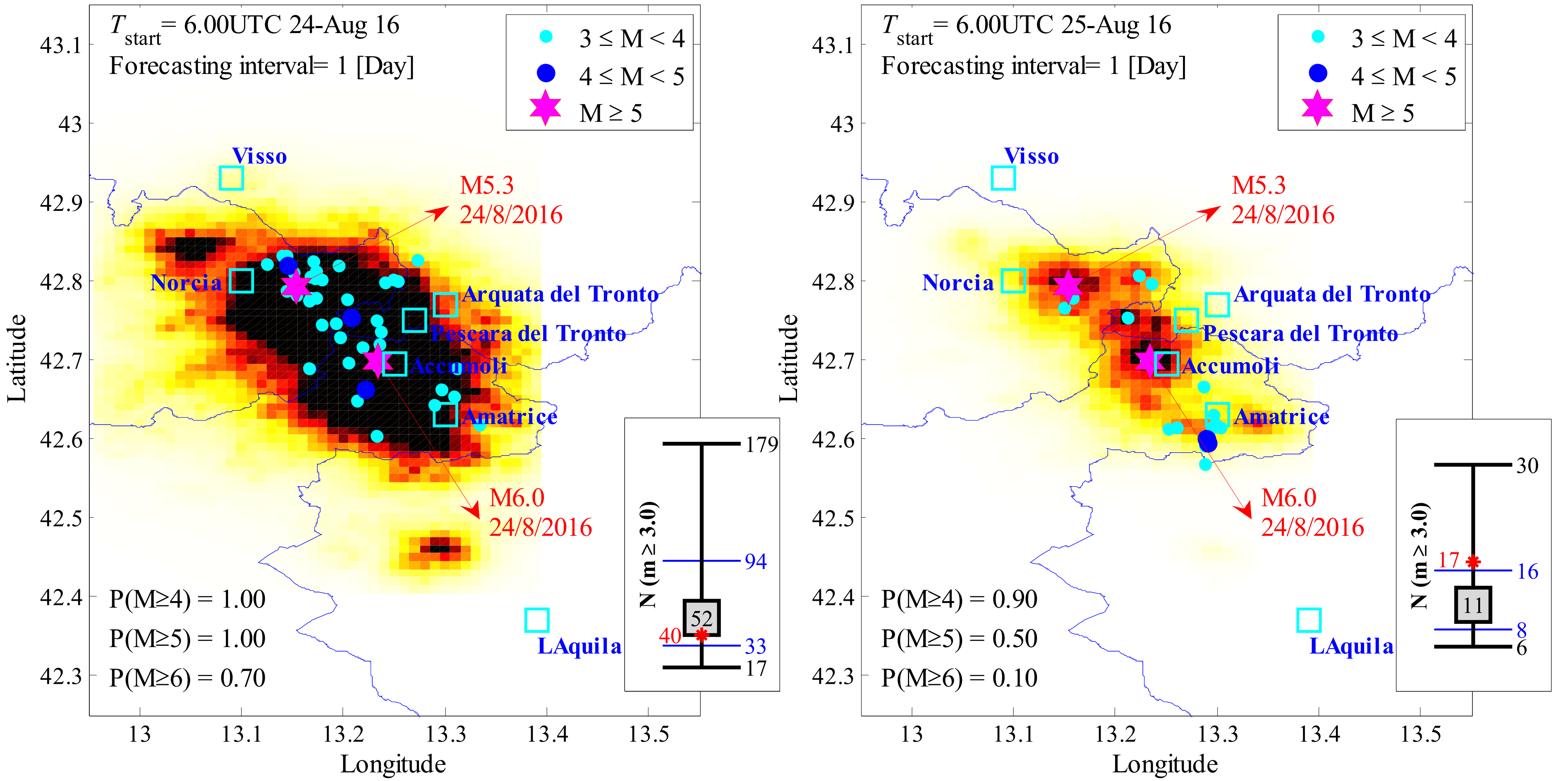

Forecasted vs. observed seismicity distribution in the aftershock zone, the maps report the 98% confidence interval for the number of events equal to or greater than magnitude M_l=3 in the indicated 24-hour forecasting time window

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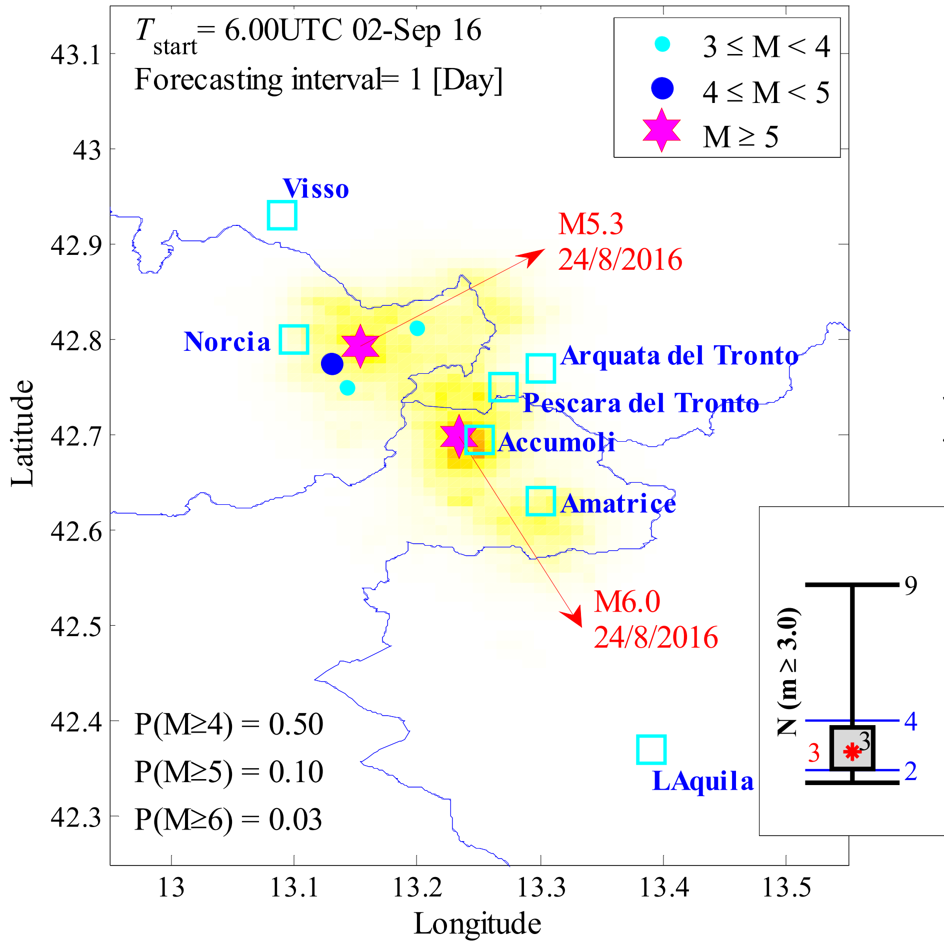

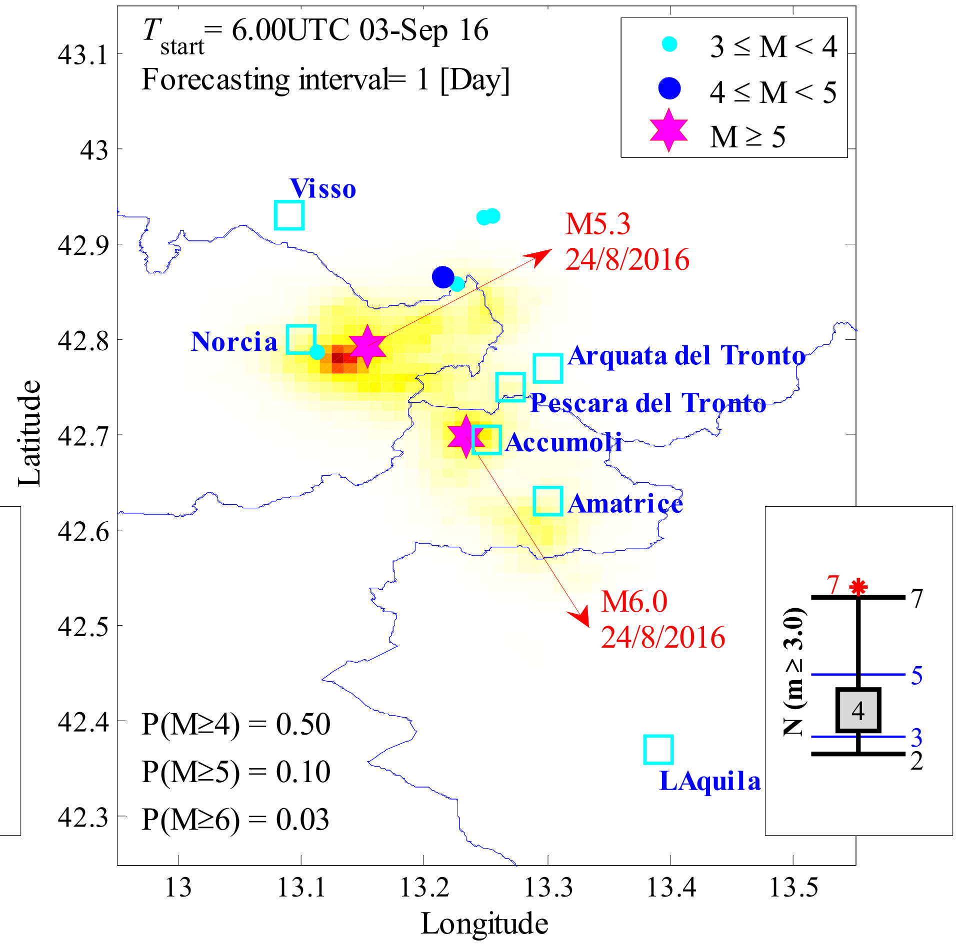

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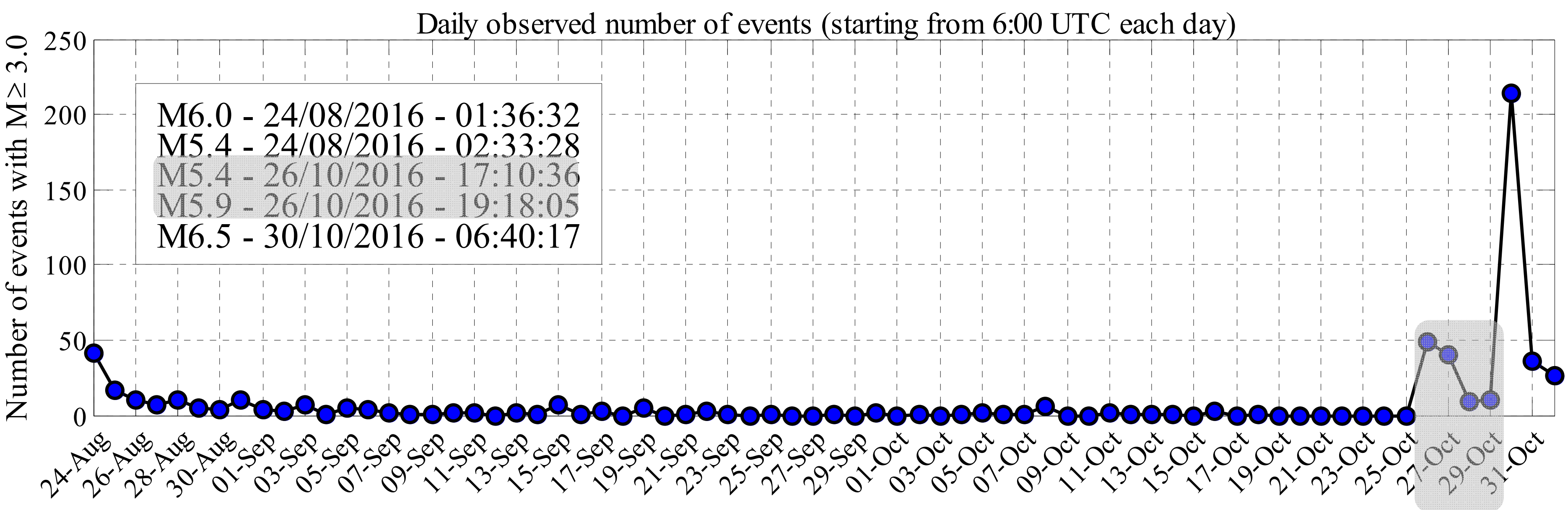

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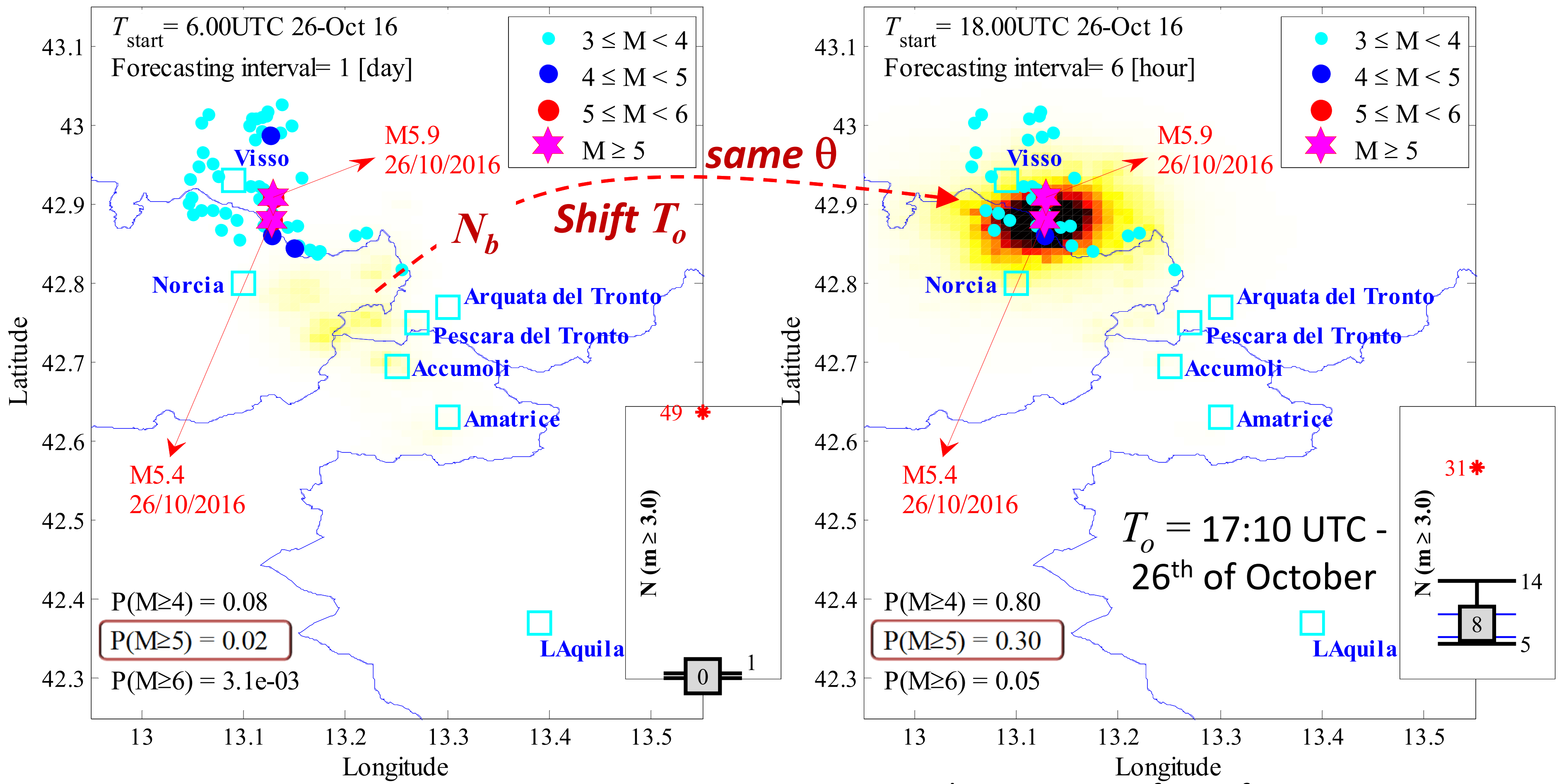

ZS9 (Italian Seismogenic Zonation data): a daily probability of around **3.83×10^{-4} for *M*≥5**

Given the presence of very few events in **seq**, we did not perform Bayesian updating on the model parameters θ.

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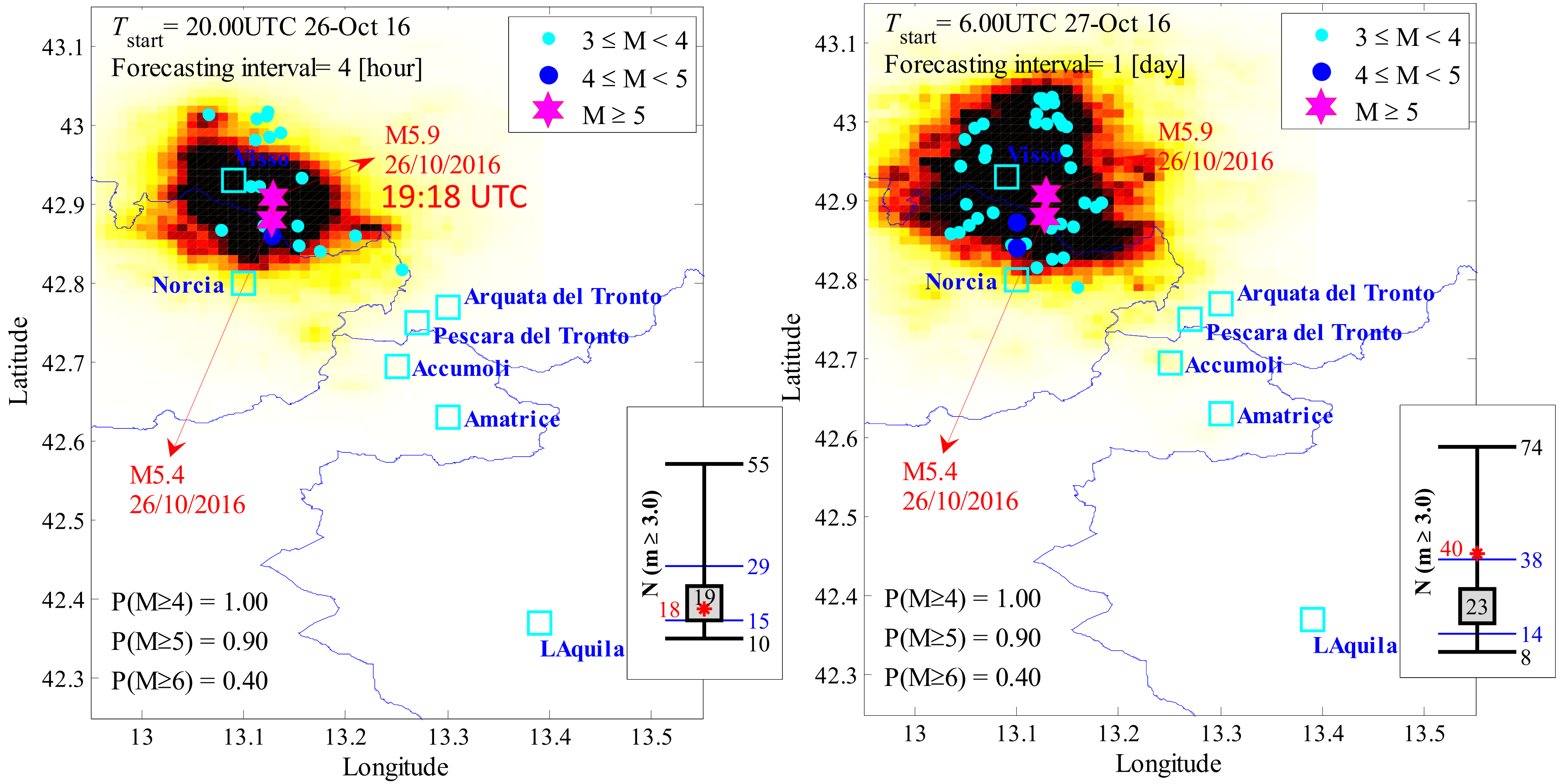

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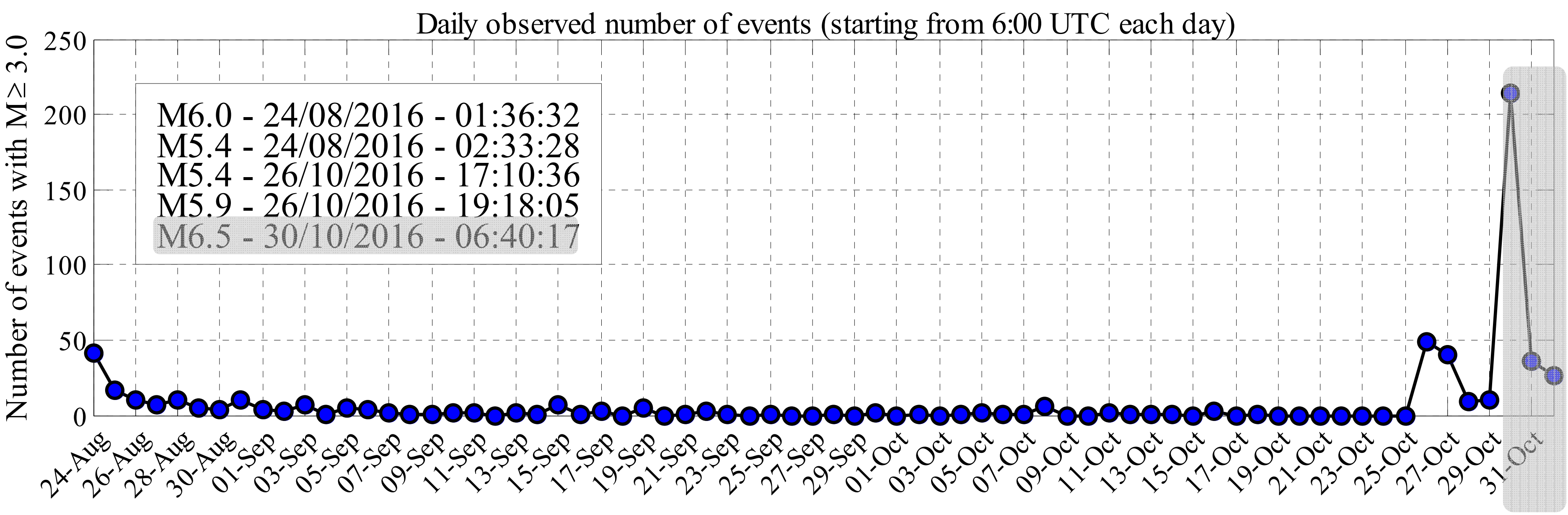

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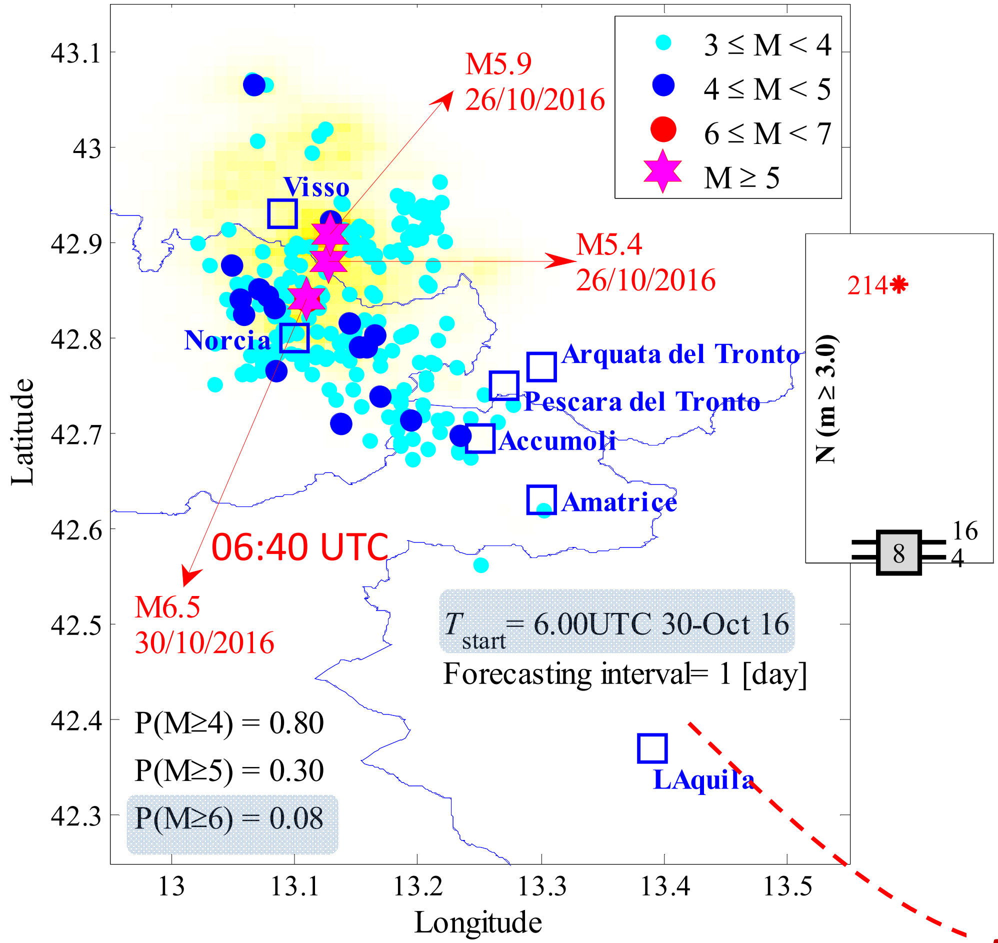

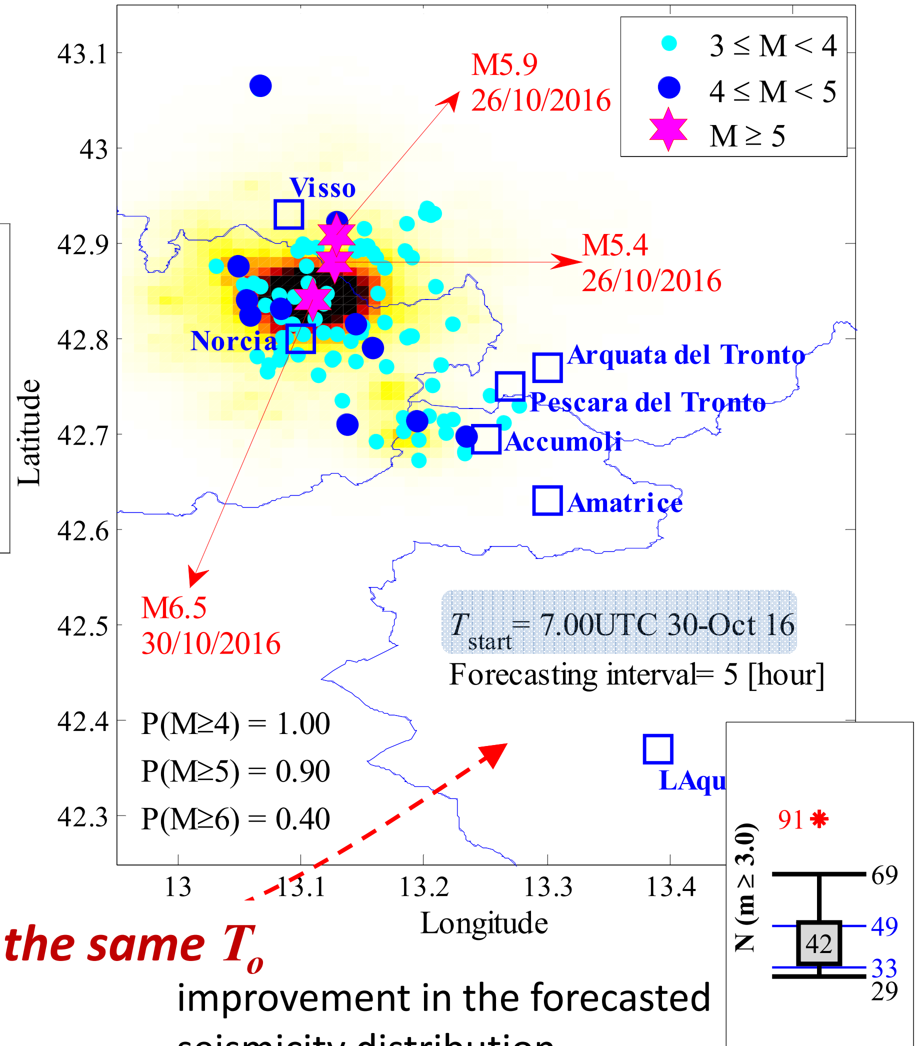

Note: the forecasted $P(M\geq6)$ is equal to the forecast provided for October 29; this can be viewed as somewhat alarming (no decay with time)

the same T_o

improvement in the forecasted seismicity distribution

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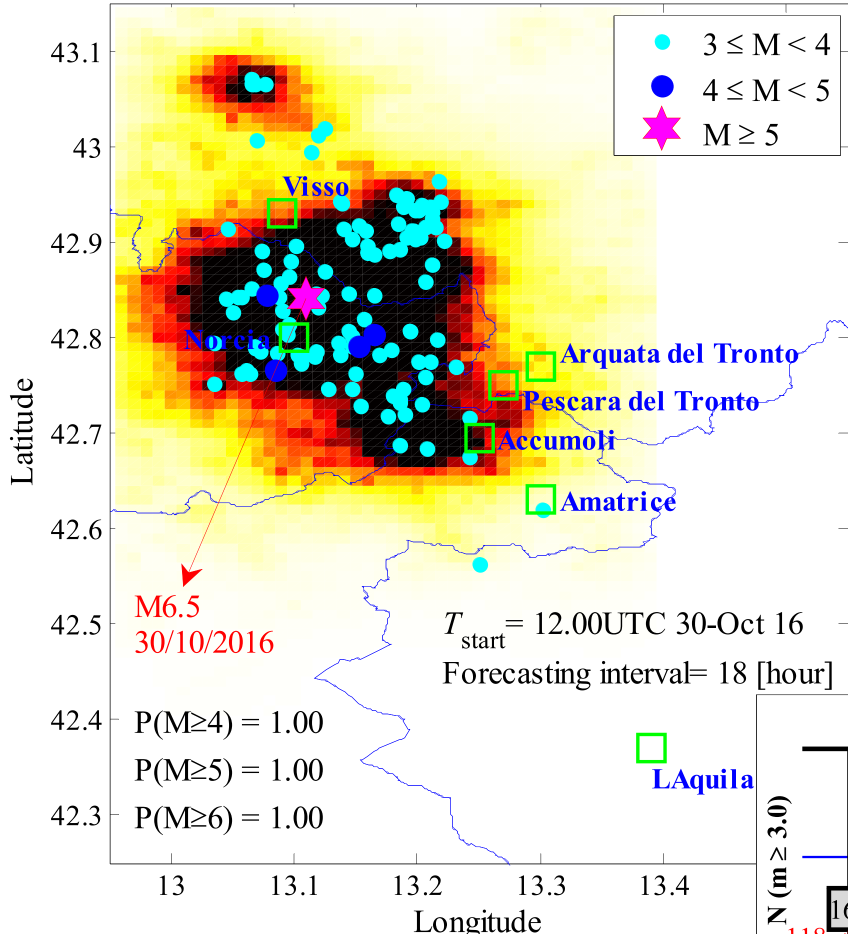
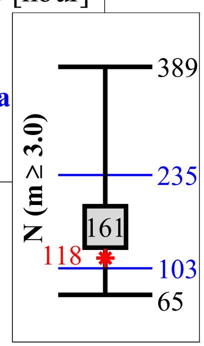
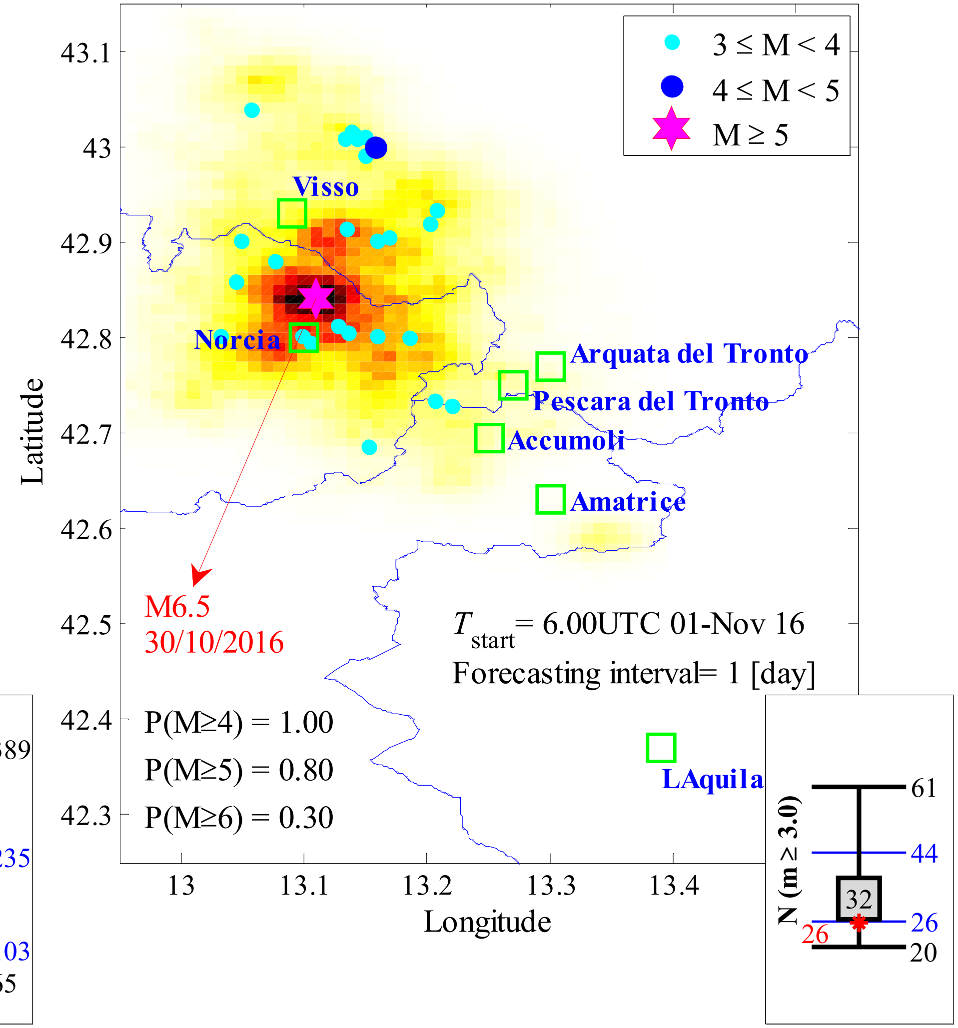




T_o = 6:40 UTC - 30th of October

Change N_b



- **A shift in the time of origin** T_o by conservatively introducing a constant background seismicity N_b. This shift proved to be quite useful as it relieved us from the burden of summing up the triggering properties of all the events that took place in the previous part of the sequence (neglecting the time-decay in their triggering contribution).
- We observe that after an **initial transition time (in the order of few hours to accumulate enough events for updating the model parameters)**, the model quickly tunes into the sequence and provides forecasting that is reliable in most cases up to plus/minus one standard deviations.
- As expected, the procedure falls short of predicting the First "main-shock" M6.0 October 24. The procedure, however, did a better job for forecasting the events M5.9 of October 26 and M6.5 October 30. This relative success can be attributed to the fact that these events took place at the initial stages of the newly triggered sequence of 26th of October when the seismic activity was still very high.
- The proposed procedure for robust forecasting is conditioned on the available catalogue of events and the epidemiological model adopted for capturing the spatio-temporal aftershock clustering

Thank You for your Attention!