Towards next-generation earthquake forecasting by embracing short-term aftershock incompleteness

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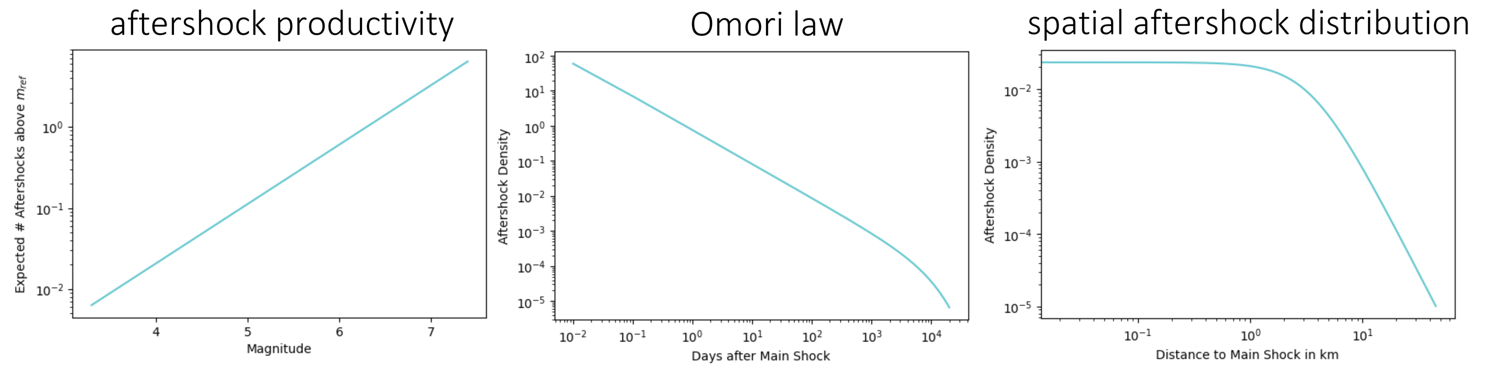
1 Next-generation earthquake forecasting?

Epidemic-Type Aftershock Sequence (**ETAS**) models are the most successful earthquake forecasting models currently available, both for short- and long-term hazard assessment. They account for the spatio-temporal clustering of earthquakes intrinsically using basic **empirical triggering laws**.



$$\lambda(x,y,t) = \mu + \sum_{i:t_i<t} g(m_i, t - t_i, x - x_i, y - y_i)$$

The rate of events at location (x,y) and time t is the sum of background event rate plus rate of aftershocks of all previous events.

It is reasonable to build on top of these **simple yet effective** models when developing next-generation earthquake forecasting models.
... but how?

2 Possibilities to build on top of ETAS

Additional knowledge about **earthquake physics** could be incorporated into existing models through

- the effective use of Coulomb stress changes,
- spatial variations of the b-value (WIP),
- anisotropic triggering based on fault geometry (WIP), etc.

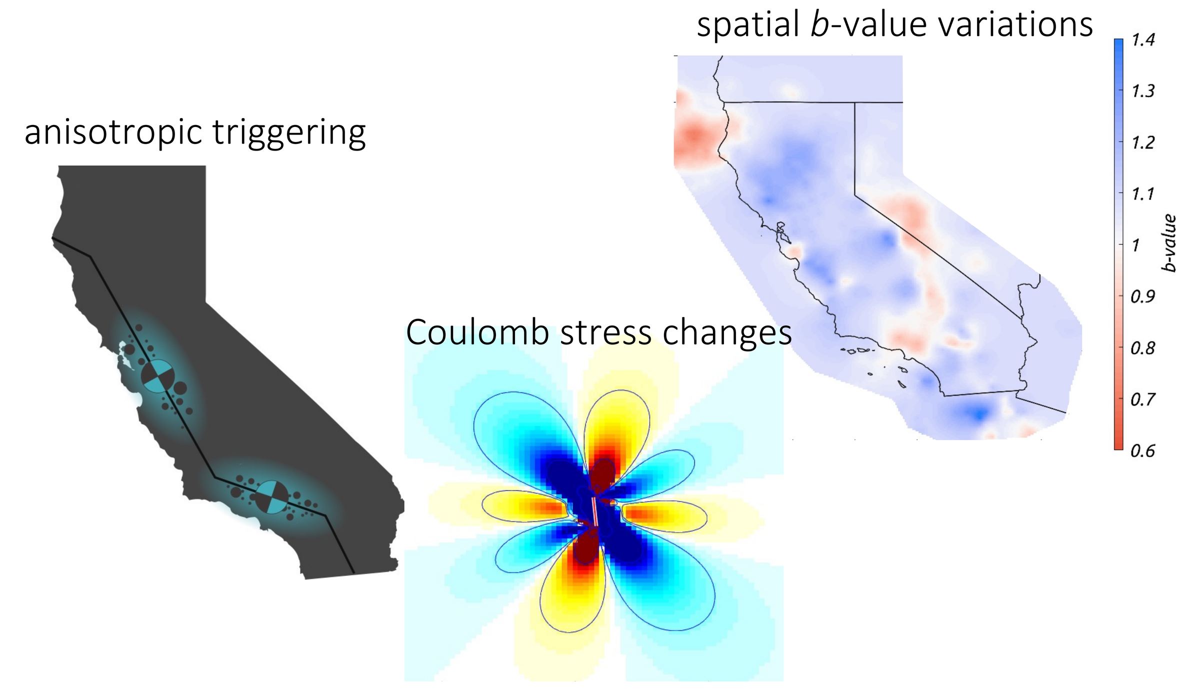


Figure 1: Possibilities to build on top of ETAS.

On the other hand, current models can be enhanced to leverage the **growing amount of data** made available by continually improving seismic networks.

For this, we generalized the concept of completeness magnitude M_c and consider a rate- and magnitude-dependent **detection probability**.
→ No need to cut-off data below M_c

3 Probabilistic, epidemic-type aftershock incompleteness (PETAI)

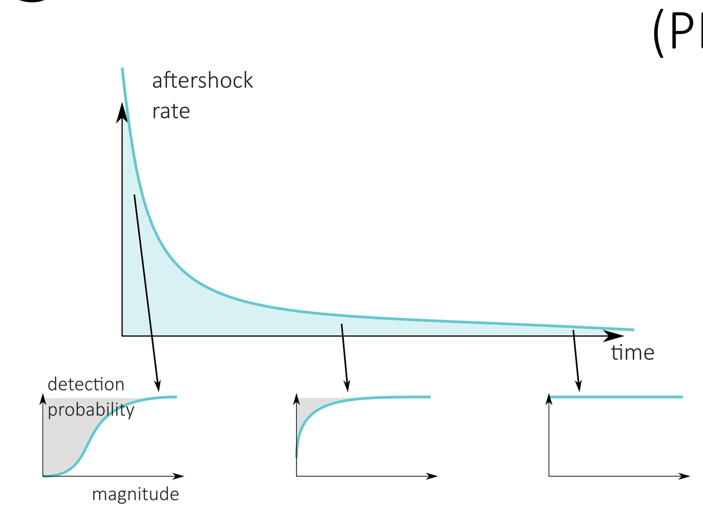


Figure 2: Detection probability is lower for small magnitude events, and during times when event rate is high.

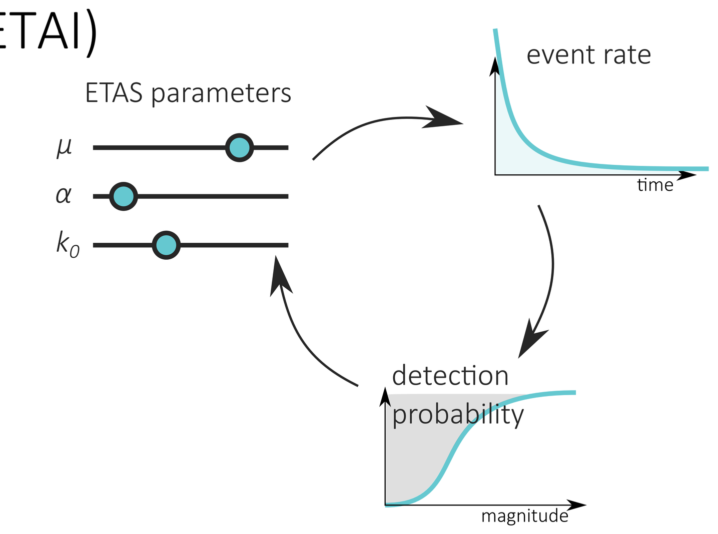


Figure 3: Simplified schematic illustration of the inversion algorithm.

Algorithm 1: Jointly estimate high-frequency detection incompleteness and ETAS parameters:

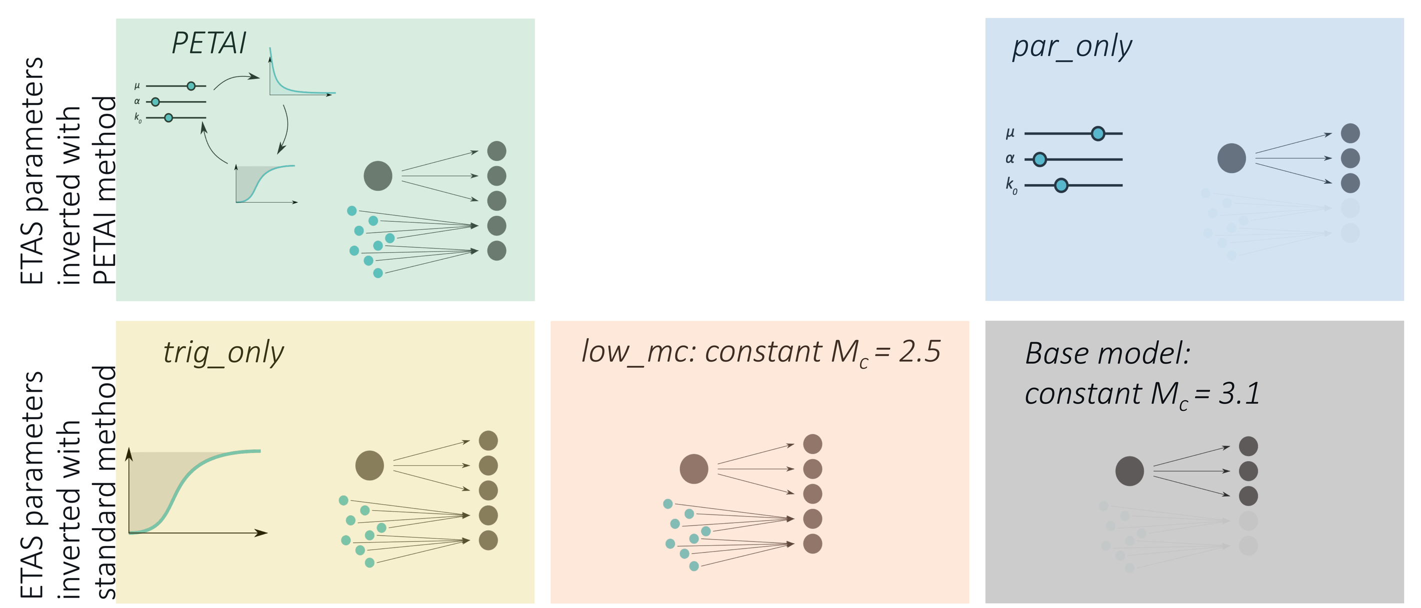
1. Estimate ETAS assuming constant M_c
2. Calculate rates, accounting for unobserved events ($\xi(t_i)$):

$$\lambda(t) = \mu + \sum_{i:t_i<t} (1 + \xi(t_i)) \cdot \iint_R g(m_i, t - t_i, x - x_i, y - y_i)\, dx\, dy$$

3. Calibrate detection probability
4. Re-estimate ETAS parameters knowing high-frequency detection probability
5. Repeat from 2. until convergence

Using pseudo-prospective forecasting experiments, we test the **usefulness for forecasting** of different components of the PETAI model.
→ Which aspects of the model, if any, are the most promising to pursue?

4 Forecasting experiments: competing models

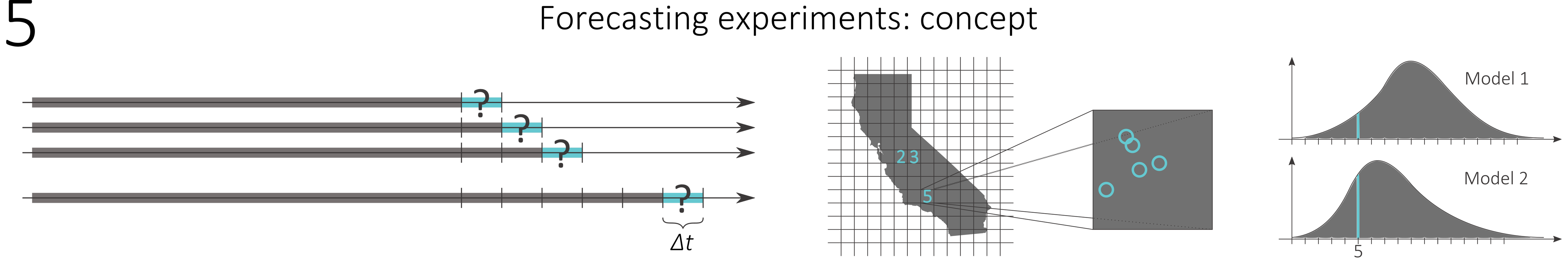


Uses detection incompleteness, simulates above M2.5
No detection incompleteness, simulates above M2.5
No detection incompleteness, simulates above M3.1

6 Forecasting experiments: setup

- California, 1970 - 2020
- 243 non-overlapping 30 day forecast testing periods, starting on January 1st, 2000, ending in January 2020
- Spatial resolution: 0.1° lat x 0.1° long (≈ 10km x 10km)
- Magnitude thresholds for target events: 3.1, 3.5, 4.0, 4.5, 5.0

5 Forecasting experiments: concept



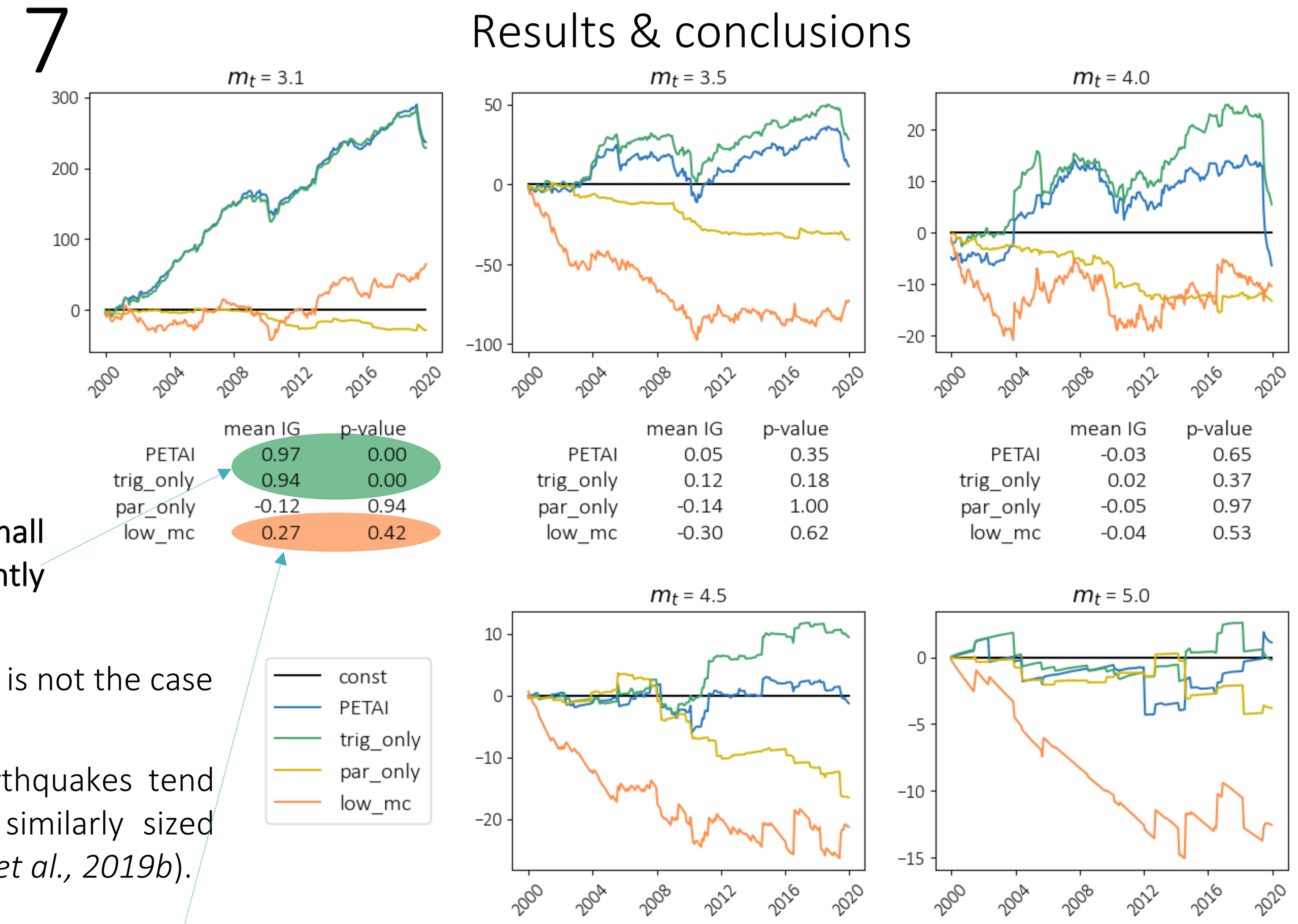
Pseudo-prospective forecasting experiment:

- Train different models using data until time t
- Issue forecasts for testing period $(t, t+\Delta t]$
- Compare forecasts to actual data during testing period
- Repeat for multiple testing periods

Forecast evaluation (see *Nandan et al., 2019a*):

- In each grid cell, count the number of events that actually happened
- Calculate the likelihood of this to occur under each of the models (M1, M2) based on 100,000 simulations
- Information gain of M1 vs M2: difference in log likelihood, summed over all grid cells

7 Results & conclusions



m_t = 3.1

	mean IG	p-value
PETAI	0.97	0.00
trig_only	0.94	0.00
par_only	-0.12	0.94
low_mc	0.27	0.42

m_t = 3.5

	mean IG	p-value
PETAI	0.05	0.35
trig_only	0.12	0.18
par_only	-0.14	1.00
low_mc	-0.30	0.62

m_t = 4.0

	mean IG	p-value
PETAI	-0.03	0.65
trig_only	0.02	0.37
par_only	-0.05	0.97
low_mc	-0.04	0.53

m_t = 4.5

	mean IG	p-value
PETAI	-0.01	0.56
trig_only	0.04	0.11
par_only	-0.07	0.98
low_mc	-0.09	0.61

m_t = 5.0

	mean IG	p-value
PETAI	0.00	0.42
trig_only	-0.00	0.52
par_only	-0.02	0.81
low_mc	-0.05	0.66

For m_t = 3.1, **allowing small event triggering significantly improves the forecast**.

For larger thresholds, this is not the case anymore.

Possible explanation: earthquakes tend to preferentially trigger similarly sized aftershocks (see *Nandan et al., 2019b*).

Accounting for incompleteness is necessary to achieve the improvement (simply assuming lower M_c doesn't do the job).

Figure 4: Cumulative information gain (IG) of the 4 alternative models vs. base model for different target magnitudes. Below each plot, mean IG and t-test p-value (testing whether base model is outperformed) are given for the 4 alternative models.

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References

Nandan, S., Ouillon, G., Sornette, D. and Wiemer, S., 2019a. Forecasting the full distribution of earthquake numbers is fair, robust, and better. *Seismological Research Letters*, 90(4), pp.1650-1659.

Nandan, S., Ouillon, G. and Sornette, D., 2019b. Magnitude of earthquakes controls the size distribution of their triggered events. *Journal of Geophysical Research: Solid Earth*, 124(3), pp.2762-2780.

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