Pseudo-prospective testing of five year inlabru earthquake forecasts for California

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Abstract

Probabilistic forecasts estimate the likelihood of future seismicity in some specified time-space-magnitude window, but a forecast can only truly be considered meaningful if it demonstrates a degree of proficiency at describing future seismicity. Log-Gaussian Cox processes with a spatially varying, random intensity field may be used to flexibly model the spatial pattern formed by the locations of earthquakes. Using the Bayesian inlabru approach we fit models that use different combinations of spatial covariates that might help describe observed seismicity, including fault location, slip rate and strain rate. We use these spatial models to develop time-independent earthquake forecasts for California using both full and declustered earthquake catalogs. We then test these models in a pseudo-prospective way by comparing with observed events over three contiguous 5-year time periods, using forecast tests developed by the Collaboratory for the Study of Earthquake Predictability (CSEP) and implemented in the PyCSEP package (Savran et al, 2021).

We compare the inlabru seismicity forecasts with previous results for the California testing region and explore the differences in forecast performance arising from both input data and the use of grid-based or simulated catalog-based tests. We demonstrate that the inlabru models perform well overall in pseudo-prospective testing, especially when using the simulated catalog-based tests that make use of full model posteriors.

Background

In light of the ever-increasing amount of data available to modellers, we applied a point process method popular in ecology to build a framework for constructing and ranking seismicity models that include spatial covariates in the point process (Bayliss et al, 2020). Here, we further develop this method to produce full time-independent earthquake forecasts and test them in a pseudo-prospective manner with the python package pycsep (Savran et al, 2020).

The seismicity rate models are developed as log-Gaussian Cox processes (LGCP) models, where the spatially-varying point process intensity is a function of some included spatial covariates (Fig. 2) and a Gaussian random field (RF) that accounts for spatial structure not described by the covariates. We fit these models with the R package inlabru (Bachl et al, 2019), which uses integrated nested Laplace approximations to estimate model parameter posteriors. The resulting posterior mean intensity is shown in Fig. 3. The steps involved in modelling seismicity in this way are shown in Fig 1., with step 7 being the main focus of this poster.

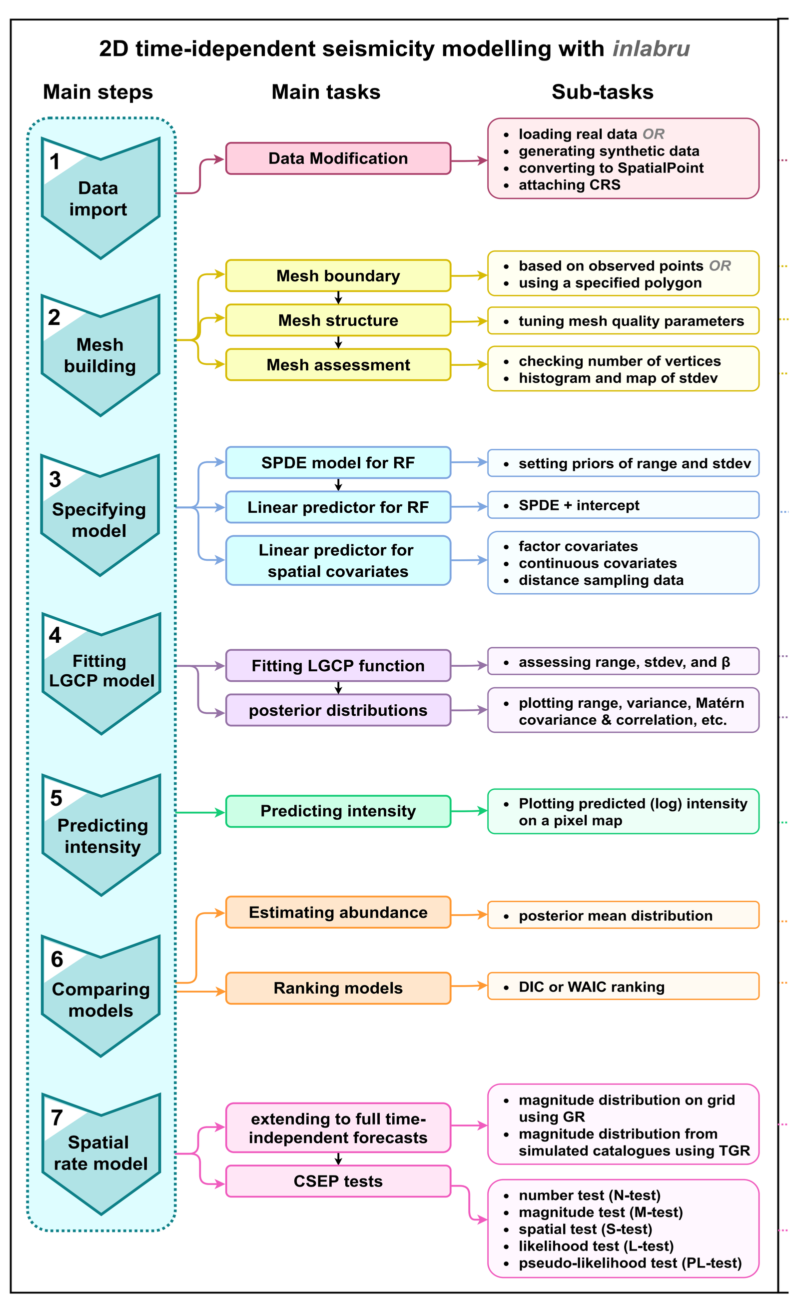

Figure 1 *(left)*: Flow chart describing the steps required to produce a spatial seismicity model with inlabru. The stochastic partial differential equation (SPDE) model sets up the random field component. Models are compared initially with their deviance information criterion (DIC). Magnitudes are sampled from a Gutenberg-Richter (GR) or tapered Gutenberg-Richter (TGR) distribution with fixed b/beta/Mc values.

Input spatial covariates

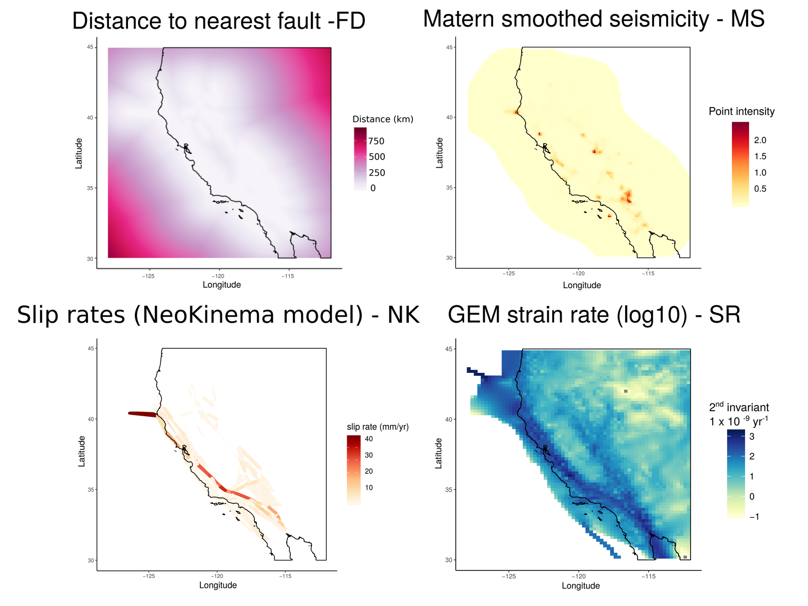

Fig. 2: Input covariates for inlabru models. Slip rates from UCERF3 (Field et al, 2014), distance to fault and smoothed seismicity are also derived from UCERF3 data. Strain rates from global strain rate model (Kreemer et al. 2014)

Spatial seismicity rate model

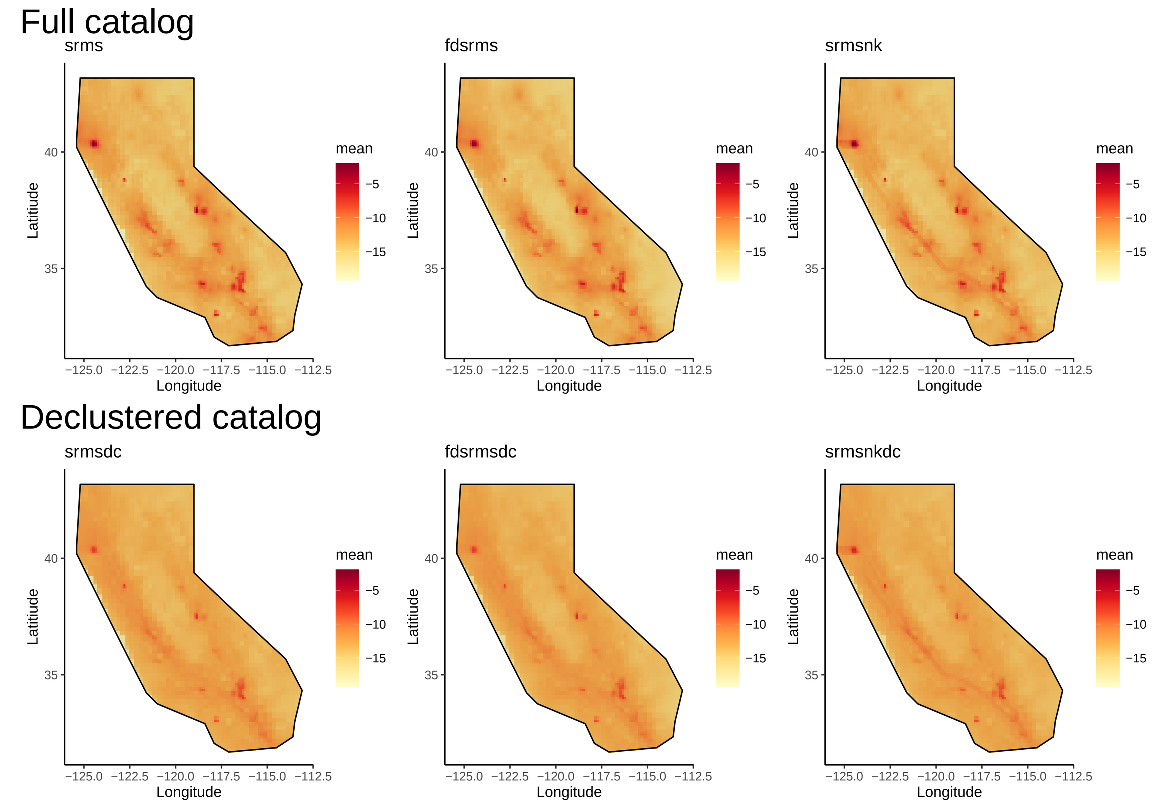

Fig. 3: Posterior mean (log) intensities for the six tested models covering the California testing region (step 5 of workflow in Fig. 1.). The top row shows the models using full catalogs while the bottom row shows the results when the input catalogs have been declustered (dc).

Forecast testing

We test the models using a collection of CSEP tests implemented in the pycsep library (Savran et al, 2020) over three contiguous time periods (Fig.4). These tests aim to compare a forecast of seismicity with observed events, either using grid-based or synthetic-catalogue based forecasts.

Grid-based tests rely upon a uniform spatial grid and assume a Poisson variability in the forecast to calculate a likelihood of observed events. The S-test sums over magnitude bins to return a spatial consistency estimate and the N-test considers the number of forecast events. Fig 5. shows the results for the 6 models.

Catalog-based forecasts rely upon synthetic catalogs simulated from the model itself to construct a likelihood, relaxing Poisson assumptions. The pseudo-likelihood is calculated using a point process likelihood estimate. Results are shown in Fig.6.

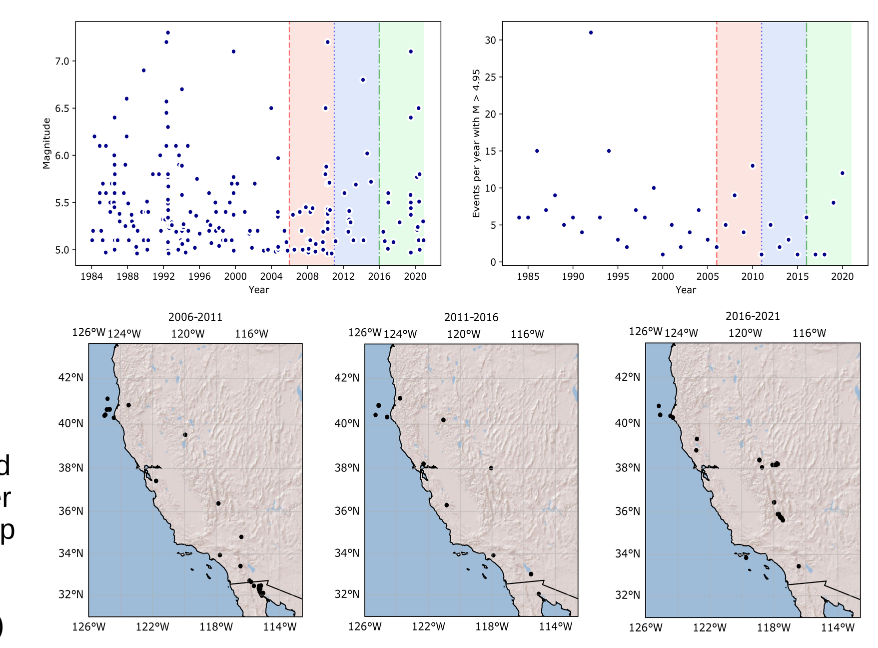

Fig. 4: Training and testing data for the model and three testing periods (top left, colors correspond to Fig. 6). The number of events per year (top right) and spatial distribution of test catalogs (bottom row)

Grid-based forecasts

- Project rates to uniform testing grid
- Retreive a-value from grid-rate
- Distribute magnitudes according to GR with fixed b-value

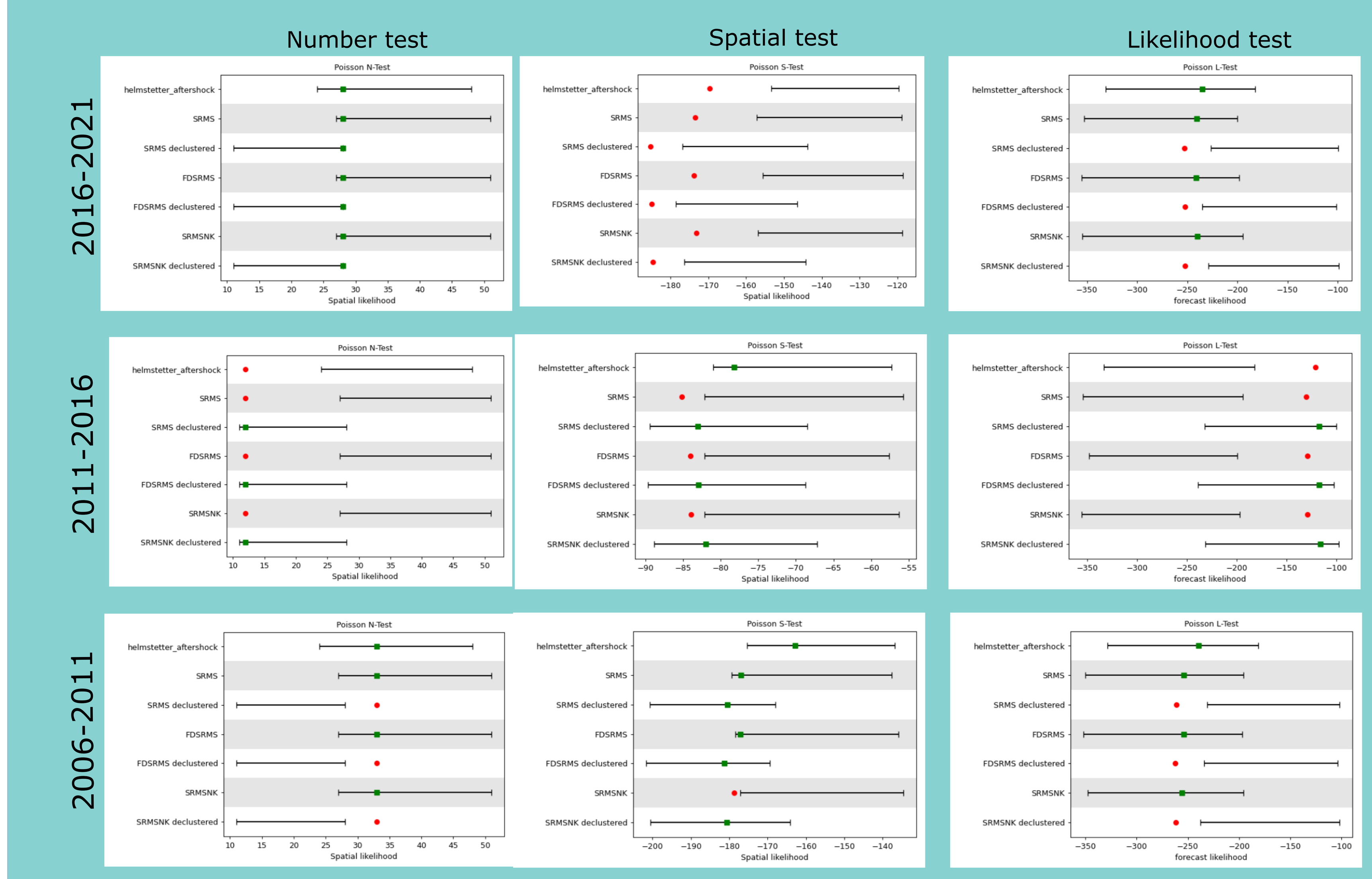

Fig. 5: N-test (left), S-Test (centre) and L-test (right) results for the gridded models for the three testing time periods (earliest at bottom). Error bars represent 95% confidence intervals on the forecast calculated assuming Poisson uncertainty. The symbol represents the observed test statistic in each time period, with a green square symbol indicated the forecast passes the test and a red circle symbol indicating that the model does not pass the test. Models are compared to the Helmstetter et al (2007) forecast as a reference.

Catalog-based forecasts

- Generate 10 000 samples from model posteriors
- Sample points according to ratio of maximum intensity in sample with rejection sampler
- Sample number of points as determined by overall model rate
- Sample catalog magnitudes from truncated GR

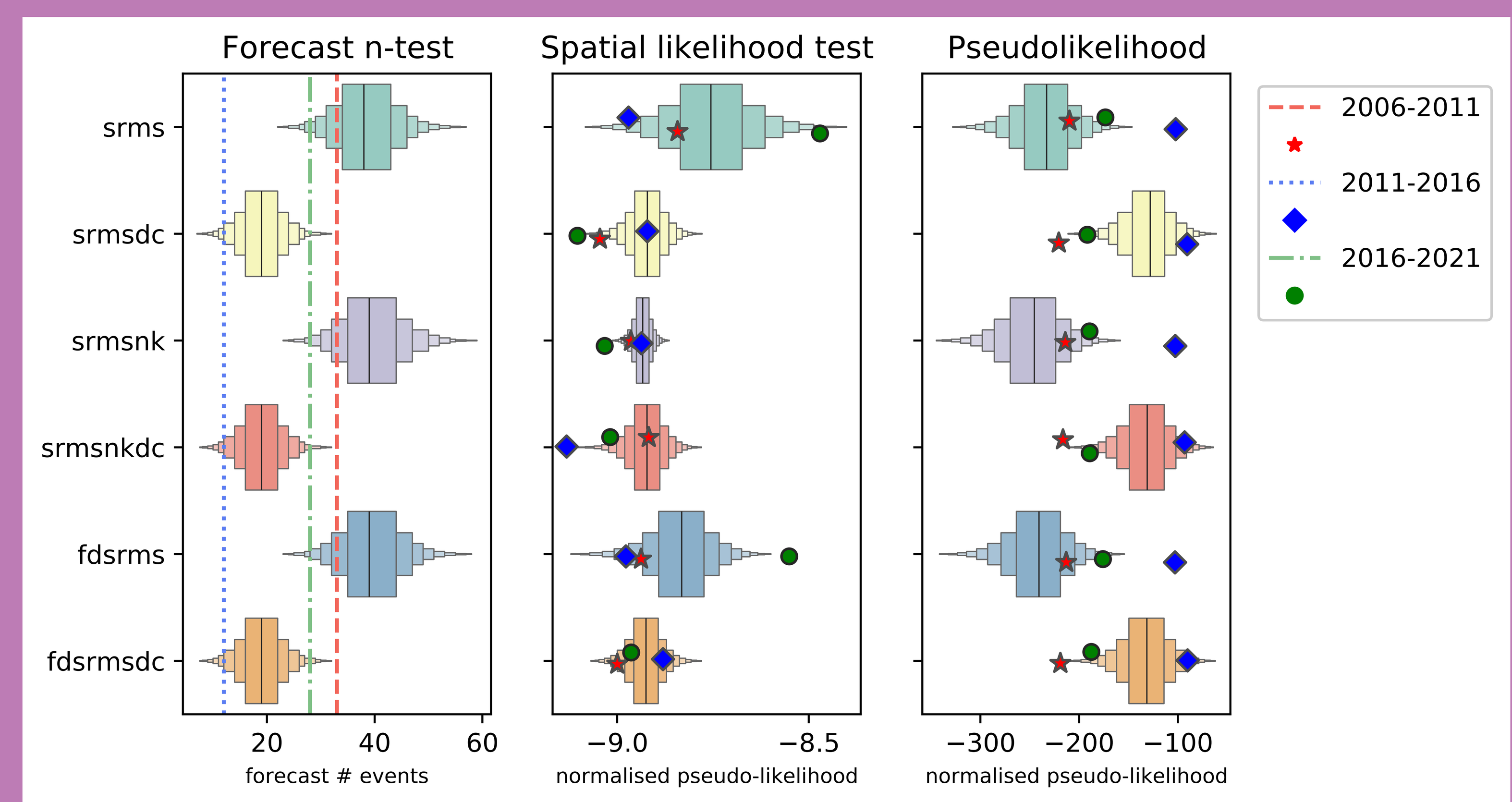

Fig 6: Catalog-based test results: Plots show the distribution of likelihoods for number of events (left), spatial distribution of events (centre) and combined pseudo-likelihood (right) from 10, 000 simulated catalogs. Observed test statistic for each test and time period is shown with a dashed line (n-test) or a symbol (S-test, pseufo-likelihood test).

Conclusions

The inlabru models do a good job of forecasting seismicity when tested in a pseudo-prospective manner. Each of the six tested models passed multiple consistency tests in several time periods.

The catalog-based forecasts are more likely to pass a consistency test than the grid-based forecasts, likely due to the relaxing of the assumption of Poisson likelihood and the wider range of uncertainty that the simulated catalog models are able to include. The models with slip rate (NK) in particular perform better in catalog-based testing.

The performance of the full or declustered catalog (dc) models is highly dependent on the number of events occurring in the testing period, with the spatial performance of the models generally very good when assessed by the catalog-type testing.

The next stage for our inlabru models is therefore a model with self-exciting clustering that can better capture local and short temporal-scale seismicity. This will form the basis of future operational earthquake forecasting models with inlabru.

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