

# Deliverable

## D3.3 A new generation of OEF models

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## Summary

The main goal of WP3 is to advance the operational earthquake forecasting capabilities at different spatial scales. This deliverable contains the description of the repository where all promising codes of the OEF models that have been produced in the first 30 months of the project have been uploaded. Since all codes have to be tested in WP7 in the last year of the project, the structure of this deliverable has been agreed with colleagues working at WP7. The repository contains both the codes that will be used in the WP7 testing phase, and a detailed description of each model. In this document we will describe the main features of the repository and the link where codes and descriptions can be found. Then, we will briefly summarize the main features of the models that are contained in the repository. At the time of this deliverable, eight models have been submitted to the repository; however, at the end of the project we expect to have more; in fact, some additional models are almost finished, but not yet ready for the testing phase and so they have not been uploaded yet; very likely, they will be uploaded soon and tested in WP7 in the last year of the project.

In this first phase the repository is kept private (available only after a specific request to the WP leader) to leave the time to the modelers to finalize the scientific papers relative to their models. The repository will be then made public through the platform Zenodo at the end of the project.

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## 1. The repository

The codes uploaded to the repository will be tested in WP7 in different phases. The most important one is the prospective test of the models applied to the Italian region. This initiative will be carried out in collaboration and synergy with the Collaboratory for the Study of Earthquake Predictability (CSEP).

To achieve a full interaction between WP3 and WP7, we take advantage of powerful tools developed for open science: versioning control, open-source software and open-access repositories. Versioning control allows us to clearly document the model implementation process, while quickly highlighting code errors or unclear algorithms. The experiment models, setup and deployment are set in a GitLab versioning control server hosted at GFZ. In here, testers and modelers act collaboratively as model maintainers, with rapid communication centered around the codes themselves. The open-source software pyCSEP (Deliverable D7.1) acts as a full wrapper of the experiment forecasts, authoritative data sets and testing methods, to which modelers had full access to the source code and workshops where its use was explained. Moreover, to ensure full reproducibility, once a model is compatible with the experiment infrastructure, the whole repository will be uploaded to Zenodo, from which any user may download and execute the models in the future. Zenodo is an open-data repository hosted in high-performing computational infrastructure of the European Organization for Nuclear Research (CERN), meant to share and curate scientific data with a unique DOI identification.

The Gitlab repository is currently hosting the models developed within RISE WP3 and briefly described in the next section. The models have full access to the experiment rules and authoritative data, along with guidelines to make their codes fully compatible with the test experiment. At the moment, seven model repositories had been set up, number that is expected to increase once we invite modelers of the scientific community. In the repositories, the modelers described the software and libraries required to create their forecasts. A virtual environment is automatically created to setup the model computational architecture, which will be continuously integrated (CI) to ensure the code integrity as the model undergoes through any technical modification prior to the prospective experiment start. At the end of this alpha-test of the experiment, models will be set in Docker containers, which freeze the code library dependencies and requirements, so they models can reproduced even if a model-incompatible version of an external software is released.

The repository can be found in [https://git.gfz-potsdam.de/csep-group/rise\\_italy\\_experiment](https://git.gfz-potsdam.de/csep-group/rise_italy_experiment). Models which had not been published yet, remain closed to the general public, until they are either uploaded to Zenodo. In here, the testing experiment architecture will also be deployed, which will have full access to the latest version of the models' code.

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## 2. A brief description of the OEF models

During the first part of the project, modelers have explored a wide range of possible improvements. Only part of them have been committed in the repository, because the preliminary tests have shown that some models do not perform better than the classical model already available. For example, one important achievement of the project is also that some more complex models, such as the ETAS with the b-value varying in space does not bring any improvements in earthquake forecasting skill.

The models uploaded in the repository explore a wide range of possible OEF improvements; in particular, the models can be grouped in different classes that are summarized here:

- the tweaking of the existing best performing OEF models, which correspond to different flavors of the Epidemic-type aftershock sequence (ETAS) model.
- The development of a more refined clustering ETAS model that includes the innovative description of a time memory that is not included in classical ETAS models.
- A flavor of simplified/basic versions of clustering models that are still able to capture the essence of the earthquake clustering, but, at the same time, easy and flexible enough to be used in regions where the earthquake catalogs make difficult to set up of complicated models; for example, like regions that do not have good and long instrumental catalogs, or wide and inhomogeneous regions like Europe. Not less important, this kind of models may also represent a good reference model to be applied in any experiment carried out by CSEP, in order to have a homogeneous reference from which the information gain of each model can be measured.
- An innovative time-independent and time-dependent models that are based on the Bayesian INLABRU philosophy, i.e. a non-parametric Bayesian data-driven earthquake spatial and temporal models.
- An innovative model that takes into account one of the most important problems in delivering reliable earthquake forecasts: the time variability of the completeness magnitude. In fact, it is well known that after a large earthquake (when the model should be more useful), the magnitude of completeness markedly increases; if not properly addressed, this issue may bring to severe underestimation of the forecasting model, in particular after a major event.
- An innovative testable time-dependent model entirely based on continuum mechanics, which accounts for the physics of the rate and state and the coulomb failure function. The novelty of this model is that it accounts for the slip distribution on the source fault to describe the nearby stress heterogeneities that were one of the main reasons for the poor forecasting performances of this kind of models in the past.

A full description of the models can be found in the repository described in the previous section. In the following, we summarize only the main features of the models.

## 2.1 ETES (Epidemic-type earthquake sequence; resp. Giuseppe FALCONE)

This model (Falcone et al., 2010) is a tweaking of one of the models currently used in the OEF-Italy system (Marzocchi et al., 2014) and used for the first version of the OEF in Israel. It contains a few important novelties. The most important one is a better description of the aleatory variability, which is not anymore described by the Poisson distribution with the parameter average estimated the intensity rate of the ETES model; in particular, the new version of the model describes the forecast through a set of simulated earthquake catalogs that allow scientists to describe numerically the aleatory variability. Besides this novelty, we emphasize that the utility of this model is crucial, because it facilitates the comparison of the new OEF models with the current forecasting skill that is described by ETES.

## 2.2 SimpiETAS (resp. Ilaria SPASSIANI)

The model ETAS describes the current state of knowledge in OEF (Taroni et al., 2018). However, the set-up of this kind of model can be very challenging in some regions with short earthquake catalogs and/or small seismicity rate. In the RISE project we propose to set up a simple ETAS model which may capture the essence of the earthquake clustering. The main motivation is not to improve earthquake forecasting, but to deliver a model that could be applied everywhere, also where classical ETAS models have problems to be set up. This model has some very important applications and uses:

- i) it may be used to build a first OEF model for Europe, starting from the background provided by the last version of the seismic hazard model;
- ii) it can be used as a common reference model in any prospective CSEP experiment to have a common benchmark from which we can measure the improvement in forecasting skill;
- iii) it can be applied for specific sequences in any part of the world, where more complex models do not exist.

The first basic version of SimpiETAS is build reducing drastically the parameters to be estimated (prerequisite to make the model applicable almost everywhere). The two parameters that remain to be estimated by the data are related to the productivity of the triggering part.

## 2.3 fIETAS (resp. Leila MIZRAHI)

As the previous one, this model explores the balancing between complexity of the model and its usability and reliability. The main idea behind this modeling is that when developing next-generation earthquake forecasting models, the key is to more carefully account for the real world (which has fault systems with different properties, site specific properties, swarm-like episodes of temporally elevated seismicity, etc.), without constructing overly complicated models that are hard to comprehend and even harder to use. For this reason, the name of the models is fIETAS that means “flexible ETAS”; in particular fIETAS aims at capturing new model which naturally captures the diversity of conditions under which earthquakes take place. Within the ETAS statistical framework, the model

relaxes the assumptions of parametrically defined aftershock productivity and background earthquake rates. Instead, both productivity and background rates are calibrated with data such that their variability is optimally represented by the model. This allows for an impartial view on the behavior of background and triggered seismicity in different regions, different time periods, or different sequences. The preliminary pseudo-prospective forecasting experiments for Southern California to evaluate models based on their accuracy at forecasting the next event is ongoing. These experiments reveal when, where, and under which conditions our proposed model yields better forecasts than the standard ETAS null model.

#### **2.4 PETAI (resp. Leila MIZRAHI)**

One important issue that may hamper the reliability of an OEF model is the temporal variability of the completeness of the catalog which is particularly pronounced after a major event. The model PETAI (probabilistic, epidemic-type aftershock incompleteness) calibrates the parameters of the epidemic-type aftershock sequence (ETAS) model based on expectation maximization (EM) while accounting for temporal variation of catalog completeness. The method generalizes the concept of completeness magnitude, considering rate- and magnitude-dependent detection probability, and allows for self-consistent estimation of ETAS parameters and high-frequency detection incompleteness. With this approach, it is possible to address the potential biases in parameter calibration due to short-term after-shock incompleteness (STAI), embracing incompleteness instead of avoiding it. A forecast issued using this probabilistic, epidemic-type aftershock incompleteness (PETAI) model has two main differences compared to a standard ETAS model. First, the estimated ETAS parameters are different due to the inversion which accounts for STAI. Second, when simulating possible scenarios of how the current situation could evolve, the number of simulated events is inflated to account for aftershocks of events that were not observed, where the extent of inflation is based on the estimated incompleteness of the observed catalog at each point in time. In pseudo-prospective forecasting experiments for California, the PETAI model significantly outperforms the ETAS null model, with decreasing information gain for increasing target magnitude threshold (as expected).

The full description is available in:

<https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2021JB022379>

#### **2.5 TimeMemory-ETAS (resp. Yongwen ZHANG)**

This model represents a possible evolution of the current ETAS model including a novel physical property. Temporal and spatial memory (correlations) exists widely in many natural systems, including in earthquake activity. For example, Livina et al. (2005) identified the short-term memory of successive inter-event times in real earthquake catalogs using a conditional probability method. They found a strong short-term memory in which a short (long) inter-event time tends to follow a short (long) inter-event time. Other correlation detection methods, such as the detrended fluctuation analysis (Peng et al., 1994), have also been applied to detect the memory of inter-event times (Lennartz et al., 2008). The empirical short-term memory between successive

inter-event times in real catalogs has been found to be reproduced by the ETAS model, only for a narrow range of model parameters.

Recently, a new measure has been introduced, called 'lagged' conditional probability, to explore long-term memory, both in successive and non-successive inter-event times and distances (Zhang et al., 2020). This analysis has resulted in a memory measure versus (time or distance) lag for which a crossover between two distinct behaviors has been found: a slowly decaying power law at short scales (time or distance) and a significantly faster decay (that may be exponential) at long scales. This behavior, discovered in real catalogs, could not be reproduced by the ETAS model. More specifically, the model's analysis resulted in the memory without the crossover that was observed in the real catalogs; the model's memory is weaker (stronger) in short (long) time scales than the real catalogs. The value of the power law exponent depends on the productivity parameter  $\alpha$ , which is associated, in the model, with the Utsu law. Earthquakes can trigger more correlated events with a larger  $\alpha$ , resulting in enhanced earthquake memory. Therefore, based on the empirical finding of crossover in the memory behavior, here we introduce into the ETAS model two productivity parameters, large and small,  $\alpha_1$  and  $\alpha_2$ , for short and long-term time scales. This new model reproduces the observed double power law behavior of memory, as well as the crossover observed in the real data. The first retrospective analyses show that this new model improves the forecasting performance of earthquake events.

## 2.6 INLABRU time-independent (resp. Kirsty BAYLISS)

The time-independent INLABRU model (an R-version of this model is described here: Bach et al., 2019) is mostly addressed in improving the spatial background seismicity which may be used for medium-to-long term forecasts and as a starting background model at which an ETAS model may be added on top of it (see next section).

The proposed model is focused on the 1-year time-independent models for Italian seismicity using INLABRU. A first application in California and the procedure to get forecasts are described in Bayliss et al. (2020, 2022). The application of these models to the Italian territory uses a homogenised catalogue from 1960-2020 as input events, and combine spatial covariates including strain rate, distance from fault, fault slip rates and historic seismicity. The full posteriors of each spatial model are used to generate the required simulated catalogue forecasts and select the number of events in each simulated catalogue from a Poisson distribution with rate returned by the model. These forecasts are currently scaled to one year, but they can be rescaled for any forecasting time window of interest.

Previous CSEP testing experiments demonstrated that smoothed past seismicity was the best-performing forecast model in California, but did not perform as well in Italy, where models which included historic seismicity or fault information performed better. Our goal is to develop a forecast for mainshock activity in Italy, to act as a long-term time-independent model in its own right, and a background component to short-term forecasting.

The advantage of a detailed, spatially-varying background is two-fold, in that it should not only account for the locations of large mainshocks but could also provide us with useful insight on spatial



distributions of aftershocks. Recent work by Hardebeck (2021) demonstrated that background seismicity patterns were a significant influence on the locations of aftershocks. At present, few attempts have been made to account for spatially-varying background in time-dependent forecast models. Other authors have accounted for some spatial-variation of ETAS parameters (Nandan et al., 2017) or the inclusion of some spatial covariates (Bach and Hainzl, 2012), however the INLABRU approach allows for more complex spatial models than have currently been implemented with these approaches, allows us to follow a flexible framework for assessing covariates and allows us to build fully Bayesian earthquake forecasts.

We previously demonstrated the flexibility of the INLABRU approach and its use in generating data-driven earthquake spatial models in California (Bayliss et al., 2020) and recently demonstrated how it could be extended to produce time-independent earthquake forecasts (Bayliss et al., 2022). Our simulated catalogue forecasts include uncertainty in the model itself by using different posterior samples for each catalogue forecast, thus making fully Bayesian time-independent earthquake forecasts.

## **2.7 INLABRU time-dependent (resp. Francesco SERAFINI)**

Here the INLA algorithm through the INLABRU R-package (Bach et al., 2021) is used to approximate the ETAS model. The key of the approach is to approximate the different components of the log-likelihood using three Poisson Counts model with log-intensity linear in the parameters. More specifically, this approach will maintain the Hawkes process structure, in which every single earthquake, belonging to the background or triggering part, may trigger other earthquakes; the implementation in the INLA algorithm (Rue et al., 2009; 2017) requires a different parameterization of the ETAS model. Through this suitable re-parameterization, the parameters can be considered as Gaussian processes which can be used to incorporate different hypotheses in the models. Possible examples are: parameters varying in time, parameters varying in space, parameters as functions of covariates, mixtures of the previous ones.

Notably, the model follows the Bayesian logic, in which every single parameter may be described by a distribution and possibly adjusted as long as new data come in.

## **2.8 CRS model (resp. Junhao CHENG)**

The previous Italian experiment of CSEP carried out in 2009-2014 included two Coulomb-based earthquake forecasting models submitted targeting the seismicity in a 5-year time window from 2010 to 2014. However, both models implement a simplified modelling strategy for the receiver faults, rate-and-state parameters, and the seismic sources. Prospective evaluations of this CSEP experiment (Taroni et al., 2018) have shown that neither model has a satisfying performance in testing due to the underestimation of observed events. Another critical limitation of this 5-year CSEP-Italy experiment is that the prospective long-term forecasting model does not allow any update during the testing period (Schorlemmer et al., 2010), but recent advances have shown the significant advantage behind continuous updates especially in evolving earthquake sequences (e.g., Mancini et al., 2020). Although the CSEP-Italy project introduced a one-day time interval that allows daily updates about the earthquake sources, there was no prospective short-term physics-based

forecast submitted to the CSEP for the whole of Italy. This study will fill this gap and compare the performance of our one-day CRS model against the standard ETAS model with the purpose to become a future candidate to be implemented in the current OEF system in Italy.

This model targets the idea that an enhanced CRS framework involving improved source and fault characterization and model updates could improve the skill of forecasts on the Italy-wide scale for the 1-day intervals. The main features include independent constraints from geological and seismological data, such as the receiver fault model based on active faults data (DISS working group, 2021) and the moment tensor catalogue (Pondrelli and Salimbeni, 2006; Scognamiglio et al., 2006), Coulomb stress transfer using either finite-sized fault models or synthetic fault slip distributions, and secondary triggering effects. The output CRS model is the first physics-based short-term forecasting model targeting the CSEP-Italy area. It provides a direct link between the stress triggering and the forecast; the results are also comparable with other models using the pyCSEP testing metrics.

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