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The Collaboratory for the Study of Earthquake Predictability: Achievements and Priorities

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1 The Collaboratory for the Study of Earthquake
2 Predictability: Achievements and Priorities

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19 **Abstract**

20 The Collaboratory for the Study of Earthquake Predictability (CSEP) is a global cyberinfras-
21 tructure for prospective evaluations of earthquake forecast models and prediction algorithms.
22 CSEP’s goals are to improve our understanding of earthquake predictability, advance fore-
23 casting model development, test key scientific hypotheses and their predictive power, and
24 to improve seismic hazard assessments. Since its inception in California in 2007, the global
25 CSEP collaboration has been conducting forecast experiments in a variety of tectonic set-
26 tings and at the global scale, and now operates four testing centers on four continents to
27 automatically and objectively evaluate models against prospective data. These experiments
28 have provided a multitude of results that are informing operational earthquake forecasting
29 systems and seismic hazard models, and they have provided new, and sometimes surprising,
30 insights into the predictability of earthquakes and spurred model improvements. CSEP has
31 also conducted pilot studies to evaluate ground-motion and hazard models. Here, we report
32 on selected achievements from a decade of CSEP, and we present our priorities for future
33 activities.

34 **Introduction**

35 Earthquake forecasts and ground-motion models are the key ingredients to one of the most
36 important products of seismological research: seismic hazard assessments. To better capture
37 and assess the epistemic uncertainties of earthquake forecast models, the Southern California
38 Earthquake Center (SCEC) and the United States Geological Survey (USGS) started the Re-
39 gional Earthquake Likelihood Models (RELM) project. In the early 2000s, RELM initiated

40 the development and rigorous prospective testing of a suite of such models for California
41 [*Field, 2007*, and articles in the same special issue]. Each participating model’s forecast
42 was submitted to the testing group before 1 January 2006, the starting time of the 5-year
43 prospective testing period. This concept of rigorous and prospective testing quickly gained
44 support, and SCEC started the Collaboratory for the Study of Earthquake Predictability
45 (CSEP) with funding provided by the W. M. Keck Foundation [*Jordan, 2006*]. Its first
46 achievement was the development of the testing center software system [*Schorlemmer and*
47 *Gerstenberger, 2007; Zechar et al., 2010b*] for the RELM experiment [*Field, 2007; Schorlem-*
48 *mer et al., 2007; Zechar et al., 2013; Strader et al., 2017*]. Over the following years, CSEP has
49 expanded to four international testing centers that collectively test over four hundred models
50 and model versions in a variety of tectonic settings and on a global scale. Besides Califor-
51 nia, testing centers are located in New Zealand [*Gerstenberger and Rhoades, 2010*], Japan
52 [*Tsuruoka et al., 2012*] and Europe [*Marzocchi et al., 2010*], while a Chinese testing center
53 is under development [*Mignan et al., 2013*], see Figure 1. In 2011, the Global Earthquake
54 Model (GEM) Foundation provided funds to develop procedures and metrics for evaluat-
55 ing intensity-prediction equations (IPEs), ground-motion prediction equations (GMPEs),
56 and hazard models at a new testing center at the German Research Centre for Geosciences
57 (GFZ) with the goal to integrate these in the CSEP framework. The centers have produced
58 a plethora of results. Here, we present a selection of highlights and broader achievements
59 from a decade of CSEP. We also outline CSEP’s priorities for the future.

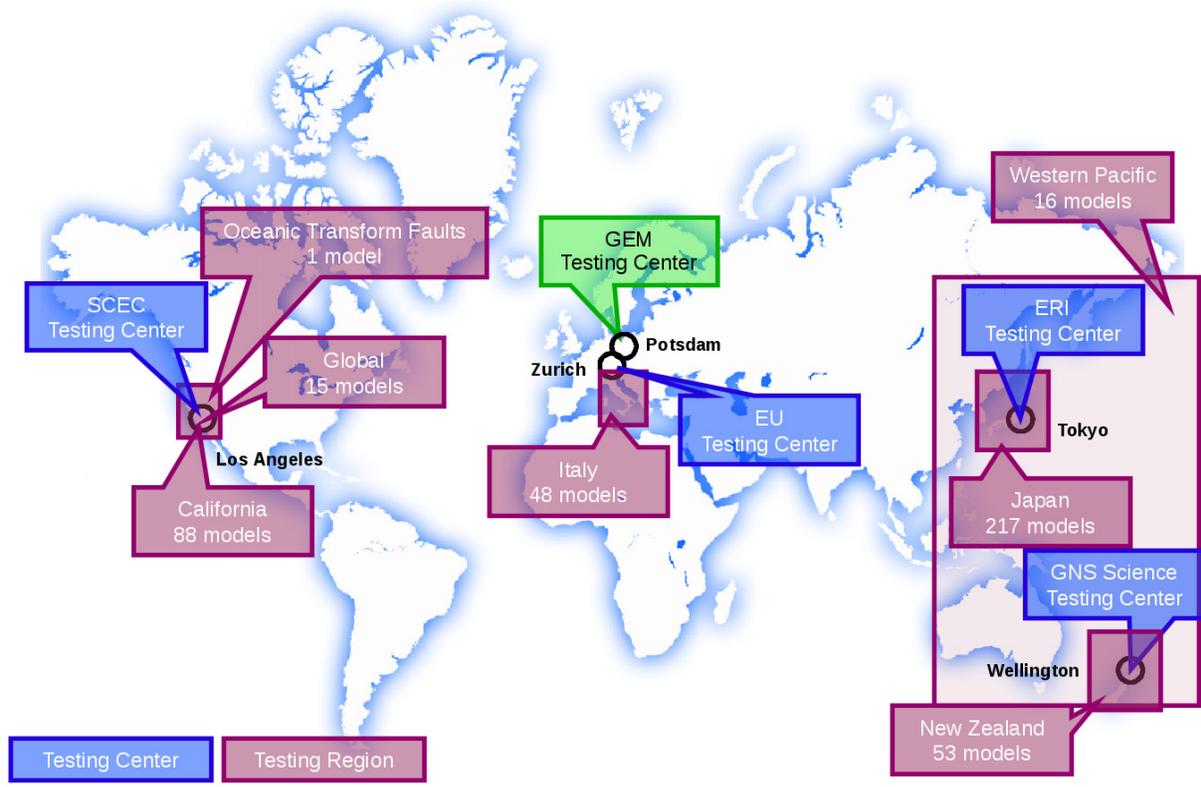


Figure 1: Map showing the locations of CSEP testing centers and testing regions. The SCEC testing center in Los Angeles is operating the testing regions of California, western Pacific, oceanic transform faults (in the Pacific) and the global experiment. The EU testing center in Zurich operates the testing region of Italy, the New Zealand testing center in Wellington the New Zealand experiment, and the Japan testing center the three testings regions in Japan. The GEM testing center in Potsdam develops ground-motion and hazard-related testing procedures and implemented case studies but, unlike the other centers, does not run earthquake forecast experiments.

60 **The Philosophy behind CSEP**

61 The fundamental idea of CSEP is simple in principle but complex in practice: forecasting
62 models should be tested against future observations to assess their performance, thereby
63 ensuring an unbiased test of the forecasting power of a model. The more common retro-
64 spective tests (testing a model's forecast against past data or parts of past data not used
65 in the forecast) or pseudo-prospective tests (dividing past data into a learning dataset and
66 an observational dataset so that time-dependent causality is preserved) bear the problem
67 that features of the observations used for testing might have been known to the modeler and
68 included in the model consciously or unconsciously.

69 The CSEP concept of prospective testing requires scientists to express their hypotheses
70 and models quantitatively for testing against pre-agreed datasets, and to comply with agreed
71 test procedures and metrics. For each experiment, the test area, its subdivision into spatial
72 cells and magnitude bins, the type of forecast (usually number of earthquakes expected
73 during a pre-defined period), the input data, the observations, and the metrics are defined
74 through a community process: modelers have to fully specify (with zero degrees of freedom)
75 their forecast according to standards. Observations come from authoritative sources, agreed
76 upon in advance, and are used without any further or a posteriori interpretation by the
77 modelers or testers, ensuring full independence from the testing process. The standardization
78 also allows for comparative testing as all models participating in one experiment produce
79 compatible forecasts, covering the same region, magnitude range, and testing period. Models
80 producing time-varying forecasts are compiled and installed from source codes registered in
81 the testing center to allow for automated and repeated forecast generation.

82 The CSEP approach showcases a wide range of plausible forecasts and their compar-
83 ison. Previously, comparisons were often difficult because of the preferences of individual
84 researchers for specific regions, testing periods, magnitude scales, or datasets. CSEP thereby
85 elicits otherwise implicit assumptions and requires that abstract ideas are made concrete and
86 testable, and reduces various cognitive inference biases (e.g. confirmation or hindsight bias).
87 The history of earthquake prediction is riddled with controversies, disputes and biased in-
88 ferences and although vigorous scientific debate continues, peer review is not sufficient to
89 settle many of these disputes. CSEP has set an international standard for transparent,
90 reproducible, and prospective experiments against the reproducibility crisis in science and
91 created an infrastructure for more objective debates.

92 **A Decade of CSEP: An Overview of Achievements**

93 **New Insights Into Earthquakes and Their Predictability**

94 The longest-running experiment in CSEP covers the 5-year RELM forecasts for California.
95 This experiment has been continued with unchanged forecasts after the initial 5-year period
96 (1 January 2006–1 January 2011). It provided evidence that the locations of past shocks,
97 particularly the many small (M2+) ones recorded by dense networks, can contain more
98 predictive skill of moderate to strong earthquakes over a 5- to 10-year period than many
99 other forecast approaches, including geological (fault-based), geodetic, and tectonic models
100 [*Schorlemmer et al.*, 2010c; *Zechar et al.*, 2013; *Strader et al.*, 2017]. One of the participating
101 forecasts, the Uniform California Earthquake Rupture Forecast version 2 (UCERF2), is
102 particularly important because it provided government agency hazard estimates that set

103 Californian building codes and insurance rates, and underlies catastrophe models [*Field*
104 *et al.*, 2009]. UCERF2 was consistent with observed moderate-to-strong seismicity during
105 2007–2016 and had greater forecast skill than most other RELM forecasts [*Strader et al.*,
106 2017]. Evaluation of the new UCERF3 [*Field et al.*, 2014, 2015, 2017] will be a major future
107 CSEP activity.

108 Models based on geodetic strain-rate data have shown promise. The RELM forecast by
109 *Shen et al.* [2007] for southern California was about as informative as UCERF2 in forecasting
110 M5+ shocks. The strongest evidence, however, is based on two years of testing global
111 forecasts: the GEAR1 model [*Bird et al.*, 2015], a hybrid model of the global strain rate
112 map and smoothed seismicity, outperformed both of its individual components (*Strader et*
113 *al.*, this issue). Retrospective test results from New Zealand also support the predictive skill
114 of strain-rate data converted to seismicity rates [*Rhoades et al.*, 2017].

115 CSEP is testing statistical clustering models in California, Italy, New Zealand, Japan,
116 and globally. Multiple versions of the Epidemic Type Aftershock Sequence (ETAS) models
117 demonstrated reliable forecasts of the 2011 M9 Tohoku earthquake sequence [*Nanjo et al.*,
118 2012; *Ogata et al.*, 2013]. Importantly, measured probability gains during major aftershock
119 sequences are consistent with theoretical gains of two to three orders of magnitude over
120 time-independent models [*Taroni et al.*, this issue; *Cattania et al.*, this issue; *Woessner*
121 *et al.*, 2011; *Rhoades et al.*, this issue]. CSEP also identified the most skillful version of
122 the Every Earthquake a Precursor According to Scale (EEPAS) model, that is based on the
123 precursory scale increase phenomenon, during the period 2009–2012 in California [*Schneider*
124 *et al.*, 2014] and 2009–2017 in New Zealand [*Rhoades et al.*, this issue].

125 Physics-based models, i. e. models that use physical concepts like rate-and-state [*Di-*

126 *eterich*, 1994] behavior or Coulomb-stress changes [*King et al.*, 1994] for forecasting rather
127 than being based purely on statistics, have drawn a lot of attention in the past decade.
128 The performance of the first generation of such models of aftershock sequences was poor
129 in a retrospective evaluation during the 1992 M7.3 Landers earthquake sequence [*Woessner*
130 *et al.*, 2011]. The authors concluded that Coulomb/rate-state models [e.g., *Stein*, 1999]
131 were substantially less informative than several ETAS and STEP [*Gerstenberger et al.*, 2005]
132 models. Subsequent model development, however, has led to dramatic improvements: the
133 second generation of Coulomb-based models suggests much improved skill and reliability in
134 a retrospective test of the 2010–2012 Canterbury, New Zealand, earthquake sequence [*Cat-*
135 *tania et al.*, this issue]. These results are encouraging for the prospects of physics-based
136 forecasting.

137 One of the main CSEP priorities for the future is to test also ground-motion and seismic
138 hazard models. A pilot study has explored the feasibility to carry out CSEP-type exper-
139 iments in these domains. The analysis on IPEs in Italy showed that the global model by
140 *Allen et al.* [2012] performed well for Italian earthquakes, comparable to the best local model.
141 Among the local models, some newer models based on more data did surprisingly not per-
142 form better than older ones based on the same functional form [*Mak et al.*, 2015]. This is
143 contrary to the belief that using more and newer data per se will necessarily lead to better
144 models, underlining the need for future independent and prospective testing experiments. A
145 similar observation was made in the GMPE pilot study in Japan, where the newest NGA-
146 West2 global model [*Campbell and Bozorgnia*, 2014] outperformed pre-NGA local models on
147 which the Japanese hazard model is based [*Mak et al.*, in press], supporting again the notion
148 of testing rather than assuming that models created specifically for local conditions are per

149 se better.

150 The final element in the chain are hazard models. While site-specific hazard is often the
151 focus of many applications, *Mak et al.* [2014] showed that the statistical power of testing a
152 site-specific hazard model is in general very low and thus only a regional hazard model can be
153 meaningfully tested. Testing the last four US National Seismic Hazard Maps [*Petersen et al.*,
154 2014] in a prospective sense, *Mak and Schorlemmer* [2016] showed in their pilot study that in
155 the central and eastern US the model is consistent with observed peak-ground-acceleration
156 (PGA) and spectral accelerations (SA) at 1s, while in California the model is consistent with
157 the observation for PGA but overpredicts the hazards for SA at 1s. However, given the long
158 forecasting horizon of the hazard models, long-term testing is needed to increase the power
159 of these results.

160 **New Insights Into Model Evaluation Methods**

161 CSEP developed a suite of new, community-endorsed tests and metrics that probe forecasts
162 from different perspectives, and identify strengths and weaknesses by highlighting discrep-
163 ancies between forecast and data [*Schorlemmer et al.*, 2007; *Zechar et al.*, 2010a; *Werner*
164 *et al.*, 2011]. Some initially promising tests have been replaced by others [e.g., *Rhoades*
165 *et al.*, 2011]. CSEP stimulated innovation in performance metrics, e.g. those based on point
166 process residuals [*Clements et al.*, 2011; *Gordon et al.*, 2015], gambling and betting frame-
167 works [*Zhuang*, 2011; *Zechar and Zhuang*, 2010, 2014], and an extension of Molchan error
168 diagrams [*Zechar and Jordan*, 2008]. Strengthening the evaluation methods further remains
169 a CSEP priority [e.g., *Werner and Sornette*, 2008; *Lombardi and Marzocchi*, 2010; *Molchan*
170 *et al.*, 2017].

171 CSEP stimulated new ensemble modeling techniques, which aim to combine multiple
172 forecasts optimally to exploit complementary strengths. Techniques include Bayesian model
173 averaging and other additive models [*Marzocchi et al.*, 2012; *Taroni et al.*, 2013], as well
174 as multiplicative models [*Rhoades et al.*, 2014; *Bird et al.*, 2015]. Ensemble models can
175 also express epistemic uncertainty arising from data incompleteness, parameter uncertainty,
176 and model uncertainty. For example, *Omi et al.* [2015] concluded that Bayesian ensemble
177 forecasts were more reliable than forecasts that did not consider epistemic uncertainty.

178 In the hazard domain, a new metric for GMPE testing has been proposed, based on
179 the widely used LLH score [*Scherbaum et al.*, 2009]. It is applicable to model GMPEs
180 with complicated correlation structure [*Mak et al.*, 2017]. *Mak and Schorlemmer* [2016] also
181 applied a formal test of the number of exceedances to hazard forecasts, paving the way to
182 future hazard-testing experiments within the CSEP framework.

183 **Future CSEP Activities**

184 CSEP activities during the next decade will be guided by three main objectives: expanding
185 the data space, expanding the model space, and testing key hypotheses and questions.

186 (1) Expanding the data space. The main limitation in the testing of earthquake forecasts
187 is the lack of data. CSEP will extend spatial coverage by encouraging forecast testing in other
188 regions with good earthquake catalogs (e. g., seismic belts of Asia and South America), as
189 well as globally. It will extend temporal coverage by expanding its retrospective testing
190 capabilities to take advantage of well-recorded aftershock sequences and other datasets,
191 including information on large, infrequent earthquakes from pre-instrumental historical and

192 paleoseismic observations.

193 Another limitation is the data quality, i.e. the errors in the estimates of occurrence
194 times, epicenter locations, and magnitudes, but also missing small events in earlier periods
195 of aftershock sequences and in places of low earthquake detectability. CSEP analyzed data
196 quality in test regions [*Schorlemmer et al.*, 2010b,a, 2018] but is still in need of models
197 to assess the difference between catalogs and actual seismicity. Such models can quantify
198 uncertainties in model evaluations.

199 Finally, CSEP will address the important question of the minimum duration of an ex-
200 periment to derive conclusions about model performances with sufficient power. While some
201 models can be rendered wrong with an earthquake considered impossible by the model, posi-
202 tive statements about model performances, in particular of long-term models, can technically
203 only be made after the forecasting period has passed completely. Such an approach is not
204 feasible for e. g. 50-year models and a shorter but sufficient period needs to be determined for
205 meaningful and practical tests. This question touches on the practical limits of testability
206 of models and will involve the developments of alternative approaches like component-based
207 testing of models or model reformulations to match observables that can be obtained.

208 (2) Expanding the model space, focusing on new types of forecasts. Earthquake forecast-
209 ing is a rapidly growing scientific endeavor, motivated by the needs of long-term PSHA and
210 shorter-term operational earthquake forecasting (OEF). CSEP will promote this research by
211 striving to test the most advanced and innovative earthquake forecasts.

212 **3D models** CSEP has thus far evaluated epicentral forecasts of shallow earthquakes, rather
213 than hypocenter distributions. However, 3D forecasts are needed to assess hypotheses
214 and seismic hazard in structurally complex tectonic settings, such as subduction zones.

215 The 3D Kanto experiment provides a blueprint for such activities. It covers the densely-
216 populated metropolitan area of Tokyo down to depths of 100km, where three tectonic
217 plates meet. Interactions among the inter-plate and intraplate earthquakes are not well
218 captured in 2D, and preliminary results show an advantage of 3D models [*Tsuruoka,*
219 2017].

220 **Ensemble forecasting** Recent studies on hybrid/ensemble models of several different types
221 (additive, multiplicative, maximum, and using different weighing schemes) concluded
222 that these models can sometimes outperform individual models based on a single idea or
223 data source [*Rhoades and Gerstenberger, 2009; Rhoades and Stirling, 2012; Marzocchi*
224 *et al., 2012; Taroni et al., 2013; Rhoades, 2013; Steacy et al., 2014; Rhoades et al., 2014,*
225 *2015, 2016, 2017*], and are never much worse than the best individual model, which is
226 not known a priori. CSEP will support methods to test combinations of two or more
227 existing models or to assimilate new gridded covariates into existing models. Likewise,
228 component-based combinations (e.g. taking the smoothing kernel of one model and
229 the spatial magnitude distribution of another model) can be explored, either through
230 ensemble techniques or on the model source-code level to improve capturing of model
231 uncertainties.

232 **Fault-based models** Models that explicitly incorporate known faults are thought to pro-
233 vide better long-term forecasts than models lacking such information [*Field et al.,*
234 *2009*]. Fault-based models rely on fault geometry to forecast large fault ruptures. The
235 *association problem*, matching of a future observed rupture with a specific hypothetical
236 rupture, is currently unsolved because finite ruptures are not consistently reported by

237 a community-agreed independent source. Thus to compare future earthquakes against
238 fault-based models like UCERF3 [*Field et al.*, 2014], CSEP will need to develop new
239 methods.

240 **Event-based models** CSEP models forecast earthquake rates in each space-time-magnitude
241 bin independently of the earthquakes in all other bins assuming a Poisson distribution.
242 It has been recognized early that earthquake occurrence is clustered and does not follow
243 a Poisson distribution [*Schorlemmer et al.*, 2007]. Clustering implies that earthquakes
244 are not independent of previous events. In Japan, 1-year forecasts became meaningless
245 after the 2011 Tohoku earthquake because its triggered events dominated the seismic-
246 ity. This dependency can be accounted for by models and experiments that allow
247 forecast updates after each event, in contrast to regular time intervals.

248 **Physics-based models** A major CSEP objective is to improve forecasting accuracy by
249 harnessing the explanatory power of rupture physics. The Canterbury experiment
250 [*Cattania et al.*, this issue] also highlighted the difficulties of prospectively testing
251 stress-transfer models that must be updated with slip models during a seismic se-
252 quence. Further experiments using well-recorded aftershock sequences are planned.
253 On a different scale, simulators like RSQSim [*Dieterich and Richards-Dinger*, 2010;
254 *Richards-Dinger and Dieterich*, 2012] are employing rupture physics and are capable
255 of simulating very long (more than a million years) earthquake catalogs that are, in
256 principal, suitable for producing time-dependent forecasts on all relevant time scales.
257 This will require the inclusion of off-fault seismicity and, more important, schemes for
258 initializing the fault-system simulations with stress states consistent with the observed

259 earthquake history, which is a difficult, unsolved problem. Testing such forecasts will
260 also require a solution to the association problem.

261 **Complete probabilistic models** A proper model validation requires a full description
262 of all uncertainties [*Marzocchi and Jordan, 2014, 2017*]. CSEP will overcome these
263 limitations by considering a more complete description of a model’s forecast, allowing
264 it to specify not only the expected number in each bin but also the distribution of the
265 number of target earthquakes in each bin and the correlations between bins to account
266 for epistemic uncertainties. A wider range of test statistics, describing various features
267 of the earthquake process, will also be possible in this framework.

268 **Ground-motion and hazard models** Testing ground-motion models will need to extend
269 the association problem with more rupture-specific parameters provided by an author-
270 itative source. Similar to the complete probabilistic models, testing hazard models
271 needs to take into account spatial (and temporal, for time-dependent hazard models)
272 correlations of models. These correlations will be included in the test, especially for
273 hypothesis tests with well-defined mathematical meaning. The first step will be a test
274 of the Japanese national seismic hazard model.

275 **Precursor models** Some studies concluded that geodetic and electromagnetic anomalies
276 can be exploited for earthquake forecasting, even though the information gain is low
277 [*Zhuang et al., 2005*]. Tailored, prospective experiments are necessary for an assessment
278 of forecast improvements through possible precursory models.

279 **External forecasts** Thus far, CSEP has been evaluating internal forecasts, namely those
280 generated by model software compiled and installed within its testing centers. This

281 ensures reproducibility and transparency within a controlled environment, and means
282 that the model under evaluation is not a moving target. However, CSEP also aims
283 to support the evaluation of select External Forecasts and Predictions (EFPs), such
284 as operational forecasts issued (elsewhere) by government agencies or predictions from
285 precursor models that cannot be installed within CSEP. External forecasts and predic-
286 tions seldom fit the requirements of CSEP forecasts. Solution are to 'collapse' CSEP
287 forecasts to the same format of the external forecasts or to tailor an experiment to
288 the forecast. This will require automated transfer protocols for verified and unambigu-
289 ous forecasts and predictions, along with versioning of underlying models to document
290 model changes. CSEP's internal models can serve as benchmarks. However, the prob-
291 lem of possible biases of non-documented forecasts remain.

292 (3) Testing key hypotheses and questions. Formal testing provides a valuable tool for
293 probing, improving, and possibly discarding fundamental assumptions about earthquake be-
294 haviour. Many scientific questions could be refined by carefully formulated forecast models,
295 especially if a tailored experiment is specified simultaneously.

- 296 • *Are big earthquakes fundamentally different from smaller ones in their clustering, scal-*
297 *ing behavior or long-term behavior?* Scaling relations between rupture dimensions and
298 moment often suggest a break at a certain magnitude, presumably related to seis-
299 mogenic depth. How can these observations be exploited to improve predictive skill?
300 Regional and global tests against a null hypothesis could help answer these questions.
- 301 • *What is the magnitude distribution of earthquakes on a single master fault?* A Gutenberg-
302 Richter distribution, or something else? Do on-fault and off-fault earthquakes have the

303 same size limits? Effective tests would require a good definition of 'on-fault' over a
304 region and sufficient time to supply large on-fault events.

305 • *Elastic rebound?* Do large mainshocks reduce the probability of other ones nearby
306 (rebound model), or do they increase the probability preferentially (traditional ETAS
307 model)?

308 • *Are moderate earthquakes more likely to trigger big ones if they are near 'ripe' major*
309 *faults?* If so, how much more likely? Can we identify 'sleeping giants', or places where
310 prior probability is high? As above, large regions and sufficient time would be required.

311 • *Do b-values (or other features of relative magnitude distribution) as a possible proxy*
312 *to stress have predictive power?* Do they help forecast locations and focal mechanisms
313 of future events? Tailored experiments on *b*-value anomalies could provide an analysis
314 of the change in forecasting power when including *b*-values.

315 • *Is the location of small earthquakes the best predictor of the location of coming bigger*
316 *ones?* Or do rate-state Coulomb models add significant new information? This ques-
317 tion has been pursued in aftershock studies, with improved results [*Cattania et al.*, this
318 issue]. In Japan, inland background seismicity rates of the HIST-ETAS model [e. g.,
319 *Ogata*, 2011, 2017] correlate well with future and historical (599-1884) large earth-
320 quakes. Challenges include approximating the initial stress conditions, and accurately
321 modeling the stresses. Because each event changes the conditions, forecasts must adapt
322 automatically without human interaction.

323 • *Can foreshocks be discriminated?* One way to solve this question is by combining an

324 existing space-time forecast model with a magnitude-frequency model of a foreshocks
325 forecast [Ogata and Katsura, 2014; Nomura and Ogata, this issue] for comparison with
326 an independent Gutenberg-Richter magnitude sequence. Another way would be in a
327 tailored test to assign each event a foreshock probability and compare it with future
328 activity.

329 **Conclusions**

330 CSEP is building a community of earthquake forecasting researchers, who share data, mod-
331 els, ideas, and evaluation approaches. CSEP has set an international standard for conduct-
332 ing forecast experiments and evaluating the predictive power of models and hypotheses.
333 Through insistence on prospective testing, quantitative metrics, independent authoritative
334 data streams, transparency, and reproducibility, CSEP has reduced subjective biases from
335 evaluations of earthquake forecast models and prediction algorithms. This has inspired other
336 communities to follow suit, including induced seismicity [e. g., Király-Proag et al., 2016] and
337 earthquake early warning [Böse et al., 2014].

338 CSEP has also explored the current limits of predictability and of testing forecasts or their
339 components. Meaningful evaluations of hypotheses about the long-term behavior of large
340 earthquakes may take decades or centuries in regional fault systems, necessitating global
341 models for testing hypotheses such as characteristic earthquakes, segmentation, and quasi-
342 periodic recurrences. Such hypotheses inform important seismic hazard models in California,
343 Italy, Japan, and Europe; however, the dearth of large earthquakes in individual regions
344 is a major limitation of evaluations. For the same reason, models of expected maximum

345 magnitude on a fault (segment) are not readily testable [*Holschneider et al.*, 2011, 2014].

346 Despite these fundamental problems, CSEP’s model evaluations have influenced and im-
347 proved seismic source models for hazard estimates. In California, the performance of the
348 *Helmstetter et al.* [2007] RELM model led to the inclusion of adaptive smoothing of the
349 locations of small quakes in UCERF3 [*Field et al.*, 2014], while the demonstrated skill of
350 the ETAS model class underpins the UCERF3-ETAS model [*Field et al.*, 2017]. In New
351 Zealand, short-term and medium-term models under CSEP evaluation were used to provide
352 operational forecasts and hazard estimates during and after the 2010–2012 Canterbury and
353 2016 Kaikoura sequences [*Gerstenberger et al.*, 2014, 2016; *Rhoades et al.*, 2016]. In Japan,
354 real-time aftershock forecasts at the National Research Institute for Earth Science and Dis-
355 aster Resilience in Japan provide information for the government [*Omi et al.*, 2016]. Finally,
356 the Italian OEF system for the Civil Protection Agency employs an ensemble of CSEP-tested
357 models [*Marzocchi et al.*, 2014; *Iervolino et al.*, 2015]. These examples suggest that CSEP
358 evaluations are leading to safer and better informed societies through dynamic earthquake
359 probabilities, and a better decision-making basis for building codes and retrofitting priorities.

360 **Data and Resources**

361 No data were used in this paper.

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