

Impact of topography on earthquake static slip estimates

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Abstract

Our understanding of earthquakes is limited by our knowledge, and our description, of the physics of the Earth. When solving for subsurface fault slip, it is common practice to assume minimum complexity for characteristics such as topography, fault geometry and elastic properties. These characteristics are rarely accounted for because our knowledge of them is often partial and they can be difficult to include in simulations. However, topography and bathymetry are known all over the Earth's surface, and recently developed software packages such as SPECFEM-X have simplified the process of including them in calculations. Here, we explore the impact of topography on static slip estimates. We also investigate whether the influence of topography can be accounted for with a zeroth-order correction which accounts for variations in distance between subfaults and the surface of the domain. To this end, we analyze the 2015 M_w 7.5 Gorkha, Nepal, and the 2010 M_w 8.8 Maule, Chile, earthquakes within a Bayesian framework. The regions affected by these events represent different types of topography. Chile, which contains both a deep trench and a major orogen, the Andes, has a greater overall elevation range and steeper gradients than Nepal, where the primary topographic feature is the Himalayan mountain range. Additionally, the slip of the continental Nepal event is well-constrained, whereas observations are less informative in a subduction context. We show that topography has a non-negligible impact on inferred slip models. Our results suggest that the effect of topography on slip estimates increases with limited observational constraints and high elevation gradients. In particular, we find that accounting for topography improves slip estimates where topographic gradients are large. When topography has a significant impact on slip, the zeroth-order correction is not sufficient.

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1 Introduction

Estimates of subsurface fault slip are mainly constrained by observations of earthquake-induced deformation on the surface of the Earth, but they are also sensitive to information specified a priori to characterize the forward model. The forward model will always be an approximation to the real Earth, and these approximations can affect inferences of fault slip (e.g., Beresnev, 2003; Hartzell et al., 2007). We often assume minimum complexity for the forward problem, partly because we are not certain about many detailed aspects of Earth structure, but also to simplify Green’s functions computations. The simplest, and commonly used, description of the forward problem is a planar fault in a homogeneous elastic half-space with a flat surface. It is true that certain characteristics of the forward model, such as fault geometry and elastic heterogeneity, are often poorly known, but topography and bathymetry are well-constrained at the global scale.

In previous studies, synthetic tests have shown that topography of the free surface, within a simple configuration, can have a significant impact on predicted static surface deformation, particularly if the source is located at shallow depths (e.g., McTigue and Segall, 1988; Huang and Yeh, 1997; Williams and Wadge, 1998; Tinti and Armigliato, 2002). Within a realistic setup, several studies have found that Green’s functions produced with a 3D model which includes topography and 3D elastic structure yield more accurate sub-surface fault slip estimates (e.g., Zhao et al., 2004; Moreno et al., 2012; Kyriakopoulos et al., 2013; Gallovič et al., 2015; Tung and Masterlark, 2016; Wang et al., 2017; Wang and Fialko, 2018). However, because most of these studies did not separate the effects of topography from those of heterogeneous elastic structure, it is not possible to determine the impact of topography alone from their results.

A few studies did examine the effect of topography on predicted surface deformation or estimated sub-surface fault slip. Most of those studies analyzed earthquakes in regions with relatively small topographic gradients, so the effects of topography were not found to be significant. Masterlark (2003) suggested that the effect of topography on both predicted surface displacements and inferred slip, within a subduction context, is negligible when compared to the impact of elastic heterogeneity. However, the earthquake used in that study was the 1995 M_w 8.0 Jalisco-Colisma earthquake in Mexico, where the topography gradient is of limited amplitude and confined near the trench. Similarly, Trasatti et al. (2011) showed that the addition of topography had a minimal effect on the slip distribution of the 2009 M_w 6.3 L’Aquila event in Italy due to the lack of strong topographic variations in the region. Williams and Wallace (2018) investigated shallow slow slip

32 at the Hikurangi Subduction Margin in New Zealand, where the topographic gradient is relatively
33 smooth. They determined that accounting for topography would only yielded a slight variation in
34 their slip models (5% difference in seismic potency), which is much smaller than the effect they
35 found for crustal heterogeneity (>50% difference in seismic potency). In contrast, Hsu et al. (2011)
36 did examine the impact of topography on the predicted surface displacement for an earthquake that
37 occurred in a region with significant topographic variations: the 2005 M_w 8.7 Sumatra subduction
38 event. They demonstrated than the effect of topography on predicted surface deformation can be
39 significant, especially if the fault slip occurs close to areas with strong topographic gradients.

40 Most studies that included topographic structure used finite-element (or other numerical) meth-
41 ods to calculate Green's functions for quasi-static deformation. In some settings, it is possible to
42 calculate these Green's functions semi-analytically. Williams and Wadge (2000) developed a
43 semi-analytical method for calculating deformation in a region with topography via a first-order
44 perturbation to the elastic half-space solution. This first-order correction accounts for both as-
45 pects of the topographic effect: topography-induced variations in distance between the fault and
46 the surface of the domain, and the elastic effect caused by the shape of the topographic surface.
47 However, this solution is only valid when topographic gradients are mild, and cannot be used in
48 settings with extreme topography. Numerical simulation methods are required to produce Green's
49 functions in those settings.

50 A previous study by some of these authors, Langer et al. (2019), found that the inclusion of
51 topography has a significant effect on predicted surface deformation in a variety of settings. In
52 particular, they modeled the 2015 Gorkha earthquake and found that 3D elastic structure and
53 topography each caused differences of 10% in predicted coseismic surface deformation. However,
54 the differences due to topography were more significant because they affected the shape of the
55 deformation pattern, not only its magnitude. In this study, we seek to build on those results by
56 investigating the extent to which those differences in the predicted surface displacement pattern
57 are mapped onto the inferred slip distribution.

58 Although previous studies have made some progress in investigating the impact of Green's
59 functions with 3D structure on coseismic slip models, the effects of topography have not been
60 thoroughly examined. Topography is very well known for every region in the world, and thus
61 above any earthquake rupture, and yet its influence remains poorly investigated. Accounting
62 for topography is a simple way to include accurate information about the Earth in our inverse
63 problem. We wish to know whether the inclusion of topography is necessary to infer accurate
64 results in regions with topographic variations, and whether neglecting topography can impact our
65 estimates of slip distribution.

66 An additional question that we wish to investigate is whether Green’s functions with a zeroth-
67 order correction, which can be computed easily, can reproduce the results found using Green’s
68 functions with topography. We refer to this correction as the receiver elevation correction (REC).
69 The REC is a method of accounting for the variations in distance between source and receiver
70 caused by topography. This method was first explored by Williams and Wadge (1998, 2000) in a
71 volcanic setting, and was found to be somewhat effective when considering a spherical deformation
72 source with axial symmetry. The REC was implemented in a tectonic setting by some of these
73 authors in Langer et al. (2019) and by Yang et al. (2019), but its efficacy in tectonic settings,
74 which have a very different geometry from volcanic settings, has not been determined.

75 In this study, we aim to demonstrate that topography can have a significant impact on static
76 slip estimates. To this end, we base our analysis on the study of the 2015 M_w 7.5 Gorkha,
77 Nepal event and the 2010 M_w 8.8 Maule, Chile event. These earthquakes were chosen because
78 the regions of Nepal and Chile represent two end-members of topographic structure (Figure 1).
79 Nepal’s topography consists of many mountains and valleys that are close to one another, while
80 Chile is segmented into large topographic domains: the trench and abyssal plain below 4000m,
81 the margin and coastal plain around sea-level and the Andes mountain range mostly above 1500m
82 altitude. The two events also differ in their data coverage: while the Gorkha event occurred on
83 a terrestrial fault that is well-constrained by numerous data covering the entire region of interest,
84 the Maule earthquake is only constrained by data from the landward side of the fault.

85 For both events, we sample the possible slip parameters with a Bayesian approach, which
86 allows us to thoroughly compare estimated slip models and to obtain detailed information on the
87 posterior uncertainty of inferred parameters. We compare slip models estimated using Green’s
88 functions calculated with and without topography and with the receiver elevation correction. We
89 first analyze these events within a synthetic framework to show that neglecting topography can lead
90 to large biases in source estimates. We then use the real datasets to demonstrate how slip estimates
91 are altered when neglecting topography for these particular events. Note that our aim here is to
92 investigate the impact of topography on slip estimates for two particular events, not to produce
93 the most realistic slip models of these events. We therefore make simple approximations for the
94 other forward model parameters, such as fault geometry and elastic heterogeneity, to simplify our
95 interpretations.

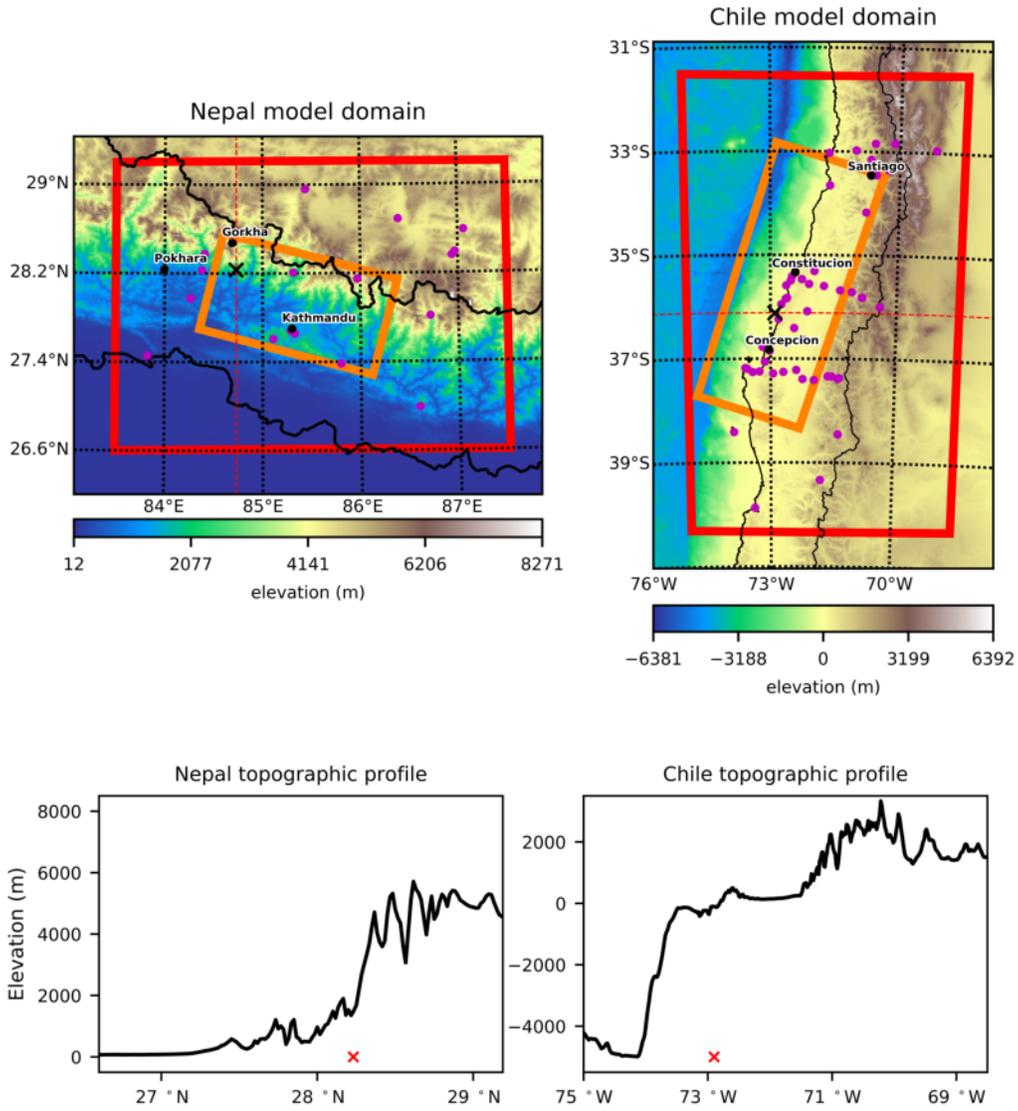


Figure 1: Topography of Nepal (left) and Chile (right). Red rectangles show the outlines of the meshes used to calculate Green's functions with topography for each of these regions. Orange rectangles show the outlines of the faults used in this study. Purple dots show the locations of the GPS stations. The black X symbols indicate the epicenters of the April 2015 Gorkha main shock and the February 2010 Maule main shock. Lower panels show topographic profiles for each region. The locations of the profiles are indicated by a red dashed line. Both profiles are near the epicenters of the two events, but the Nepal profile is north-south and the Chile profile is east-west so that the primary topographic features may be seen. The red X indicates the location of the epicenter along each profile.

96 **2. Tools and methods**

97 *2.1. Generating 3D Green's functions*

98 A coseismic Green's function G_{ij} is the displacement at a point i on the surface of a domain
99 due to slip on a subfault j . Green's functions for a particular region may be calculated by dividing
100 the fault into subfaults and calculating the displacement on the surface of the domain due to a
101 unit quantity of slip on each subfault. In our study, we do not constrain rake in the inversion, so
102 we must calculate Green's functions for one meter of slip along strike and one meter of slip along
103 dip. Thus, we must perform two calculations of surface displacement for each subfault.

104 To calculate Green's functions, we use a software package called SPECFEM-X (Gharti et al.,
105 2019). SPECFEM-X, which is based on the spectral-infinite-element method, uses the (un)coupled
106 elastic-gravitational equations to solve quasi-static problems. Since our Green's functions require
107 only calculations of coseismic deformation, we can neglect gravity. The governing equations then
108 become

$$\nabla \cdot \mathbf{T} + \mathbf{f} = \mathbf{0}. \quad (1)$$

109 Here, \mathbf{T} is the incremental Lagrangian Cauchy stress and \mathbf{f} represents external forces.

110 There are several ways to implement a fault in SPECFEM-X. In this study, we use the moment-
111 density tensor fault implementation. Each subfault is subdivided into a grid of patches, and each
112 patch has an associated moment-density tensor given by (Dahlen and Tromp, 1998)

$$\mathbf{m} = \Delta s \mathbf{C} : \hat{\mathbf{s}} \hat{\boldsymbol{\nu}}. \quad (2)$$

113 \mathbf{C} is the elastic tensor at the location of the fault patch. \mathbf{C} varies in a heterogeneous domain, but
114 the models in this study are homogeneous, so for our purposes \mathbf{C} is constant. $\hat{\boldsymbol{\nu}}$ is the normal
115 vector and $\hat{\mathbf{s}}$ is the slip direction. In general, these vectors must be calculated for each patch, but
116 this study uses uniform fault geometry, so $\hat{\boldsymbol{\nu}}$ and $\hat{\mathbf{s}}$ do not vary between patches. Δs is the slip
117 magnitude. When calculating Green's functions, we set $\Delta s = 1$ m.

118 SPECFEM-X calculates deformation throughout the mesh volume. However, we only need
119 Green's functions at the locations on the surface where we have observations. The displacements
120 at each of these observation points due to each fault patch are combined into a single matrix of
121 Green's functions, \mathbf{G} .

122 *2.2. Receiver elevation correction*

123 Despite the efficiency of SPECFEM-X, we cannot match the speed of Green's functions cal-
124 culations performed with the elastic half-space analytical solution (Steketee, 1958; Mansinha and

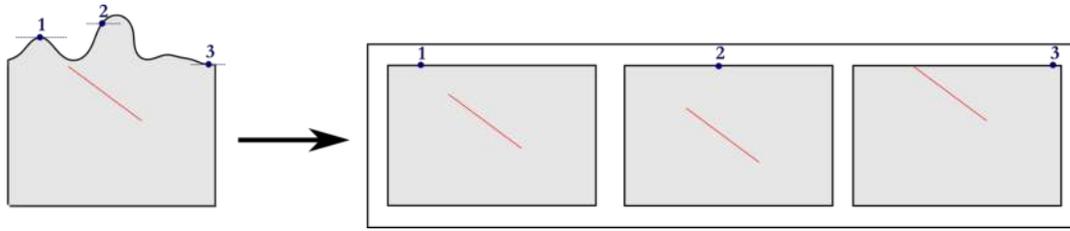


Figure 2: Green’s functions with a receiver elevation correction are computed by calculating a separate homogeneous half-space solution for each point on the surface where Green’s functions are needed. We would like to raise the flat surface to the elevation of the desired point (left). Since this is not possible, we lower the fault instead so that the distance between the fault and the surface is correct (right). For each homogeneous half-space setup in the right-hand panel, the Green’s function is only calculated at the blue point on the surface.

125 Smylie, 1971). It would therefore be advantageous if there was a method of correcting the elastic
 126 half-space solution for topographic effects. There are two contributions to the topographic effect:
 127 the varying distance between the fault and the surface, and the elastic effects caused by the shape
 128 of the topographic surface (Williams and Wadge, 2000). The first of these effects can easily be
 129 accounted for by a zeroth-order correction which we refer to as the receiver elevation correction
 130 (REC), in which all calculations are done with the elastic half-space approximation but, for each
 131 receiver, with the fault raised or lowered to preserve its absolute distance to the receiver position
 132 if topography had been there. A diagram of this method is shown in Figure 2.

133 The REC is very easy to implement and can be calculated quickly, since it requires only a slight
 134 modification to the standard homogeneous elastic half-space calculation. However, in volcanic set-
 135 tings, it was found to not be a good approximation when topographic gradients are steep (Williams
 136 and Wadge, 2000); in this case, a more complicated semi-analytical solution or FEM must be used.
 137 We wish to determine whether the REC is a good approximation for topography in slip inversions
 138 of the Gorkha and Maule events. To this end, we calculate Green’s functions for these events
 139 with the receiver elevation correction, and perform inversions to determine whether the REC can
 140 recover the result found with topographic Green’s functions calculated with SPECFEM-X.

141 2.3. Bayesian sampling

142 Instead of trying to find a single solution to the inverse problem, we choose to sample the
 143 solution space and image a selection of its probable models. This sampling approach allows us
 144 to precisely compare various slip models and their posterior uncertainty. We do not incorporate
 145 any spatial smoothing that may bias or induce unwanted artifacts in inferred slip models (Du

146 et al., 1992; Beresnev, 2003; Aster et al., 2005; Causse et al., 2010; Gallovič et al., 2015; Gombert
 147 et al., 2017). This choice will allow us to more precisely quantify the effects of topography. We
 148 use the Bayesian sampling approach implemented in the AlTar package, which is a rewrite of the
 149 code CATMIP (Minson et al., 2013). AlTar combines the Metropolis algorithm with a tempering
 150 process to perform an iterative sampling of the solution space of source models. A large number of
 151 samples are tested in parallel at each transitional step. Additionally, resampling is performed at
 152 the end of each step to replace less probable models. The probability that a given sample will be
 153 selected depends on its ability to fit the observations \mathbf{d}_{obs} within the uncertainties $\mathbf{C}_\chi = \mathbf{C}_d + \mathbf{C}_p$,
 154 where \mathbf{C}_d represents the observational errors and \mathbf{C}_p the epistemic uncertainties introduced by
 155 approximations of the forward model (e.g., Minson et al., 2013; Duputel et al., 2014; Ragon et al.,
 156 2018, 2019b).

157 The ability of each model parameter to solve the source problem is evaluated through repeated
 158 updates of the Probability Density Functions (PDFs):

$$f(\mathbf{m}, \beta_i) \propto p(\mathbf{m}) \cdot \exp[-\beta_i \cdot \chi(\mathbf{m})], \quad (3)$$

159 where \mathbf{m} is the current sample, $p(\mathbf{m})$ is the prior distribution on this sample, i corresponds to the
 160 current iteration and β evolves dynamically from 0 to 1 to ensure an exhaustive exploration of the
 161 solution space (Minson et al., 2013). $\chi(\mathbf{m})$ is the misfit function:

$$\chi(\mathbf{m}) = \frac{1}{2} [\mathbf{d}_{\text{obs}} - \mathbf{G} \cdot \mathbf{m}]^T \cdot \mathbf{C}_\chi^{-1} \cdot [\mathbf{d}_{\text{obs}} - \mathbf{G} \cdot \mathbf{m}]. \quad (4)$$

162 The final output from our Bayesian sampling procedure is a series of models sampled from
 163 among the most plausible models of the full solution space. This set of samples provides information
 164 on the possible parameter values and on their uncertainty. Average models (average value for every
 165 parameter) are probabilistic values that do not correspond to a sampled model, but which can give a
 166 good insight on the slip value of the most likely solutions. The posterior standard deviation of every
 167 parameter informs on the amount of slip uncertainty associated with each subfault. More detailed
 168 quantities, such as the marginal posterior distribution of a given parameter, reflect what has been
 169 learned relative to our prior information. In particular, the shape and width of the posterior
 170 marginal PDFs can be considered a proxy for the model resolution of the inferred parameter. To
 171 visualize the results in the following sections, we plot average slip models and associated standard
 172 deviations in map view, and the posterior marginal PDFs for a few representative subfaults. In
 173 the following, we use the term spatial resolution when describing whether model parameters can
 174 be independently resolved in theory (Menke, 2012, e.g.), and the term model resolution when
 175 describing their associated uncertainty.

176 **3. A continental thrust test case: The 2015 M_w 7.8 Gorkha, Nepal earthquake**

177 On April 25, 2015, a magnitude M_w 7.8 earthquake occurred in central Nepal along the boundary
178 between the Indian and Eurasian tectonic plates. This region is home to extreme topographic
179 variations, and it is entirely terrestrial, so extensive data coverage from InSAR and GPS is available
180 throughout the area of interest. These qualities make this earthquake an ideal event for a study
181 on the impact of Green’s functions with topography.

182 The 2015 Gorkha mainshock has been extensively studied with seismic and geodetic data (Wang
183 and Fialko, 2015; Feng et al., 2015; Yagi and Okuwaki, 2015; Yi et al., 2017; Yue et al., 2017; Liu and
184 Yao, 2018; Ingleby et al., 2020). Most studies recovered an inferred slip distribution consisting of an
185 oval-shaped slip pattern with its center slightly northwest of Kathmandu and a small bulge to the
186 northeast. The ruptured area was found to be approximately 150 km long, with a maximum slip of
187 6 m. Most of the previously published slip studies of this event used Green’s functions calculated in
188 a homogeneous half-space, with a few exceptions. Tung and Masterlark (2016) calculated Green’s
189 functions for the Gorkha event using a finite element model with heterogeneous crustal structure
190 and realistic topography, and used those Green’s functions to invert for a slip model using GPS
191 and InSAR data. The resulting slip model was compared to one found using Green’s functions
192 with topography but homogeneous elastic structure. They found that the heterogeneous Green’s
193 functions yielded a slip model that fit their data better. However, they did not investigate the
194 impact of topography. Similarly, Wang et al. (2017) compared slip models recovered using Green’s
195 functions calculated in a homogeneous half-space and in a heterogeneous, topographic domain. The
196 two models had slightly different slip distributions and different slip amplitudes. However, their
197 tests showed that the dominant effect was likely due to the heterogeneous elastic structure, which
198 makes it difficult to determine the impact of topography in isolation. A study on the effects of
199 topography was performed by Yang et al. (2019), which computed Green’s functions with and
200 without the receiver elevation correction. They found that the two resulting slip models differed
201 in both slip amplitude and distribution. However, as we discussed in Section 2.2, the REC does
202 not capture the full topographic effect and is not always a good approximation, especially when
203 topographic gradients are large. Is this correction sufficient for the 2015 Gorkha earthquake? In
204 this section, we seek to answer this question by assessing the full topographic effect on the static
205 fault slip estimate.

206 Because of the good instrumentation of this event, combined with the fact that most of the slip
207 occurred on a shallowly dipping part of the fault (see a more detailed explanation in Section 3.1.3),
208 the coseismic deformation is unusually well constrained. This exceptional spatial resolution ex-

209 plains why the published slip models are almost all identical. With this in mind, we might ask
210 whether the inclusion of topography is necessary to improve our slip models or the fit to our data.
211 To answer this question, we invert for synthetic slip models to determine whether Green’s functions
212 with topography can truly improve inversion results.

213 The unusually high constraint on the slip distribution of the Gorkha event is not shared by most
214 earthquakes, especially subduction events, which occur in areas with strong topographic gradients
215 that are far from any terrestrial data. It is conceivable that the impact of topography may not be
216 noticeable with lower slip resolution. We therefore also investigate the Gorkha event using only
217 GPS data to find out whether our results can be generalized to a less well-constrained case.

218 *3.1. Data and Forward Model*

219 *3.1.1. Data*

220 Our geodetic data set contains static co-seismic offsets from 18 3-component continuous GPS
221 stations and 4 SAR interferograms. The data points are scattered over our model domain. The
222 GPS offsets were provided by Galetzka et al. (2015) and Yadav et al. (2017). One Sentinel-1
223 ascending frame was used, collected by the European Space Agency and processed by Grandin et al.
224 (2015). Two ALOS-2 descending frames and one ALOS-2 ascending frame, collected by the Japan
225 Aerospace Exploration Agency (JAXA), were processed by Lindsey et al. (2015). The InSAR data
226 have been downsampled based on model resolution (Lohman and Simons, 2005), and the data errors
227 have been calculated following Jolivet et al. (2012). A more detailed description of our data can be
228 found in Section S1 of the Supplementary Material. Note that the surface displacements derived
229 from the InSAR data contain between 8 and 9 days of post-seismic deformation, and that our GPS
230 displacements are daily solutions, which might affect our modeling of the coseismic phase (e.g.
231 Ragon et al., 2019a; Twardzik et al., 2019)

232 *3.1.2. Crustal domain parameters*

233 Our model domain extends from 83.5°E to 87.5°E and 26.6°N to 29.2°N. The mesh, shown
234 in Figure S2, measures approximately $390 \times 280 \times 83$ km and has a mesh spacing of 3 km, for
235 a total of 323830 elements. This mesh is used for all topographic Green’s functions calculations,
236 whether the full dataset or only GPS data are used. Each forward model calculation runs on 40
237 processors in approximately 5.2 minutes. The model domain has a Poisson’s ratio of 0.25 and
238 Young’s modulus of 82.4 GPa. These are the material properties used for the homogeneous model
239 of Nepal in Langer et al. (2019).

240 Our benchmarks, shown in Figure S3, showed that solutions produced by SPEC-FEM-X with

241 a flat mesh are nearly identical to those produced with homogeneous elastic half-space solu-
242 tions (Okada, 1992) for coseismic deformation. Since homogeneous half-space calculations are
243 much faster, we generated the Green’s functions without topography using those analytical solu-
244 tions. We choose to put the surface of the flat domain for the non-topographic Green’s functions
245 calculations at an elevation of 244 m, which corresponds to the elevation of the deepest point where
246 the fault meets the surface in the topographic mesh.

247 *3.1.3. Assumed MHT fault geometry*

248 Many attempts have been made to determine the structure of the Main Himalayan Thrust
249 (MHT) fault in Nepal. Some studies have found evidence that the MHT has a ramp-flat-ramp
250 structure (Nábělek et al., 2009; Wang and Fialko, 2015; Elliott et al., 2016; Wang et al., 2017;
251 Almeida et al., 2018b). Others have argued that instead of a lower ramp, the MHT has a duplex
252 system of steeply dipping faults (Herman et al., 2010; Grandin et al., 2012; Mendoza et al., 2019).
253 Others have found that a planar fault provides the best fit to the data for the 2015 Gorkha
254 earthquake (Whipple et al., 2016; Wang and Fialko, 2018). Even if a ramp-flat-ramp structure
255 does exist in the region of interest, it probably would not have a significant effect on our inversion
256 because nearly all studies agree that the vast majority of slip took place on the flat section of
257 the fault (Elliott et al., 2016; Wang and Fialko, 2018; Yang et al., 2019; Ingleby et al., 2020).
258 Additionally, Ingleby et al. (2020) suggests that coseismic data do not require a shallow splay
259 fault. Therefore, we have chosen to use a planar fault when generating Green’s functions.

260 We assume a 180 km long and 100 km wide planar fault, with a strike of 285° and a dip of 7°
261 northeast. Because the slip that occurred during this event did not reach the surface, we eliminated
262 the upper section of the fault, so that the starting depth of the fault is at 3.9 km. For the inversions
263 with the complete dataset, the fault is divided into a grid of 10 km \times 10 km subfaults, so that
264 there are 18 subfaults along strike and 10 subfaults along dip. When calculating Green’s functions
265 with topography using SPECFEM-X, we use 400 moment-density tensor patches for each subfault.
266 Given the results of the tests presented in Gharti et al. (2019), this number of patches is more
267 than enough to guarantee convergence.

268 When only GPS data are used, the spatial resolution is less. Therefore, we increase the size of
269 each subfault to 15 km \times 12.5 km. The fault has only 12 subfaults along strike and 8 subfaults
270 along dip. When calculating Green’s functions with topography using SPECFEM-X, we use 9216
271 moment-density tensor patches for each subfault. The other fault parameters are detailed in Table 3
272 of the Supplementary Material.

273 *3.1.4. Other assumed prior information*

274 We perform our static slip estimation as previously detailed in Section 2.3. We specify a zero-
275 mean Gaussian prior $p(\mathbf{m}) = \mathcal{N}(-1 \text{ m}, 1 \text{ m})$ on the strike-slip component, since we assume that,
276 on average, the slip direction is along dip. For the dip-slip component, we consider each possible
277 value of displacement equally likely if it is positive and does not exceed 25 m of normal slip:
278 $p(\mathbf{m}) = \mathcal{U}(0 \text{ m}, 25 \text{ m})$. We account for the data uncertainties as detailed in Section S1 of the
279 Supplementary Material. We assume conservative uncertainty values of $(-1^\circ, 1^\circ)$ around the prior
280 value for the fault dip and $(-1 \text{ km}, 1 \text{ km})$ for the fault position.

281 *3.2. Results*

282 We first wish to investigate the impact of topography on slip models without contamination
283 from potential uncertainties or bias that may result from our choices of crustal properties and fault
284 structure, or from data errors. Therefore, we will start by analyzing the results of synthetic tests.
285 This will allow us to determine whether Green’s functions with topography can truly improve
286 the inferred slip distribution. We will then use our inversion procedure to estimate slip models
287 using real data from the Gorkha earthquake. In both cases, we will perform inversions using two
288 datasets, one consisting of all data points from GPS and InSAR, and one with GPS stations only.

289 *3.2.1. Synthetic tests*

290 For the synthetic inversions with the full dataset, our target model, shown in Figure 3A, consists
291 of five pure dip-slip patches of 6 m amplitude: four $20 \times 20 \text{ km}$ patches located at each corner
292 of the fault, and a central patch 50 km long and 20 km wide. In the GPS-only case, shown in
293 Figure 3E, the corner slip patches are 30 km long and 25 km wide, and the central slip patch is
294 60 km long and 25 km wide. Using a topographic domain and the fault geometry specified in
295 Section 3.1.3, we compute the surface displacements induced by each of these target models at
296 the data locations. We then solve for slip distributions with these synthetic data using Green’s
297 functions with and without topography. In our inversions, we assume the same fault geometry
298 and crustal structure used when calculating the synthetic data. A first set of tests is done without
299 noise added to the synthetic data, so that the inversion process is only perturbed by changes in the
300 Green’s functions. In another set of tests which are presented in Supplementary Material, we add
301 white noise and spatially correlated noise (with a Gaussian covariance matrix of variance 1 and
302 correlation length 10 km and 50 km) to the synthetic data, so that the noise amplitude reaches up
303 to 10% of the maximum amplitude of the data. The assumed data error is the same as for the real
304 dataset. We do not account for uncertainty in the fault geometry, since the geometry is perfectly
305 known. The results of these tests are shown in Figures 3 and S5.

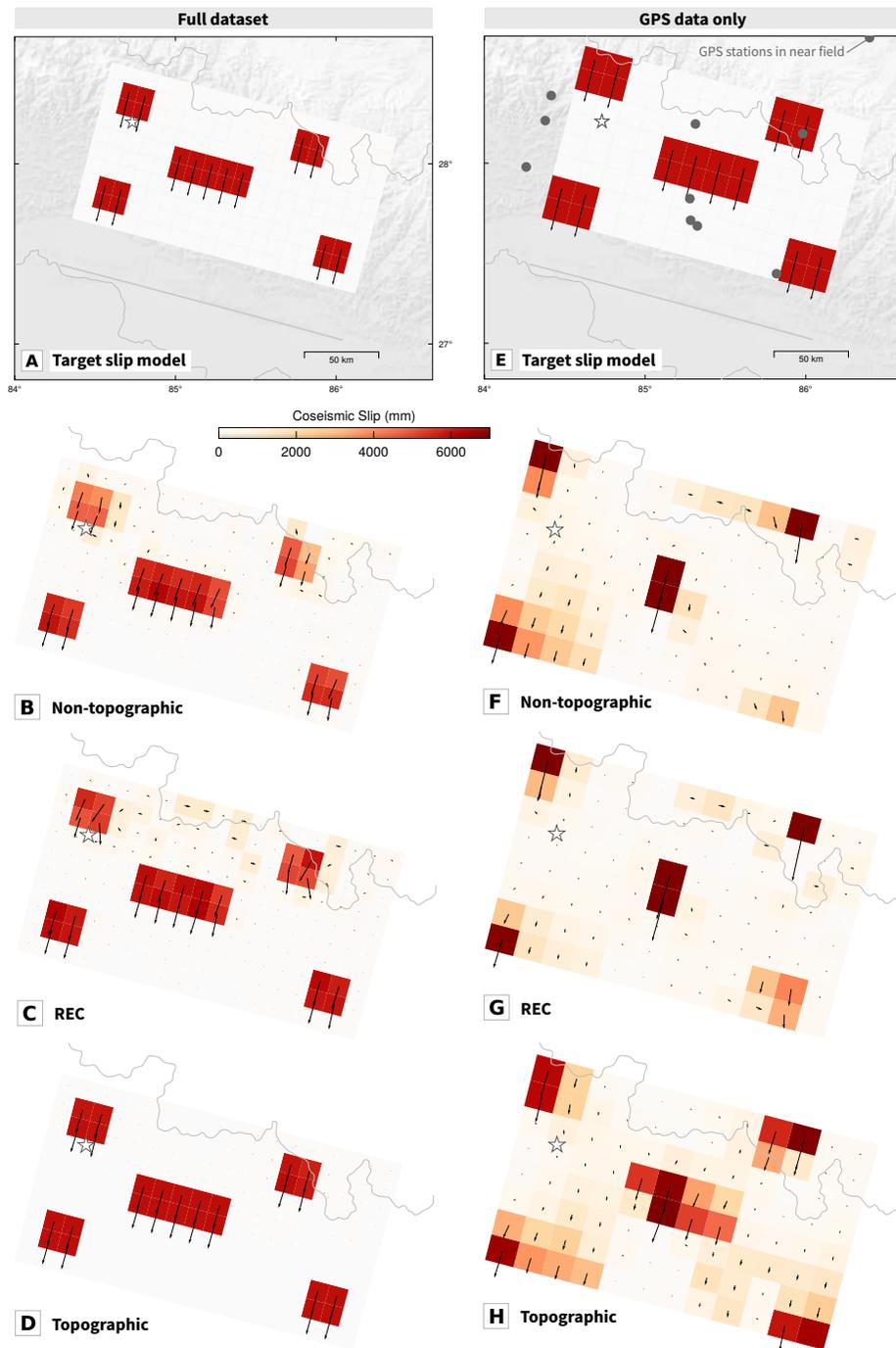


Figure 3: Comparison of slip models estimated from synthetic data for the Gorkha earthquake. (A) and (E): Target slip models used to calculate the full synthetic data set or synthetic GPS-only dataset, respectively. In (E), gray dots show the locations of the GPS stations. The remaining panels show average slip amplitude and rake inferred with non-topographic, REC and topographic Green's functions using the full synthetic data set (left columns) and synthetic GPS data only (right columns). Color scale is the same for all figures.

306 When the noise-free full synthetic data set is used, the slip model is perfectly recovered with
307 topographic Green's functions (Figure 3D). When Green's functions without topography are used,
308 only some slip patches are recovered (Figure 3B). The non-topographic Green's functions do espe-
309 cially poorly in the intermediate and deep sections of the fault, where topographic gradients are
310 largest and where the data are less informative because the slip is farther from the location where
311 the fault reaches the surface. If we use Green's functions with the receiver elevation correction
312 (Figure 3C), the slip model is recovered better than with non-topographic Green's functions but
313 not as well as when using Green's functions with topography. Results are even farther from the
314 target model when using noisy data, with the exception of the topographic case, in which the
315 target slip model is estimated fairly well (Figure S5).

316 When only GPS data are used, several slip patches can be recovered somewhat with topographic
317 Green's functions (Figure 3H), and for most parameters, more than 30% of inferred values (and up
318 to 60%) lie within 1.5 m of the non-zero target slip. None of the inversions can perfectly recover the
319 target model, which is expected given that the data coverage is too poor to be fully compensated
320 by increasing the size of the subfaults. However, the difference between the models estimated
321 using Green's functions with and without topography is even more pronounced in this case. In
322 particular, the non-topographic model fails to infer the eastern shallow slip patch, and concentrates
323 the other slip patches into a fourth of their actual spatial distribution (Figures 3F, G), so that
324 less than 10% of the inferred parameters lie within 1.5 m of the non-zero target slip. Interestingly,
325 Green's functions with the REC produce a slip model very similar to the non-topographic result,
326 and in fact seem to do an even poorer job in the shallow section of the fault. Inferred models are
327 similar when using a noisy dataset (Figure S8).

328 Synthetic data are well fitted by the predictions of the inferred models, whether noise has
329 been added or not (Figures S4, S6 and S7). However, only the models recovered with topographic
330 Green's functions can explain the ~ 10 cm uplift occurring where topographic gradients are greatest
331 (around 29°N , Figure S4). The REC method, in contrast, does not significantly improve the fit to
332 the synthetic data.

333 These synthetic tests show that the use of Green's functions with topography leads to a signif-
334 icant improvement in the recovered slip models. This is also true if realistic amounts of noise are
335 added to the synthetic data, demonstrating that topographic effects are significant enough to affect
336 an inversion with real data. Accounting for topography becomes even more necessary when the
337 slip is not well-constrained due to poor spatial resolution since, in this case, use of non-topographic
338 Green's functions leads to very poor estimates of the slip distribution. Green's functions with the
339 receiver elevation correction were able to recover a better slip model than non-topographic Green's

340 functions when the full dataset was used, but they performed more poorly in the GPS-only case.
341 With this in mind, we will now analyze inferred slip distributions found with these different types
342 of Green’s functions using the real dataset from the Gorkha earthquake.

343 *3.2.2. Inferred Slip Distributions with the Full Dataset*

344 Inferred slip distributions for the 2015 Gorkha earthquake found with the full dataset of GPS
345 and InSAR data are shown in Figure 4. The main characteristics of the inferred slip distributions
346 appear, at first glance, to be similar regardless of which type of Green’s functions is used. The
347 slip is concentrated in a well-resolved patch reaching 7 m in amplitude located near the center of
348 our fault. Some deep slip can also be observed, particularly on the eastern side of the fault. This
349 slip distribution is similar to previously published slip models for this event (e.g. Feng et al., 2015;
350 Zuo et al., 2016). The main difference between the distribution of slip in the models is at depth:
351 the topographic and REC models have more slip in the deeper part of the fault. The topographic
352 and REC models also have slightly greater uncertainty in the deeper part of the fault.

353 We can perform a more detailed analysis using Figure 4(D), which shows the marginal posterior
354 Probability Density Functions (PDFs) for the subfaults selected in panels (A), (B) and (C). Overall,
355 the posterior PDFs are narrow, especially in the shallowest part of the fault, because the slip is
356 well resolved and restricted epistemic uncertainties are assumed. Topographic and REC PDFs
357 have significant overlap, showing that their average slip values are very close. This is consistent
358 with our findings in Section 3.2.1 that the REC can approach the topographic solution when the
359 full dataset is used. In contrast, the PDFs which correspond to the inversion with non-topographic
360 Green’s functions do not even overlap with the topographic PDFs. This means that it is not only
361 the average value that differs between these two inferred models; the full posterior distributions
362 are different. Therefore, we cannot find a parameter value that satisfies both results; there is
363 no latitude to reconcile non-topographic and topographic results. Our results might therefore
364 imply that non-topographic models are inherently wrong (within the limitations of our study),
365 because they are unable to capture the parameter values imaged with topography. However, it is
366 important to note that in this study, we made simplified assumptions regarding fault geometry,
367 crustal structure, and epistemic uncertainties. Additionally, for this particular event, the slip
368 distribution is particularly well-constrained. If more realistic model characteristics and associated
369 epistemic uncertainties were assumed, this would probably increase the posterior uncertainty and
370 may enable reconciliation of non-topographic and topographic results.

371 Figure 5 shows the fit to the observed data using predictions from the topographic model.
372 These fits are quite good, but the observations are fitted well with any of our models. Additional

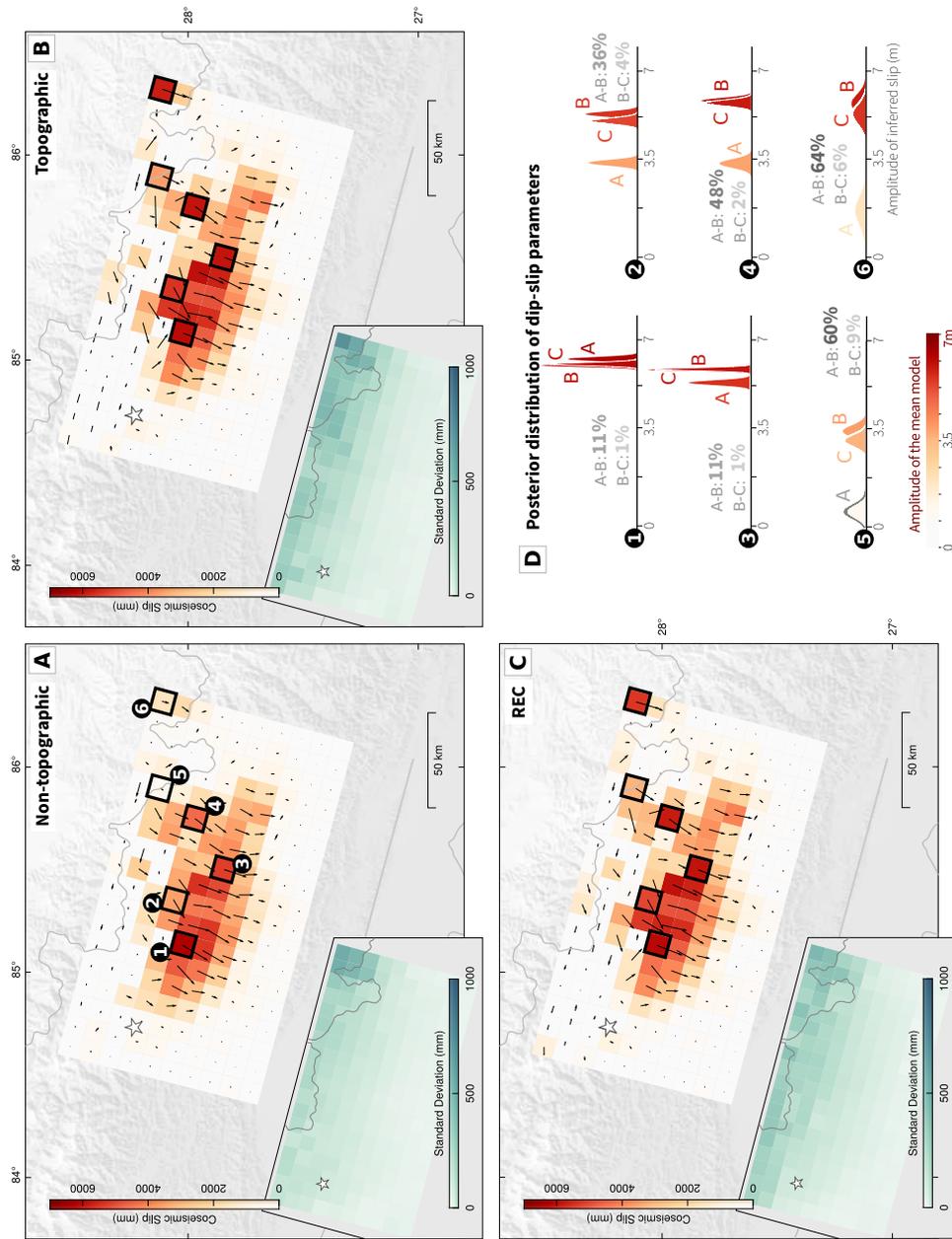


Figure 4: Comparison of finite-fault slip models of the 2015 Gorkha earthquake inferred with the complete dataset of GPS and InSAR data. Slip amplitudes are shown in red, and posterior standard deviations are shown in green. White star shows the location of the epicenter. (A) Map view of average slip amplitude and rake inferred with non-topographic Green's functions. (B) Average slip model inferred with topographic Green's functions. (C) Average slip model inferred with REC Green's functions. (D) Comparison between posterior marginal Probability Density Functions (PDFs) of dip-slip parameters for selected subfaults. PDF colors correspond to amplitude of the average model. Offsets between average models are shown as a percentage of slip amplitude. Plots of posterior PDFs are truncated between 0 and 7 m to simplify the visualization.

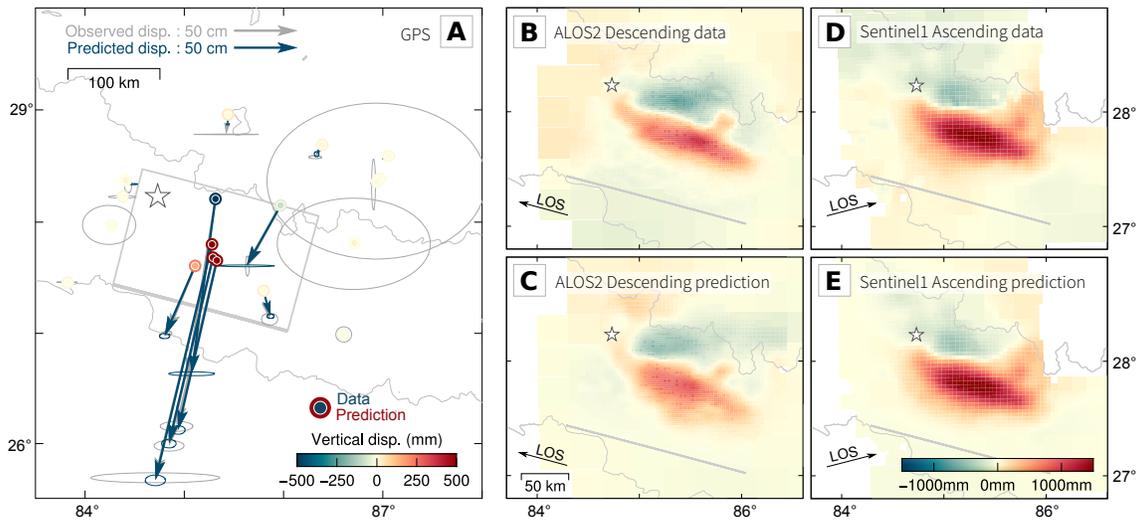


Figure 5: Fit to the observations for the topographic model of the 2015 Gorkha earthquake. (A) Observed and predicted static GPS offsets shown in map view. Observed horizontal surface displacements are in gray with 95% confidence ellipses, and predicted displacements are in blue with 95% confidence ellipses. Vertical displacements are color-coded with color-scale truncated at (-50 cm, 50 cm). The inner circle represents the data and the outer circle represents predicted displacements. (B) and (C), respectively: Observed and predicted surface displacement in the line of sight of the ALOS 2 descending interferogram. (D) and (E), respectively: Observed and predicted surface displacement in the line of sight of the Sentinel 1 ascending interferogram. The fault trace is represented as a gray line, and the epicenter as a white star.

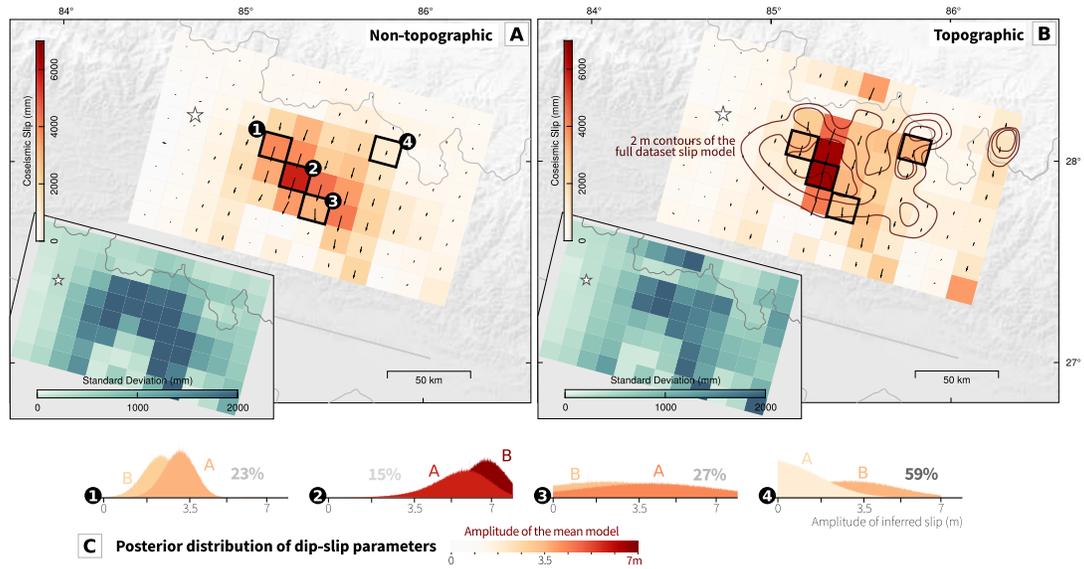


Figure 6: Comparison of finite-fault slip models of the 2015 Gorkha event estimated using the GPS-only dataset. Slip amplitudes are shown in red, and posterior standard deviations are shown in green. White star shows the location of the epicenter. (A) Average slip model inferred with non-topographic Green’s functions. (B) Average slip model inferred with topographic Green’s functions. (C) Comparison between posterior marginal Probability Density Functions (PDFs) of dip-slip parameters for selected subfaults. PDF colors correspond to amplitude of the average model. Offsets between average models are shown as a percentage of slip amplitude. Plots of posterior PDFs are truncated between 0 and 7 m to simplify the visualization.

373 figures can be found in the Supplementary Material: Figure S9 shows the fit to the GPS data, and
 374 Figures S10, S11 and S12 show the fits to the InSAR data for the non-topographic, topographic
 375 and REC models, respectively. Accounting for topography does not significantly improve the fit
 376 to the observed data.

377 3.2.3. Slip estimates with GPS data only

378 Figure 6 shows that when only GPS data are used, inversions using Green’s functions with
 379 and without topography yield noticeably different slip distributions. The differences are especially
 380 pronounced in the center of the fault, where average slip is 1.5 m greater for the topographic
 381 model, and in the deepest part of the fault, which lies beneath the largest topographic variations.
 382 Given the results of our synthetic tests, we expect that the two high amplitude patches seen in the
 383 topographic model (Figure 6(B)) are probably of lesser amplitude. The selected posterior marginal
 384 Probability Density Functions (PDFs) shown in Figure 6(C) are very broad, and the PDFs from

385 the two inversions overlap significantly. As expected, the slip is thus less constrained than with
386 the full dataset, so the posterior uncertainty is much greater, even with a coarser discretization of
387 the fault plane. However, if the topography is accounted for, the location of large slip is similar
388 whether the full dataset or GPS data only are used (Figure 6(B)).

389 *3.2.4. Conclusion for the Gorkha earthquake*

390 Our synthetic tests for the Gorkha event suggest that the impact of topography can depend on
391 spatial resolution of slip. When the slip is well constrained by geodetic data, neglecting topography
392 will lead to incorrect slip estimates where topographic gradients are large, but with limited biases
393 due to the great data constraints. Only incorporating topography will yield correct results. Where
394 topographic variations are mild, estimates are correct whether topography is accounted for or not.
395 On the other hand, when the slip is poorly constrained (GPS only), neglecting topography has a
396 large impact on the inferred slip distribution. In this case, the REC approximation is not sufficient.

397 In our inversions with real data, topography mostly impacts the amplitude of the main slip
398 patch and the mid-crustal part of the fault, where larger slip values are imaged. The topographic
399 effect could thus explain why there is not yet a consensus on the mid-crustal geometry of the Main
400 Himalayan Thrust (see references in Section 3.1.3).

401 Altogether, our results suggest that accounting for topography is necessary when topographic
402 variations are significant, even if good data coverage can limit the biases induced by neglecting
403 topography.

404 The Gorkha earthquake is an unusual type of dip-slip event with a very shallow dip angle and
405 good data coverage directly above the fault plane. Our preferred slip model thus does not vary
406 much when topography is accounted for, because most of the slip is located where topographic
407 gradients are low and data are informative.

408 This type of good data coverage generally does not exist for subduction events, where the
409 greatest amount of slip often occurs several tens of kilometers away from the coast, while all
410 observations are on land, and at very different elevations from the trench (up to 6 km in some
411 cases). In the following section, we investigate the 2010 M_w 8.8 Maule, Chile, earthquake to
412 determine whether these results hold for a subduction setting.

413 **4. A subduction megathrust test case: the M_w 8.8 2010 Maule, Chile, earthquake**

414 The second earthquake that we investigate is the M_w 8.8 2010 Maule, Chile earthquake. This
415 event occurred at the interface between the Nazca and South-American plates, within a region
416 previously recognized as a seismic gap (e.g., Comte et al., 1986; Nishenko, 1991; Ruegg et al.,

417 2009; Madariaga et al., 2010). The slip distribution of this event was studied using geodetic,
418 seismic and/or tsunami data (e.g., Delouis et al., 2010; Vigny et al., 2011; Lay, 2011; Lin et al.,
419 2013; Yue et al., 2014; Yoshimoto et al., 2016).

420 Our choice of the Maule event was guided by the fact that it is a major and well studied
421 event. It is also located on a subduction zone with a intermediate width (distance from the coast
422 to the trench) of about 100 km. In the most favorable cases, like the Costa Rica and Sumatra
423 subductions, this distance can be reduced to 20 to 30 km, while in cases like Tohoku/North Japan,
424 it is closer to 200 km.

425 The Maule region, and subductions zones in general, differ from the Gorkha case in three
426 critical ways. First, there are no near-field observations to constrain the shallow slip because it
427 usually occurs far from the coast. Imaging slip on the fault requires sampling the gradient of the
428 surface deformation, but in cases like Maule, the distance between parts of the fault and some
429 observations can be greater than 200 km. The second major difference is that all data are on
430 one side of the fault (landward) and some distance away from it, thus only covering a fraction
431 of the surface deformation field. Any epistemic error will thus appear as a systematic bias in
432 the Green’s functions and is more likely to distort the model space. The third major difference
433 is that observations are spread over two major topography domains, the coastal plain and the
434 Andes mountain range (Figure 1). For both Gorkha and Maule, there are major short-wavelength
435 topographic variations (40° slopes over distances of a few km), but a good data coverage across
436 these variations might limit their impact on estimated slip, even if topography is not accounted
437 for in the Green’s functions.

438 The 2010 Maule earthquake has been intensively studied, and its rupture has been consistently
439 modeled as bilateral, extending over 500 km along strike. Most of the inferred rupture models
440 show two main slip patches located around longitudes of 35°N and 37°N , with the northern-most
441 patch having higher slip amplitudes. Since the available geodetic data are located onshore, on one
442 side of the rupture and far from the trench, derived rupture characteristics are poorly resolved near
443 the trench. This lack of model resolution may explain why most geodetic studies find that the
444 rupture did not reach the shallowest parts of the fault (e.g., Tong et al., 2010; Pollitz et al., 2011;
445 Vigny et al., 2011; Lin et al., 2013) when direct (Maksymowicz et al., 2017) and indirect (Sladen
446 and Trevisan, 2018) observations indicate the opposite. One exception to these geodetic models is
447 the one of Moreno et al. (2012), which imaged a northern slip patch reaching the trench with 5 m
448 amplitude. Conversely, most studies using seismic data do image moderate slip amplitudes (6-10
449 m) at the trench (e.g., Delouis et al., 2010; Lay et al., 2010; Koper et al., 2012; Ruiz et al., 2012).
450 This is also supported by deep ocean tsunami data, which are located offshore and on the other

451 side of the rupture, and can provide better resolution at the trench (Yue et al., 2014; Yoshimoto
452 et al., 2016). Earlier coseismic slip models relying on these tsunami data were probably biased
453 by the fact that they did not consider long wavelength dispersion (e.g., Tsai et al., 2013; Watada
454 et al., 2014; Yue et al., 2014).

455 Most of the published slip models for the Maule event do not account for the effects of topog-
456 raphy and bathymetry. Moreno et al. (2012) did account for these effects using a spherical finite
457 element model, and they imaged slip near the trench using geodetic data only. Would this mean
458 that Green’s functions with topography can increase the accuracy of slip models near the trench?
459 In the following section, we will investigate the effects of topography and bathymetry on inferred
460 slip distributions of the 2010 Maule earthquake.

461 *4.1. Data and Forward Model*

462 *4.1.1. Data*

463 Although there are GPS and InSAR data available for the Maule earthquake, we choose to rely
464 on GPS data only for the sake of simplicity and because of the great coverage already provided.
465 The results of Moreno et al. (2012) suggest that although adding InSAR data to the inversion
466 procedure improves the calculated spatial resolution at the trench by 15-20%, it does not lead to
467 a change in the inferred slip model. Our data consists of 53 static daily offsets processed by Vigny
468 et al. (2011), and continuous GPS and survey sites processed by Lin et al. (2013).

469 *4.1.2. Crustal domain parameters*

470 Our model domain extends from -75.0°E to -68.5°E and -40.3°N to -31.5°N . The mesh measures
471 approximately $553 \times 958 \times 136$ km and has a mesh spacing of 6 km, for a total of 318400 elements.
472 A single forward calculation with this mesh runs on 40 processors in approximately 7.5 minutes.
473 An image of the mesh is shown in Figure S13. The model domain has a Poisson’s ratio of 0.25 and
474 Young’s modulus of 100.0 GPa. These are the material properties used for the homogeneous model
475 of Chile in Langer et al. (2019). This mesh was only used to generate the Green’s functions with
476 topography. For the Green’s functions without topography, we used the homogeneous half-space
477 solution at 0 km elevation.

478 *4.1.3. Geometry of the assumed fault*

479 The portion of the slab that ruptured during the Maule earthquake can be approximated as a
480 planar surface, with the exception of a change in strike at around 34°S (Hayes et al., 2018). We
481 chose to assume a planar fault geometry. Given that our models have almost no inferred slip in the
482 northernmost part of the fault (see Figure S19 of the Supplementary Material), this approximation

483 might not affect our slip estimates. Our fault is 570 km long and 240 km wide, with a strike of
484 198° and a dip of 18° . Since the slip is very poorly constrained near the trench, we experimented
485 with two different fault parameterizations. The first one has homogeneous subfaults measuring
486 43.8 km along strike and 24 km along dip, and in the other parameterization, the two shallowest
487 subfault rows have been merged into 8 bigger subfaults measuring 81.4×48 km. For all subfaults,
488 we use 16900 moment-density tensor patches per subfault when calculating topographic Green’s
489 functions with SPECFEM-X. The first parameterization has extremely poor model resolution, so
490 in the main text, we only present the results inferred with the second parameterization. The fault
491 geometry parameters are detailed in Table 5 of the Supplementary Material.

492 *4.1.4. Other assumed prior information*

493 We perform our static slip estimation as previously detailed in Section 2.3. We specify a zero-
494 mean Gaussian prior $p(\mathbf{m}) = \mathcal{N}(-2 \text{ m}, 2 \text{ m})$ on the strike-slip component, since we assume that, on
495 average, the slip direction is along dip. For the dip-slip component, we consider each possible value
496 of displacement equally likely if it positive and does not exceed 60 m of normal slip: $p(\mathbf{m}) = \mathcal{U}(0 \text{ m},$
497 $60 \text{ m})$. We account for the data uncertainty and for the uncertainty due to our a priori assumed
498 fault geometry (Ragon et al., 2018, 2019b). We assume conservative uncertainty values of $(-2^\circ, 2^\circ)$
499 around the prior value for the fault dip and $(0 \text{ km}, 2 \text{ km})$ for the fault position.

500 *4.2. Results*

501 We will first present the results of synthetic tests, which enable us to analyze the impact of
502 topography on slip estimates without contamination from assumptions made when calculating
503 Green’s functions and from data errors. Then we will examine the results of our slip estimates for
504 the Maule earthquake to determine whether Green’s functions with topography can impact slip
505 distribution, particularly near the trench.

506 *4.2.1. Synthetic Tests*

507 Our target model for the synthetic tests, shown in Figure 7A, consists of five $\sim 80 \times 48$ km
508 pure dip-slip patches of 20 m amplitude. These slip patches are located near the trench and
509 at intermediate depth. Using the fault geometry specified in Section 4.1.3, we compute surface
510 displacements due to our target model at the data locations in a topographic domain. We then
511 solve for the slip distribution using these synthetic data and the same fault geometry and crustal
512 structure that were used to generate the data. The resulting slip models found using Green’s
513 functions without topography, with the receiver elevation correction, and with topography are
514 shown in Figures 7B,C, and D, respectively. One set of tests is performed with noise-free data and

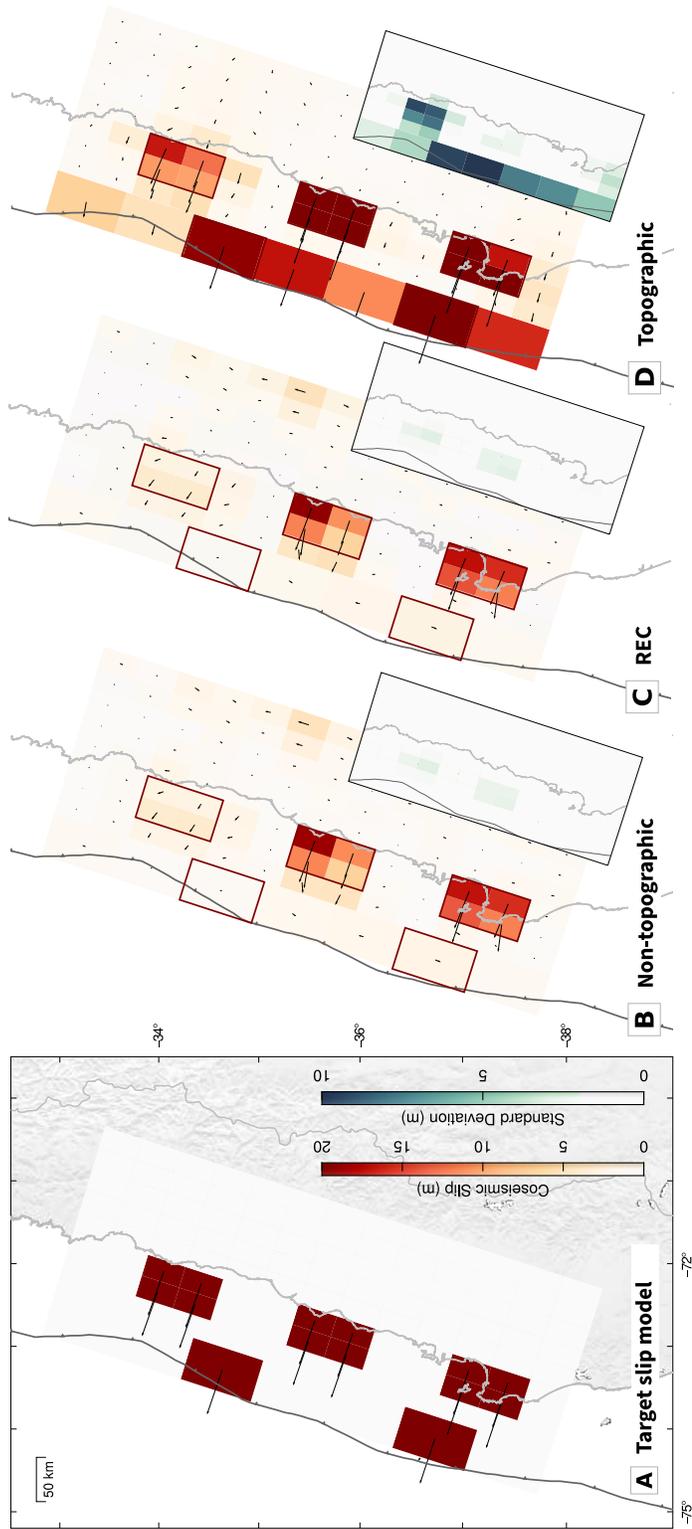


Figure 7: Comparison of slip models estimated from synthetic data for the Maule earthquake. (A) Target slip model used to calculate the synthetic data. (B), (C) and (D), average slip amplitude (red color scale) and rake estimated with non-topographic, REC and topographic Green's functions, respectively. Posterior standard deviations are shown in green at the bottom right of each slip model.

515 presented in the main text. For another set of tests, presented in the Supplementary Material, we
516 add white noise and spatially correlated noise (with a Gaussian covariance matrix of variance 1
517 and correlation length 10 km and 50 km) to the synthetic data, so that the noise amplitude can
518 reach up to 10% of the maximum amplitude of the data. The assumed data error is the same as
519 for the real dataset. We do not account for error due to uncertainty in the fault geometry, since it
520 is perfectly known.

521 Inversions with non-topographic and REC Green’s functions fail to capture the target slip
522 model whether noise is added to the synthetic data or not (Figures 7B,C and S14). Only two
523 intermediate depth slip patches are even slightly recovered, with 15 to 70% of inferred values
524 within 5 m of the target, likely because those patches are located closer to the shore and are
525 therefore better resolved. The accuracy is very poor near the trench: estimated slip amplitude
526 is less than 3 m, and the standard deviations are low, so that 100% of inferred values fall out 5
527 m of the target. Interestingly, the REC model is almost identical to the non-topographic model.
528 This may be due to the poor spatial resolution at the trench, since a similar result was found with
529 the GPS-only synthetic test of the Gorkha event (Figure 3H). An additional factor may be the
530 steepness of the trench; Williams and Wadge (2000) showed that the REC does not work when
531 topographic gradients are large. This result is also consistent with the findings of Langer et al.
532 (2019) that lowering the surface of a flat mesh to the elevation of the seafloor does not allow one
533 to capture the forward modelling result found with a topographic mesh for the Maule earthquake.

534 In contrast, the use of topographic Green’s functions improves the recovery of the target model
535 (Figures 7D and S14). The two intermediate depth patches that were somewhat recovered by the
536 non-topographic and REC models are well-estimated in the topographic model, with almost 100%
537 of inferred values within 5 m of the target, and the northernmost intermediate depth slip patch
538 is retrieved too, although with a larger posterior uncertainty, so that more than 15% of inferred
539 parameters are less than 5 m away from the target value. Near the trench, we infer large slip
540 amplitudes with large standard deviations reaching up to 75% of the slip amplitude, from 30% to
541 65% of inferred parameters being within 5 m of the non-zero target. The two patches with the
542 highest slip amplitudes and relatively low posterior uncertainties match the target slip patches.
543 However, we also infer large amplitudes for neighboring subfaults, possibly because the information
544 carried by the topographic Green’s functions is too weak to differentiate the target patches from
545 the neighboring subfaults. But this implies that the information brought by the topography allows
546 us to infer that some slip was shallow. Note that adding realistic noise to the data leads to
547 poorer estimates, which nonetheless remain closer to the target model than when no topography
548 is accounted for, especially when considering the posterior uncertainty of inferred parameters

(Figure S14). To get rid of the possible correlation between slip patches, we also perform some tests with independent patches. With only two near-trench target slip patches (Figure S16), we find that only introducing topography allows us to recover the target model reasonably well, although its amplitude is overestimated where the spatial resolution is correct, and underestimated to the north. Similarly, with only two mid-crustal target slip patches (Figure S17), topographic Green's functions do a better job at recovering the target model, but in this case, the non-topographic slip model is close to the target model too. This is probably because the topographic gradients are more mild in this mid-crustal location.

The synthetic data are explained well by the predictions of all of our models, whether topography is accounted for or not, and whether noise is added or not (Figures S18 and S15). However, only the topographic slip model can recover the synthetic secondary zone of uplift, corresponding to ~ 20 cm of upward surface displacement located east of 72°W .

The results of these synthetic tests are similar to our findings for the Gorkha event: Green's functions without topography are unable to recover target slip where topographic variations are large, and in particular where spatial resolution is low (here, the northern part and at the trench), even when the receiver elevation correction is used. When Green's functions with topography are used, the accuracy of the slip model is improved, regardless of the level of data coverage.

4.2.2. Slip Estimates

Using the real data from the 2010 Maule event, we now invert for slip models using non-topographic, REC and topographic Green's functions. The inferred slip models, shown in Figure 8, are all characterized by two main high-amplitude slip patches located at intermediate depth, around 35°S and 37°S . This slip distribution is similar to the ones found by previous studies discussed in Section 4. The non-topographic and REC models (Figures 8A,B) are nearly identical, with large slip amplitudes of up to 20 m near the trench in the southern half of the fault, and some slip estimated on the deepest row. The slip appears well constrained in the southern half of the fault, with reasonably small standard deviations (Figure 8D, subfaults (1) and (3)). Posterior uncertainty is higher for the northern half of the fault, with larger or Dirichlet-shaped posterior PDFs (Figure 8D, subfaults (2), (5) and (6)).

The topographic slip model (Figure 8C) is very different from the two other results. The two intermediate-depth high slip patches still have large amplitudes (up to 20 m), but there are also intermediate-depth subfaults with moderate slip amplitudes in between those two patches. The most striking difference is that only the northern slip patch reaches the trench, with up to 17 m of slip, and very small slip amplitudes are inferred near the trench in the southern half of the

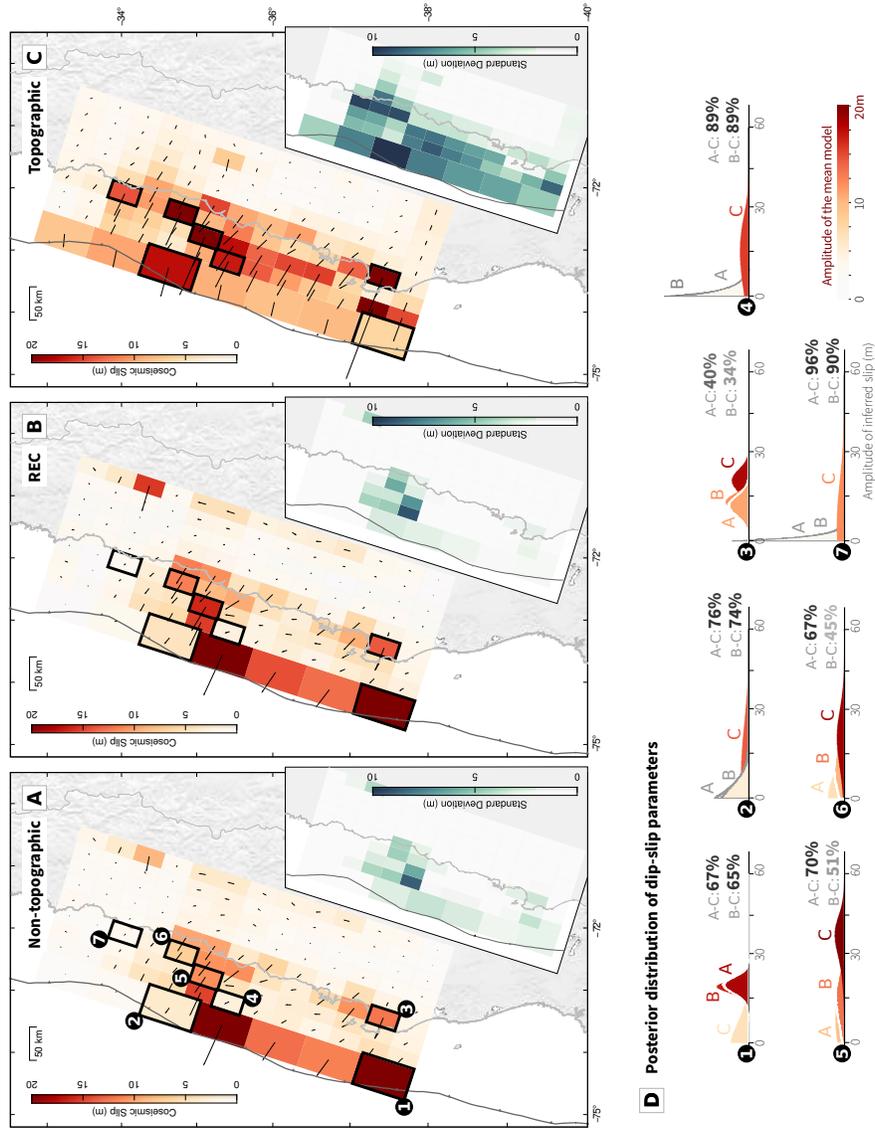


Figure 8: Comparison of finite-fault slip models of the 2010 Maule earthquake. Slip amplitudes are shown in red and posterior standard deviations for each slip model are shown in green. (A) Average slip amplitude and rake inferred with non-topographic Green’s functions. (B) Average slip model inferred with REC Green’s functions. (C) Average slip model inferred with topographic Green’s functions. (D) Comparison between posterior marginal Probability Density Functions (PDFs) of dip-slip parameters for selected sub-faults. PDF colors correspond to amplitude of the average model. Offsets between average models are shown as a percentage of slip amplitude. Plots of the posterior PDFs are truncated between 0 and 60 m to simplify the visualization.

582 fault. Overall, posterior uncertainties (Figure 8D) are larger, and can often be greater than 50%
583 of the slip amplitude. Given the results of the synthetic tests presented in the previous section,
584 the topographic slip model is the only one able to provide meaningful results, even if associated
585 with greater uncertainties. We note that this model is also coherent with the tsunami data (e.g.,
586 Yue et al., 2014; Yoshimoto et al., 2016), outer-rise aftershock distribution (Sladen and Trevisan,
587 2018) and a differential bathymetry study (Maksymowicz et al., 2017). Again, from the synthetic
588 tests, we can suggest the medium slip amplitudes (5-10 m) along the trench are probably artefacts
589 (also because the mean of the Dirichlet shape of the PDFs does not reflect the posterior mean),
590 but the high amplitude patch (~ 17 m) imaged above the northern patch is likely realistic.

591 The slip model with the receiver elevation correction shows behavior that is consistent with the
592 results of our synthetic tests. Average slip values for the REC model are approximately halfway
593 in between average non-topographic and topographic slip values for intermediate depth subfaults
594 (Figure 8D, subfaults (3) to (6)), but is very close to the non-topographic slip values for the near-
595 trench subfaults (Figure 8D, subfaults (1) and (2)). This suggests that the REC only improves
596 our estimates where spatial resolution is large enough, and is not effective at the trench where
597 resolution is too low.

598 As discussed in Section 4.1.3, we performed similar slip inversions using a fault parameterized
599 with homogeneous subfaults. This fault parametrization also yields very different results with
600 topographic and non-topographic Green's functions, particularly near the trench where average
601 slip reaches 20 m of amplitude for the non-topographic and REC models, but is close to 0 m in
602 the topographic model (Figure S19 of the Supplementary Material). However, the near-trench
603 posterior PDFs for the non-topographic and REC models are close to the uniform distribution
604 (Figure S19D, subfaults (2) and (3) in particular), implying that the model resolution at the
605 trench is so poor that the results are not meaningful. However, the resolution is better in the
606 topographic model.

607 The fit of our model predictions to the data are shown in Figures 9 (for topographic and
608 non-topographic Green's functions) and S20 (for REC Green's functions). Vertical and horizon-
609 tal displacements appear to be well explained by both non-topographic and topographic models.
610 There are two West-East rows of stations that can be used to investigate the fit in more detail.
611 The predicted horizontal displacements are similar for both the topographic and non-topographic
612 models, and both provide a good fit to the observations within the data errors and the posterior
613 uncertainties of the predictions (Figure 9). However, the non-topographic model has difficulty
614 explaining the complex shape and amplitude of uplift near the shoreline for both profiles: data
615 points fall outside the prediction zone, which is shown as a gray area around the profiles. In con-

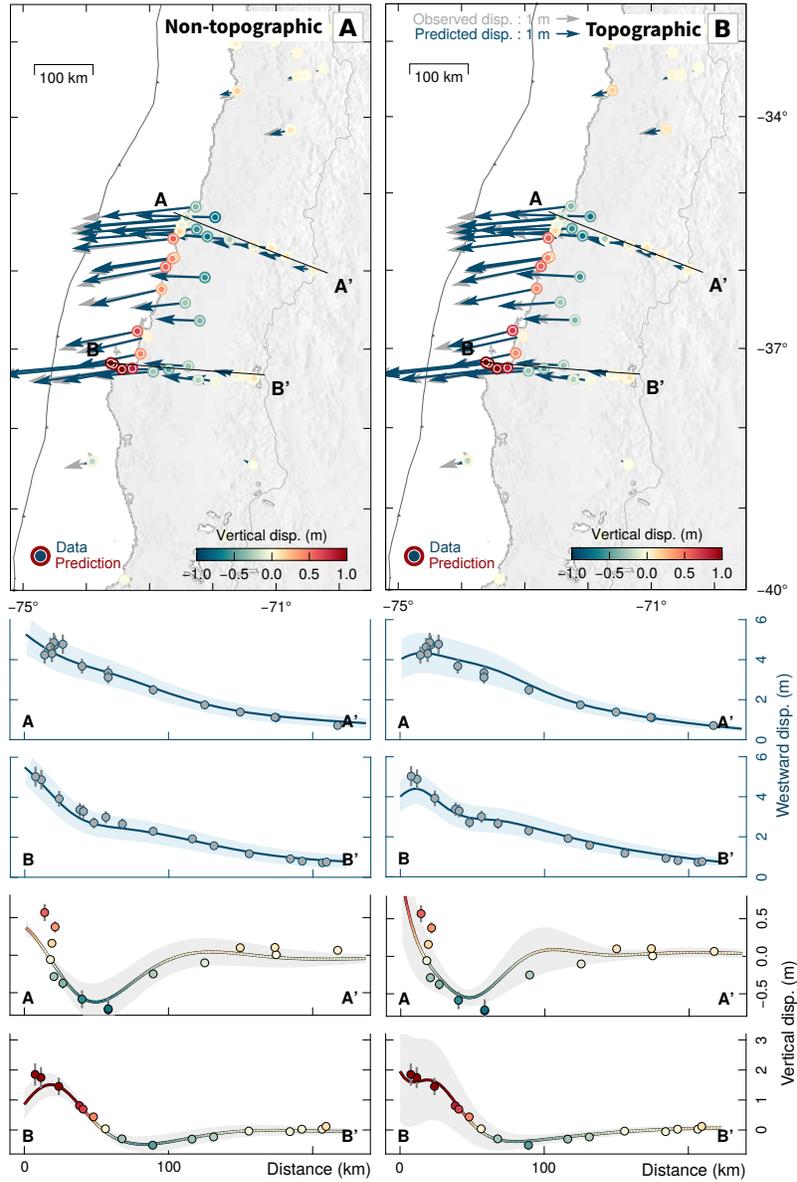


Figure 9: Comparison between static GPS offsets and predicted surface displacements for slip models of the Maule earthquake. Top panels show horizontal and vertical displacements in map view, along with predictions from non-topographic (A) and topographic (B) models. Inner circles show the data and outer circles show predictions. Observed horizontal surface displacements are in gray with 95% confidence ellipses, and predicted displacements are in blue with 95% confidence ellipses. Vertical displacements are color-coded with color-scale truncated at (-1 m, 1 m). Lower panels: Profiles A-A' at 35.5°S and B-B' at 37.5°S. For each profile, horizontal displacements are shown with gray dots and error bars for the data and a blue line with light blue area for predictions and associated posterior uncertainties. Vertical displacements are represented with the same color scale as in the map view, with dots and error bars for the data and a line with light gray area for predictions and uncertainties.

616 trast, the topographic model provides a better fit to the observed vertical surface displacement,
617 especially near the coast. Note the large difference between the prediction uncertainties for the
618 vertical displacements in the topographic and non-topographic profiles. This is because posterior
619 slip uncertainty is greater in the topographic model, especially at shallow and intermediate depths.

620 *4.2.3. Conclusion for the Maule earthquake*

621 Our investigation of the Maule event indicates that the use of topographic Green’s functions
622 significantly affects slip estimates. Our synthetic tests demonstrate that topography is required
623 to accurately infer slip distribution where gradients are steep, particularly if spatial resolution is
624 low, e.g. at the trench and in the northernmost region of the fault. In our inversions with real
625 data, only the topographic Green’s functions allow us to explain some features of the vertical
626 displacement data. Therefore, both the synthetic tests and the better fit to the observations seem
627 to indicate that the average topographic slip model represents a better estimate of coseismic slip
628 of the Maule event, even if the associated posterior uncertainties are larger. Our results also
629 demonstrate that the receiver elevation correction is not a sufficient proxy for topographic Green’s
630 functions, especially for areas where slip is poorly constrained and topographic gradients are large,
631 such as near the trench.

632 **5. Discussion and Conclusions**

633 Topographic variations are rarely accounted for in finite fault slip inversions, even when earth-
634 quakes take place in regions with extreme topography. Previous research (e.g., Hsu et al., 2011;
635 Langer et al., 2019) showed that topography can have a significant effect on estimated surface
636 displacements. In this study, we extended that work by assessing the effect of topography on static
637 earthquake slip inversions.

638 With SPEC-FEM-X, a quasi-static spectral element software package, we are able to efficiently
639 compute Green’s functions in a topographic domain. We used SPEC-FEM-X to investigate the
640 impact of topography on two earthquakes that represent two different types of topography and
641 geodetic data coverage: the M_w 7.8 2015 Gorkha and M_w 8.8 2010 Maule earthquakes. The study
642 of the Gorkha event is motivated by its exceptionally strong observational constraints and the fact
643 that the highest amplitude slip occurs away from the greatest topographic gradients. On the other
644 hand, the Maule earthquake is characterized by a large amount of slip occurring away from the
645 data (especially near the trench), where topographic gradients are very high. The slip of the Maule
646 event is also more poorly constrained because data are only available on the landward side of the
647 fault.

648 For these two events, we compared slip models estimated with a Bayesian sampling approach
649 using Green’s functions calculated with topography, without topography, and with a zeroth-order
650 topographic correction. We first investigated these events in a synthetic framework, and then we
651 used the real datasets.

652 *5.1. Impact of topography on slip models*

653 Our synthetic tests for these earthquakes demonstrate that neglecting topography where gra-
654 dients are large leads to incorrect slip estimates. In most cases, the target slip model is not even
655 among the possible models recovered in an inversion with non-topographic Green’s functions. How-
656 ever, if the observational constraints are very good (which is only true in rare cases), the biases
657 introduced by the lack of topography might be limited. For instance, the locations of mid-crustal
658 slip patches on the Main Himalayan Thrust are well-resolved, though the amplitudes are locally
659 off by up to 80%. In contrast, where data coverage is less, artifacts caused by the absence of to-
660 pography are more significant. For instance, when neglecting topography, we are unable to recover
661 large slip amplitudes (20 m) at the trench for the Maule subduction event.

662 For both earthquakes, the use of Green’s functions with topography produced different slip
663 distributions. For the Gorkha event, this difference was relatively minor when the full dataset
664 was used, probably because most of the slip is located where topographic gradients are mild. The
665 impact of topography is more pronounced in slip models of the Maule earthquake. Accounting for
666 topography leads to slip amplitudes and distributions that differ for every region of the fault, and
667 in particular near the trench, where data are uninformative and topographic gradients are large.
668 Interestingly, we also note that introducing topographic Green’s functions leads to larger posterior
669 uncertainties where the observational constraints are low. This is probably because assuming a
670 more realistic forward model broadens the range of possible solutions, which can become even
671 larger if the slip is poorly constrained. In contrast, assuming an incorrect forward model (without
672 topography) leads to an incorrect sampling of the solution space and overfitting of the observations.

673 For both events, topographic Green’s functions allow us to improve the consistency of the
674 predictions with the observations. In particular, we find that topographic results are the only ones
675 able to explain complexities in the surface uplift for the Maule event.

676 Given the results of our synthetic tests and the improved fit to observations, we may infer
677 that slip models estimated with topographic Green’s functions probably represent more accurate
678 estimates of coseismic deformation than slip models estimated without topography. We note,
679 however, that the forward model assumptions that we made, such as planar fault geometry and
680 homogeneous crustal structure, and the other prior choices that were made in this study, such as

681 our parameterization of the forward problem, may also affect our estimates, so further study is
682 required to determine the effect of these factors.

683 *5.2. Effectiveness of the receiver elevation correction*

684 The receiver elevation correction (REC) accounts for variations in distance between the fault
685 and the surface, but neglects the shape of the topographic surface (Williams and Wadge, 2000).
686 It was previously known that the REC fails when topographic gradients are large (Williams and
687 Wadge, 2000), as they are in the Maule region. In this study, we additionally found that spatial
688 resolution of slip (largely controlled by data coverage) also plays a role in determining when the
689 REC will be effective. Using both synthetic tests and analysis of real events, we showed that the
690 REC only reduces a small fraction of the biases introduced by neglecting topography. The REC is
691 not sufficient even when those biases are limited, and when the data are uninformative, the REC
692 fails to recover any of the differences in the topographic model.

693 In conclusion, the effect of topography on static slip models is significant, and can only some-
694 times be accounted for using the receiver elevation correction. Our findings suggest that, in many
695 cases, it is advisable to use topographic Green’s functions when inferring slip models in regions
696 with strong topographic gradients and/or poor observational constraints, such as in a subduction
697 zone. In regions with excellent data coverage (e.g. InSAR data with two different lines-of-sight)
698 and mild topographic variations, the REC may be used to account for topography.

699 *5.3. Perspectives*

700 Although the two examples of the Gorkha and Maule earthquakes represent two endmembers of
701 topography and data coverage, they are not sufficient for a complete understanding of the impact
702 of topography on static slip inversions because they both belong to the same class of earthquake
703 – namely, dip-slip events that occur close to the surface on shallowly dipping faults. Additional
704 research is needed to determine whether the results found in this work extend to other types of
705 earthquakes and faults. Does topography still have a significant effect when deformation is mostly
706 horizontal, as it is for a strike-slip fault? Furthermore, it seems intuitive that deeper earthquakes
707 would sense topography less. Is there a cut-off depth below which topography can be neglected?
708 What role, if any, does the dip of a fault play? How extreme must the topography of a region be for
709 the effect to start being considered significant? Topography may be short-wavelength (many small
710 structures) or long-wavelength (several large features); does the length scale of the topography
711 matter when determining whether it is likely to be impactful?

712 We must also remember that topography is only one aspect of 3D Earth structure. In this
713 study, we chose to focus on topography because the results of a previous study (Langer et al., 2019)

714 implied that it was likely to have the greatest impact on inferred slip models of the earthquakes
715 that we analyzed in this study. Topography also has the advantage of being known everywhere with
716 sufficient precision to be acknowledged a priori in a routine way. In comparison, fault geometry
717 and elastic structure are only known for a few areas and events. Where these properties are poorly
718 known, a good approach is to characterize the associated uncertainties and include them in the
719 inverse problem (e.g., Minson et al., 2013; Duputel et al., 2014; Ragon et al., 2018, 2019b). These
720 effects have been investigated by a few studies (see Section 1 for a thorough review), but since
721 they can take many forms, their generic impact is not yet known. More research is needed before
722 we can start to determine the trade-offs between these different contributions.

723 Finally, our conclusions are not restricted to coseismic deformation; topography may also af-
724 fect estimates of postseismic stress relaxation, which is generally modeled by several interacting
725 mechanisms, such as afterslip (e.g., Marone et al., 1991) or viscoelastic deformation in the lower
726 crust or mantle (e.g., Pollitz et al., 1998; Perfettini and Avouac, 2004; Barbot and Fialko, 2010).
727 Afterslip is of the same nature as coseismic deformation (slip on a fault surface) but of lower
728 amplitude: it is thus constrained by less informative observations. The impact of topography on
729 afterslip estimates is therefore probably even greater than for coseismic slip models. In contrast,
730 viscoelastic deformation usually occurs at greater depths (e.g., Pollitz et al., 1998), so its estimates
731 might be less influenced by topography.

732 Additionally, topography may affect images of interseismic slip rate deficit (or kinematic cou-
733 pling ratio), which is usually modeled to decipher which portions of thrust faults are likely to
734 rupture and which portions slip aseismically. A megathrust is usually coupled at intermediate to
735 shallow depths (e.g. Stevens and Avouac, 2015; Xue et al., 2015; Métois et al., 2016; Michel et al.,
736 2019). Almeida et al. (2018a) concluded that the coupling is generally underestimated in shallow
737 regions, and thus where spatial resolution is low and topographic gradients are high. Yet, megath-
738 rust coupling is usually modeled using the homogeneous elastic half-space approximation (e.g.
739 Chlieh et al., 2011; Loveless and Meade, 2016; Nocquet et al., 2017; Dal Zilio et al., 2020, and
740 previous citations).

741 Incorporating 3D complexity would be more easily done if Green’s functions with 3D structure,
742 especially topography, could be calculated automatically by SPECFEM-X with minimal input
743 from the user. The main barrier towards achieving this goal is that mesh generation is a complex
744 process. High-quality topographic meshes are often difficult to construct, even with the simple
745 requirements of SPECFEM-X, and each mesh must be fine-tuned by hand. However, we do plan
746 to share the scripts required to produce the Green’s functions used in this study on Github so that
747 others may use them as a guide.

748 In summary, we showed that neglecting topography can lead to biased estimates of slip dis-
749 tribution on faults, especially in areas where topographic gradients are large. Accounting for
750 topography, something which can now be done almost routinely with numerical tools such as
751 SPECFEM-X, is thus an essential step towards achieving a reliable and detailed estimate of fault
752 slip behavior (slip episodes or slip deficit) in region with large topographic variations.

753 The meshes used to calculate Green’s functions in a topographic domain for the Gorkha and
754 Maule earthquakes can be found in our repository ([doi:10.5281/zenodo.3675999](https://doi.org/10.5281/zenodo.3675999)).

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762 was used to build inputs for the Bayesian algorithm, in particular to compute non-topographic
763 Green’s functions. 3D data were visualized using the open-source parallel visualization software
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770 **References**

- 771 Almeida, R., Lindsey, E.O., Bradley, K., Hubbard, J., Mallick, R., Hill, E.M., 2018a. Can the
772 Updip Limit of Frictional Locking on Megathrusts Be Detected Geodetically? Quantifying the
773 Effect of Stress Shadows on Near-Trench Coupling. *Geophysical Research Letters* 45, 4754–4763.
774 doi:10.1029/2018GL077785.
- 775 Almeida, R.V., Hubbard, J., Liberty, L., Foster, A., Sapkota, S.N., 2018b. Seismic imaging of
776 the Main Frontal Thrust in Nepal reveals a shallow décollement and blind thrusting. *Earth
777 and Planetary Science Letters* 494, 216–225. URL: [http://www.sciencedirect.com/science/
778 article/pii/S0012821X18302486](http://www.sciencedirect.com/science/article/pii/S0012821X18302486).
- 779 Aster, R.C., Borchers, B., Thurber, C.H., 2005. *Parameter Estimation and Inverse Problems*.
780 Academic Press.
- 781 Barbot, S., Fialko, Y., 2010. A unified continuum representation of post-seismic relaxation mecha-
782 nisms: Semi-analytic models of afterslip, poroelastic rebound and viscoelastic flow. *Geophysical
783 Journal International* 182, 1124–1140. doi:10.1111/j.1365-246X.2010.04678.x.
- 784 Beresnev, I.A., 2003. Uncertainties in Finite-Fault Slip Inversions: To What Extent to Believe?
785 (A Critical Review). *Bulletin of the Seismological Society of America* 93, 2445–2458. doi:10.
786 1785/0120020225.
- 787 Causse, M., Cotton, F., Mai, P.M., 2010. Constraining the roughness degree of slip heterogeneity.
788 *J. Geophys. Res.* 115. doi:10.1029/2009jb006747.
- 789 Chlieh, M., Perfettini, H., Tavera, H., Avouac, J.P., Remy, D., Nocquet, J.M., Rolandone, F.,
790 Bondoux, F., Gabalda, G., Bonvalot, S., 2011. Interseismic coupling and seismic potential
791 along the Central Andes subduction zone. *Journal of Geophysical Research: Solid Earth* 116.
792 doi:10.1029/2010JB008166.
- 793 Comte, D., Eisenberg, A., Lorca, E., Pardo, M., Ponce, L., Saragoni, R., Singh, S.K., Suárez, G.,
794 1986. The 1985 Central Chile Earthquake: A Repeat of Previous Great Earthquakes in the
795 Region? *Science* 233, 449–453. doi:10.1126/science.233.4762.449.
- 796 Dahlen, F.A., Tromp, J., 1998. *Theoretical Global Seismology*. Princeton University Press.
- 797 Dal Zilio, L., Jolivet, R., van Dinther, Y., 2020. Segmentation of the main himalayan thrust
798 illuminated by bayesian inference of interseismic coupling. *Geophysical Research Letters*

799 47, e2019GL086424. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2019GL086424>, doi:10.1029/2019GL086424.

801 Delouis, B., Nocquet, J.M., Vallée, M., 2010. Slip distribution of the February 27, 2010 Mw =
802 8.8 Maule Earthquake, central Chile, from static and high-rate GPS, InSAR, and broadband
803 teleseismic data. *Geophysical Research Letters* 37. doi:10.1029/2010GL043899.

804 Du, Y., Aydin, A., Segall, P., 1992. Comparison of various inversion techniques as applied to the
805 determination of a geophysical deformation model for the 1983 Borah Peak earthquake. *bssa* 82,
806 1840–1866.

807 Duputel, Z., Agram, P.S., Simons, M., Minson, S.E., Beck, J.L., 2014. Accounting for prediction
808 uncertainty when inferring subsurface fault slip. *Geophysical Journal International* 197, 464–482.
809 doi:10.1093/gji/ggt517.

810 Elliott, J., Jolivet, R., González, P.J., Avouac, J.P., Hollingsworth, J., Searle, M.P., Stevens, V.,
811 2016. Himalayan megathrust geometry and relation to topography revealed by the Gorkha
812 earthquake. *Nature Geoscience* 9, 174–180. URL: <https://doi.org/10.1038/ngeo2623>.

813 Feng, G., Zhu, J., Li, Z., Zhang, G., Shan, X., Zhang, L., 2015. Geodetic model of the 2015 April
814 25 Mw 7.8 Gorkha Nepal Earthquake and Mw 7.3 aftershock estimated from InSAR and GPS
815 data. *Geophysical Journal International* 203, 896–900. doi:10.1093/gji/ggv335.

816 Galetzka, J., Melgar, D., Genrich, J.F., Geng, J., Owen, S., Lindsey, E.O., Xu, X., Bock, Y.,
817 Avouac, J.P., Adhikari, L.B., Upreti, B.N., Pratt-Sitaula, B., Bhattarai, T.N., Sitaula, B.P.,
818 Moore, A., Hudnut, K.W., Szeliga, W., Normandeau, J., Fend, M., Flouzat, M., Bollinger, L.,
819 Shrestha, P., Koirala, B., Gautam, U., Bhattarai, M., Gupta, R., Kandel, T., Timsina, C.,
820 Sapkota, S.N., Rajaure, S., Maharjan, N., 2015. Slip pulse and resonance of the Kathmandu
821 basin during the 2015 Gorkha earthquake, Nepal. *Science* 349, 1091–1095. URL: <https://science.sciencemag.org/content/349/6252/1091>, doi:10.1126/science.aac6383.

823 Gallovič, F., Imperatori, W., Mai, P.M., 2015. Effects of three-dimensional crustal struc-
824 ture and smoothing constraint on earthquake slip inversions: Case study of the Mw 6.3
825 2009 L’Aquila earthquake. *Journal of Geophysical Research: Solid Earth* 120, 428–449.
826 doi:10.1002/2014JB011650.

827 Gharti, H.N., Langer, L., Tromp, J., 2019. Spectral-infinite-element simulations of coseismic
828 and post-earthquake deformation. *Geophysical Journal International* 216, 1364–1393. URL:
829 <http://dx.doi.org/10.1093/gji/ggy495>, doi:10.1093/gji/ggy495.

- 830 Gombert, B., Duputel, Z., Jolivet, R., Doubre, C., Rivera, L., Simons, M., 2017. Revisiting
831 the 1992 Landers earthquake: a Bayesian exploration of co-seismic slip and off-fault damage.
832 *Geophysical Journal International* 212, 839–852. doi:10.1093/gji/ggx455.
- 833 Grandin, R., Doin, M.P., Bollinger, L., Pinel-Puysségur, B., Ducret, G., Jolivet, R., Sapkota,
834 S.N., 2012. Long-term growth of the Himalaya inferred from interseismic InSAR measurement.
835 *Geology* 40, 1059–1062. URL: <https://doi.org/10.1130/G33154.1>, doi:10.1130/G33154.1.
- 836 Grandin, R., Vallée, M., Satriano, C., Lacassin, R., Klinger, Y., Simoes, M., Bollinger, L.,
837 2015. Rupture process of the Mw=7.9 2015 Gorkha earthquake (Nepal): Insights into Hi-
838 malayan megathrust segmentation. *Geophysical Research Letters* 42, 8373–8382. doi:10.1002/
839 2015gl066044.
- 840 Hartzell, S., Liu, P., Mendoza, C., Ji, C., Larson, K.M., 2007. Stability and Uncertainty of Finite-
841 Fault Slip Inversions: Application to the 2004 Parkfield, California, Earthquake. *Bulletin of the*
842 *Seismological Society of America* 97, 1911–1934. doi:10.1785/0120070080.
- 843 Hayes, G.P., Moore, G.L., Portner, D.E., Hearne, M., Flamme, H., Furtney, M., Smoczyk, G.M.,
844 2018. Slab2, a comprehensive subduction zone geometry model. *Science* 362, 58–61. doi:10.
845 1126/science.aat4723.
- 846 Herman, F., Copeland, P., Avouac, J.P., Bollinger, L., Mahéo, G., Le Fort, P., Rai, S., Foster,
847 D., Pêcher, A., Stüwe, K., Henry, P., 2010. Exhumation, crustal deformation, and thermal
848 structure of the Nepal Himalaya derived from the inversion of thermochronological and thermo-
849 barometric data and modeling of the topography. *Journal of Geophysical Research: Solid Earth*
850 115. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2008JB006126>,
851 doi:10.1029/2008JB006126.
- 852 Hsu, Y.J., Simons, M., Williams, C., Casarotti, E., 2011. Three-dimensional FEM derived
853 elastic Green's functions for the coseismic deformation of the 2005 Mw 8.7 Nias-Simeulue,
854 Sumatra earthquake. *Geochemistry, Geophysics, Geosystems* 12. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011GC003553>,
855 doi:10.1029/2011GC003553, arXiv:<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/2011GC003553>.
- 857 Huang, B.S., Yeh, Y.T., 1997. Effect of Near-fault Terrain upon Dislocation Modeling. *pure and*
858 *applied geophysics* 150, 1–18. doi:10.1007/s000240050060.
- 859 Ingleby, T., Wright, T.J., Hooper, A., Craig, T.J., Elliott, J.R., 2020. Constraints on the Ge-
860 ometry and Frictional Properties of the Main Himalayan Thrust Using Coseismic, Postseismic,

861 and Interseismic Deformation in Nepal. *Journal of Geophysical Research: Solid Earth* 125,
862 e2019JB019201. doi:10.1029/2019JB019201.

863 Jolivet, R., Duputel, Z., Riel, B., Simons, M., Rivera, L., Minson, S.E., Zhang, H., Aivazis,
864 M.a.G., Ayoub, F., Leprince, S., Samsonov, S., Motagh, M., Fielding, E.J., 2014. The 2013
865 Mw 7.7 Balochistan Earthquake: Seismic Potential of an Accretionary Wedge. *Bulletin of the*
866 *Seismological Society of America* 104, 1020–1030. doi:10.1785/0120130313.

867 Jolivet, R., Lasserre, C., Doin, M.P., Guillaso, S., Peltzer, G., Dailu, R., Sun, J., Shen, Z.K., Xu,
868 X., 2012. Shallow creep on the Haiyuan fault (Gansu, China) revealed by SAR interferometry.
869 *Journal of Geophysical Research: Solid Earth* 117. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011JB008732>, doi:10.1029/2011JB008732.

871 Koper, K.D., Hutko, A.R., Lay, T., Sufri, O., 2012. Imaging short-period seismic radiation from
872 the 27 February 2010 Chile (MW 8.8) earthquake by back-projection of P, PP, and PKIKP
873 waves. *Journal of Geophysical Research: Solid Earth* 117. doi:10.1029/2011JB008576.

874 Kyriakopoulos, C., Masterlark, T., Stramondo, S., Chini, M., Bignami, C., 2013. Coseismic
875 slip distribution for the Mw 9 2011 Tohoku-Oki earthquake derived from 3-D FE modeling.
876 *Journal of Geophysical Research: Solid Earth* 118, 3837–3847. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/jgrb.50265>,
877 doi:10.1002/jgrb.50265,
878 arXiv:<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/jgrb.50265>.

879 Langer, L., Gharti, H.N., Tromp, J., 2019. Impact of topography and three-dimensional
880 heterogeneity on coseismic deformation. *Geophysical Journal International* 217, 866–878.
881 doi:10.1093/gji/ggz060.

882 Lay, T., 2011. A Chilean surprise. *Nature* 471, 174–175. doi:10.1038/471174a.

883 Lay, T., Ammon, C.J., Kanamori, H., Koper, K.D., Sufri, O., Hutko, A.R., 2010. Teleseismic
884 inversion for rupture process of the 27 February 2010 Chile (Mw 8.8) earthquake. *Geophysical*
885 *Research Letters* 37. doi:10.1029/2010GL043379.

886 Lin, Y.n.N., Sladen, A., Ortega-Culaciati, F., Simons, M., Avouac, J.P., Fielding, E.J., Brooks,
887 B.A., Bevis, M., Genrich, J., Rietbrock, A., Vigny, C., Smalley, R., Socquet, A., 2013. Coseismic
888 and postseismic slip associated with the 2010 Maule Earthquake, Chile: Characterizing the
889 Arauco Peninsula barrier effect. *Journal of Geophysical Research: Solid Earth* 118, 3142–3159.
890 doi:10.1002/jgrb.50207.

- 891 Lindsey, E.O., Natsuaki, R., Xu, X., Shimada, M., Hashimoto, M., Melgar, D., Sandwell, D.T.,
892 2015. Line-of-sight displacement from ALOS-2 interferometry: Mw 7.8 Gorkha earthquake and
893 Mw 7.3 aftershock. *Geophysical Research Letters* 42, 6655–6661. doi:10.1002/2015g1065385.
- 894 Liu, W., Yao, H., 2018. A New Strategy of Finite-Fault Inversion Using Multiscale Waveforms
895 and Its Application to the 2015 Gorkha, Nepal, Earthquake. *Bulletin of the Seismological*
896 *Society of America* 108, 1947–1961. URL: <https://doi.org/10.1785/0120170309>, doi:10.
897 1785/0120170309.
- 898 Lohman, R.B., Simons, M., 2005. Some thoughts on the use of InSAR data to constrain mod-
899 els of surface deformation: Noise structure and data downsampling. *Geochemistry, Geo-*
900 *physics, Geosystems* 6. URL: [https://agupubs.onlinelibrary.wiley.com/doi/abs/10.](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2004GC000841)
901 1029/2004GC000841, doi:10.1029/2004GC000841.
- 902 Loveless, J.P., Meade, B.J., 2016. Two decades of spatiotemporal variations in subduction zone
903 coupling offshore Japan. *Earth and Planetary Science Letters* 436, 19–30. doi:10.1016/j.epsl.
904 2015.12.033.
- 905 Madariaga, R., Métois, M., Vigny, C., Campos, J., 2010. Central Chile Finally Breaks. *Science*
906 328, 181–182. doi:10.1126/science.1189197.
- 907 Maksymowicz, A., Chadwell, C., Ruiz, J., Tréhu, A., Contreras-Reyes, E., Weinrebe, W., Díaz-
908 Naveas, J., Gibson, J., Lonsdale, P., Tryon, M., 2017. Coseismic seafloor deformation in the
909 trench region during the mw8. 8 maule megathrust earthquake. *Scientific reports* 7, 1–8.
- 910 Mansinha, L.a., Smylie, D., 1971. The displacement fields of inclined faults. *Bulletin of the*
911 *Seismological Society of America* 61, 1433–1440.
- 912 Marone, C.J., Scholtz, C.H., Bilham, R., 1991. On the mechanics of earthquake afterslip. *Journal*
913 *of Geophysical Research: Solid Earth* 96, 8441–8452. doi:10.1029/91JB00275.
- 914 Masterlark, T., 2003. Finite element model predictions of static deformation from disloca-
915 tion sources in a subduction zone: Sensitivities to homogeneous, isotropic, Poisson-solid, and
916 half-space assumptions. *Journal of Geophysical Research: Solid Earth* 108. doi:10.1029/
917 2002JB002296.
- 918 McTigue, D.F., Segall, P., 1988. Displacements and tilts from dip-slip faults and magma chambers
919 beneath irregular surface topography. *Geophysical Research Letters* 15, 601–604. doi:10.1029/
920 GL015i006p00601.

921 Mendoza, M.M., Ghosh, A., Karplus, M.S., Klemperer, S.L., Sapkota, S.N., Adhikari, L.B.,
922 Velasco, A., 2019. Duplex in the Main Himalayan Thrust illuminated by aftershocks of
923 the 2015 Mw 7.8 Gorkha earthquake. *Nature Geoscience* URL: <https://doi.org/10.1038/s41561-019-0474-8>.
924

925 Menke, W., 2012. *Geophysical Data Analysis: Discrete Inverse Theory*. Academic press.

926 Métois, M., Vigny, C., Socquet, A., 2016. Interseismic Coupling, Megathrust Earthquakes and
927 Seismic Swarms Along the Chilean Subduction Zone (38–18S). *Pure and Applied Geophysics*
928 173, 1431–1449. doi:10.1007/s00024-016-1280-5.

929 Michel, S., Gualandi, A., Avouac, J.P., 2019. Interseismic Coupling and Slow Slip Events
930 on the Cascadia Megathrust. *Pure and Applied Geophysics* 176, 3867–3891. doi:10.1007/
931 s00024-018-1991-x.

932 Minson, S.E., Simons, M., Beck, J.L., 2013. Bayesian inversion for finite fault earthquake source
933 models I—theory and algorithm. *Geophysical Journal International* 194, 1701–1726. doi:10.
934 1093/gji/ggt180.

935 Moreno, M., Melnick, D., Rosenau, M., Baez, J., Klotz, J., Oncken, O., Tassara, A., Chen, J.,
936 Bataille, K., Bevis, M., Socquet, A., Bolte, J., Vigny, C., Brooks, B., Ryder, I., Grund, V.,
937 Smalley, B., Carrizo, D., Bartsch, M., Hase, H., 2012. Toward understanding tectonic control
938 on the Mw 8.8 2010 Maule Chile earthquake. *Earth and Planetary Science Letters* 321–322,
939 152–165. doi:10.1016/j.epsl.2012.01.006.

940 Nishenko, S.P., 1991. Circum-Pacific Seismic Potential: 1989–1999, in: Okal, E.A. (Ed.), *Aspects*
941 *of Pacific Seismicity*. Birkhäuser, Basel. Pageoph Topical Volumes, pp. 169–259. doi:10.1007/
942 978-3-0348-5639-3_2.

943 Nocquet, J.M., Jarrin, P., Vallée, M., Mothes, P.A., Grandin, R., Rolandone, F., Delouis, B., Yepes,
944 H., Font, Y., Fuentes, D., Régnier, M., Laurendeau, A., Cisneros, D., Hernandez, S., Sladen,
945 A., Singaicho, J.C., Mora, H., Gomez, J., Montes, L., Charvis, P., 2017. Supercycle at the
946 Ecuadorian subduction zone revealed after the 2016 Pedernales earthquake. *Nature Geoscience*
947 10, 145–149. doi:10.1038/ngeo2864.

948 Nábělek, J., Hetényi, G., Vergne, J., Sapkota, S., Kafle, B., Jiang, M., Su, H., Chen, J., Huang,
949 B.S., Team, t.H.C.L.I.M.B., 2009. Underplating in the Himalaya-Tibet collision zone revealed
950 by the Hi-CLIMB experiment. *Science* 325, 1371–1374. URL: <http://science.sciencemag.org/content/325/5946/1371.abstract>.
951

- 952 Okada, Y., 1992. Internal deformation due to shear and tensile faults in a half-space. *Bulletin of*
953 *the Seismological Society of America* 82, 1018–1040.
- 954 Perfettini, H., Avouac, J.P., 2004. Postseismic relaxation driven by brittle creep: A possible
955 mechanism to reconcile geodetic measurements and the decay rate of aftershocks, application to
956 the Chi-Chi earthquake, Taiwan. *Journal of Geophysical Research: Solid Earth* 109, B02304.
957 doi:10.1029/2003JB002488.
- 958 Pollitz, F., Brooks Ben, Tong Xiaopeng, Bevis Michael G., Foster James H., Bürgmann Roland,
959 Smalley Robert, Vigny Christophe, Socquet Anne, Ruegg Jean-Claude, Campos Jaime, Barrien-
960 tos Sergio, Parra Héctor, Soto Juan Carlos Baez, Cimbaro Sergio, Blanco Mauro, 2011. Coseismic
961 slip distribution of the February 27, 2010 Mw 8.8 Maule, Chile earthquake. *Geophysical Research*
962 *Letters* 38. doi:10.1029/2011GL047065.
- 963 Pollitz, F.F., Bürgmann, R., Segall, P., 1998. Joint estimation of afterslip rate and postseismic
964 relaxation following the 1989 Loma Prieta earthquake. *Journal of Geophysical Research: Solid*
965 *Earth* 103, 26975–26992. doi:10.1029/98JB01554.
- 966 Ragon, T., Sladen, A., Bletery, Q., Vergnolle, M., Cavalié, O., Avallone, A., Balestra, J., Delouis,
967 B., 2019a. Joint Inversion of Coseismic and Early Postseismic Slip to Optimize the Information
968 Content in Geodetic Data: Application to the 2009 Mw6.3 L’Aquila Earthquake, Central Italy.
969 *Journal of Geophysical Research: Solid Earth* doi:10.1029/2018JB017053.
- 970 Ragon, T., Sladen, A., Simons, M., 2018. Accounting for uncertain fault geometry in earthquake
971 source inversions – I: theory and simplified application. *Geophysical Journal International* 214,
972 1174–1190. doi:10.1093/gji/ggy187.
- 973 Ragon, T., Sladen, A., Simons, M., 2019b. Accounting for uncertain fault geometry in earth-
974 quake source inversions – II: Application to the Mw 6.2 Amatrice earthquake, Central Italy.
975 *Geophysical Journal International* doi:10.1093/gji/ggz180.
- 976 Ruegg, J.C., Rudloff, A., Vigny, C., Madariaga, R., de Chabalier, J.B., Campos, J., Kausel, E.,
977 Barrientos, S., Dimitrov, D., 2009. Interseismic strain accumulation measured by GPS in the
978 seismic gap between Constitución and Concepción in Chile. *Physics of the Earth and Planetary*
979 *Interiors* 175, 78–85. doi:10.1016/j.pepi.2008.02.015.
- 980 Ruiz, S., Madariaga, R., Astroza, M., Saragoni, G.R., Lancieri, M., Vigny, C., Campos, J., 2012.
981 Short-Period Rupture Process of the 2010 Mw 8.8 Maule Earthquake in Chile. *Earthquake*
982 *Spectra* 28, S1–S18. doi:10.1193/1.4000039.

- 983 Sladen, A., Trevisan, J., 2018. Shallow megathrust earthquake ruptures betrayed by their outer-
984 trench aftershocks signature. *Earth and Planetary Science Letters* 483, 105–113.
- 985 Steketee, J., 1958. On volterra’s dislocations in a semi-infinite elastic medium. *Canadian Journal*
986 *of Physics* 36, 192–205.
- 987 Stevens, V.L., Avouac, J.P., 2015. Interseismic coupling on the main Himalayan thrust. *Geophys-*
988 *ical Research Letters* 42, 5828–5837. doi:10.1002/2015GL064845.
- 989 Tinti, S., Armigliato, A., 2002. A 2-D hybrid technique to model the effect of topography on
990 coseismic displacements. Application to the Umbria-Marche (central Italy) 1997 earthquake
991 sequence. *Geophysical Journal International* 150, 542–557. doi:10.1046/j.1365-246X.2002.
992 01721.x.
- 993 Tong, X., Sandwell, D., Luttrell, K., Brooks, B., Bevis, M., Shimada, M., Foster, J., Smalley,
994 R., Parra, H., Soto, J.C.B., Blanco, M., Kendrick, E., Genrich, J., Caccamise, D.J., 2010. The
995 2010 Maule, Chile earthquake: Downdip rupture limit revealed by space geodesy. *Geophysical*
996 *Research Letters* 37. doi:10.1029/2010GL045805.
- 997 Trasatti, E., Kyriakopoulos, C., Chini, M., 2011. Finite element inversion of DInSAR
998 data from the Mw 6.3 L’Aquila earthquake, 2009 (Italy). *Geophysical Research Letters*
999 38. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/2011GL046714>,
1000 doi:10.1029/2011GL046714.
- 1001 Tsai, V.C., Ampuero, J.P., Kanamori, H., Stevenson, D.J., 2013. Estimating the effect of Earth
1002 elasticity and variable water density on tsunami speeds. *Geophysical Research Letters* 40, 492–
1003 496. doi:10.1002/grl.50147.
- 1004 Tung, S., Masterlark, T., 2016. Coseismic slip distribution of the 2015 Mw7.8 Gorkha, Nepal,
1005 earthquake from joint inversion of GPS and InSAR data for slip within a 3-D heterogeneous
1006 domain. *Journal of Geophysical Research: Solid Earth* 121, 3479–3503. URL: <https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015JB012497>, doi:10.1002/2015JB012497.
- 1008 Twardzik, C., Vergnolle, M., Sladen, A., Avallone, A., 2019. Unravelling the contribution of
1009 early postseismic deformation using sub-daily GNSS positioning. *Scientific Reports* 9, 1775.
1010 doi:10.1038/s41598-019-39038-z.
- 1011 Vigny, C., Socquet, A., Peyrat, S., Ruegg, J.C., Métois, M., Madariaga, R., Morvan, S., Lancieri,
1012 M., Lacassin, R., Campos, J., Carrizo, D., Bejar-Pizarro, M., Barrientos, S., Armijo, R., Aranda,

1013 C., Valderas-Bermejo, M.C., Ortega, I., Bondoux, F., Baize, S., Lyon-Caen, H., Pavez, A.,
1014 Vilotte, J.P., Bevis, M., Brooks, B., Smalley, R., Parra, H., Baez, J.C., Blanco, M., Cimbaro, S.,
1015 Kendrick, E., 2011. The 2010 Mw 8.8 Maule Megathrust Earthquake of Central Chile, Monitored
1016 by GPS. *Science* 332, 1417–1421. doi:10.1126/science.1204132.

1017 Wang, K., Fialko, Y., 2015. Slip model of the 2015 Mw 7.8 Gorkha
1018 (Nepal) earthquake from inversions of ALOS-2 and GPS data. *Geophysical
1019 Research Letters* 42, 7452–7458. URL: [https://agupubs.onlinelibrary.
1020 wiley.com/doi/abs/10.1002/2015GL065201](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015GL065201), doi:10.1002/2015GL065201,
1021 arXiv:<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2015GL065201>.

1022 Wang, K., Fialko, Y., 2018. Observations and modeling of coseismic and post-
1023 seismic deformation due to the 2015 Mw 7.8 Gorkha (Nepal) earthquake. *Journal of Geophysical Research: Solid Earth* 123, 761–779. URL: [https://agupubs.
1024 onlinelibrary.wiley.com/doi/abs/10.1002/2017JB014620](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2017JB014620), doi:10.1002/2017JB014620,
1025 arXiv:<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1002/2017JB014620>.

1027 Wang, X., Wei, S., Wu, W., 2017. Double-ramp on the Main Himalayan Thrust revealed by
1028 broadband waveform modeling of the 2015 Gorkha earthquake sequence. *Earth and Planetary
1029 Science Letters* 473, 83–93. URL: [http://www.sciencedirect.com/science/article/pii/
1030 S0012821X1730300X](http://www.sciencedirect.com/science/article/pii/S0012821X1730300X).

1031 Watada, S., Kusumoto, S., Satake, K., 2014. Traveltime delay and initial phase reversal of distant
1032 tsunamis coupled with the self-gravitating elastic Earth. *Journal of Geophysical Research: Solid
1033 Earth* 119, 4287–4310. doi:10.1002/2013JB010841.

1034 Wessel, P., Luis, J.F., Uieda, L., Scharroo, R., Wobbe, F., Smith, W.H.F., Tian, D., 2019. The
1035 Generic Mapping Tools Version 6. *Geochemistry, Geophysics, Geosystems* n/a. doi:10.1029/
1036 2019GC008515.

1037 Whipple, K.X., Shirzaei, M., Hodges, K.V., Ramon Arrowsmith, J., 2016. Active shortening within
1038 the Himalayan orogenic wedge implied by the 2015 Gorkha earthquake. *Nature Geoscience* 9,
1039 711–716. URL: <https://doi.org/10.1038/ngeo2797>.

1040 Williams, C.A., Wadge, G., 1998. The effects of topography on magma chamber deformation
1041 models: Application to Mt. Etna and radar interferometry. *Geophysical Research Letters* 25,
1042 1549–1552. doi:10.1029/98GL01136.

- 1043 Williams, C.A., Wadge, G., 2000. An accurate and efficient method for in-
1044 cluding the effects of topography in three-dimensional elastic models of ground
1045 deformation with applications to radar interferometry. *Journal of Geo-*
1046 *physical Research: Solid Earth* 105, 8103–8120. URL: [https://agupubs.](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/1999JB900307)
1047 [onlinelibrary.wiley.com/doi/abs/10.1029/1999JB900307](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1029/1999JB900307), doi:10.1029/1999JB900307,
1048 arXiv:<https://agupubs.onlinelibrary.wiley.com/doi/pdf/10.1029/1999JB900307>.
- 1049 Williams, C.A., Wallace, L.M., 2018. The Impact of Realistic Elastic Properties on Inversions
1050 of Shallow Subduction Interface Slow Slip Events Using Seafloor Geodetic Data. *Geophysical*
1051 *Research Letters* 45, 7462–7470. doi:10.1029/2018GL078042.
- 1052 Xue, L., Schwartz, S., Liu, Z., Feng, L., 2015. Interseismic megathrust coupling beneath the Nicoya
1053 Peninsula, Costa Rica, from the joint inversion of InSAR and GPS data. *Journal of Geophysical*
1054 *Research: Solid Earth* 120, 3707–3722. doi:10.1002/2014JB011844.
- 1055 Yadav, R.K., Roy, P.N.S., Gupta, S.K., Khan, P.K., Catherine, J.K., Prajapati, S.K., Kumar, A.,
1056 Puviarasan, N., Bhu, H., Devachandra, M., Malik, J., Kundu, B., Debbarma, C., Gahalaut,
1057 V.K., 2017. Rupture model of Mw 7.8 2015 Gorkha, Nepal earthquake: Constraints from
1058 GPS measurements of coseismic offsets. *Journal of Asian Earth Sciences* 133, 56–61. URL:
1059 <http://www.sciencedirect.com/science/article/pii/S136791201630092X>.
- 1060 Yagi, Y., Okuwaki, R., 2015. Integrated seismic source model of the 2015 Gorkha, Nepal, earth-
1061 quake. *Geophysical Research Letters* 42, 6229–6235. URL: [https://agupubs.onlinelibrary.](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015GL064995)
1062 [wiley.com/doi/abs/10.1002/2015GL064995](https://agupubs.onlinelibrary.wiley.com/doi/abs/10.1002/2015GL064995), doi:10.1002/2015GL064995.
- 1063 Yang, Y., Chen, Q., Xu, Q., Liu, G., Hu, J.C., 2019. Source model and coulomb stress change
1064 of the 2015 Mw 7.8 Gorkha earthquake determined from improved inversion of geodetic surface
1065 deformation observations. *Journal of Geodesy* 93, 333–351. URL: [https://doi.org/10.1007/](https://doi.org/10.1007/s00190-018-1164-9)
1066 [s00190-018-1164-9](https://doi.org/10.1007/s00190-018-1164-9).
- 1067 Yi, L., Xu, C., Zhang, X., Wen, Y., Jiang, G., Li, M., Wang, Y., 2017. Joint inversion of GPS,
1068 InSAR and teleseismic data sets for the rupture process of the 2015 Gorkha, Nepal, earthquake
1069 using a generalized ABIC method. *Journal of Asian Earth Sciences* 148, 121–130. URL: [http:](http://www.sciencedirect.com/science/article/pii/S1367912017304601)
1070 [//www.sciencedirect.com/science/article/pii/S1367912017304601](http://www.sciencedirect.com/science/article/pii/S1367912017304601).
- 1071 Yoshimoto, M., Watada, S., Fujii, Y., Satake, K., 2016. Source estimate and tsunami forecast
1072 from far-field deep-ocean tsunami waveforms—The 27 February 2010 Mw 8.8 Maule earthquake.
1073 *Geophysical Research Letters* 43, 659–665. doi:10.1002/2015GL067181.

- 1074 Yue, H., Lay, T., Rivera, L., An, C., Vigny, C., Tong, X., Soto, J.C.B., 2014. Localized fault slip
1075 to the trench in the 2010 Maule, Chile Mw = 8.8 earthquake from joint inversion of high-rate
1076 GPS, teleseismic body waves, InSAR, campaign GPS, and tsunami observations. *Journal of*
1077 *Geophysical Research: Solid Earth* 119, 7786–7804. doi:10.1002/2014JB011340.
- 1078 Yue, H., Simons, M., Duputel, Z., Jiang, J., Fielding, E., Liang, C., Owen, S., Moore, A., Riel,
1079 B., Ampuero, J.P., Samsonov, S.V., 2017. Depth varying rupture properties during the 2015
1080 Mw 7.8 Gorkha (Nepal) earthquake. Special Issue on the 25 April 2015 Mw 7.8 Gorkha (Nepal)
1081 Earthquake 714-715, 44–54. URL: [http://www.sciencedirect.com/science/article/pii/
1082 S0040195116302566](http://www.sciencedirect.com/science/article/pii/S0040195116302566).
- 1083 Zhao, S., Kaneda, Y., Müller, R.D., Takahashi, Y., 2004. 3-D finite-element modelling of defor-
1084 mation and stress associated with faulting: effect of inhomogeneous crustal structures. *gji* 157,
1085 629–644. URL: <https://dx.doi.org/10.1111/j.1365-246X.2004.02200.x>.
- 1086 Zuo, R., Qu, C., Shan, X., Zhang, G., Song, X., 2016. Coseismic deformation fields and a fault slip
1087 model for the Mw7.8 mainshock and Mw7.3 aftershock of the Gorkha-Nepal 2015 earthquake
1088 derived from Sentinel-1A SAR interferometry. *Tectonophysics* 686, 158–169. URL: [http://www.
1089 sciencedirect.com/science/article/pii/S0040195116303146](http://www.sciencedirect.com/science/article/pii/S0040195116303146).