

1 **Optimization of local scale seismic networks applied to geothermal fields. The case**
2 **of the Acoculco caldera, Mexico.**

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13 **Abstract**

14 The exploitation of a geothermal field can be accompanied by both natural and induced
15 seismicity. Hence the installation of a seismic network suitable for locating also low
16 magnitude earthquakes is of great interest for geothermal development, especially for
17 monitoring the activity related to the injection or production.

18 Here we propose an improvement of the D-OPTIMAL algorithm (Tramelli et al., 2013) that
19 tries and find optimal station positions minimizing the volume of the error ellipsoid of the
20 event location using the D-criterion. In this version, we introduced the possibility to account
21 for several prior information that is generally available when instrumenting a monitoring site
22 permanently or temporarily. The a priori parameters introduced are: i) three-dimensional
23 seismic velocity models, ii) seismic noise levels, iii) topographic gradient, and iv) H/V ratio

24 values. The last three parameters are introduced in the station position selection using a
25 weighting system.

26 We applied the methodology to the Acoculco geothermal field (Mexico) where an injection
27 test was planned and executed in 2021. The comparison between the network defined using
28 the standard approach and this updated version shows the importance of introducing a priori
29 information during the selection of the network. Installation sites resulted better distributed
30 on the region, resulting in an overall increase of the sensitivity, and in a decreasing of the
31 error location estimation in the target region.

32 The methodology presented here is easy to apply to other study cases such as active
33 volcanoes, anthropogenic activities, or whatever other study at local scale.

34 **Keywords**

35 Seismic network optimization, Seismic monitoring, Acoculco geothermal field, Seismic
36 noise level, Topographic gradient, H/V ratio.

37 **1. Introduction**

38 Production activities in a geothermal field can be affected by both natural and induced
39 seismicity (e.g., Gaucher et al., 2015; Schoenball et al., 2010;2013; Toledo et al., 2020).
40 Geothermal fluid extraction and injection causes pressure variations generating changes in
41 the property of the medium that may trigger or induce seismic activity. Although most of
42 these events are low in magnitude (Mukuhira et al., 2013; Urban and Lermo, 2017), induced
43 events large enough to be felt by the population are an undesirable possible result of the
44 geothermal exploitation operations (Buijze et al., 2019). The reliable monitoring and location
45 of the seismic activity in a geothermal field is a key factor for hazard assessment. Hence an
46 optimal planning of a seismic network is of great interest for geothermal development.

47 Seismic network improvement has been approached from different perspectives and several
48 authors used different approaches. The most common methods contemplate: i) the
49 computation of the magnitude of completeness (M_c) and assessment of the spatial
50 distribution of the location error (e.g., the Seismic Network Evaluation through Simulation -
51 SNES, Mahani et al., 2016; D'Alessandro et al., 2011b; 2013; 2014); ii) the location of the
52 seismic events using a combination of random station locations applying probabilistic
53 methods (e.g., Monte Carlo) to decrease the location errors (e.g., Bondár et al., 2004); iii)
54 correction of teleseismic travel times (e.g., Myers and Schultz, 2000); iv) mapping the
55 expected location errors and assessment of the lowest magnitude of events that the seismic
56 network can detect (e.g., Stabile et al., 2013; De Landro et al., 2020); and v) employment of
57 the D-criterion to identify an optimal seismic network configuration to decrease the location
58 error (e.g., Steinberg and Rabinowitz 2003). In this last case, the network optimization can
59 contemplate genetic algorithm (e.g., Bartal et al., 2000), simulated annealing (e.g., Hardt
60 and Scherbaum, 1994; Kraft et al., 2013), or Bayesian techniques (e.g., Coles and Curtis
61 2011; Tramelli et al., 2013).

62 In any case, seismic monitoring depends on five main aspects: i) seismic network geometry,
63 ii) sensitivity to detect targeted seismicity, iii) location method, and iv) knowledge of the
64 velocity model.

65 In this study, we focus on the seismic network geometry improvement proposing an updated
66 version of the algorithm D-Optimal proposed by Tramelli et al. (2013) that tries and find the
67 optimal station positions minimizing the volume of the error ellipsoid of the location for
68 synthetic earthquakes using the D-criterion (Rabinowitz and Steinberg, 1990; 2000;
69 Steinberg and Rabinowitz, 2003). The optimization process accounts for every stations
70 combination based on permutation of preestablished sites using the Monte Carlo method
71 and covariance to restrict the ellipsoid error of the hypocenter location.

72 In this version of the program, we improved the procedure considering several prior
73 information such as maps of seismic noise levels, amplitude picks obtained from H/V
74 analysis, and three-dimensional seismic models of the study region. This information is
75 usually produced during the exploration stage of a geothermal site and available before an
76 injection test. Additionally, we introduced the topographic gradient as selection parameter
77 to allow a better planning of the installation campaigns in regions with rugged topography.

78 We applied the methodology to the Acoculco geothermal field (Mexico) where an injection
79 test was carried out in June 2021, and an intense exploration campaign was performed
80 between 2018 and 2020 in the framework of the Mexican European consortium GeMex
81 (Cooperation in Geothermal energy research Europe-Mexico).

82 Comparison between the standard approach and this updated version shows the importance
83 to use different prior parameters for a more suitable optimization of the local scale seismic
84 networks, including the topography of the region that allowed to simplify the logistic of the
85 installation.

86 **2. Seismic Network Optimization**

87 The approach proposed by Tramelli et al. (2013) finds a suite of possible optimal networks
88 starting from an initial hypothetical set of N possible sites and computes synthetic amplitude
89 of a hypothetical earthquake to determine the detection capability for each station. Source
90 amplitude is computed using the source parameters expected for an event that may occur
91 in the analyzed region (i.e., stress drop ($\Delta\sigma$), hypocenter coordinates and moment
92 magnitude (M_W)) and using the Brune model (Brune, 1970). Additionally, a reference model,
93 with mean shear wave velocity (V_S), density (ρ), and quality factor (Q), is used to account for
94 the attenuation properties to properly calculate the signal amplitude at each hypothetical

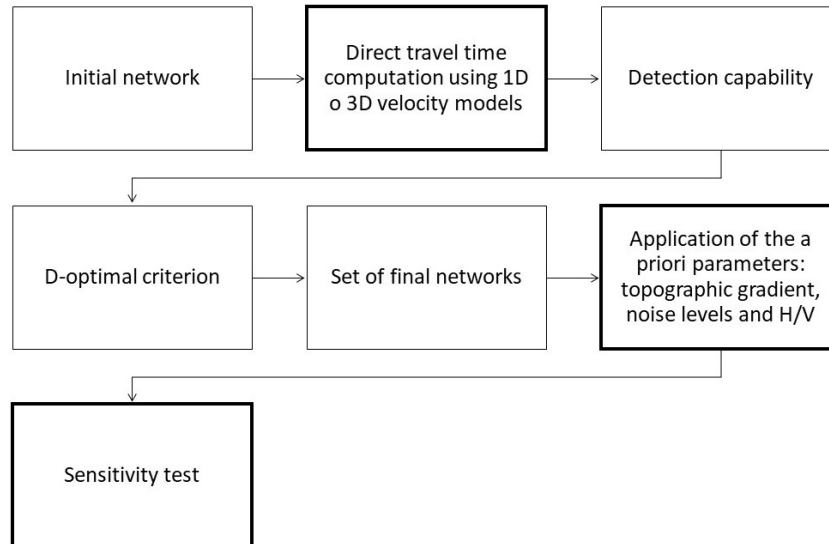
95 station position. Finally, the Signal Noise to Ratio (SNR) is computed for each site where a
96 station could be installed.

97 Monte Carlo method is then used to construct random stations combinations from M
98 available stations situated in N possible sites. For each configuration, the algorithm
99 computes the covariance matrix, and applies the D-criterion (Rabinowitz and Steinberg,
100 1990;2000) to find the optimal configuration. The D-Optimal algorithm uses the confidence
101 ellipsoid error as parameter for finding the optimal network configuration. This parameter is
102 used to optimize the geometry of seismic networks because it provides a good
103 approximation of the real location error (e.g., D'Alessandro et al., 2011a;2011b; Tramelli et
104 al., 2013; Toledo et al., 2020). The minimization of the volume of the error ellipsoid is
105 achieved through iterative changes of the station positions.

106 The standard version of the D-Optimal algorithm computes the travel times between events
107 and stations using 1D velocity models of the P and S waves and it can read travel times
108 computed from 3D velocity model in an external process. In this version, we incorporated
109 into the algorithm the direct computation of the travel times using 3D seismic velocity models
110 using the pseudo-bending method. This was achieved extracting the subroutines from the
111 well-established tomographic code Simul2000 (Thurber, 1993; Eberhart-Phillips, 1993;
112 Thurber y Eberhart-Phillips, 1999) and incorporating them into the code. The other
113 parameters that could influence the selection of a network are instead incorporated using a
114 weighting system applied a posteriori.

115 The procedure of Tramelli et al. (2013) has then been modified with a workflow (Figure 1)
116 that contemplates the following steps: i) computing of the travel times using 1D or 3D velocity
117 models, ii) computation of the detection capability, iii) applying the D-Optimal criterion to
118 obtain the corresponding determinant values (D) of potential final networks, iv) reduction of
119 the final networks space by applying a weighting system of the a-priori parameters to the

120 potential networks with the highest determinant, and v) estimation of the sensitivity for the
121 best configurations that meet the a-priori parameters.



122

123 Figure 1. Workflow of the optimization of a seismic network. Bold rectangles are the steps
124 added with respect to the procedure of Tramelli et al. (2013).

125

126 3. A priori parameters

127 In our procedure, the a priori parameters were added as a weight system that help to choose
128 between a set of configurations with similar D values, penalizing the selection of networks
129 whose installation sites are characterized by high topographic gradient values, high noise
130 levels and low amplification factors (H/V values).

131 3.1 Topographic gradient

132 Instrument installation on a strong slope could be difficult and may increase the installation
133 and maintenance costs. In addition, the recorded seismic signal would be affected by
134 topographical effects. Therefore, the topography of a region is an important characteristic to
135 consider during the planning of an installation campaign.

136 We used the topographic gradient (TG) as parameter to avoid sites where the accessibility
137 can be difficult. The topographic gradient for the entire region was computed as

$$TG = \sqrt{G_{NS}^2 + G_{EW}^2} \quad (5)$$

138 where G_{NS} is the gradient in North-South direction, and G_{EW} is the gradient in the East-West
139 direction. For each possible site we assign a topographic gradient calculated as the mean
140 value on a radius of 150 m from the site. Finally, we computed a normalized average
141 topographic gradient value for each seismic network with respect to the maximum mean
142 value of topographic gradient. This mean value is considered as a representative gradient
143 value of the network and used as weighting factor for the site selection.

144 **3.2 Noise levels**

145 Root Mean Square amplitude (RMS) or Power Spectral Density (PSD) are usually used to
146 characterize the seismic noise level in a site. In our procedure we generate maps of noise
147 levels at different frequency bands by interpolating the PSD calculated in sites within a grid
148 using the cube interpolation technique. Subsequently, for each potential network we
149 calculate the corresponding mean noise level as the average of the values at each station
150 composing the network for the bandwidth of interest. Finally, the weights relative to the noise
151 level of a network is obtained normalizing the vector of the mean values with respect to the
152 maximum mean noise level.

153 **3.3 H/V ratio**

154 H/V ratio is related to the amplification power of a particular site and depends on its specific
155 geological and topographical characteristics. Larger is H/V, stronger the amplification of the
156 shear waves is. Although high H/V in a site could make more difficult to estimate the P wave
157 arrivals, the fact that the S waves are amplified would ensure a better detection of the event
158 because the latter are almost always more energetic than the first ones. Then, amplitude

159 increase is estimated for various frequency ranges and considered as a parameter that can
160 facilitate the microseismicity detection when the amplification of the S waves is high in the
161 frequency range of interest.

162 Similarly, as in the case of the noise level, the weights of H/V ratio are considered as
163 normalized mean value with respect to the maximum value calculated on cubic-interpolated
164 maps for each possible seismic network.

165 **3.4 Ponderation system**

166 The ponderation system establishes how the a priori information is accounted during the
167 selection of an optimal seismic network. We considered the determinant value as the main
168 parameter because the aim of the optimization is the resolving power of the network. For
169 this reason, we organized the networks proposed by D-OPTIMAL algorithm in decreasing
170 order as a function of D. High values of TG and noise levels are unfavored parameters, we
171 then organized them in increasing order. Conversely, H/V values were organized in
172 decreasing order because high values are considered a parameter in favor of the networks
173 considered. We then used the organized vectors, in the ascending or descending order,
174 obtaining the potential networks ordered as function of the a priori parameters. In this way,
175 the optimal networks were selected depending on if they are associated with high D, low
176 TG, low noise level and high H/V ratio.

177 **3.5 Sensitivity test**

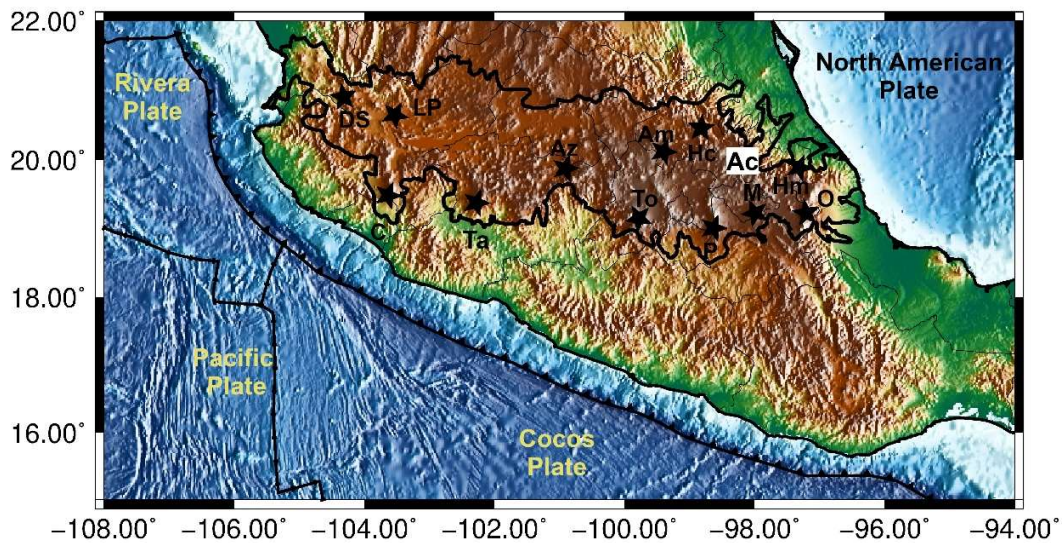
178 Once some of the a priori parameters are introduced to the procedure, we can obtain a
179 reduced set of seismic networks that maximizes determinant value and H/V ratio and
180 minimizes topographic gradient and noise levels. The procedure allows to set the number
181 of the potential configurations that will be admitted for further analyses. Finally, the choice
182 of the best seismic configuration is obtained calculating the network sensitivity.

183 In this case, we calculate the network sensitivity using the Sensitivity Estimate of a Seismic
184 Network algorithm (SENSI) developed by Tramelli *et al.* (2015). SENSI computes synthetic
185 seismic signals using the Brune model (Brune, 1970) for a source point as a function of the
186 magnitude, stress drop, shear wave velocity, density, and a minimum number of stations to
187 detection or location. The minimum magnitude event is calculated for every source point
188 distributed in a regular grid (Orazi *et al.*, 2013; Tramelli *et al.*, 2015) considering the signal
189 to noise ratio.

190 **4. Application to Acoculco Geothermal Field (Puebla, Méx.)**

191 **4.1 Geological Settings**

192 Acoculco caldera is located in easternmost part of the Trans Mexican Volcanic Belt (TMVB)
193 (Figure 2). Rhyolites-dacites-andesites-basaltic and rhyolites-dacites tuffs from 1.4 to 0.24
194 Ma characterize the main volcanic rock composition (López-Hernández and Castillo-
195 Hernández, 1997). Eruptive chronology has been grouped in four main eruptive phases:
196 syn-caldera, early post-caldera, late post-caldera and extra-caldera (Avellán *et al.* 2020).
197 The latter began around 2.7 Ma with the dispersion of andesitic ignimbrite followed by the
198 collapse of the magma chamber. The volcanic complex is affected by two regional stress
199 regimes with NE-SW and NW-SE orientations (López-Hernández and Castillo-Hernández,
200 1997; López-Hernández *et al.*, 2009). Three-dimensional heat flow modeling using an
201 estimated Curie temperature isotherm suggests the presence of a heat source of at least
202 750°C between 3100 m and 3400 m of depth (Guerrero-Martínez *et al.*, 2019).



203

204 Figure 2. Tectonic setting of Mexico. Location of the Trans-Mexican Volcanic Belt (TMVB)
 205 is marked with a black bold line. Main active volcanoes and geothermal sites of interest
 206 located inside the TMVB are: Domo San Pedro (DS), La Primavera (LP), Fuego de Colima
 207 (C), Tancitaro (Ta), Los Azufres (Az), Amealco (Am), Huichapan (Hc), Nevado de Toluca
 208 (To), Popocatépetl (P), Malinche (M), Pico de Orizaba (O) y Humeros (Hm). White filled
 209 rectangle marks the location of the Acozulco Caldera (AC) (modified from Avellán et al.,
 210 2020).

211 Since the early nineties, because of the intense hydrothermal manifestations, acid springs,
 212 and gas discharges present near the Acozulco caldera, the Mexican Federal Electricity
 213 Commission (CFE) started several exploration activities and in 1995 the first exploratory
 214 borehole (EAC01) was drilled to a depth of 1810 m near to Los Azufres, a hydrothermal
 215 manifestation with many gas emissions. In 2008 a second borehole (EAC02) was drilled
 216 with a depth of 1900 m confirming high temperatures in depth. However, the low permeability
 217 found at these depths discouraged the development of conventional high enthalpy
 218 geothermal systems (Kruszewski et al., 2021; López-Hernández et al., 2009; Bolós et al.,
 219 2022).

220 A hydraulic stimulation of the borehole EAC01 was planned in 2018 and executed in 2021.
 221 Different scenarios as hydraulic fractures, fracture network stimulation, fault zone

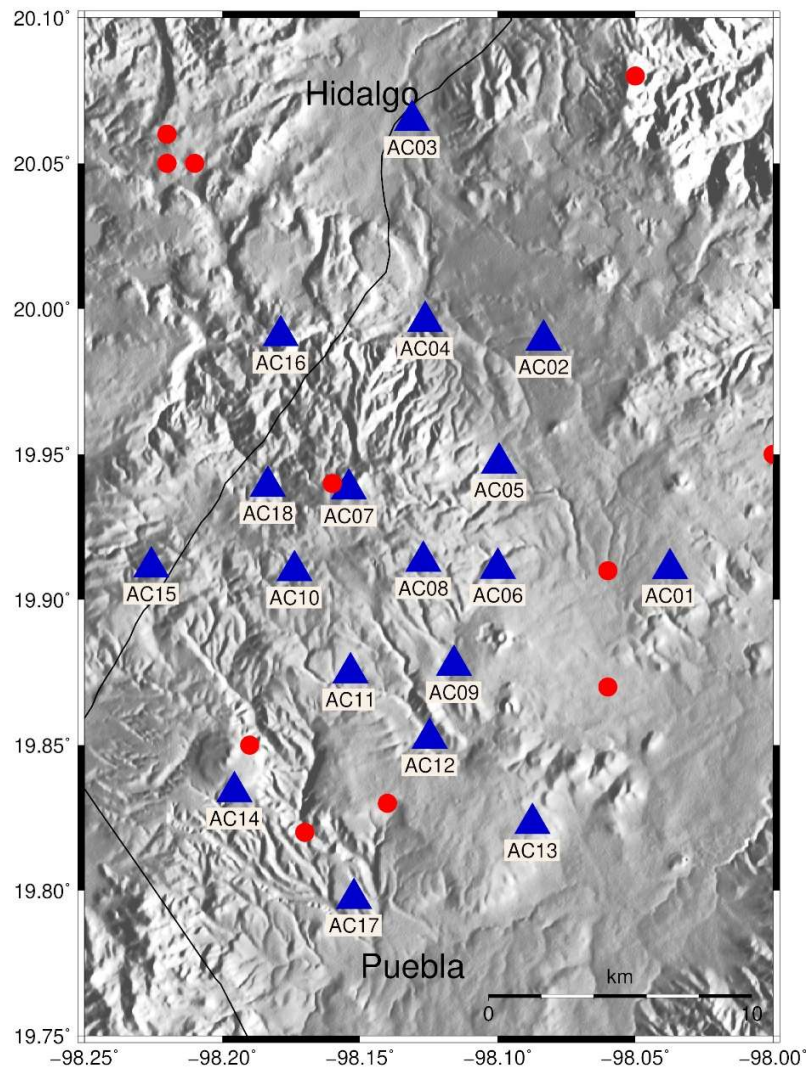
222 reactivation and a combination of the previous scenarios have been studied with the
223 integration of geological, geophysical, and geochemical information (GEMex W.P. 7.1,
224 2020). Finally, a fracture network stimulation was tested injecting fluids on July 14, 2021 as
225 a final activity within the GEMex project.

226

227 **4.2 Seismicity and velocity models**

228 Acoculco geothermal field had a limited monitoring activity. Between 1995 and 2018 only a
229 temporal network of seven sensors (4 velocimeters and 3 accelerometers) was deployed for
230 four months in 2004 (Lermo *et al.*, 2009). No local seismicity was detected during this period
231 and 30 regional seismic events were used to build a preliminary 1D velocity model of the
232 region using the Spatial Autocorrelation method (SPAC).

233 Recently, as a part of W.P. 5.2 of GEMex, 18 broadband seismic stations were installed in
234 the Acoculco complex (Figure 3) and recorded from May 2018 to July 2019. The network
235 was specifically designed to apply ambient noise and SPAC techniques. Maldonado-
236 Hernández *et al.* (2019) obtained a three-dimensional velocity model of the S waves (Figure
237 4) using the first order and overtones of the group velocities extracted employing the ambient
238 noise cross-correlation method. The model is characterized by the presence of strong lateral
239 heterogeneities and the presence of a marked low velocity zone at depths of 0.5-3 km b.s.l.
240 Additionally, the network allowed to record 33 local events with magnitude up to 3 and mainly
241 located outside of the caldera rim (Figuroa-Soto *et al.*, in submission). Among these, 11
242 events are located within 25 km of the study area.

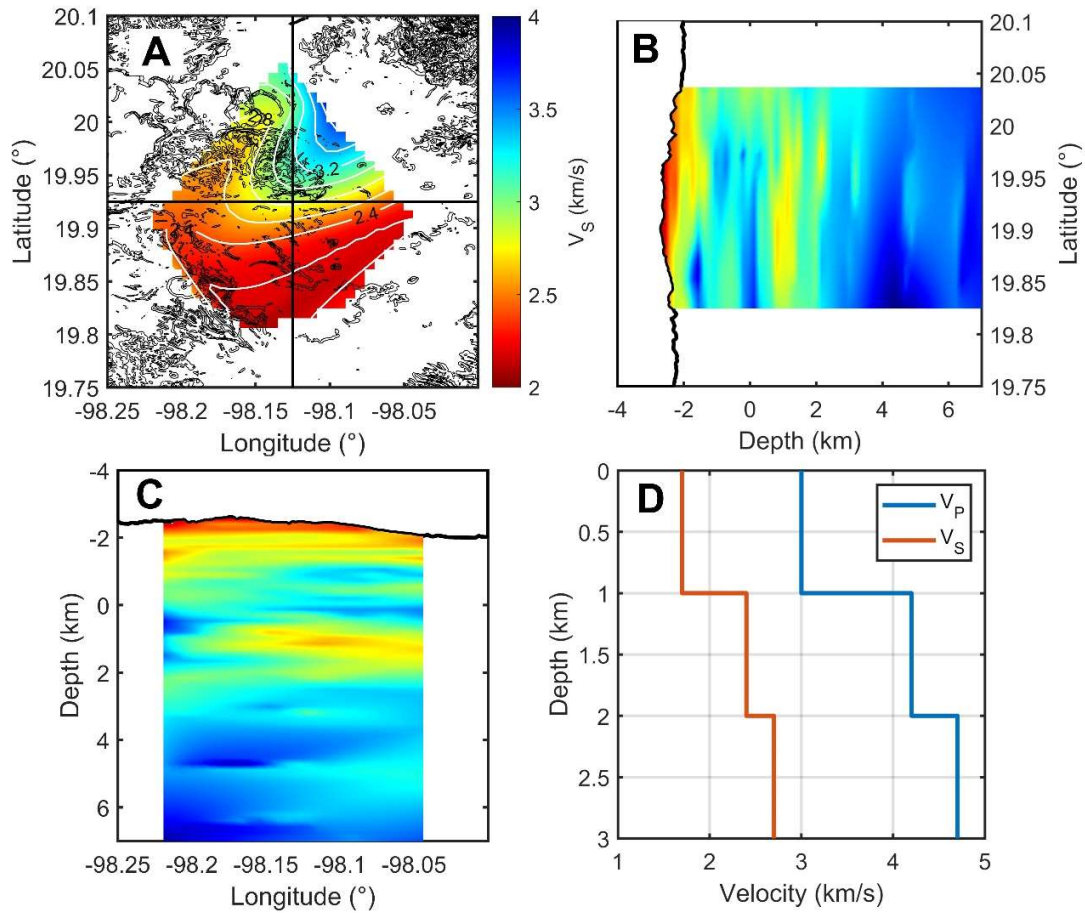


243

244 Figure 3. Temporal seismic network installed in 2018 at the Acozulco volcanic complex (blue
 245 triangles) and local seismicity located within 25 km of the study area (red dots).

246

247



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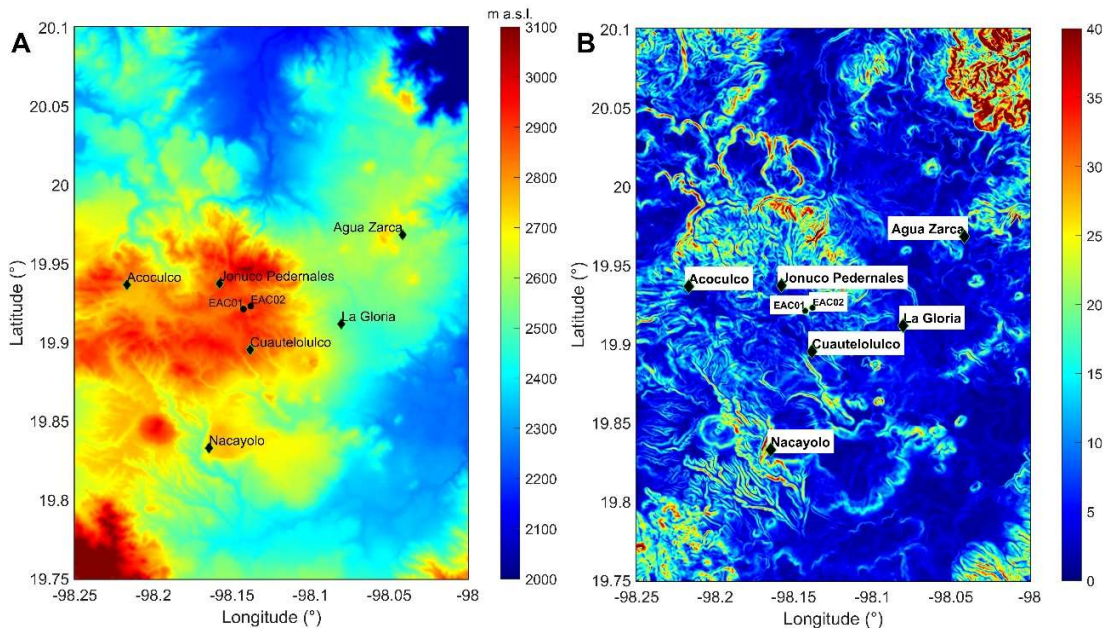
249 Figure 4. Three-dimensional S wave velocity model (V_s) of Acoculco geothermal field. A)
 250 Horizontal section of the V_s model at 1 km a.s.l, B), N-S and C) E-W vertical sections. (d)
 251 Mean layered one-dimensional velocity model of P and S waves used to locate the seismicity
 252 and to perform the tests described in the main text. (Modified from Maldonado-Hernández
 253 et al., 2019).

254

255 4.4 Topographic gradient

256 According to the digital elevation model (DEM) provided by the Mexican National Institute of
 257 Statistics and Geography (INEGI), Acoculco volcanic complex has a rugged topography
 258 (Figure 5.A). Local topography ranges between 2000 to 3100 m a.s.l. over an area of approx.

259 20x20 km². Specifically, the volcanic caldera extends between 2600 to more than 3000 m
260 a.s.l.



261

262 Figure 5. Topography (A) and topographic gradient (B) of the Acoculco volcanic complex.
263 Principal towns are indicated with black diamonds. Boreholes EAC01 and EAC02 are
264 indicated with black circles.

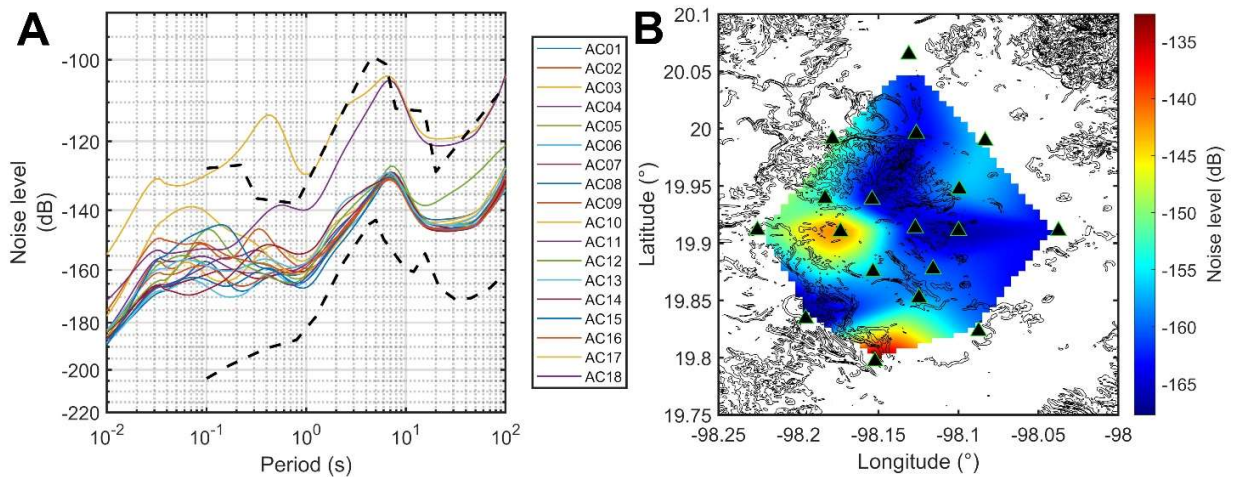
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266 The computation of the topographic gradient (Figure 5.B) empathizes the shape of the
267 caldera border and the main drainage pattern, which is characterized by strong variations of
268 the slope. Resolution of the map is 50 meters and TG can reach 30-40 in several parts of
269 the mesh corresponding to a slope of about 80%.

270 4.5 Seismic noise levels

271 Seismic noise levels were computed using the continuous records of the temporal seismic
272 network (Figure 3) composed by 18 broadband seismic stations installed from September
273 2018 to April 2019 (W.P. 5.2, GEMex).

274 Figure 6.A shows that the median of the PSD estimated at the stations are within the
 275 minimum and maximum levels of the Peterson curves (Peterson, 1993). However, two of
 276 them (AC17 and AC18) exhibit slightly higher levels than the rest of the curves. This is
 277 attributed to the vicinity of the stations to the populated regions and to site effects.



278

279 Figure 6. (A) Median of the PSD calculated from September 2018 to April 2019 at the 18
 280 temporary stations installed. (B) Noise level map in the frequency range of 10-40 Hz; black
 281 triangles are station locations of the temporary network.

282

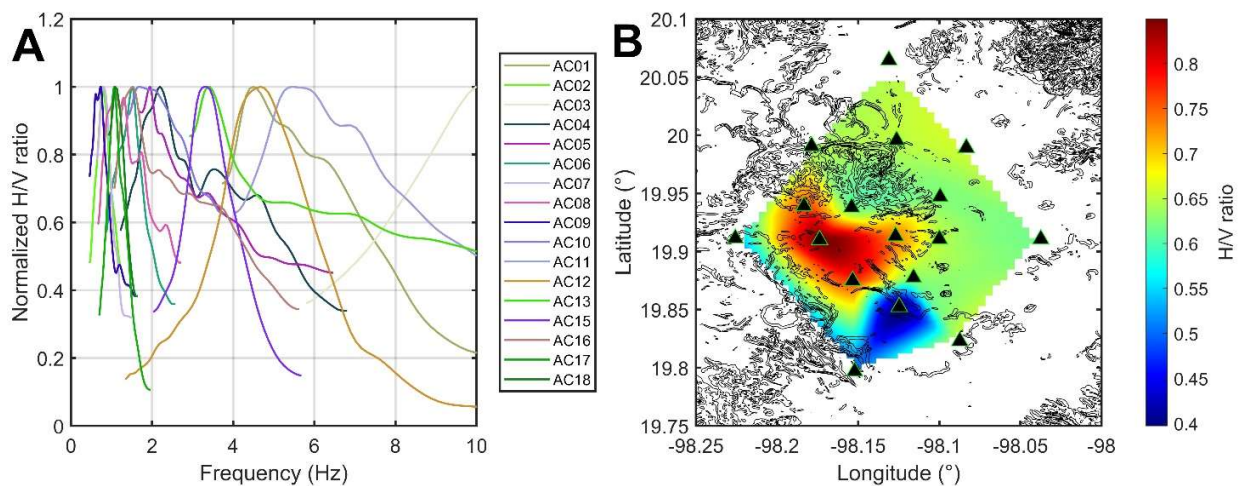
283 Generally, induced seismicity observed in geothermal fields has small magnitude ($M < 2$;
 284 Gupta, H. K., 1992) and exciting mostly high frequency. Thus, we computed the spatial
 285 distribution of the mean seismic noise level of the entire geothermal field in the frequency
 286 range of 10-40 Hz (Figure 6.B). The map shows that the highest values are in the northwest
 287 and south regions, where AC17 and AC18 stations are placed.

288

289 4.6 H/V values

290 To estimate this parameter, we used the *H/V* values computed by Ibarra-Bustos (2019) using
 291 the seismic network deployed in 2018 at the Acoculco volcanic complex. A map was

292 computed using a cubic interpolation of the mean values of the normalized H/V curves
 293 (Figure 7.A) in the frequency range of 0.1-10 Hz. Although different from the frequency band
 294 selected for the seismic noise levels, this is the bandwidth that includes all the maximum
 295 amplitudes measured at the stations (figure 7.A) and where the S waves are better amplified.
 296 With this approach even when the curves have maximum H/V ratio values at different
 297 frequencies, normalized values guarantee to account for them with the same weight during
 298 the map building. Figure 7.B shows the distribution of the mean normalized amplitudes
 299 highlighting the presence of low values in the southern region close to AC12, and high
 300 amplification values in the western region.



301
 302 Figure 7. (A) Normalized H/V curves estimated by Ibarra-Bustos (2019) for the temporal
 303 network installed between May 2018 to July 2019 (B) Map of the H/V ratio computed using
 304 the H/V ratio values. Black triangles are the station locations of the temporary network.

305

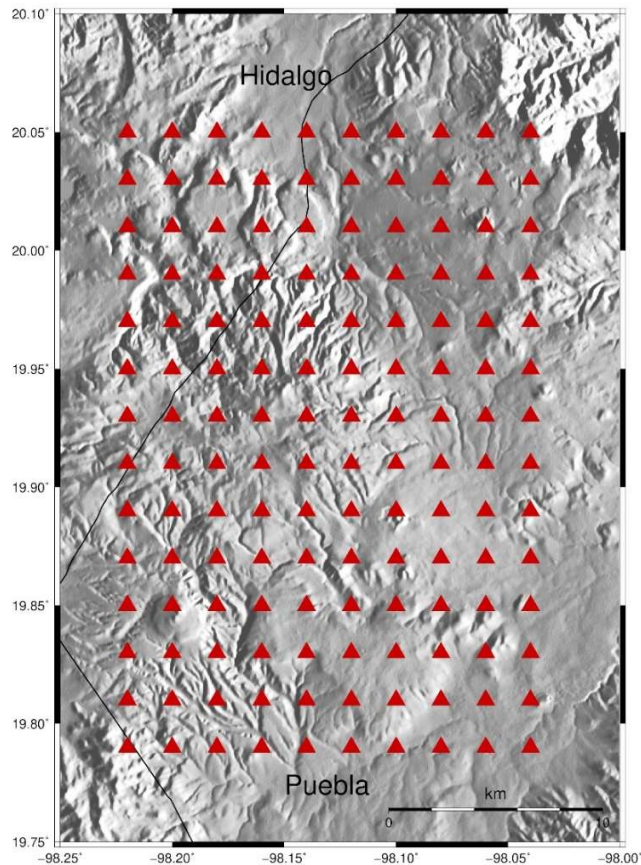
306 4.7 Optimization network

307 In order to assess how sensitive is the procedure to the velocity model used in the travel
 308 time computation in D-optimal, we applied the whole process using both the 1D reference
 309 model and the 3D one. Since the 1D and 3D velocity models proposed by Maldonado et al.
 310 (2019) are relative to the S waves, the P ones were retrieved using a constant $V_p/V_s=1.6$.

311 Subsequently, a grid of 2378 potential stations sites are generated locating them on a
312 regular grid of 20 x 28 km covering the study area with a station spacing of 500 m (Figure
313 8). For our analysis, the number of stations available for the potential network is 16 and can
314 be distributed over 2378 possible sites. The determinant and the a priori parameters are
315 then calculated for each potential configuration. Also, we normalized the determinant values
316 to easily identify the seismic network configuration with the best determinant value. The
317 normalization was computed with respect to the maximum determinant value of all potential
318 seismic networks. We set the maximum number of potential final configurations to 6, in
319 order to evaluate the performance of the ponderation system and analyze the event
320 detection capability of more than one network. The sensitivity of the networks was estimated
321 simulating the occurrence of an event located within the well EAC01 at a depth of 2 km.
322 Since the depth of the wells is 1.9 km, we consider that the expected stimulation would occur
323 at its bottom.

324 The parameters used to simulate the synthetic event are a mean shear wave velocity of 1.7
325 km/s (Maldonado-Hernández et al., 2019), a density of 2.4 g/cm³ (López-Hernández,
326 2009), a Q=90 (W.P. 5.2 of GEMex, 2021), and a stress drop of 0.5 MPa. The last one is
327 compatible with the range between 0.01 to 3 MPa of an expected event induced during a

328 hydraulic stimulation (Lengliné et al., 2014). Moreover, we consider only events that can be
329 detected at least three stations with a signal to noise ratio greater than 2.



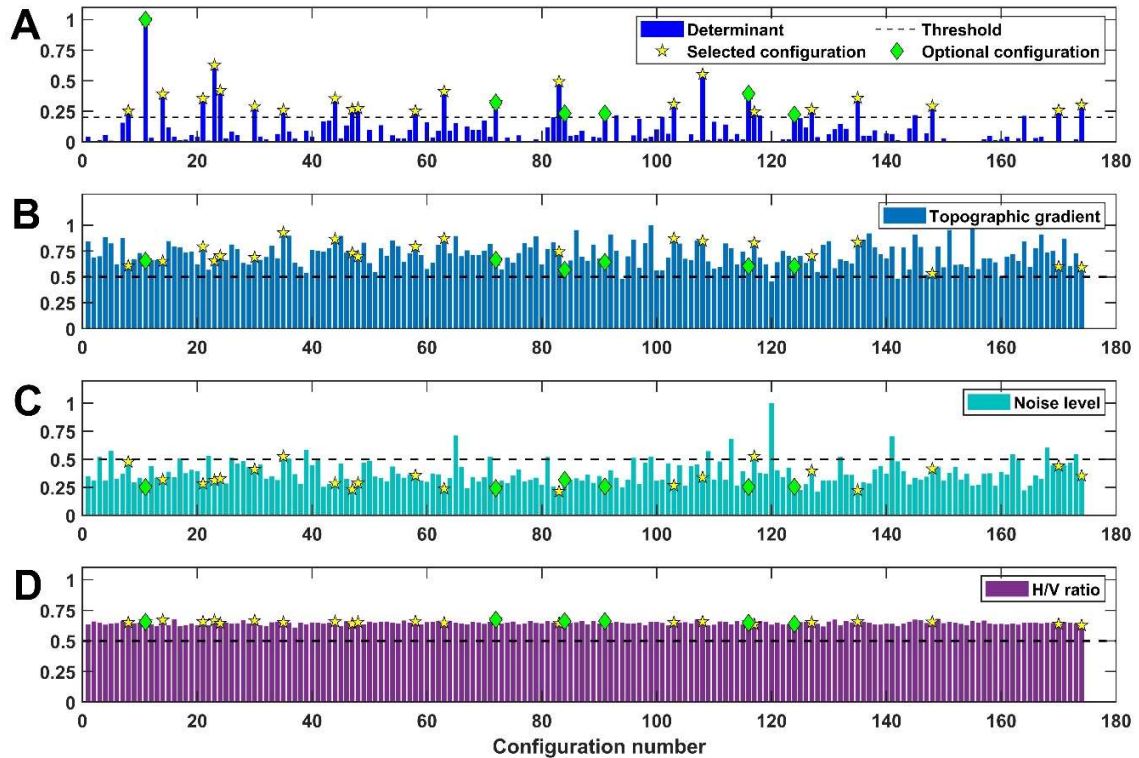
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331 Figure 8. Location of 140 station sites representative of the 2378 possible sites available for
332 the virtual network. The spacing of the initial virtual station sites is 500m.

333

334 Results obtained using the travel times calculated on the 1D model together with the
335 normalized values of the determinant, topographic gradient, noise level, and H/V ratio are
336 reported in Figure 9. The D-Optimal algorithm selected 174 potential networks able to locate
337 events in the region with a determinant average of 0.09. This set can be reduced to 24
338 potential configurations when considering a $D > 0.2$ (diamonds and stars in Figure 9). This
339 set of configurations is further reduced to 6 potential networks when the a priori parameter

340 ponderation is added (diamonds in Figure 9). The selected configurations reflect the
 341 following conditions: 1) $D > 0.2$, 2) $TG > 0.5$, 3) noise levels ≤ 0.5 , and 4) the highest
 342 amplification factors of the H/V values.

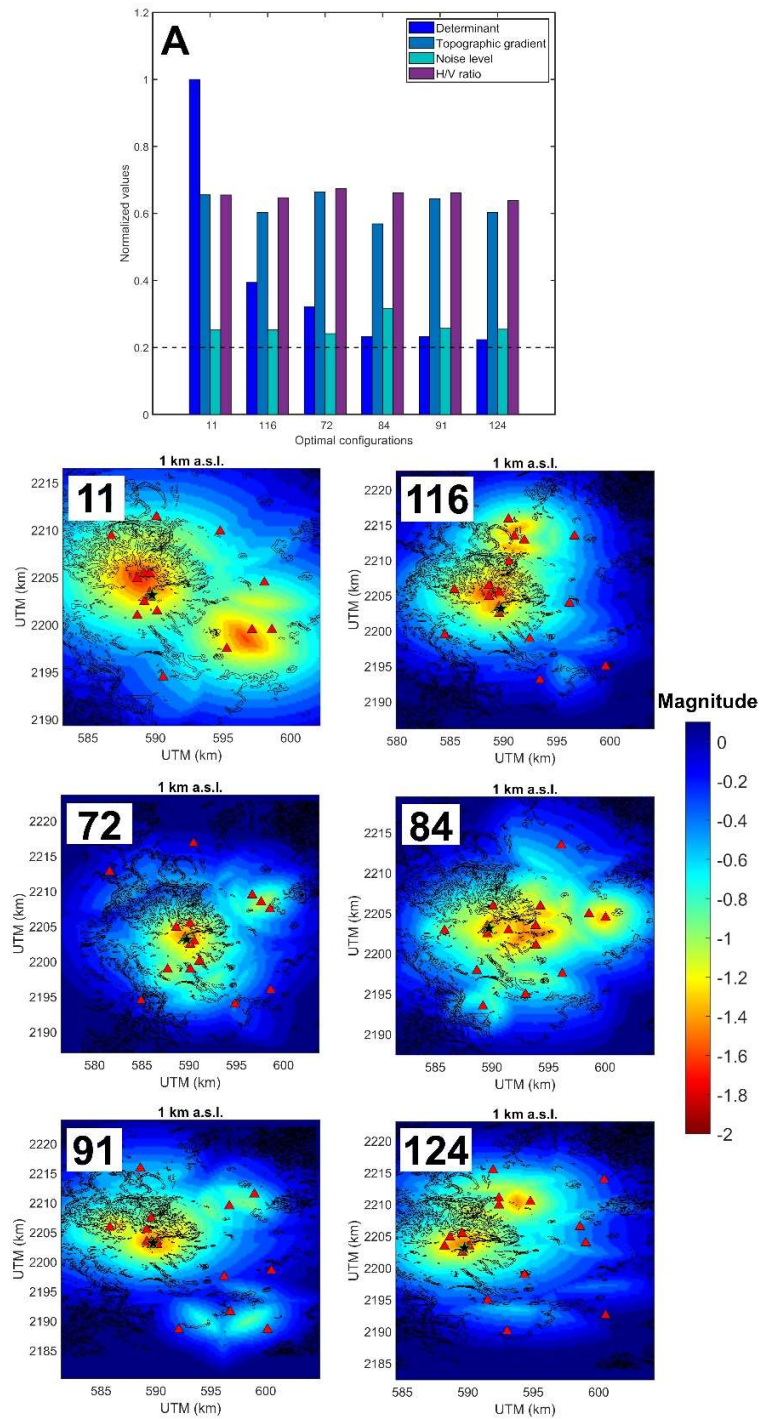


343
 344 Figure 9. Normalized determinants (A), topographic gradients (B), noise levels (C), and H/V
 345 ratios (D) for different seismic network configurations using the 1D velocity model. Dashed
 346 lines are the thresholds or reference values used for the network selection. Yellow stars are
 347 the configurations that meet the threshold parameters whereas green diamonds are the six
 348 best optimal seismic networks selected.

349

350 Although yellow stars pointed seismic configurations with D values suitable for the selection
 351 of a network, the TG and noise levels resulted the main a priori parameters that influenced
 352 their exclusion due to unfavorable conditions related to logistic and/or noisy locations.

353 Another relevant aspect resulted in this test, is the low contribution of the H/V in the
354 ponderation system. This is because the calculated average values are almost the same for
355 all the 174 potential configurations.



356

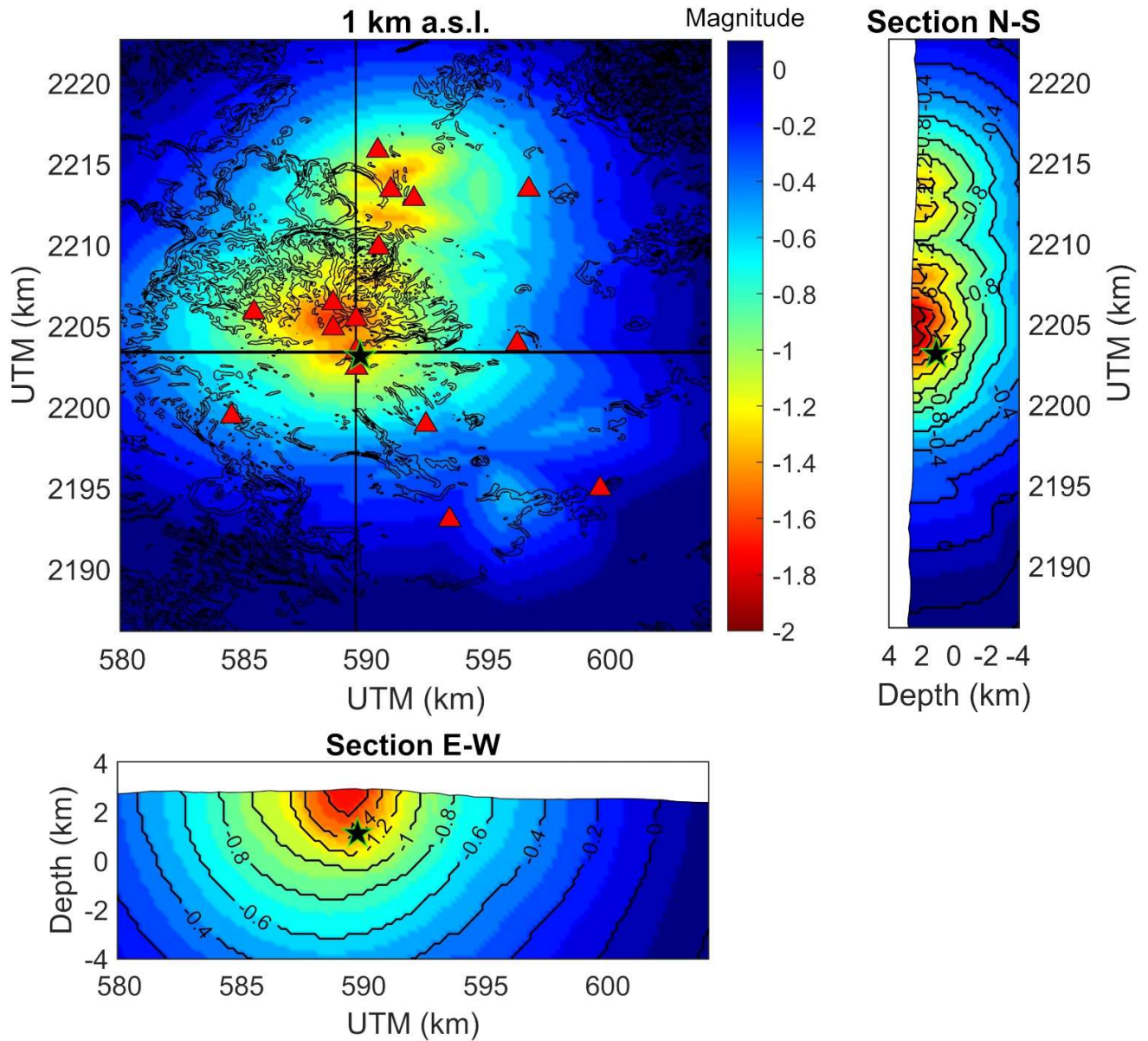
357 Figure 10. Top: Histograms of the six seismic networks selected using the 1D velocity model.
 358 Bottom: Sensitivity maps at 1 km a.s.l. (approx. 1.8 km of depth). Red triangles are the
 359 station locations proposed. Black star is the earthquake position.

360

361 Figure 10 reports the parameters of the 6 networks that have been selected and ordered
362 according to the D value together with the other parameters. Therefore, we analyzed the
363 histogram of each seismic configuration, their spatial distribution, and their sensitivity. Since
364 configuration 11, although reports the best values of D, shows a high heterogeneity of the
365 station distribution and a sensitivity not centered at the location of the targeted event
366 (marked with the black star in figure 10), we discarded it and we preferred the network 116
367 (Figure 11) which displays a better azimuth coverage and a sensitivity more centered on the
368 target region.

369 The map at 1 km a.s.l. (i.e., about 1.8 km of depth) (Figure 11) indicates that this kind of
370 configuration offers the largest sensitivity NW of target region. North-South vertical section
371 shows the spreading of the sensitivity in the north direction and that, events of magnitude of
372 ~ -1.2 or larger can be detected and located at the targeted depths. The east-west section
373 shows the highest sensitivity concentration near the hypothetical hypocentral zone with a
374 maximum detection power of $M \sim -1.7$ in the first km of depth.

375



376

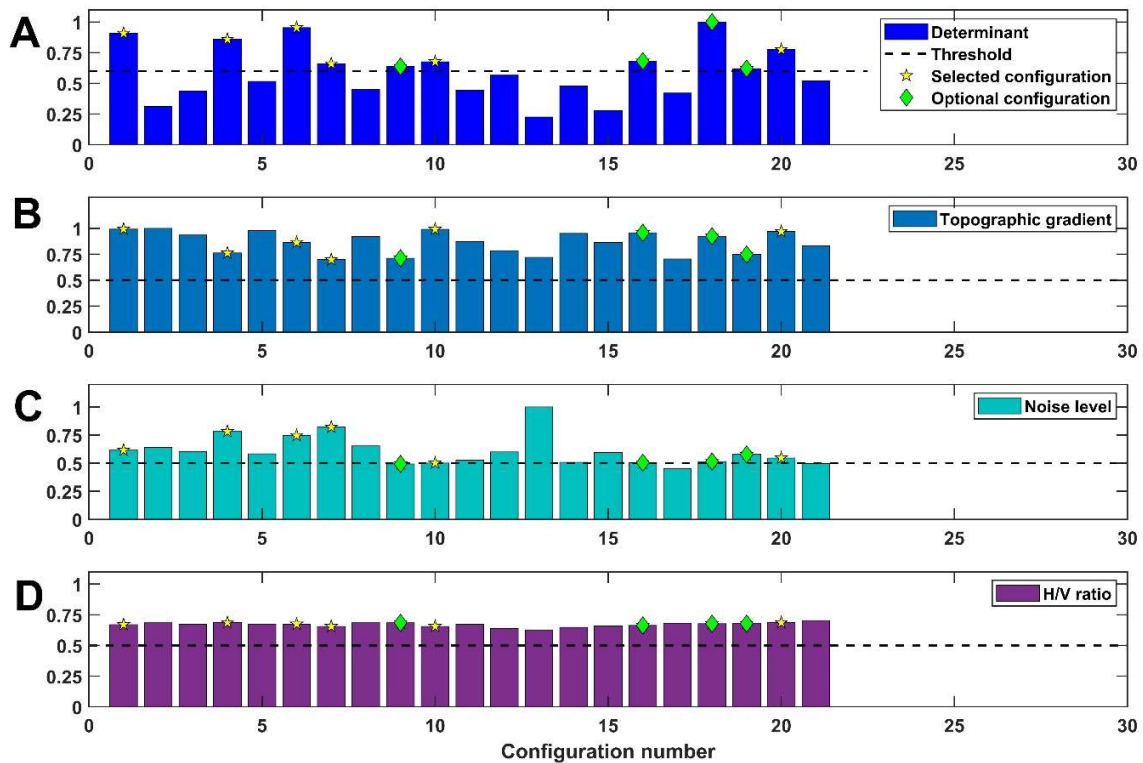
377 Figure 11. Sensitivity map for the seismic network numbered 116 at 1.8 km depth (1 km
 378 a.s.l.) using the 1D velocity model. The magnitude range capable of being detected is
 379 indicated by the color bar, red triangles represent the stations, and the black star the
 380 hypocenter. Vertical and horizontal solid lines indicate North-South and East-West sections.

381

382 The same procedure was applied using the modified version of D-OPTIMAL that allows
 383 direct travel times computation using the 3D velocity models (Figure 12. Normalized

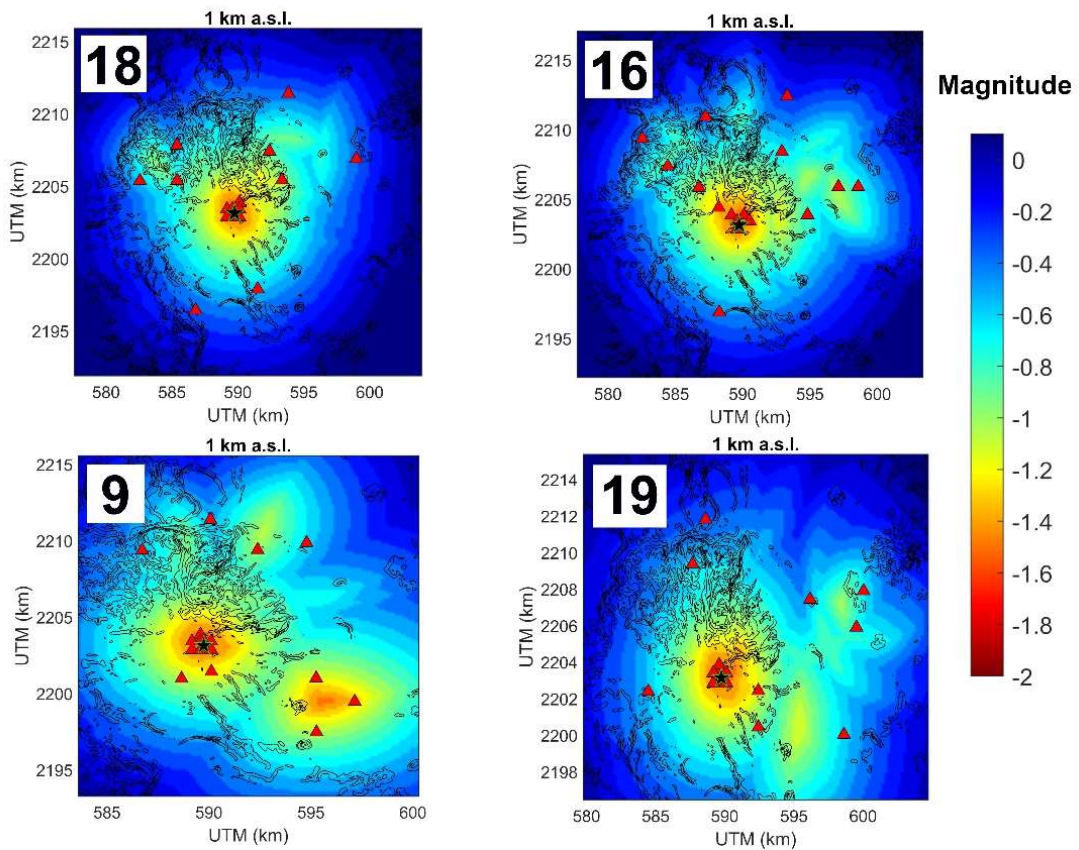
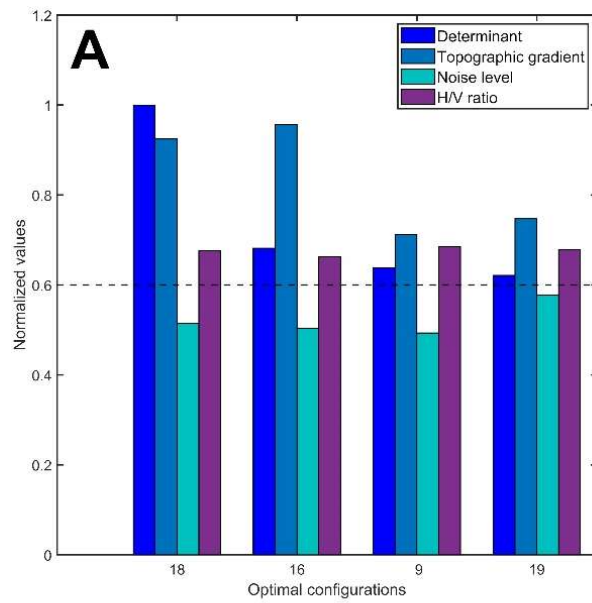
384 determinants (A), topographic gradients (B), noise levels (C), and H/V ratios (D) for
 385 different seismic network configurations using the 1D velocity models. Dashed lines are
 386 the thresholds or reference values used for the network selection. Yellow stars indicate the
 387 configurations that meet the threshold parameters whereas green diamonds are the six
 388 best optimal seismic networks selected.

389). In this case we observed that the possible configurations obtained were only 21. With the
 390 threshold of $D > 0.6$ almost 50% of the total are kept and at least 5 of them have normalized
 391 determinant greater than 0.75, TG > 0.6 , noise level ≥ 0.5 and $H/V \approx 0.6$.



392

393 Figure 12. Normalized determinants (A), topographic gradients (B), noise levels (C), and
 394 H/V ratios (D) for different seismic network configurations using the 1D velocity models.
 395 Dashed lines are the thresholds or reference values used for the network selection. Yellow
 396 stars indicate the configurations that meet the threshold parameters whereas green
 397 diamonds are the six best optimal seismic networks selected.



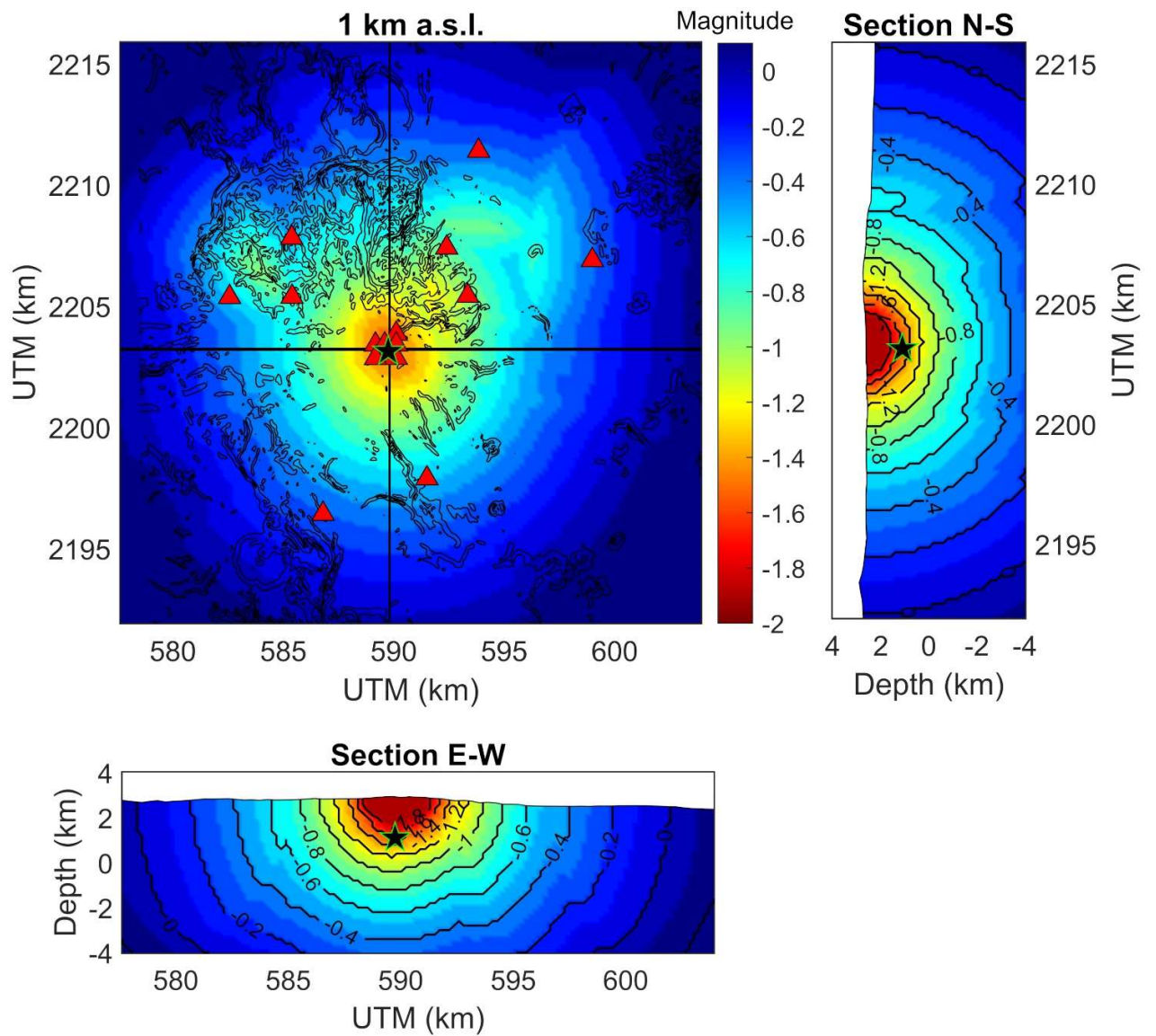
399

400 Figure 12. Histograms of the 4 seismic networks selected as optimal using 3D velocity model
 401 at the top. Resolving distribution for each optimal seismic network with stations (red
 402 triangles) and hypocenter (black star) at the bottom.

403

404 Figure 13 show histogram of the 4 best configurations together with their spatial distribution,
405 and their sensitivity at 1.8 km of depth. In this case we can observe that all the seismic
406 networks selected produce the greatest sensitivity concentrated in the hypocentral region.
407 However, networks 16, 9 and 19 show low D values and a dispersion of the sensitivity in
408 regions different from the one of interest.

409 Map at 1 km a.s.l. of network 18 (Figure 13) suggests a good azimuth coverage in the
410 hypocentral area. North-South and East-West sections show that sensitivity is concentrated
411 in the hypocentral volume. On average, events with $M \geq -1.5$ can be detected and located at
412 the targeted depths in an area with diameter of approximately 5 km.



413

414 Figure 13. Sensitivity test for seismic network number 18 at 2 km depth (1 km a.s.l.) using
 415 the 3D velocity model. The magnitude range capable of being detected is indicated by the
 416 color bar, red triangles represent the stations, and black star the hypocenter. Vertical and
 417 horizontal solid lines indicate North-South and East-West sections.

418

419 **5. Discussions and Conclusions**

420 Design of a seismic network is always a difficult task, especially when the targeted seismicity
421 is of low magnitude such as the one expected in operative geothermal power plants. Most
422 of the existing algorithms are designed to find suitable network configurations without
423 considering valuable a priori information that can make the difference in the selection of the
424 best sites (Toledo *et al.*, 2020; Edwards *et al.*, 2015; Baujard *et al.*, 2018). The standard D-
425 OPTIMAL algorithm resulted a performant and flexible tool to optimize the network
426 configuration at local scale. However, this upgraded version, that allows the direct
427 computation of travel times in 3D models, highlighted how important the lateral
428 heterogeneities of the wavefield are on the planning of the optimized networks. This aspect
429 is often neglected and may lead the operators to potential evaluation errors that may strongly
430 affect the efficiency and the sensitivity of the seismic network.

431 Seismic noise levels resulted in an important information that should be considered to make
432 the a posteriori selection of the possible configurations, demonstrating that a previous
433 campaign aimed at estimating the local fluctuations of this parameter is of great importance
434 for achieving performant networks. Conversely, and surprising, H/V resulted without
435 influence for the site selection. This may be attributed to the fact that the range of
436 frequencies in which most of the pick amplitudes were observed fall outside the frequencies
437 expected for of the microseismicity (>10 Hz).

438 Finally, the decision to add the topographic gradient as constraint in the network selection
439 resulted of great importance to properly plan the logistic of installation. In Acoculco, slopes
440 can reach 80% in several regions making difficult not only the installation but also the
441 subsequent maintenance of the sites.

442 With the approach presented here, further parameters can be easily added in the procedure
443 of the network selection, e.g., geological, and structural maps, phone and

444 telecommunication coverage, route accessibility, etc. All this analysis has the aim to
445 maximize the efficiency of the network lowering the installation and maintenance costs.

446 For the Acoculco volcanic complex, the sensitivity of the designed network shows that
447 events of magnitude of down to -1.1 could be detected and located at depths of around 2
448 km. Although theoretical, this value seems in agreement with the size of small events that
449 have been detected in other geothermal fields equipped with dense surface networks.
450 Indeed, catalogs with magnitude of completeness equal to 0 are currently generated with
451 the seismicity detected in the geothermal site of Landau at 6-8 km of depth (Vasterling and
452 Vegler, 2017); earthquakes with $M \geq -0.6$ and depth of 3 km are present in the catalogue of
453 Rittershoffen geothermal site (Meyer *et al.*, 2017) and at the Habanero and Paralana sites
454 (Australia), where the microseismicity occurs at more than 4 km of depth, earthquakes with
455 $M \geq -0.8$ are located (Riffault *et al.*, 2018). Therefore, the SENSI algorithm is providing
456 estimations that seem to reflect the real potential sensitivity of the network.

457 Finally, thanks to the network designed in this manuscript, 10 stations were installed in 2021
458 and allowed to record the seismic activity associated with the hydraulic stimulation realized
459 to enhance the permeability of the reservoir. 57 events with duration magnitude ranging
460 between -1.6 and -0.5 were recorded during and after an injection of fluids (Figuroa-Soto
461 *et al.*, in submission). Events were mainly located at about 1.2 – 1.5km of depth and the
462 epicentral errors were estimated on 0.14km for most of the induced events (Figuroa-Soto
463 *et al.*, in submission).

464

465 **7. Data and resources**

466 Seismic noise records used in this study were collected as part of the Work Project 5.2 of
467 GEMex using Trillium Compact 120 s instruments. Digital Elevation Model (DEM) was

468 obtained from Instituto Nacional de Estadística y Geografía de México at
469 www.inegi.org.mx/app/geo2/elevacionesmex/

470 **Acknowledgment**

471 This work is performed in the framework of the Mexican European consortium GeMex
472 (Cooperation in Geothermal energy research Europe-Mexico, PT5.2 N: 267084 funded by
473 CONACyT-SENER: S0019, 2015-04, and of the joint agreement between UNAM and INGV
474 on the development of seismological research of volcanic and geothermal field (N:44753-
475 1023-22-IV-16/1).

476

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