

Measuring the seismic risk along the Nazca-Southamerican subduction front: Shannon entropy and mutability

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Abstract. Four geographical zones are defined along the trench that is formed due to the subduction of the Nazca Plate underneath the South American plate; they are denoted A, B, C and D from North to South; zones A, B and D had a major earthquake after 2010 (Magnitude over 8.0), while zone C has not, thus offering a contrast for comparison. For each zone a sequence of intervals between consecutive seisms with magnitudes ≥ 3.0 is set up and then characterized by Shannon entropy and mutability. These methods show correlation after a major earthquake in what is known as the aftershock regime, but show independence otherwise. Exponential adjustments for these parameters reveal that mutability offers a wider range for the parameters characterizing the recovery compared to the values of the parameters defining the background activity for each zone before a large earthquake. It is found that the background activity is particularly high for zone A, still recovering for zone B, reaching values similar to those of zone A in the case of zone C (without recent major earthquake) and oscillating around moderate values for zone D. It is discussed how this can be an indication for more risk of an important future seism in the cases of zones A and C. The similarities and differences between Shannon entropy and mutability are discussed and explained.

I. INTRODUCTION

A recent advance on information theory techniques, with the introduction of the concept of mutability (Vogel et al., 2017a), opens new ways of looking at the tectonic dynamics in subduction zones. The main goals of the present paper are five-fold: 1) To establish the similarities and differences between mutability and the well-known Shannon entropy to deal with seismic data distributions; 2) To find out which of the aforementioned parameters gives an advantageous description of the subduction dynamics in order to discern different behaviors along the subduction trench; 3) To apply this description to characterize the recovery regime after a major earthquake; 4) To use this approach to establish background activity levels prior to major earthquakes; 5) To apply all of the above to different geographical zones looking for possible indications for regions with indicators pointing for possible future major earthquakes.

Several statistical and numeric techniques have been proposed to analyze seismic events. For a recent review we refer the interested reader to the paper by de Arcangelis et al. and references therein (de Arcangelis et al., 2016). We shall concentrate here in the use of Shannon entropy and mutability which are introduced and discussed in the next paragraphs; they will be applied to the intervals between consecutive seisms in each region.

Data may come from a variety of techniques used to record variations in some earth parameters like infrared spectrum recorded by satellites (Zhang et al., 2019), earth surface displacements measured by Global Positioning System (GPS) (Klein et al., 2018), variations of the earth magnetic field (Cordaro et al., 2018; Venegas-Aravena et al., 2019), changes in the Seismic Electric Signals (Varotsos et al., 1984a) 1984b); Varotsos et al., 1986; Varotsos et al., 1991; Varotsos et al., 1993; Varotsos et al. 2001; Varotsos et al., 2005; Sarlis et al., 2018; Varotsos et al. 2011c), Varotsos et al., 2019), among others. In the present work we make use of the seismic sequence itself as in natural time analysis (see, e.g., Varotsos et al. 2001; Varotsos et al. 2002; Varotsos et al. 2011a), 2011b)) analyzing the time intervals between filtered consecutive seisms.

Shannon entropy is a useful quantifier for assessing the information content of a complex system (Shannon, 1948). It

53 has been applied to study a variety of nonlinear dynamical phenomena such as magnetic systems, the rayleigh-Bernard
 54 convection, 3D MHD model of plasmas, turbulence or seismic time series, among others (Crisanti et al., 1994; Xi et
 55 al., 1995; Cakmur et al., 1997; Chian et al., 2010; Miranda et al., 2015; Manshour et al. 2009).

56 Analysis of the statistical mechanics of earthquakes can provide a physical rationale to the complex properties of
 57 seismic data frequently observed (Vallianatos et al., 2016). A number of studies have shown that the complexity
 58 in the content information of earthquakes can be elucidated by Shannon entropy. Telesca et al. (2004) applied
 59 Shannon entropy to study the 1983-2003 seismicity of Central Italy by comparing the full and the aftershock-depleted
 60 catalogues, and found a clear anomalous behaviour in stronger events, which is more evident in the full catalogue
 61 than in the aftershock-depleted one. De Santis et al. (2011) used Shannon entropy to interpret the physical meaning
 62 of the parameter b of the Gutenberg-Richter law that provides a cumulative frequency-magnitude relation for the
 63 statistics of the earthquake occurrence. Telesca et al. (2012) studied the interevent-time and interevent-distance series
 64 of seismic events in Egypt from 2004 to 2010, by varying the depth and the magnitude thresholds.

65 Telesca et al. (2013) combined the measures of the Shannon entropy power and the Fisher information measure to
 66 distinguish tsunamigenic and non-tsunamigenic earthquakes in a sample of major earthquakes. Telesca et al. (2014)
 67 applied the Fisher-Shannon method to confirm the correlation between the properties of the geoelectrical signals
 68 and crust deformation in three sites in Taiwan. Nicolis et al. (2015) adopted a combined Shannon entropy and
 69 wavelet-based approach to measure the spatial heterogeneity and complexity of spatial point patterns for a catalogue
 70 of earthquake events in Chile. Bressan et al. (2017) used Shannon entropy and fractal dimension to analyze seismic
 71 time series before and after eight moderate earthquakes in Northern Italy and Western Slovenia.

72 In the last two decades the concept of "natural time" for the study of earthquakes has been introduced by Varotsos
 73 et al. (Varotsos et al., 1984; Varotsos et al. 1991; Varotos et al. 1993; Varotsos et al., 2011) This method proposes a
 74 scaling of the time in a time series, by using the index $\chi_k = k/N$, where k indicates the occurrence of the k -th event
 75 and N is the total number of the events in a time series. For example, for seismic time series the evolution of the pair
 76 (χ_k, M_{0k}) is following, where M_{0k} is proportional to the energy released in an earthquake, finding interesting results
 77 in the Seismic Electric Signal previous to an earthquake occurrence (Sarlis et al., 2013; Sarlis et al., 2015; Sarlis et
 78 al., 2018a; Sarlis et al. 2018b; Rundle et al., 2018). An entropy has been defined in natural time (Varotsos et al.,
 79 2011b) -being dynamic and not static (Varotsos et al. 2003; Varotsos et al. 2007)- by $S \equiv \langle \chi \ln(\chi) \rangle - \langle \chi \rangle \ln \langle \chi \rangle$, and
 80 has been very useful in the analysis of global seismicity (Rundle et al., 2019).

81 On the other hand, the method based on information theory (Luenberg, 2006; Cover et al., 2006; Roederer 2005)
 82 was introduced a decade ago when it was successfully used to detect phase transitions in magnetism (Vogel et al.,
 83 2009; Vogel et al., 2012; Cortez et al., 2014). Then a new data compressor was designed to recognize compatible data,
 84 namely, data based on specific properties of the system. This method required comparing strings of fixed length and
 85 starting always at the same position within the digits defining the stored record. For this reason it was named "word
 86 length zipper" (wlzip for short) (Vogel et al., 2012). The successful application of wlzip to the 3D Edwards-Anderson
 87 model came immediately afterwards, where one highlight was the confirmation of a reentrant transition that is elusive
 88 for some of the other methods (Cortez et al., 2014). Another successful application to critical phenomena was for the
 89 disorder to nematic transition that occurs for the depositions of rods of length k (in lattice units) on square lattices:
 90 for $k \geq 7$ one specific direction for depositions dominates over when deposition concentration overcomes a critical
 91 minimum value (Vogel et al., 2017b).

92 But wlzip proved to be useful not only for the case of phase transitions. It has been used in less drastic data
 93 evolution revealing different regimes or behaviors for a variety of systems. The first of such applications were in
 94 econophysics dealing with stock markets (Vogel et al., 2014) and pension systems (Vogel et al., 2015). The alteration
 95 of the blood pressure parameters was also investigated using wlzip (Contreras et al., 2016). At a completely different
 96 time scale the time series involved in wind energy production in Germany was investigated by wlzip yielded recognition
 97 of favorable periods for wind energy (Vogel et al., 2018).

98 The first application of wlzip to seismology came recently using data from a Chilean catalogue finding that wlzip
 99 results clearly increase several months prior to large earthquakes (Vogel et al., 2017a), thus being in accordance
 100 with natural time analysis which reveals (Varotsos et al., 2011b) that before major earthquakes there is a crucial
 101 time scale of around a few to several months in which changes in the correlation properties of physical quantities
 102 like seismicity or crustal deformation are observed. This early application of wlzip intended to establish the method
 103 without attempting further analyses or comparison with other methods or to compare possible seismic risk among
 104 regions, which are among the aims of the present paper.

105 In the present paper we make a new analysis comparing results from mutability and Shannon entropy applied to
 106 data of seismic data along the subduction front parallel to the Chilean coast. The complete tectonic context shows
 107 an active and complex seismic region for all the coast, driven by the convergence of the Nazca plate and the South
 108 American plate, at a rate of 68 mm yr^{-1} (Altamimi et al., 2007) approximately. In the last 100 years, many large
 109 earthquakes have been localized in the shock between these two plates, such as Valparaíso 1906 ($M_w=8.2$), Valdivia
 110 1960 ($M_w=9.6$), Cobquecura 2010 ($M_w = 8.8$), Iquique 2014 ($M_w=8.2$), and Illapel 2015 ($M_w =8.4$). So, this zone

111 is an attractive source for studying seismic activity associated to large earthquakes. But although the dynamics
 112 along the Chilean coast may be dominated by the interaction between these two plates, various works have pointed
 113 out variations along the coast which may yield information about the details of that interaction. For instance, the
 114 coupling between these two plates has been studied by Metois et al. (Metois et al., 2012; Metois et al. 2013) in the
 115 last years, concluding that the subduction area has alternated zones of high and low coupling (Metois et al., 2012;
 116 Metois et al., 2013). This suggests that it is interesting to apply novel nonlinear techniques to study such variability.
 117 Here, we propose new ways to characterize some of the various dynamics that may be present along the subduction
 118 zone in this trench. In order to do that, we will consider four regions along the coast of Chile characterizing them
 119 mainly by their latitudes.

120 The paper is organized in the following way. Next Section is about methodology dealing with the data and
 121 parameters to be measured. Section 3 presents the results discussing them and comparing the alternative methods.
 122 Section 4 is devoted to conclusions.

123 II. METHODOLOGY

124 A. Data organization

125 Earthquakes originated in the subduction zone of the Nazca plate underneath the South American plate have been
 126 recorded, interpreted and stored in several data seismic data banks. In the present study we shall use the data
 127 collected by the Chilean National Seismic Centre (Centro Sismológico Nacional: CNS) (Web, 2019), which are very
 128 accurate regarding the location of the epicenters. In particular, we have used a seismic data set collected from March
 129 2005 until March 2017, containing 22 697 events, distributed along the coast of Chile, from Arica in the far north up
 130 to Temuco in the south of Chile. These data are freely available through CNS (www.sismologia.cl).

131 In order to analyze the spatial evolution of the mutability and Shannon entropy along this part of the subduction
 132 zone, we have focused our attention on four regions defined below. For each region we have corroborated that the
 133 Gutenberg-Richter law holds, finding a common completeness magnitude of $M_w = 3.0$. Thus, all the following analysis
 134 will be made using only the seismic events with magnitudes of at least $M_w = 3.0$. We have considered seismic data
 135 sequences for four specific geographical zones: three of them include one earthquake over 8.0 occurring after 2010,
 136 and we have added for comparison a neighboring area with no such large earthquake during several recent years.

137 Starting from the North, the zones are the following: A) around the earthquake near Iquique (2014; $M_w = 8.2$)
 138 including 6891 events; B) around the earthquake near Illapel (2015; $M_w = 8.4$) including 6626 events, C) a quieter
 139 geographical region (calm zone) at the center of Chile (where the greatest seismic event is $M_w = 6.5$), including 2824
 140 events; and D) around the earthquake in Cobquecura (2010, $M_w = 8.8$) including 6356 events. The observation time
 141 is from January 1, 2011 to March 23, 2017 for zones A, B and C, while it is from January 1, 2009 to March 23, 2017
 142 for zone D (no special reason for this last date). We extended the analysis in the case of zone D to include the regime
 143 previous to the big earthquake of 2010. Since the analysis is either relative to the size of the sample or dynamical
 144 along the series this difference should not affect the discussion below.

145 All zones have a similar geographical extension with some singularities that we explain here. Regions A, B, and D
 146 have latitudes centered at the epicenter of the largest earthquake of each zone; the span in longitude is the same for
 147 these zones. Zone A misses the 4.0° spans in latitude of zones B and D, since the Chilean catalogue ends at -17.926°
 148 which is the northern limit for this zone (for homogeneity of the data we do not mix catalogues). The largest span
 149 for the zones under study is 4 degrees in each direction; it was chosen as a mean to consider enough data within
 150 each zone in order to have good statistics. On the other hand, zone C was chosen to include a populated area of the
 151 country but with no earthquake over 8.0 and showing less important activity than previous ones. Details are given
 152 in Table I, and are illustrated in Fig. 1. As it can be seen in this map zone C overlaps with both B and D: to avoid
 153 getting close to the epicenter of the main earthquake in zone D, zone C was shortened in its South extension. So
 154 the data catalogues have been filtered by latitude, longitude and magnitude. At this point we do not filter by depth
 155 which should not greatly influence the comparison among zones since it is a common criteria for all of them.

156 Originally the study contemplated zones A, B and D only concentrating on the main three earthquakes of the
 157 decade. In spite the main purposes of this work are accomplished by looking at zones A, B, and D, only, we decided
 158 to broaden the geographical coverage a bit. The area in between zones B and D could be unstable as subductions
 159 took place both south and north of it. Eventually, the subduction here is stuck and it could be interesting to find
 160 out the behavior of this densely populated zone. We paid the price of overlapping with the neighboring zones but
 161 special care has been taken as to avoid in zone C the epicenters and immediate vicinity of the major earthquakes and
 162 to initiate the analysis in 2011, several months after the largest earthquake included in this study.

163 For all seismic events characterized above we calculate the interval in minutes (rounding off seconds) between
 164 consecutive events. Then a vector file is produced storing the consecutive intervals between these seisms within each

| Zone | Latitudes | | Longitudes | | Main Earthquake | | | |
|------|-----------|----------|------------|---------|-----------------|------|---|----|
| | N | S | W | E | Magn | Y | M | D |
| A | -17.926° | -21.572° | -75.00° | -68.00° | 8.2 | 2014 | 4 | 1 |
| B | -29.637° | -33.637° | -75.00° | -68.00° | 8.4 | 2015 | 9 | 16 |
| C | -32.700° | -35.500° | -74.00° | -69.00° | (6.5) | 2012 | 4 | 17 |
| D | -34.290° | -38.290° | -75.00° | -68.00° | 8.8 | 2010 | 2 | 27 |

TABLE I. Geographical definition of the 4 zones considered in this study. The strongest seismic event in each zone is identified at the end. Zone C lacks a very strong seism during recent years which is indicated by the use of parenthesis for the strongest seism here. The geographical coordinates and time windows are explained and defined in the text.

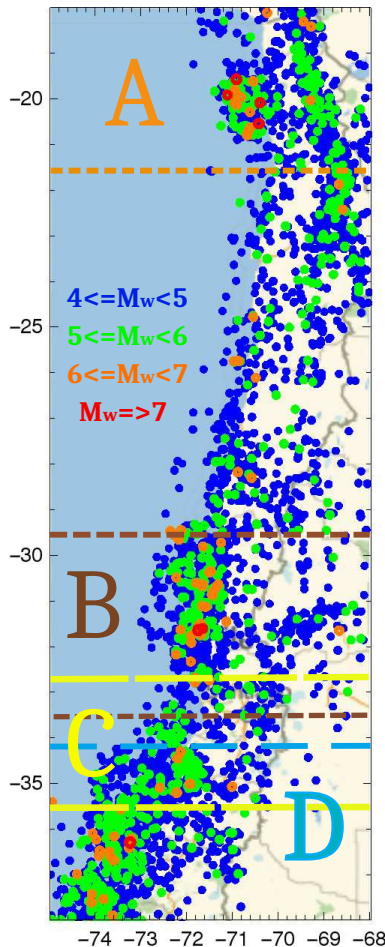


FIG. 1. Map showing the seismic events with magnitudes greater than M_w 4.0 and the division in four geographical zones A, B, C, and D defined in Table I. The seismic events are shown by circles using the following color code according to magnitude: between 4.0 and 4.9 in blue, between 5.0 and 5.9 in green, between 6.0 and 6.9 in orange, and for magnitude equal or greater than M_w 7.0 in red.

165 zone. These are the files to be analyzed by Shannon entropy and mutability. Notice that there is a close similarity
 166 between this and the “natural time” analysis discussed in the Introduction, since the resulting vector is indexed by the
 167 event number. In our case, the value of each vector component is the interevent time itself, which has been also used
 168 in the natural time analysis of electrocardiograms by considering the interevent time between consecutive heartbeats
 169 (Varotsos et al., 2007). Registers in the vector storing the information in our analysis are the interevent intervals,
 170 thus temporal information is still kept in the time series.

171 Let us consider histograms for interval distributions for each zone with consecutive bins of 60 minutes each. Per-
 172 centage of abundance $G_{K,i}$ of intervals are obtained for the i -th bin for the different zones Z : A, B, C, or D. Figure 2
 173 shows the histograms corresponding to the distribution functions $G_{Z,i}$. It can be immediately seen that shorter in-
 174 tervals have been more frequent in zones D and B, while they are less frequent in the C zone. Zone A presents and

175 intermediate presence of small intervals. This different frequency for small seisms finds an explanation in the presence
 176 of large earthquakes in *B* and *D* followed by large aftershock periods, while in zone *A* the aftershock period (and
 177 the number of short intervals) was very short as we will see in detail below; zone *C* does not include any aftershock
 178 period so short intervals are less frequent here.

179 To better establish the role of the aftershocks we compared the number of seisms (3.0+) on the month prior to the
 180 largest earthquake in the zone and the number of seisms in the same zone during the month after it. For zone *B* these
 181 numbers are 49 and 1439 respectively; for zone *D* these numbers are 11 and 1006 respectively. This comparison with
 182 the background assures the large production of aftershock seisms. This comparison is not possible for zone *A* since
 183 the main earthquake came during the aftershock period of a large precursor as discussed below. In addition we did
 184 a restricted geographical analysis for the month after each main earthquake comparing the number of seisms in the
 185 full zone to the number of seisms in a smaller zone of two degrees in each direction around the epicenter of the main
 186 seism. For zone *A* we have 939 and 736; for zone *B* 1439 and 1147; for zone *D* 1006 and 787. It is clear that the
 187 largest amount of seisms occurred in the vicinity and in the days after the largest earthquakes in each zone.

188 These plots are presented in a semilog scale to better appreciate any possible decay law. However, no general
 189 behavior is found evidencing the different dynamics among the zones. Zone *A* presents a linear decay in this scale
 190 while zone *C* is the more irregular one. On the other hand, zone *D* departs quite clearly from a linear dependence
 191 evidencing the lack of saturation several years after the huge earthquake of 2010. Scaling algorithms have been
 192 suggested to deal with the time series on the interevent sequence (Lippiello et al. 2012) but in the present study we
 193 leave the series with the natural interevent intervals to analyze them by means of information theory as proposed
 194 below.

195 We can increase the precision of the data treatment below by the use of a database providing more positions for the
 196 numeric recognition (Vogel et al., 2017a). This was achieved by choosing a numerical basis providing more positions
 197 to be matched. So the data files used both for Shannon entropy and for mutability used digits corresponding to a
 198 quaternary numerical basis.

199

B. Shannon entropy

200 Let Δ_i , $i = 1, \dots, N$ be the full sequence of time intervals between consecutive seisms in any of the already defined
 201 zones. The time that the i -th event occurred can be obtained by $t_i = t_0 + \sum_{j=1}^i \Delta_j$, where t_0 is the start time of the
 202 dataset. The Shannon entropy for Δ_i within a sliding window of size ν events can be calculated as follows

$$H(t_i, \nu) = - \sum_{j=i}^{i+\nu} p_j \ln(p_j) \quad (1)$$

203 where p_j is the probability distribution function of the time intervals within the time window, which can be determined
 204 by constructing a normalized histogram

$$p_j = g_j / \nu \quad (2)$$

205 where g_j is the number of times Δ_j occurs within the sliding window. The appropriate value for ν depends on the
 206 kind of data under consideration. Thus, for instance, application to this method to the minute variations of the
 207 stock market yielded $\nu = 30$ (half-an-hour) as a significant time window to establish tendencies in this economical
 208 activity (Vogel et. al 2014). In the case of seismic sequences ordered by real time, time windows between $\nu = 24$ and
 209 $\nu = 96$ were investigated finding that $\nu = 24$ is appropriate to deal with seismic activity (Vogel et. al 2017a). More
 210 details about the choice of ν can be found in these references in particular in Fig. 3 of the last reference. So, for all
 211 applications below we use $\nu = 24$.

212

C. Data recognizer

213 We use here the same dynamical data window of ν events used for the calculation of Shannon entropy. The weight
 214 in bytes of the sequence of ν events beginning at natural time i will be denoted by $w(t_i, \nu)$. This partial sequence is
 215 processed by wzip producing a new sequence that needs $w^*(t_i, \nu)$ bytes of storage. The relative dynamic information
 216 content of this time series of seismic events is known as mutability, which is defined as

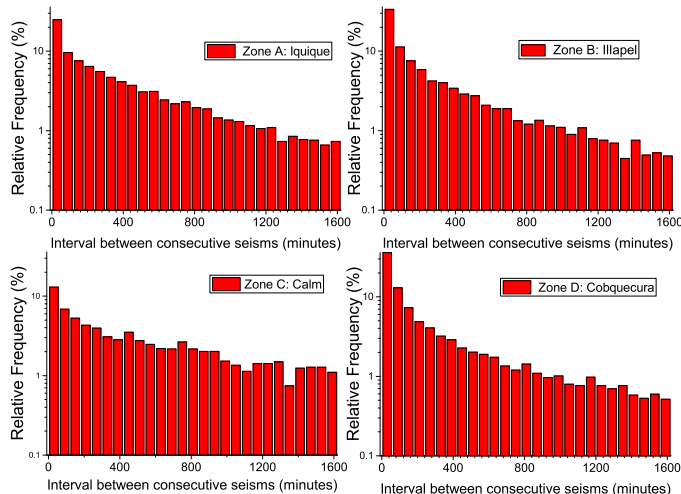


FIG. 2. colorcyan Distribution functions $G_{Z,i}$ ($Z = \{A, B, C, D\}$) for intervals between two consecutive seismic events.

$$\mu(t_i, \nu) = \frac{w^*(t_i, \nu)}{w(t_i, \nu)}, \quad (3)$$

217 where w^* is the size in bytes of the compressed dataset associated to the time intervals Δ_j within the time window
 218 of ν events.

219 As already pointed out $\nu = 24$ for all mutability calculations below. The typical value of $w(t_i, \nu)$ for the files
 220 measured here is 144 bytes, while the values of $w^*(t_i, \nu)$ vary roughly between 100 to 400 bytes thus leading to
 221 variations in mutability. Mutability is a relative measure of the information content present in a file: monotonic
 222 sequences give low mutability values; chaotic sequences (like those emanating from phase transitions) give high
 223 mutability values. Its dynamic response is advantageous to detect information content even when other methods
 224 fail; an example of this is the Edwards-Anderson model where spin-glass transitions are revealed by mutability in
 225 spite magnetization measurements fail (Cortez et al. 2014). To better illustrate this concept we include an Appendix
 226 calculating the mutability for 4 different sequences of 24 events.

227 Two comments are in order: First, wzip uses compressor algorithms to recognize information but this does not
 228 mean that $w^*(t_i, \nu)$ should be less than $w(t_i, \nu)$; Second, the value of wzip depends both on the interval distribution
 229 but also on the time sequence of the intervals, which has been also used in the natural time analysis of the consecutive
 230 heartbeat intervals, while Shannon entropy depends only on the distribution (Varotsos et al., 2007). Thus, the sooner
 231 a value in the sequence is repeated, the lower the value of $\mu(t_i, \nu)$ is (Vogel et al., 2012; Cortez et al., 2014). This fact
 232 marks a difference between these two parameters as we will see below.

233 III. RESULTS

234 Figs. 3, 4, 5 and 6 present the Shannon entropy (top) and mutability (bottom) for data corresponding to geographi-
 235 cal areas A, B, C and D respectively according to Table I and Fig. 1. The numeric recognition was done for the data
 236 files (intervals in minutes between successive seisms) in quaternary basis both for Shannon entropy and mutability.
 237 All registers have the same number of digits filling with zeroes all empty positions previous to first significant digit,
 238 The matching to recognize the same data register started at position 4 and was done for three digits including the
 239 fourth position (Vogel et al., 2017a). All zones were treated with the same precision.

240 In the upper panel the abscissa "Time" corresponds to real time t_i (as defined in Section II. B) beginning on January
 241 1, 2011 for zones A, B and C, or on January 1, 2009 for zone D. In the lower panel the abscissa labelled "Events"
 242 corresponds now to the succession of filtered seisms identified by the same label i used to define t_i . The ordinates are
 243 the same in both panels.

| Event | Zone A | | | Zone B | | | Zone C | | | Zone D | | |
|-------|--------|---|----|--------|----|----|--------|----|----|--------|----|----|
| | Y | M | D | Y | M | D | Y | M | D | Y | M | D |
| 1000 | 2012 | 2 | 29 | 2012 | 10 | 16 | 2012 | 5 | 22 | 2010 | 3 | 22 |
| 2000 | 2013 | 6 | 2 | 2014 | 8 | 19 | 2014 | 10 | 22 | 2010 | 5 | 17 |
| 3000 | 2014 | 3 | 24 | 2015 | 9 | 19 | - | - | - | 2010 | 9 | 25 |
| 4000 | 2014 | 4 | 26 | 2015 | 10 | 14 | - | - | - | 2011 | 7 | 30 |
| 5000 | 2015 | 1 | 6 | 2016 | 1 | 28 | - | - | - | 2012 | 12 | 30 |
| 6000 | 2016 | 3 | 7 | 2016 | 9 | 1 | - | - | - | 2015 | 12 | 15 |

TABLE II. Equivalence of the milestones for natural time in thousand of events in terms of real date: year (Y), month (M) and day (D) for figures 3, 4, 5, and 6.

244 In the upper panel the aftershock behavior is concealed by the large activity in the short time after a large quake,
 245 while in the lower panel it is easier to see the aftershock sequence although the large quiet periods look now more
 246 compressed. Earthquakes over a certain magnitude (as given in the inset for each zone) are marked by a star. The
 247 empty square (A, B, and D only) identifies the largest earthquake with magnitude greater than $M_w = 8.0$ within that
 248 area as listed in Table I.

249 To facilitate the interpretation of these figures and the interrelation between both abscissa axes in each figure, Table
 250 II interprets the actual real time for the milestones 1000, 2000,6000 events, for the four zones. Date is given by
 251 year (Y), month (M), and day (D).

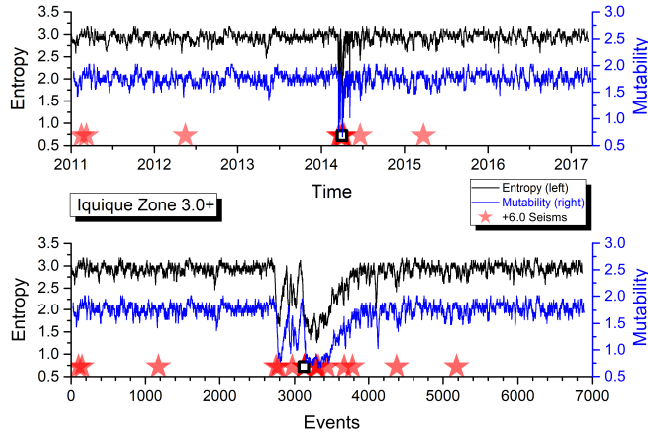


FIG. 3. Shannon entropy and mutability as functions of time for the seismic activity of the A zone. The open star marks the position of the earthquake identified in Table I. The abscissa in the upper panel corresponds to real time t_i while in the lower panel it represents natural time or successive events (filtered seisms) denoted by the order label i (Figs. 4, 5, and 6 use the same procedure).

252 As it can be observed, both H and μ present a similar behavior for the data in the four areas. Immediately
 253 after a large shock both indicators sharply decrease due to the short intervals between consecutive aftershock quakes
 254 thereafter.

255 The average activity level is relatively constant before a major earthquake and later on after the aftershocks have
 256 disappeared. However, such activity level is not the same for all the areas which is an indication of different response
 257 to similar phenomena which deserves particular attention and it will be further investigated below.

258 To better appreciate the correlation between H and μ we study the out-of-phase correlations defined as

$$C_H(\ell) = \frac{1}{(N - 2m - 1)\sigma_H\sigma_\mu} \sum_{i=m+1}^{i=N-m} [H(i) - \bar{H}][\mu(i - \ell) - \bar{\mu}] \quad (4)$$

$$C_\mu(\ell) = \frac{1}{(N - 2m - 1)\sigma_H\sigma_\mu} \sum_{i=m+1}^{i=N-m} [H(i - \ell) - \bar{H}][\mu(i) - \bar{\mu}] \quad (5)$$

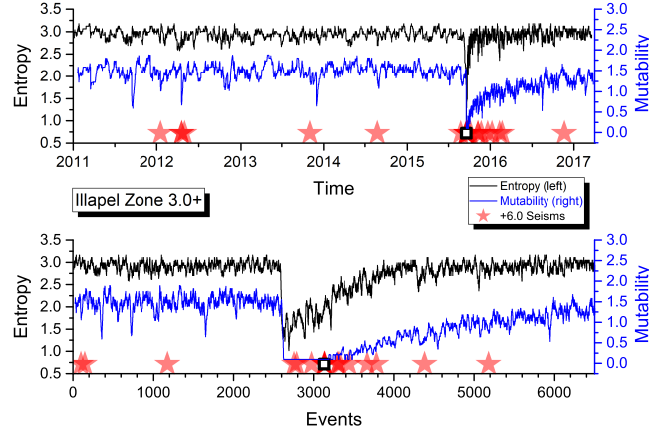


FIG. 4. Shannon entropy and mutability as functions of real time (top) and natural time (or sequence of events, bottom) for the seismic activity of the B zone. The open star marks the position of the earthquake identified in Table I.

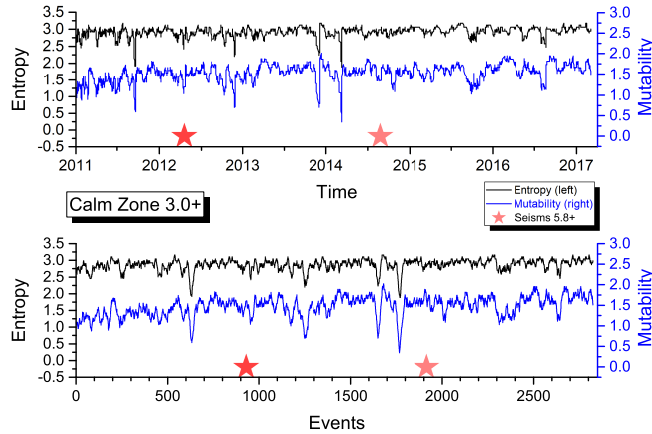


FIG. 5. Shannon entropy and mutability as functions of real time (top) and natural time (or sequence of events, bottom) for the seismic activity of the C zone.

259 where ℓ is the phase difference measured in terms of number of events separating the measurement of one parameter
 260 with respect to the other and $m = 50$ is the range or maximum phase difference in either sense considered here. This
 261 value is entirely empirical looking for a flat behavior of previously defined correlations. From Fig. 7 it may appear
 262 that $m = 30$ could be enough but we decided to explore a bit further to make sure curves are already tending to a
 263 flat behavior. Previous equations represent the average over the $(N - 2m - 1)$ possible equivalent ranges within the
 264 series on N registers. In addition σ_H and σ_μ represent the standard deviations of H and μ through the N events
 265 respectively.

266 The out-of-phase correlation between Shannon entropy and mutability is presented in Fig. 7: it was found that in
 267 general full correlation is lost after about 20 events. A general prevalence is observed in the form of a tendency towards
 268 a constant behavior far from the maximum: a value around 0.75 in the wings of zone B (top panel) and towards 0.15
 269 for the zone C (middle panel). Similar figures were analyzed for zones A and D with prevalence values near 0.75
 270 and 0.57 respectively. To test if these prevalence correlations are due to the aftershock regimes a reevaluation of the
 271 out-of-phase correlation was done for the D zone restricted to results of Shannon entropy and mutability obtained
 272 after January 1, 2013, thus diminishing the effect of the aftershock regime; these results are also shown in Fig. 7 (lower
 273 panel). So the main correlation between Shannon entropy and mutability is obtained during the aftershock period.
 274 On the other hand the out-of-phase correlation tend to be completely lost during periods without the influence of this
 275 regime. This is a first indication for partial independence between Shannon entropy and mutability.

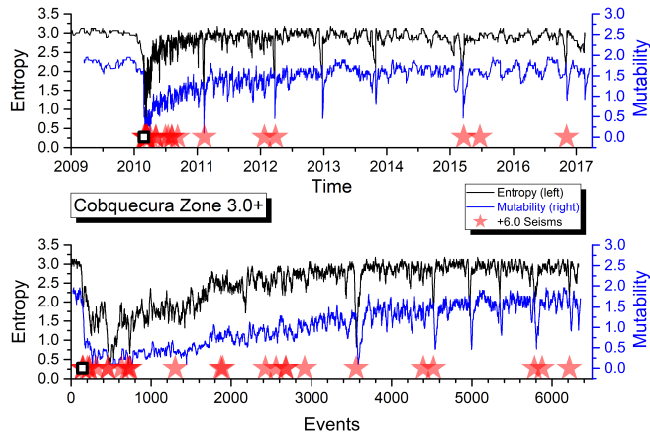


FIG. 6. Shannon entropy and mutability as functions of real time (top) and natural time (or sequence of events, bottom) for the seismic activity of the D zone. The open star marks the position of the earthquake identified in Table I.

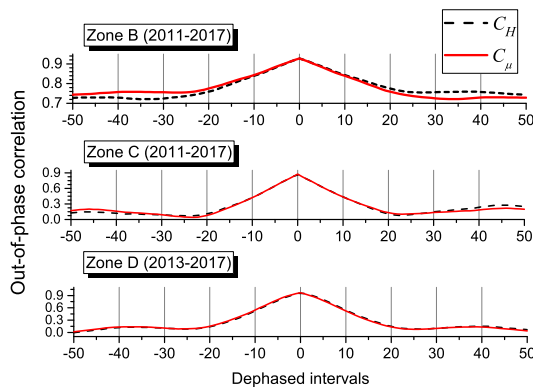


FIG. 7. Out-of-phase correlations. Upper panel: B zone data including aftershock regime (similar ones are obtained for zones A and D with aftershock regimes). Middle panel: C zone data that does not present aftershock regime. Lower panel: Truncated D zone data to exclude the aftershock regime.

276 The recovery of the activity level after a major earthquake is faster for the Shannon entropy than for the mutability.
 277 Namely, the slope in the recovery for μ is better defined after a large quake. It is interesting to notice from figures 3
 278 through 6 that zone A recovered its foreshock activity level sooner than any of the other zones. This observation will
 279 be put in a quantitative way concentrating on the recovery dynamics in real time to compare the behavior of the
 280 different zones.

281 Figure 8 presents the mutability results for region D starting at the point of minimum mutability occurring
 282 immediately after the major earthquake on February 27, 2010. The dotted (red) curve corresponds to an exponential
 283 fit to be discussed next. The inset shows the same data and exponential adjustment for the first two years on the
 284 time span. A power law can be seen at the onset of the aftershock regime resembling Omori's law.

285 For zones A, B, and D, we assume an exponential adjustment for the mutability function after the largest earthquake.
 286 A possible such function is:

$$\mu_{eZ}(t) = a_Z + b_Z \exp(-(t - t_Z)/\tau_Z), \quad (6)$$

287 where a_Z measures the “asymptotic” activity of zone Z (reached after the aftershocks regime), t_Z corresponds to the
 288 time of minimum mutability after the largest earthquake (Table I) and serves as initial time for this recovery analysis;
 289 τ_Z is the characteristic time for activity recovery in zone Z . b_Z is just a shape adjustment parameter without a direct
 290 meaning for this analysis.

291 For zone D (Fig. 8), the best least square fit for the mutability is obtained for $a_D = 1.502(2)$ and $\tau_D = 0.62212$ years
 292 (y). The results of this treatment for all the zones with major earthquakes are summarized in Table III. Fig. 8 includes

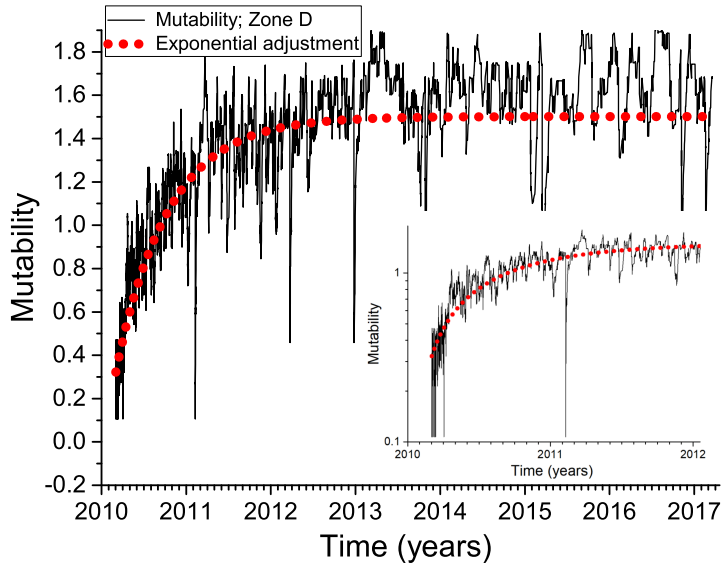


FIG. 8. Exponential fit for Cobquecura data set after February 27, 2010. This data set starts at the point of minimum mutability after the big earthquake of magnitude $M_w = 8.8$.

293 an inset with semilog scale to appreciate the recovery process under a different perspective. A linear behavior in this
 294 scale is apparent at the beginning of the plot, but then it is rapidly lost. The sudden decrease of mutability values
 295 during February 2011 is better resolved in the time scale of the inset: this is due to the short aftershock activity
 296 produced by an earthquake of magnitude 6.1 occurred on February 14, 2011. Due to their sharp appearance we
 297 propose to call "needles" these sudden and short decreases of mutability associated to the brief aftershock period left
 298 by seisms M5.0 to M6.0 approximately. Other needles can be easily spotted in Figs. 3, 4, 5, 6 and 8.

| Zone Z | a_Z | b_Z | t_Z (y) | τ_Z (y) |
|----------|---------------|----------|------------|--------------|
| A | 1.754 (0.002) | -1.64691 | 2014.24829 | 0.0134(3) |
| B | 1.208 (0.004) | -1.09124 | 2015.70784 | 0.2092(33) |
| D | 1.502 (0.005) | -1.37833 | 2010.07093 | 0.6221(110) |

TABLE III. Best fit parameters for the mutability of zones A, B, and D, after the main earthquake, using the exponential trial function given by Eq. (6).

299 A similar analysis was made for the Shannon entropy results using the same exponential fit and the corresponding
 300 parameters are given in Table IV.

| Zone Z | a_Z | b_Z | t_Z (y) | τ_Z (y) |
|----------|----------|----------|------------|--------------|
| A | 2.924(2) | -3.69218 | 2014.24516 | 0.0095(3) |
| B | 2.908(3) | -2.30957 | 2015.69997 | 0.0246(4) |
| D | 2.815(4) | -2.29226 | 2010.13133 | 0.1255(25) |

TABLE IV. Best fit parameters for Shannon entropy of zones A, B, and D, after the main earthquake, using the exponential trial function Eq. (6).

301 Figures similar to Fig. 8 were made for the mutability of zones A and B using the best fit parameters listed in
 302 Table III. The same analysis was also done for the results obtained by Shannon entropy and the corresponding
 303 parameters are given in Table IV. The figures backing such fittings are not included here since they are very similar
 304 to Fig. 8 and the procedure is the same to the one already established in the presentation of this figure.

305 Let us now discuss the results given in Tables III and IV which list the parameters defined in Eq. 6. The first
 306 striking difference between Shannon entropy and mutability is on the value for the background parameter a_Z . In
 307 the case of the adjustment for Shannon entropy this parameter does not discriminate significantly among zones with
 308 values close to 2.9 for all of them; the same parameter in the case of the mutability data spans a range [1.208,1.754],

thus indicating differences in the dynamics of these three regions. In particular, mutability indicates that in zone B there are more seismic events at regular intervals than in the other zones. Given the underlying plate subduction mechanism, this could mean that plates are sliding more regularly or even fluently in zone B, whereas the relative motion of the Nazca plate under the South-American plate is more difficult in zone A, thus leading to more dispersed set of intervals between consecutive seisms.

After a large earthquake the zones tend to recover their characteristic activity level a_Z , but this is done rather abruptly for Shannon entropy while it is more gradual for mutability. This is measured by the recovery time τ_Z in Tables III and IV. In the case of the Shannon entropy for the zone A the recovery is very fast, namely 0.00947 years ≈ 3.5 days. In the case of zones B and D the recovery times for the Shannon entropy are of 9 days and 45 days, respectively. However, when the analysis is done using the recovery time for mutability (Table III) the recovery times are 5 days, 2.5 months and 7.5 months for the zones A, B, and D, respectively.

Tables III and IV also show that recovery times τ_Z are different, shorter for Shannon entropy and longer for mutability, but the tendencies are the same. So eventually both methods can be used to characterize this aspect of the aftershock regime. In terms of the human perception experienced after any large earthquake it seems that τ_Z values obtained for the mutability results are more representative of the aftershock times experienced in each zone. Thus, for instance, seisms of magnitude around 4.0 were frequent in zone D during several months after February 10, 2010, but this was not the case for zone A where people lost perception of the aftershock regime after a week or so of the last earthquake in this area.

The main difference between Shannon entropy and mutability is that the former analyzes the distribution of registers in a sequence regardless of the order in which these entries were obtained, while the latter gives a lower result for sequences including frequently repeated registers (Cortez et al., 2014). *Shannon entropy considers the visit to a state without considering the order in which these visits take place, which is of paramount importance for the entropy in natural time being dynamic entropy and not a static one (Varotsos et al., 2005; Varotsos et al., 2007) so it pays exclusive attention to the probability of visiting a state at some instance during the observation time.* Mutability considers also the trajectory in which these visits take place, giving lower results when the system stays long periods in the same state or states directly connected to this state; on the contrary during agitated periods (chaotic dynamics would be at the apex here) mutability gives higher results. In other words, a given sequence has just one result for Shannon entropy but the permutations of the order of the registers lead to different results for mutability; in the present case the mutability results reported here corresponds to the natural sequence of the recorded seisms.

We now focus on the analysis of the background activity obtained for the 4 zones described in this work, taking semestral averages of the values of mutability in Figs. 3–6, in order to study trends in time scales longer than the one of previous figures. We have chosen a semester as the time for averages so we have a few hundreds registers in each partial sequence minimizing error, but still we have some 13 points in the overall period to appreciate tendencies and differences. In doing so, we also evaluate semestral averages of intervals between consecutive seisms, which show similar trends to the mutability results for the same period.

The semestral analysis for zones A, B, C and D is shown in Figs. 9, 10, 11 and 12, respectively; they are all presented under the same scale to allow a direct comparison. The mutability values run on the upper part (black) while the intervals tend to occupy the lower part (blue) of the plot. The first comment here is evident: these 4 regions present different responses to the evaluation of their sequences of time intervals between consecutive seisms of magnitude 3.0+ as measured both by mutability and Shannon entropy. These two measures are not equivalent either although some general similarity between them can be noticed. The only effective common feature is that an earthquake with magnitude over 8.0 produces an absolute minimum for each variables during the semester containing this seism and its aftershock sequence.

For didactical reasons we shall perform this discussion beginning with zone D, where the long recovery period already appreciated in Fig. 6 and in Table III is more enhanced. It is interesting to observe that the average semestral mutability presents recent relaxations like in the first semester of 2015 and the first semester of 2017. Generally speaking these results do not approach yet the values near 1.8 for the average semestral mutability in the foreshock period preceding the large earthquake of 2010. Interval semestral averages tend to follow the variations of mutability but some differences are noticed. The present average interval of about 2000 minutes (about 33 hours) is far from the almost 6000 minute interval before the large earthquake.

Fig. 11 is completely different to the others. There is no major earthquake included here but it is obvious that there was one prior to 2011 from which this activity is slowly recovering. The general tendency is to slowly increase the mutability values to levels similar to those constantly presented by zone A and those presented by region D previous to the large earthquake. Interval averages also increase reaching just under 2000 minutes. If this is an announcement for a future major earthquake in zone C or nearby is still too early to tell but this zone should be monitored closely.

Fig. 10 shows the foreshock mutability averages for zone B which present a nearly flat behavior around 1.6 before the major earthquake of 2015. Then, after the aftershock regime the average semestral mutability begins to recover, faster than in zone D, but still not reaching the level shown here previous to the large earthquake. The observation

367 is similar for the interval semestral average whose value is still small compared to the activity before 2016.

368 Fig. 9 shows the almost constant results (near 1.8) for the average semestral mutability of zone A, with just one
 369 semester reaching a moderate low value (1.4 with large error bar). The semestral average for intervals between seisms
 370 is also rather flat around 10 hours. The only exception is the first semester of 2014 in coincidence with the large
 371 earthquake there.

372 Error bars deserve a separate discussion. They are obtained from the standard deviations calculated for the
 373 distributions of each semester within each zone. So the number of events differ from one semester to another even
 374 within each zone. In the case of intervals the largest semestral error is of 4966 minutes for zone D during the second
 375 semester of 2009, just prior to the large earthquake of 2010. The smallest error is of 280 minutes obtained for the
 376 first semester of 2014, which includes the large earthquake and related activity in zone A. In the case of mutability
 377 its largest semestral error is for zone A during the first semester of 2014, while the smallest one is during the second
 378 semester of 2013 for this same zone. So error bars are subject to some fluctuations also but still they are a general
 379 indication for the homogeneity of the data.

380 Mutability error bars are rather small for the A zone, meaning that the intervals are rather similar along the data
 381 sequence. This is reinforced by the average interval error bars which are the smallest among the four zones (spanning
 382 only about 1200 minutes) telling that intervals are not so different among themselves. The largest error bars both for
 383 mutability and intervals are to be found in zone D; moreover they are irregular in recent years. Error bars increased for
 384 the average in zone D during 2009 just prior to the huge quake of 2010. However, for this same zone the corresponding
 385 error bars for the average semestral mutability are among the smallest to be found prior to this large earthquake. Once
 386 again it is difficult to say something about the present status of zone B since it is clearly under recovery. However,
 387 the Calm zone C is clearly showing a tendency: error bars for mutability averages are shrinking, while error bars for
 388 intervals are growing spanning about 60 hours. These two symptoms were present in zones A, B and D previous to
 389 their large respective earthquakes. In the case of zone A the error bars for the average intervals are not so large, but
 390 here is where we find the highest values for mutability and the smallest error bars for this variable.

391 If we look for common features just before a large earthquake they are: relatively high mutability values ("high"
 392 needs to be defined for each zone) and very small error bars associated with semestral mutability averages. The
 393 particular values of these indicators for zone A could be interpreted as an irregular subduction here, with no short-
 394 time accommodations or lack of fluency, leading to seismic risk of some sort, although it is not possible to specify
 395 any possible time for a large seism in the future. From this point of view, the earthquake of 2014 near Iquique was
 396 just a small accommodation of the plates but the subduction process could be somewhat stuck to the similar levels
 397 presented before the large quake.

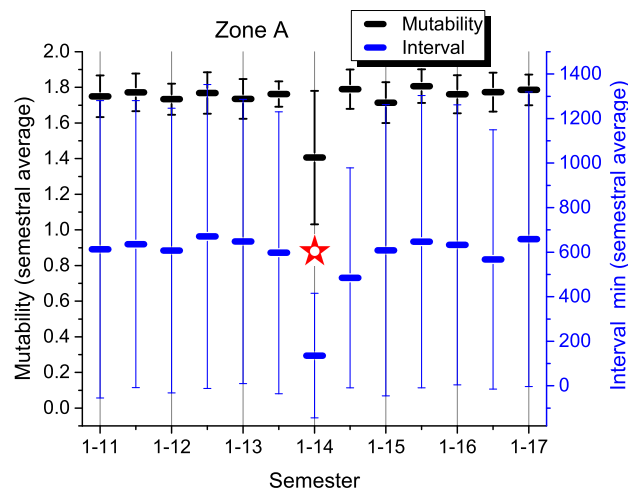


FIG. 9. Semestral average of mutability values (upper symbols; black) and intervals in minutes between consecutive seisms (lower symbols; blue) for zone A: Iquique. Odd semesters are labeled on the abscissa axis (1-13: first semester of 2013) while even semesters are only marked. A star identifies semester with earthquake with magnitude over 8.0.

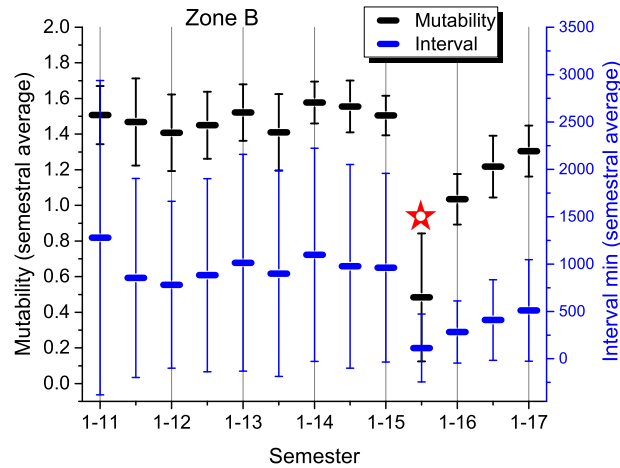


FIG. 10. Semestral average of mutability values (upper symbols; black) and intervals in minutes between consecutive seisms (lower symbols; blue) for zone B: Illapel. Odd semesters are labeled on the abscissa axis (1-13: first semester of 2013) while even semesters are only marked. A star identifies semester with earthquake with magnitude over 8.0

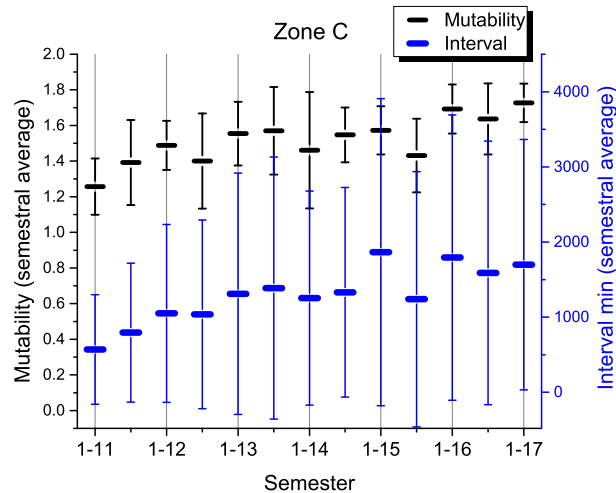


FIG. 11. Semestral average of mutability values (upper symbols; black) and intervals in minutes between consecutive seisms (lower symbols; blue) for zone C: Calm. Odd semesters are labeled on the abscissa axis (1-13: first semester of 2013) while even semesters are only marked.

398

IV. CONCLUSIONS

399 Seismic activity is different for the four zones defined here along the Nazca-South American subduction trench (Figs.
 400 1-2, Table I). Nevertheless, some general behaviors are common to the seismicity of the tectonic activity present in
 401 this region. Both Shannon entropy and mutability show a sudden decrease after an earthquake of magnitude around
 402 or over 7.0 (Figs. 3-6). Additionally, Shannon entropy and mutability reach “high” values before a major earthquake;
 403 the scale to define “high” needs to be tuned for each geographical region and observation time window.

404 A short time correlation exists between Shannon entropy and mutability during the aftershock regime. However,
 405 this correlation is lost far from this regime thus providing independent tests to characterize the seismic activity (Fig.
 406 7).

407 The aftershock regime is characterized by successions of low and medium intensity seisms at short intervals producing
 408 low values of both Shannon entropy and mutability. After some recovery time the intervals tend to go back to the kind
 409 of intervals present before the large quake. This recovery behavior can be described by exponential adjustments (Fig.

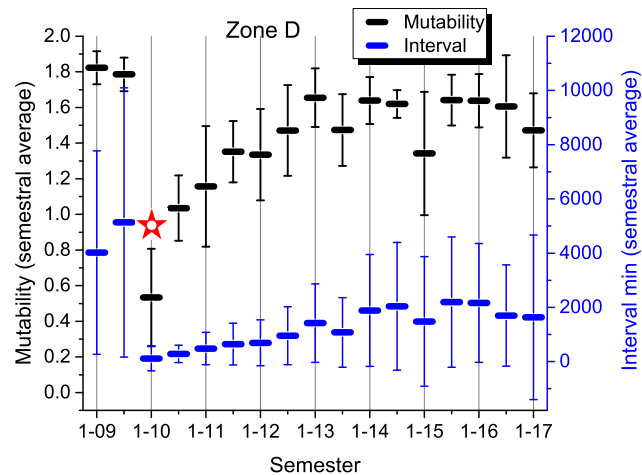


FIG. 12. Semestral average of mutability values (upper symbols; black) and intervals in minutes between consecutive seisms (lower symbols; blue) for zone D: Cobquecura. Odd semesters are labeled on the abscissa axis (1-13: first semester of 2013) while even semesters are only marked. A star identifies semester with earthquake with magnitude over 8.0.

8) which indicate that the characteristic times are longer for mutability than for Shannon entropy (Tables III-IV); eventually this speaks in favor of the former to continue the analysis. Another advantage of mutability is that the parameter reflecting the background activity span larger ranges than the one presented by the adjustment of Shannon entropy (Tables III-IV). From these results the mutability recovery time τ_Z for zone A lasted a few days, while the same parameters for zone D lasted several months, which is close to the human perception in these zones.

The difference between Shannon entropy and mutability evidenced after the recovery time are due to the handling of a static distribution by the former while the latter considers the order in which registers entered in the distribution in accordance with the concept of natural time. The differences between Shannon entropy and mutability evidenced after the recovery time are due to the handling of a static distribution by the former while the latter considers exact or approximate repetitions in the data chain. From this point of view mutability carries more information than Shannon entropy in spite both are obtained from the same sequences.

The background activity based on mutability a_Z (Tables III-IV) is quite different for each zone (Figs. 9-12). This means that the subduction process finds different difficulties in each zone. However, some general features describing the motion of the Nazca plate under the South-American plate should be present along the trench. To investigate this possibility we considered semestral averages of mutability values.

Semestral averages for mutability recovered soon for zone A after the 8.2 earthquake, which indicates that the short intervals after a major earthquake were mostly absent here. Soon, the regime with longer and different intervals reappeared raising the values of mutability and narrowing the corresponding error bars; this could be interpreted as a warning for a possible earthquake in this zone sometime in the near future. On the opposite side is zone D where the semestral averages still do not recover to the levels prior to the large 8.8 earthquake of 2010; moreover, there have been instances lowering the semestral averages for mutability with large error bars in recent times evidencing short intervals indicating activity in a rather continuous way. In the case of zone B the recovery is still under way so it is too soon to say anything at this time. Generally speaking we can observe that mutability values were high and their error bars were small just before a major earthquake in zones A, B, and D.

Semestral averages for intervals between consecutive seisms and their corresponding error bars are very different among the different regions. Both values decrease during the aftershock regime but no clear trend could be found prior to a large earthquake.

As for the Calm zone C the mutability semestral averages are clearly increasing reaching 1.8 with narrowing error bars. Although each zone can have different thresholds for triggering of a major event, such value or slightly lower ones have been present just before large earthquakes in the other zones. Eventually zone C is showing a behavior that should be further studied at the expectation of future large quakes.

Let us close by answering the 5 points raised in the introduction thus summarizing previous discussions and conclusions. 1) Both Shannon entropy and mutability give similar responses to a major earthquake and its immediate aftershock period, however they are independent and non-correlated during the quieter periods. 2) Shannon entropy deals with the distribution as a whole while mutability and the entropy defined in natural time (which is dynamic and

445 not static (Varotsos et al., 2007)) deal with a sequential distribution of intervals of natural time; this allows to the
446 latter be more effective in providing larger contrasts if the values of the characteristics parameters. 3) The recovery
447 time and background activity are very well characterized by mutability allowing to discriminate among different zones.
448 4) The mutability semestral averages reflect the seismic activity of the different zones indicating where the subduction
449 is relatively fluent or where the process could be stuck. 5) A combined analysis points to zone A as stuck for many
450 years and zone C slowly decreasing fluency in the subduction process which can be indication for accumulation of
451 energy in this zone.

452 This paper deals with the analysis of an important, but particular, seismic zone, namely the Nazca-South American
453 subduction front. Our results show that the use of mutability and Shannon entropy may distinguish the different
454 dynamics within this trench, and, specially, the fact that mutability may give a clue on the recovery time in a
455 given region between major earthquakes. Certainly, further studies should be made in order to establish the general
456 applicability of this approach, both by studying other seismic zones, and artificial catalogs, such as those given by
457 the ETAS model. We expect to develop this in future publications.

APPENDIX

458

459 In this appendix we provide examples of the way mutability is calculated following Eq. (3) for time sequences
 460 similar to those found in this problem, using $\nu = 24$ as it is done dynamically in previous presentation. Each column
 461 in Table V lists one of these sequences representing intervals between consecutive seisms in minutes. First column,
 462 called "Even", is monotonic assigning one-hour interval evenly. Second column, called "Converging", is constructed
 463 by means of two intercalated sequences: one ascending and the other descending, so correlations are diluted. Third
 464 column, called Random, is formed by a randomly generated sequence. Fourth column, called Sequential, is formed by
 465 a monotonic increase of the intervals so it is highly correlated. As it can be readily found all columns average around
 466 60 minutes between consecutive registers.

| i | Even | Converging | Random | Sequential |
|-------|--------|------------|--------|------------|
| 1 | 60 | 30 | 57 | 48 |
| 2 | 60 | 90 | 112 | 49 |
| 3 | 60 | 32 | 9 | 50 |
| 4 | 60 | 88 | 49 | 51 |
| 5 | 60 | 34 | 60 | 52 |
| 6 | 60 | 86 | 73 | 53 |
| 7 | 60 | 36 | 14 | 54 |
| 8 | 60 | 84 | 112 | 55 |
| 9 | 60 | 38 | 9 | 56 |
| 10 | 60 | 82 | 49 | 57 |
| 11 | 60 | 40 | 90 | 58 |
| 12 | 60 | 80 | 40 | 59 |
| 13 | 60 | 42 | 55 | 60 |
| 14 | 60 | 78 | 49 | 61 |
| 15 | 60 | 44 | 67 | 62 |
| 16 | 60 | 76 | 35 | 63 |
| 17 | 60 | 46 | 87 | 64 |
| 18 | 60 | 74 | 67 | 65 |
| 19 | 60 | 48 | 67 | 66 |
| 20 | 60 | 72 | 49 | 67 |
| 21 | 60 | 50 | 21 | 68 |
| 22 | 60 | 70 | 77 | 59 |
| 23 | 60 | 52 | 38 | 60 |
| 24 | 60 | 68 | 108 | 61 |
| μ | 0.1875 | 1.2347 | 1.5670 | 0.3854 |

TABLE V. Example of 4 time sequences (second to fifth columns) averaging 60 minutes between consecutive events. Mutability values for each column are given in the last row. The first column lists the sequence.

467 Results for the mutability of each column are given in the last row. As it could have been anticipated the Even
 468 sequence has the least information leading to the lowest mutability value. Next is Sequential, which reflects a
 469 monotonic increase in the time intervals. Notoriously higher is Converging where correlations are poor. The highest
 470 mutability value is for the Random sequence in spite a few values are repeated; if no repetitions are present and/or
 471 the interval span is higher the mutability value would be even larger.

472 It can be noticed that even in a 24-instant sequence mutability values can span an order of magnitude, This is
 473 even more so for real interevent sequences where intervals can reach several hours (a thousand minutes or more) thus
 474 differentiating behaviors of seismic activity.

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