

IPOC-Deep: a new seismicity catalog for Northern Chile with >2 million events

Nooshin Najafipour^{1,2,*}, Christian Sippl¹, Javad Kasravi³, Jonas Folesky³, Bernd Schurr⁴

¹Institute of Geophysics, Czech Academy of Sciences, Prague, Czech Republic

²Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic

³Institute of Geological Sciences, Freie Universität Berlin, Berlin, Germany

⁴Helmholtz-Zentrum für Geoforschung (GFZ), Potsdam, Germany

*Corresponding author: najafipour@ig.cas.cz

Preprint notice: This is a non-peer reviewed preprint submitted to EarthArXiv. This manuscript has been submitted to *Seismological Research Letters* for peer review.

Data availability: The dataset associated with this manuscript is publicly available at: <https://doi.org/10.5880/fidgeo.2026.050>

IPOC-Deep: a new seismicity catalog for Northern Chile with >2 million events

Nooshin Najafipour^{*1,2}, Christian Sippl¹, Javad Kasravi³, Jonas Folesky³, and Bernd Schurr⁴

Abstract

We present a novel seismicity catalog for Northern Chile, which covers 17 years (2007–2023) of data and contains more than 2.2 million events. Raw waveform data from nearly 200 stations including a range of temporary deployments were processed with state-of-the-art algorithms for phase picking (EQTransformer) and association (PyOcto), after which we performed absolute event relocation in a 2.5D velocity model, followed by relative relocation using hypoDD. Events in the catalog are provided with a classification for location quality, determined from properties like gap angle, number of picks and RMS residual, a probabilistic estimate for location uncertainty in horizontal and vertical direction, as well as a classifier for the tectonic unit (plate interface, upper plate, different types of intraslab seismicity). This article introduces the dataset, which is made accessible to the scientific community and highlights some overall structural features, changes in event numbers, and catalog completeness through time as a consequence of changing station geometries, as well as a zoom into the 2007 Tocopilla earthquake sequence.

Cite this article as (2022).

IPD Highlights new seismicity catalog for Northern Chile with >2 million events, *Seismol. Res. Lett.* **XX**, 1–29,

[Supplemental Material](#)

Introduction

In recent years, the advent of deep-learning-based phase picking algorithms (e.g., Zhu and Beroza, 2018; Mousavi et al., 2020) and a new generation of phase association algorithms (e.g. Zhang et al., 2019; Münchmeyer, 2024) have revolutionized the automated compilation of seismicity catalogs. Unlike earlier generations of automated approaches, the precision and hit rate of these codes are comparable to or exceed those of human analysts, and their computational efficiency allows the generation of large datasets in comparatively short times (Ni et al., 2025).

1. Institute of Geophysics, Czech Academy of Sciences, Prague, Czech Republic; 2. Faculty of Mathematics and Physics, Charles University, Prague, Czech Republic; 3. Institute of Geological Sciences, Freie Universität Berlin, Berlin, Germany; 4. Helmholtz-Zentrum für Geoforschung (GFZ), Potsdam, Germany

*Corresponding author: najafipour@ig.cas.cz

© Seismological Society of America

Compared to previous earthquake catalogs, the new generation of “deep” catalogs adds many small events that were previously missed, thereby lowering the completeness magnitude. Consequently, they do not differ substantially in first-order structural features but can more clearly image smaller-scale features such as individual faults or earthquake sequences (e.g. Ross et al., 2019), or provide a much more powerful base for statistical approaches. However, while “deep” catalogs of large temporary station deployments are currently starting to appear (e.g. Münchmeyer et al., 2025; Si et al., 2026), longer-term “deep” seismicity catalogs that extend over a decade or more are still rare.

Here, we present one of the largest consistently processed seismicity catalogs for a subduction zone segment compiled to date. Using 17 years of data from nearly 200 temporary and permanent seismic stations along the Northern Chilean margin, we retrieve more than 2 million events, which is an order-of-magnitude increase compared to previous catalogs of the region (Sippl et al., 2023; Potin et al., 2025; Riedel-Hornig et al., 2026). In the following, we summarize the data processing and describe the main features of the dataset, which will be made available to the community as a data publication (Najafipour et al., 2026).

Data

We compiled continuous seismic waveform data from Northern Chile, one of the most seismically active regions along the South American subduction margin, for the years 2007–2023. The study region extends from approximately 18°S to 25°S and from 66°W to 72°W, encompassing the offshore and onshore forearc and the volcanic arc.

The dataset incorporates a total of 196 seismic stations. The core coverage was provided by the permanent IPOC network (CX; GFZ and CNRS-INSU, 2006), which has been operating continuously since late 2006. These permanent stations were supplemented by a variety of international and regional networks, including stations from the permanent networks GEOFON (GE; GEOFON Data Centre, 1993), CSN (C and C1; Universidad de Chile, 2013), IU (Albuquerque Seismological Laboratory/USGS, 1988) and IQ (Cesca et al., 2009), as well as many temporary station deployments. For a detailed listing of all utilized networks, please refer to the Data and Resources section.

Station availability varied considerably over time. Permanent IPOC stations generally operated for most of the study period, offering more than a decade of continuous coverage, while temporary campaigns provided denser coverage in specific time intervals, particularly between 2010 and 2015. This spatially heterogeneous station coverage leads to large changes in event numbers and completeness magnitudes in our catalog (see below). Figure 1 illustrates the geographic distribution and lifetimes of all the stations used in this study. Permanent stations are indicated by distinct symbols for each network, while temporary and short-lived stations are grouped as ‘Other net’. The color bar indicates the number of years that each station was active between 2007 and 2023. Coverage is generally best in the onshore forearc, with station density significantly decreasing towards the volcanic arc (which is co-located with the national boundary between Chile and Bolivia/Argentina).

41 The majority of stations recorded broadband data at either 50 or 100 Hz sampling frequency, but some of the temporary
 42 networks also used short-period sensors (1 Hz corner frequency) and/or different sampling rates.

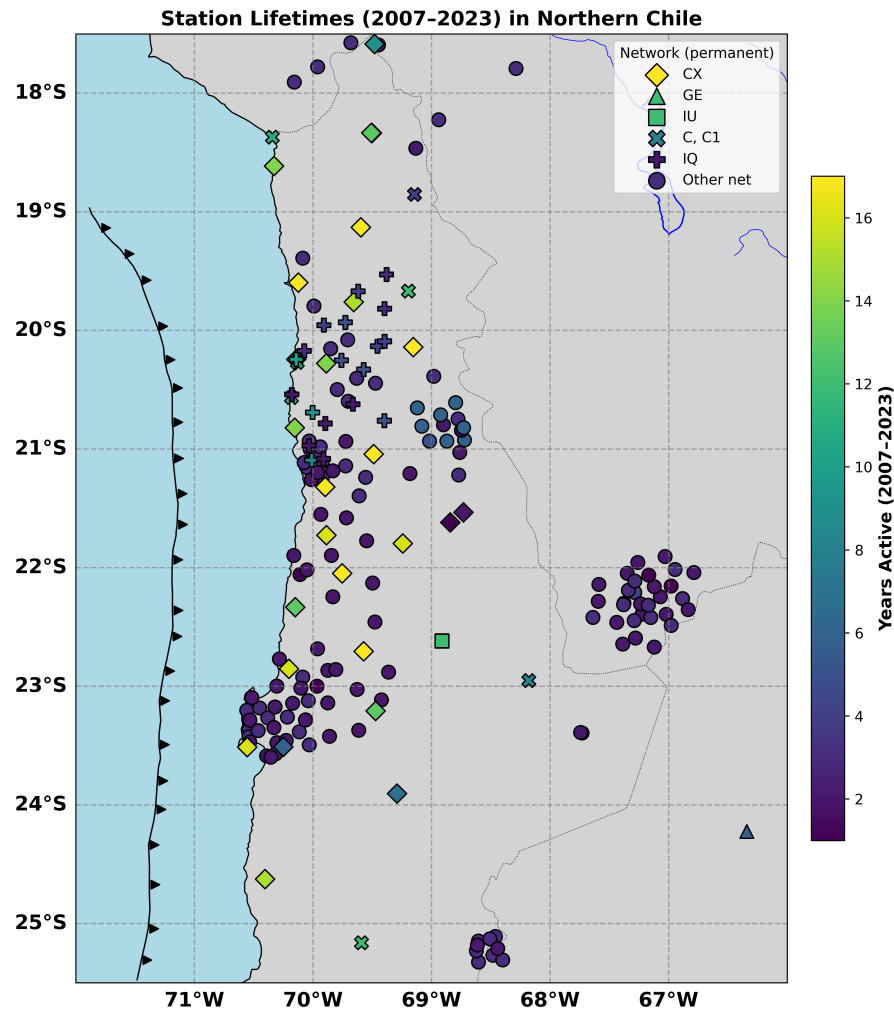


Figure 1: Distribution of utilized seismic stations in Northern Chile between 2007 and 2023. Symbols represent different networks (CX, GE, IU, C, C1, IQ, and other networks). Coloring indicates the number of years each station was active during the study period. The permanent IPOC (network CX) stations provided the most long-term continuous coverage, while temporary deployments extended network density during shorter-term campaigns.

Alt text: Spatial station coverage is shown on a map view plot of Northern Chile. The symbols marking seismic station locations show whether they belong to a temporary or permanent deployment, and how long they have been recording data.

43 Methodology

44 In order to handle the large quantity of seismic waveform data, we set up an automatic processing pipeline that relies on
 45 EQTransformer (Mousavi et al., 2020) for phase picking and PyOcto (Münchmeyer, 2024) for phase association. Events that
 46 were identified and located in PyOcto were then relocated in a 2.5D velocity model, i.e. a 2D model extended into the third
 47 dimension (here: along-strike), in order to account for the major structural features such as the geometry of the subduct-
 48 ing slab and differences between forearc and arc regions. Subsequently, relative relocation was performed using hypoDD
 49 (Waldhauser and Ellsworth, 2000).

Seismic Phase Picking

EQTransformer (EQT; Mousavi et al., 2020) is a deep learning model for seismic phase detection and picking, which outputs probability time series for the occurrence of an event, as well as the timing of the P- and S-wave arrivals. Picks are extracted by applying user-defined probability thresholds to these outputs and selecting the maxima that exceed the threshold values. We applied the implementation of EQTransformer on the SeisBench platform (Woollam et al., 2022, v0.2.3), which provides standardized access to multiple pretrained models. To have a meaningful reference dataset, we handpicked 14 randomly chosen days of continuous seismic data from 16 CX stations in the years 2007 to 2020. To avoid missing arrivals from small events that may only be visible on single stations, we manually picked each station individually, not evaluating the consistency of arrivals between stations as usual. This procedure yielded approximately 71,000 manually picked P- and S-wave arrivals (~5,000 picks per day) from six different analysts.

We tested four different pre-trained models for EQTransformer, *Original*, *ETH*, *Iquique* and *INSTANCE*. Following Münchmeyer et al. (2022), we conducted our analysis with precision-recall curves, trying to find a parameter configuration that offers maximum precision (i.e., the fraction of retrieved picks that are correct) as well as recall (i.e., the fraction of true picks that are retrieved). We analyzed such curves across different choices of threshold values and also evaluated residuals between handpicks and EQTransformer picks.

We found substantial differences in the performance of the four different pretrained models. The *INSTANCE* model (Michellini et al., 2021) consistently achieved the best results, recovering the highest proportion of the handpicked dataset and demonstrating the greatest ability to recover weak phases with high accuracy. Based on the precision-recall analysis, an event-detection threshold of 0.4 was selected as the best trade-off between detecting as many real events as possible and limiting false picks, with the P- and S-pick thresholds fixed at 0.1 to maximize sensitivity to weak arrivals.

The residual distributions (Figure 2) between manual and *INSTANCE* picks for this threshold choice show a tight and symmetric shape of the histogram for the P-picks, but a skewed distribution corresponding to a slight systematic delay (mean +0.14 s) of EQTransformer with *INSTANCE* compared to manual picks for the S-picks.

Due to this observation and since we were not entirely satisfied with the recall values of ~0.6 for our handpicked dataset, which are lower than the typical values achieved in Münchmeyer et al. (2022), we used a subset of the manually picked events to fine-tune the EQTransformer model, starting from the weights pretrained on the *INSTANCE* dataset. For this, we selected the manual picks of three of the six analysts, corresponding to slightly more than half of the available handpicks, after analyzing their hit rates as well as the distribution of their pick residuals compared to the *INSTANCE* picks.

To fine-tune the EQTransformer model for this region, we initialized the network weights from the pretrained model trained on the *INSTANCE* dataset, available through *SeisBench*. This fine-tuning was implemented in the *PyTorch* framework (Paszke et al., 2019), following the original EQTransformer architecture and the multitask loss function for detection, P and S probabilities as described by Mousavi et al. (2020). Training was performed for 30 epochs with a learning rate of 0.001,

a batch size of 200 and a dropout rate of 0.3. To prevent overfitting and improve generalization, standard data augmentation procedures were applied following Münchmeyer et al. (2022), including random 60 s window selection around phase arrivals, normalization by maximum amplitude, Gaussian noise injection (0–15% of amplitude), random channel dropout and insertion of short artificial data gaps. This procedure yielded the final *EQT-Instance-CJN* model, which is adapted to the waveform characteristics and noise conditions of the Northern Chile subduction zone.

A comparison of pick residuals using all matched arrivals is provided in the Supplementary Material (Figure S1). In this comparison, the fine-tuned *EQT-Instance-CJN* model recovers substantially more arrivals than the pretrained *INSTANCE* model and exhibits smaller mean and median residuals, particularly for S-wave picks. At the same time, the residual distributions become slightly broader. This increase in spread likely reflects the recovery of additional weak arrivals with intrinsically larger picking uncertainties and/or uncertainty in the manual reference picks. Because the number of detected arrivals differs substantially between the two models, this comparison alone cannot separate improvements in picking accuracy from changes in detection performance. We therefore additionally performed a controlled common-subset comparison to isolate changes in picking accuracy from differences in detection performance.

We retained only arrivals detected by both the pretrained *INSTANCE* model and the fine-tuned *EQT-Instance-CJN* model within ± 1.0 s of the analyst pick. In this common subset (20,685 P-wave picks and 19,829 S-wave picks), the fine-tuned model produces residual distributions that are more centered around zero, particularly for S phases, where the mean residual decreases from +0.139 s to +0.041 s, while P-wave precision remains comparable ($\sigma \approx 0.16$ s) (Figure S2).

To evaluate whether this improvement generalizes beyond the fine-tuning dataset, we additionally analyzed an independent test dataset consisting of 28,468 handpicked arrivals from seven analyst-days that were excluded from the fine-tuning procedure. Figure 2 shows residual distributions for arrivals detected by both models on this independent dataset. The positive S-wave bias observed for the pretrained *INSTANCE* model (+0.118 s) is substantially reduced in the fine-tuned model (+0.018 s), while the P-wave precision remains essentially unchanged ($\sigma = 0.169$ s versus 0.167 s). Residual distributions remain slightly asymmetric, particularly for S phases, which likely reflects a combination of emergent S-wave onsets and variability among analyst picks. These results indicate that the transfer-learning step improves S-wave timing accuracy while preserving the overall precision of P-wave picks, and that the improvement generalizes to data not used during fine-tuning.

Independent test-set evaluation: INSTANCE vs. CJN
Independent test dataset (28,468 handpicked arrivals; 7 days not used during fine-tuning)
Common subset: both models detected the pick within ± 1.0 s

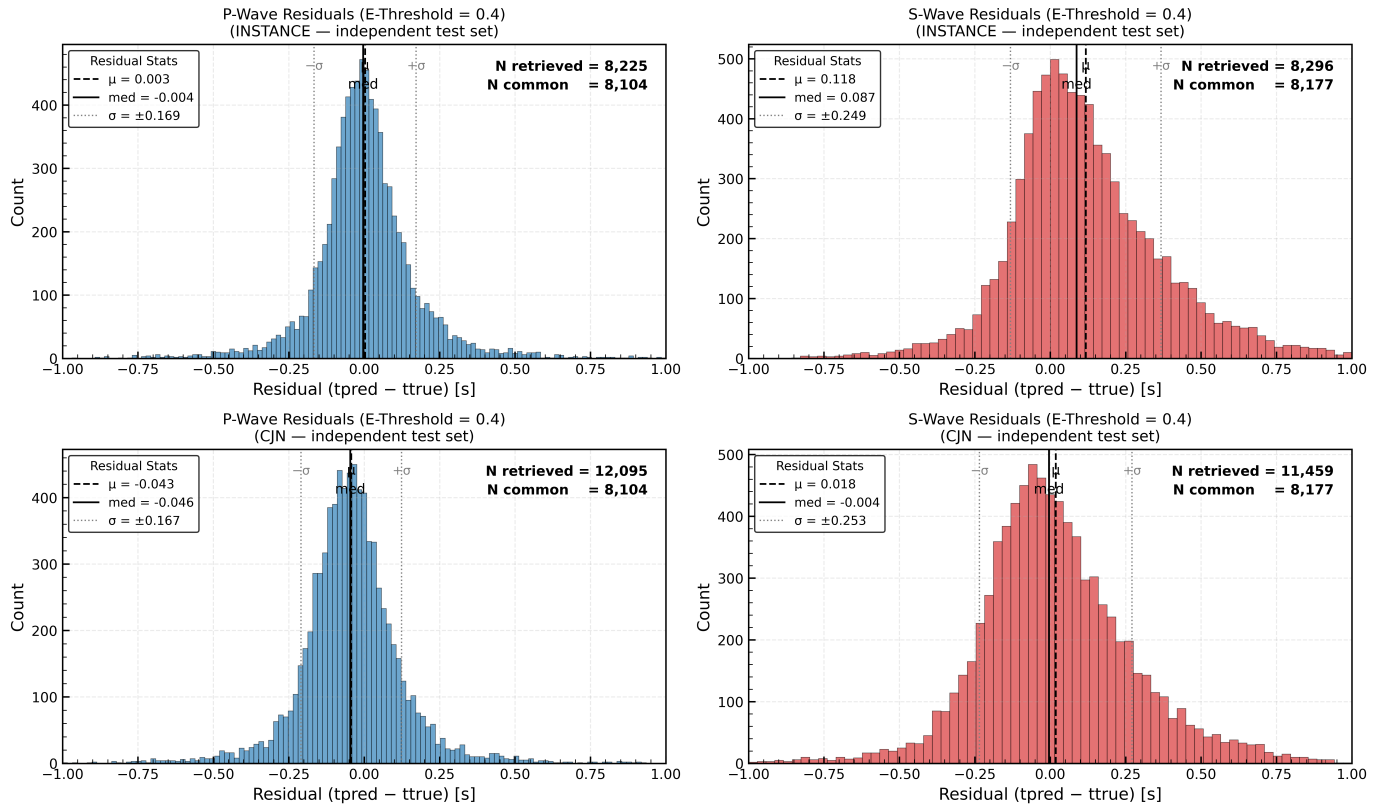


Figure 2: Residual distributions ($t_{\text{pred}} - t_{\text{true}}$) for P- and S-wave arrivals on an independent test dataset containing 28,468 handpicked arrivals from seven analyst-days excluded from the fine-tuning procedure. Only arrivals detected by both the pretrained INSTANCE model and the fine-tuned *EQT-Instance-CJN* model within ± 1.0 s of the analyst pick are included. P-wave residuals are shown on the left and S-wave residuals on the right; the pretrained INSTANCE model is shown in the upper panels and the fine-tuned *EQT-Instance-CJN* model in the lower panels. Dashed, solid, and dotted lines indicate the mean, median, and $\pm 1\sigma$ values, respectively. The fine-tuned model preserves P-wave precision while substantially reducing the systematic positive bias of S-wave picks.

Alt text: Comparison of P- and S-wave residual distributions on an independent test dataset for the pretrained INSTANCE and fine-tuned *EQT-Instance-CJN* models. The fine-tuned model reduces systematic S-wave bias while preserving comparable P-wave precision.

EQT-Instance-CJN was applied to continuous three-component waveform data from all 196 stations. The analysis was carried out on dayfiles for the entire time period 2007–2023, and the resulting picks were stored in yearly chunks across all available stations. For the complete 17-year dataset, *EQT-Instance-CJN* produced a total of 109,479,658 P picks and 78,477,006 S picks. This represents more than an order of magnitude increase compared to classical picking approaches previously applied in the region.

Event Association with PyOcto

In the next step, the resulting phase picks have to be associated with individual events. We used PyOcto (Münchmeyer, 2024) for this task, which employs an oct-tree spatial index and a travel-time graph search algorithm to find consistent

clusters of phase picks (Münchmeyer, 2024) and derives the first-break event locations. As shown in the benchmark study of Puente Huerta et al. (2025), PyOcto shows good performance at relatively moderate processing times, both for crustal and subduction zone seismicity scenarios. For our application to Northern Chile, PyOcto was set up to use a regional one-dimensional velocity model derived by Graeber and Asch (1999). We implemented this velocity structure in PyOcto as a one-dimensional travel-time table extending to 400 km depth and 300 km lateral distance. The association domain was chosen to span the latitude range -24° to -18° , the longitude range -72° to -66° and depths from 0 to 300 km, fully covering the Chilean margin north of the Mejillones Peninsula (Figure 1).

To ensure high reliability, we define an event as having at least ten picks, with at least four stations providing both P and S arrivals (similar to the thresholds adopted by Münchmeyer, 2024). Additional association parameters included a 1.5 s pick-matching tolerance, which defines the maximum allowed residual between observed pick and prediction based on the velocity model for a candidate hypocenter. We further applied a 300 s temporal window preceding the first pick of a candidate event and a 300 km spatial association cutoff. For the exact definition and implications of these parameters, the reader is referred to Münchmeyer (2024). Using this configuration, PyOcto associated approximately 45.7 million P and 41.2 million S picks, resulting in a catalog of approximately 2.5 million seismic events throughout the 2007–2023 period (see Table 1). This indicates that roughly 40% of all detected phase picks contributed to well-constrained earthquake locations, while the remainder were rejected during the association stage.

Event Relocation using simul2023 and hypoDD

After phase association with PyOcto, the event locations were refined in two stages using simul2023 (Eberhart-Phillips et al., 2024) and hypoDD (Waldhauser and Ellsworth, 2000). In the first stage, simul2023 (Eberhart-Phillips et al., 2024) was applied with a 2.5-D regional velocity model derived from Sippl et al. (2018), which represents the average crustal and upper-mantle structure of the Northern Chile subduction zone, to improve depth consistency and remove events located far outside the study area. This procedure provided improved hypocenters and corrected systematic depth offsets originating from simplified velocity assumptions used during phase association. During the simul2023 relocation, observations were weighted according to epicentral distance, travel-time residual, and phase type. Distance weights are 1 for epicentral distances below 300 km and decrease linearly to zero between 300 and 600 km; observations beyond 600 km are excluded. Residual weights are 1 for travel-time residuals smaller than 0.5 s, decrease progressively between 0.5 and 2.75 s, and reach zero for residuals exceeding 2.75 s. In addition, S-phase observations are downweighted by a factor of 0.67 relative to P phases to account for their generally larger picking uncertainty. The final observation weight is therefore the product of the input weight, phase weight, distance weight, and residual weight.

A comparison of the observed travel times with theoretical Pg, Pn, Sg, and Sn travel-time curves shows a generally tight agreement between observations and model predictions, with only a small fraction of outliers (Figure 3). The travel-time

distributions are displayed as a function of hypocentral distance for all upper-plate earthquakes with depths shallower than 60 km. Most arrivals follow the Pg and Sg branches, while only fewer earlier arrivals broadly consistent with the predicted Pn and Sn travel-time branches are seen. This tendency of often missing P_n and S_n phases, which has been observed for other automatic earthquake catalogs (e.g. Braszus et al., 2024), can be potentially problematic, as location algorithms usually require the first arriving phase as input.

However, for our study region and network, where only $\sim 12\%$ of events are located in the crust, and 76% of all epicentral distances of picked phases are shorter than 200 km, this effect is likely only of minor importance compared to other regions. Combined with the above-mentioned phase weighting scheme, the presence of few mis-identified phases from far-away stations should not affect event locations, as these phases should receive zero or near-zero weight due to their residuals. The observation that mostly Pg and Sg phases are retrieved also confirms our observations during manual phase picking, where clear Pn and especially Sn arrivals were observed only occasionally above the noise level.

Observed Travel-Time Density for Upper-Plate Earthquakes

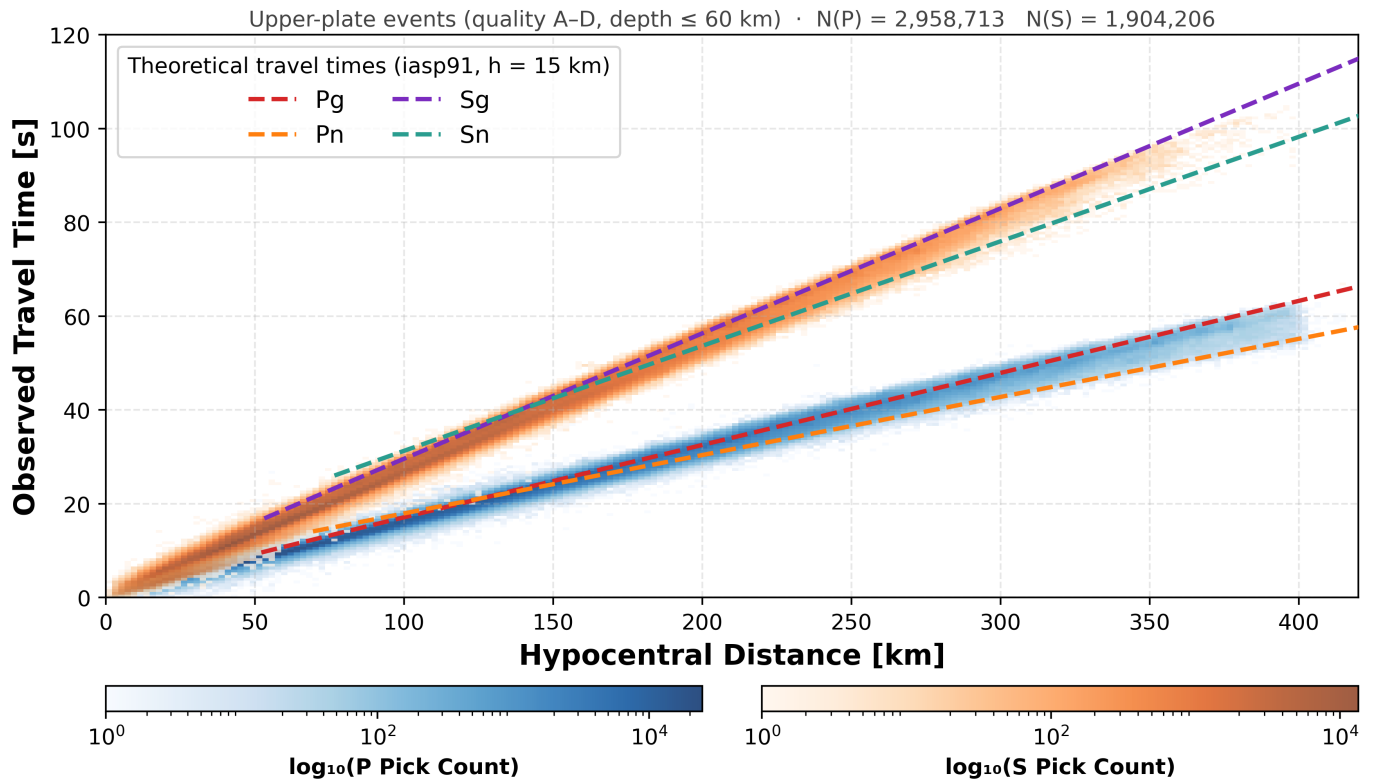


Figure 3: Travel-time density distribution of all upper-plate earthquakes (class UP; see classification scheme in Table 2) in the Northern Chile seismicity catalog. Observed P-wave and S-wave travel times are shown as logarithmic density maps as a function of hypocentral distance. Dashed curves denote theoretical Pg, Pn, Sg, and Sn travel times calculated from the iasp91 velocity model for a representative source depth of 15 km. The majority of arrivals follow the Pg and Sg branches, while only few earlier arrivals broadly consistent with the predicted Pn and Sn branches are retrieved.

Alt text: Travel-time density plot of P- and S-wave arrivals for upper-plate earthquakes, as a function of hypocentral distance. Arrivals predominantly follow the Pg and Sg travel-time branches.

157 In a second stage, hypoDD (Waldhauser and Ellsworth, 2000) was applied to obtain high-precision relative hypocenter
158 relocations using differential P- and S-wave travel times. Differential times were obtained from catalog picks, yielding a
159 total of 247.2 million P-wave and 182.9 million S-wave differential times across all relocation subsets (430.1 million in total).
160 For computational reasons, the catalog was first divided into 11 partially overlapping west-east stripes. Where necessary,
161 individual stripes were further split into randomly selected smaller subsets of approximately 30,000 events. Since subsets were
162 drawn randomly from the complete 2007–2023 catalog, events from different years are relocated together within the same
163 differential-time networks. This approach should reduce the potential influence of temporal variations in station coverage
164 on the relative hypocenter distribution. Relocation was performed using catalog-based differential times only; waveform
165 cross-correlation measurements were not incorporated, due to the extremely large size of the dataset.

166 Across all subsets, the average RMS residual decreased from 0.42 s before relative relocation to 0.18 s after relative reloca-
167 tion, reflecting a substantially tighter fit between the observed and predicted differential travel times. The relocated subsets
168 were then recombined, averaging hypocenters located in multiple overlapping subsets in the regions of spatial overlap to
169 minimize offsets and form continuous clusters along the strike of the margin. This two-stage workflow (simul2023 followed
170 by hypoDD) produced a unified relocated catalog for the period 2007–2023. Of the 2.5 million events associated with PyOcto,
171 approximately 2.2 million constitute the final earthquake catalog analyzed in this study (see Table 1).

172 Magnitude determination

173 Local magnitudes (M_L) were derived from the peak amplitudes of the horizontal components, converted to the Wood-
174 Anderson equivalent displacement using instrument response information. The epicentral and hypocentral distances were
175 calculated based on event-station geometry, and the magnitude was calculated using the IASPEI formula (Bormann, 2012).
176 Events with at least three valid station amplitudes were retained. The amplitudes were screened for outliers using a two-sigma
177 filter and averaged per event. The resulting catalog is complete above $M_L = 2.3$ in most regions and times, with detection
178 thresholds reaching below $M_L = 1.5$ in areas of dense network coverage (see Figure 10).

179 Event quality rating

180 In order to evaluate the quality of the obtained hypocenters, we used the location parameters and quality metrics provided
181 by simul2023, including the RMS travel-time residuals, azimuthal gap, number of phases, and formal horizontal and vertical
182 location uncertainties. simul2023 assigns each event a discrete quality class (A–E) based on a combined assessment of these
183 parameters. We provide this quality estimate and the individual quality metrics together with the hypocenter information.
184 In the following analysis, we primarily use earthquakes classified as classes A–D, which represent the well- to moderately
185 constrained part of the catalog. Events assigned class E are retained in the full catalog but are considered less reliable for
186 detailed structural interpretation, and hence are omitted from the following figures.

187 The merged catalog contains 2,269,867 earthquakes, of which 1,902,077 (83.8%) belong to the quality class A–D subset.
188 Figure S3 shows the distributions of azimuthal gaps, RMS residuals, and horizontal and vertical location uncertainties for
189 the full catalog and the quality A–D subset. Our analysis shows that while thresholds for all parameters are used to determine
190 the different quality classes, the azimuthal gap is the decisive parameter: events with gap angles exceeding 270° are classified
191 as class E and hence are not used in the remainder of this article.

192 To examine how location uncertainty and its spatial and temporal variation in more detail we relocated all events in
193 NonLinLoc (Lomax et al., 2000), which uses a probabilistic location approach and provides more realistic location error
194 estimates compared to the often very small formal location uncertainties in simul2023. Figure 4 shows the mean horizontal
195 (σ_h) and vertical (σ_z) location uncertainties per $0.25^\circ \times 0.25^\circ$ bin, for three time windows: the full period (2007–2023), the
196 dense-network period (2010–2015), and the sparse-network period (2016–2023). These uncertainties are retrieved from the
197 3D error ellipsoids that NonLinLoc determines; for the horizontal error estimates, we averaged the E-W and N-S errors. The
198 spatial pattern in both metrics is dominated by network geometry: uncertainties are lowest within the station footprint in the
199 central forearc ($\sigma_h < 2$ km) and increase toward the eastern and offshore margins of the network, where azimuthal coverage
200 is generally poorer.

201 This pattern is qualitatively stable across all three time windows, indicating that location quality is primarily controlled
202 by the spatial relationship between events and stations rather than by the epoch in which an event occurred. Median σ_h
203 increases from 3.22 km during the dense-network period to 3.97 km during the sparse-network period (+23%), while median
204 σ_z increases from 5.25 km to 6.65 km (+27%). Within the same quality class, the inter-period increase is smaller (e.g., class
205 B median σ_h increases from 2.71 km to 3.08 km), indicating that the quality classification already captures much of the
206 geometry-driven variation in location uncertainty.

207 Figure 5 illustrates the temporal evolution of these uncertainties across the study period. Annual median σ_h and σ_z remain
208 broadly stable for each quality class individually and for all quality A–D events combined, with a moderate increase after
209 2015 that corresponds to the transition from the dense-network to the sparse-network period. The inter-quartile ranges within
210 each class also remain relatively constant through time, confirming that the increase in median uncertainty between periods
211 is primarily driven by changes in network geometry rather than by degradation of location quality within a given quality
212 class.

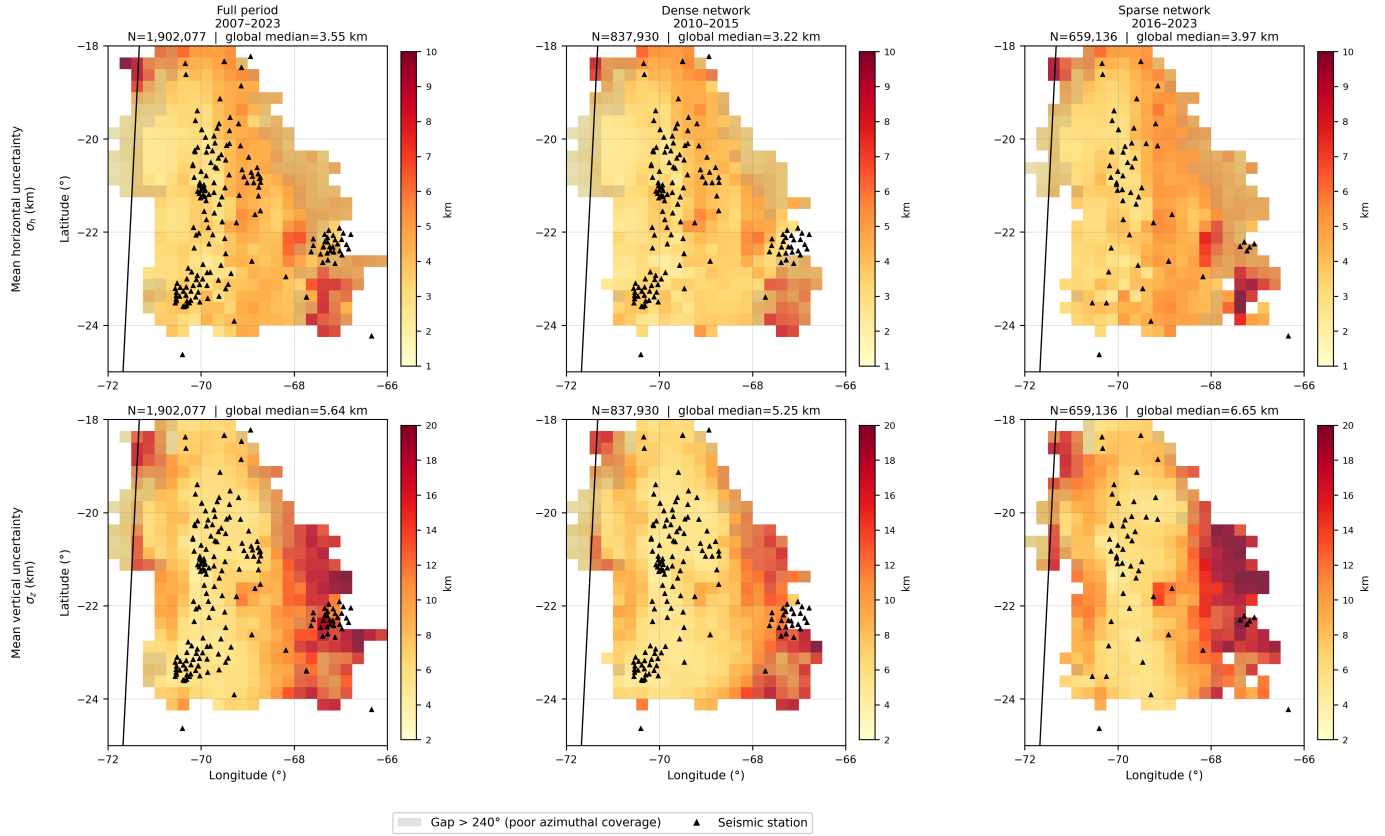


Figure 4: Spatial distribution of location uncertainties determined from NonLinLoc’s probabilistic relocation. Mean horizontal (σ_h ; upper row) and vertical (σ_z ; lower row) location uncertainties, calculated within $0.25^\circ \times 0.25^\circ$ spatial bins for quality A–D events, are shown for the full catalog period (2007–2023; left), the dense-network period (2010–2015; centre), and the sparse-network period (2016–2023; right). Only bins containing at least 10 earthquakes are displayed. Black triangles indicate seismic stations active during each period, and gray shading marks bins with a mean azimuthal gap exceeding 240° . The global median uncertainty for each period is reported above each panel.

Alt text: Maps showing the spatial distribution of mean horizontal and vertical earthquake location uncertainties for quality A–D events during the full catalog period (2007–2023), the dense-network period (2010–2015), and the sparse-network period (2016–2023). Uncertainties are lowest within the central seismic network and increase toward offshore and eastern regions with poorer azimuthal coverage. The overall spatial pattern remains similar across all three periods, although uncertainties increase moderately during the sparse-network period.

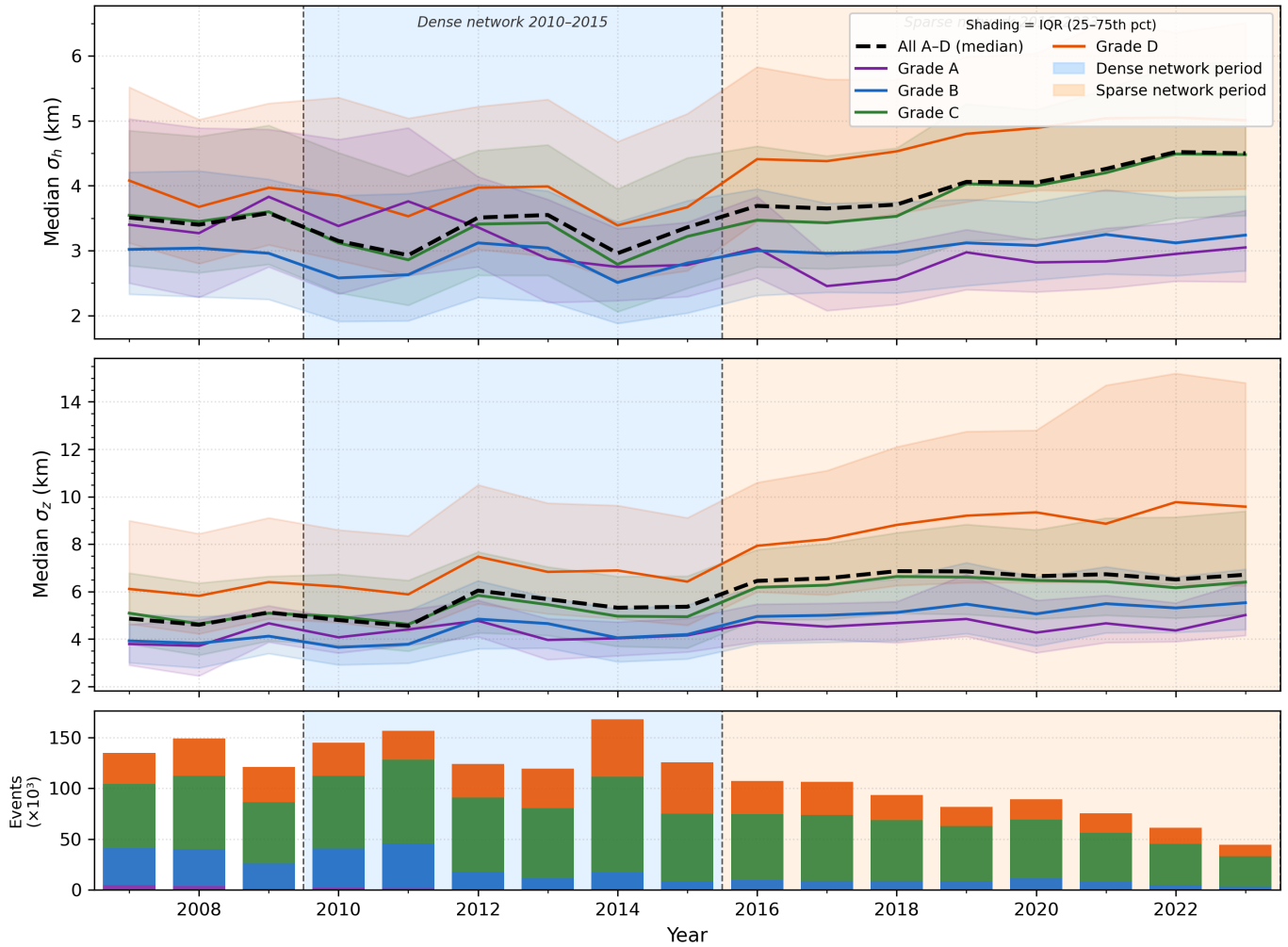


Figure 5: Temporal evolution of location uncertainties determined from NonLinLoc. Annual median horizontal (σ_h ; upper panel) and vertical (σ_z ; middle panel) location uncertainties are shown for quality classes A–D individually and for all quality A–D events combined (black dashed line). Shaded envelopes indicate the inter-quartile range (25th–75th percentile) for each quality class. The lower panel shows the annual number of earthquakes in each quality class. Blue and orange background shading denote the dense-network (2010–2015) and sparse-network (2016–2023) periods, respectively.

Alt text: Time series of annual median horizontal and vertical earthquake location uncertainties for quality classes A–D and for all quality A–D events combined, together with annual event counts. Horizontal and vertical uncertainties remain broadly stable through time, with a moderate increase after 2015 corresponding to the transition from the dense-network period to the sparser permanent-network configuration.

Catalog Summary

The final relocated catalog contains 2,269,867 earthquakes recorded between 2007 and 2023, based on more than 45 million P- and 41 million S-phase picks. Event counts vary year by year, depending on both network coverage and tectonic activity (Table 1). Years with large temporary deployments (especially 2010–2015) show increased pick numbers and event detections,

217 while sharp increases in shallower seismicity are associated with the 2007 Tocopilla (Fuenzalida et al., 2013; Schurr et al.,
218 2012) and 2014 Iquique earthquake sequences (Hayes et al., 2014; Schurr et al., 2014).

219 On a regional scale, the catalog resolves the main structural domains of the subduction system. The seismicity is dis-
220 tributed over the upper plate, the plate interface, and the subducting Nazca slab, with a clear double seismic zone observed
221 between 60–160 km depth. The catalog delineates the slab to a depth of ~ 250 km and captures widespread shallow crustal
222 seismicity. These first-order features are consistent with previous studies (Sippl et al., 2018, 2023), but in some cases they are
223 now resolved with greater clarity due to the increased number of events. To illustrate the overall distribution of seismicity in
224 our catalog, we generated density visualizations of earthquake counts in map view and along depth profiles (Figures 6 and
225 7), as classical representations with point clouds are not effective for such large event numbers.

226
227 In map view, seismicity concentrates along a north-south trending swath around 69°W , below the volcanic arc, which
228 corresponds to intermediate-depth intraslab seismicity at depths of 80 to 150 km. This zone shows the highest event numbers
229 between 20.5 and 21.5°S , where several persistently active clusters are located, separated by two sharp longitudinal offsets at
230 21 and 21.5°S . These features have been analyzed in detail in Sippl et al. (2018) and tentatively attributed to the presence of
231 subducted seafloor features by Sippl et al. (2023). Deeper intraslab activity is observed in several clusters down to about 250
232 km depth, but event locations there have high uncertainties due to the location of these features clearly outside the station
233 network. Additional intraslab activity outside the network, such as the Jujuy cluster to the southeast (Valenzuela-Malebrán
234 et al., 2022), is contained in the catalog but not shown here due to the location quality selection.

235 West of the intraslab activity, along the plate interface and the forearc and upper plate, enhanced seismicity densities are
236 observed in the rupture areas of the 2007 Tocopilla (M_w 7.7) and 2014 Iquique (M_w 8.1) earthquakes, corresponding to the
237 southernmost and northernmost cross section plots in Figure 7, respectively. We note that the hypocentral depths of the
238 westernmost portion of Iquique-sequence events could not be well determined due to their location offshore west of the
239 station network, leading to a subhorizontal appearance of this seismicity feature in profiles a through c. Pervasive upper
240 plate seismicity can be seen in the profiles between the seismic sequences on the megathrust (profiles d and e), whereas
241 most dense seismicity clusters at shallow depths in other profiles are related to mining activity.

Quality-Filtered Earthquake Density Cross-Sections (UTM projection, 2007–2023; N = 1,902,077)

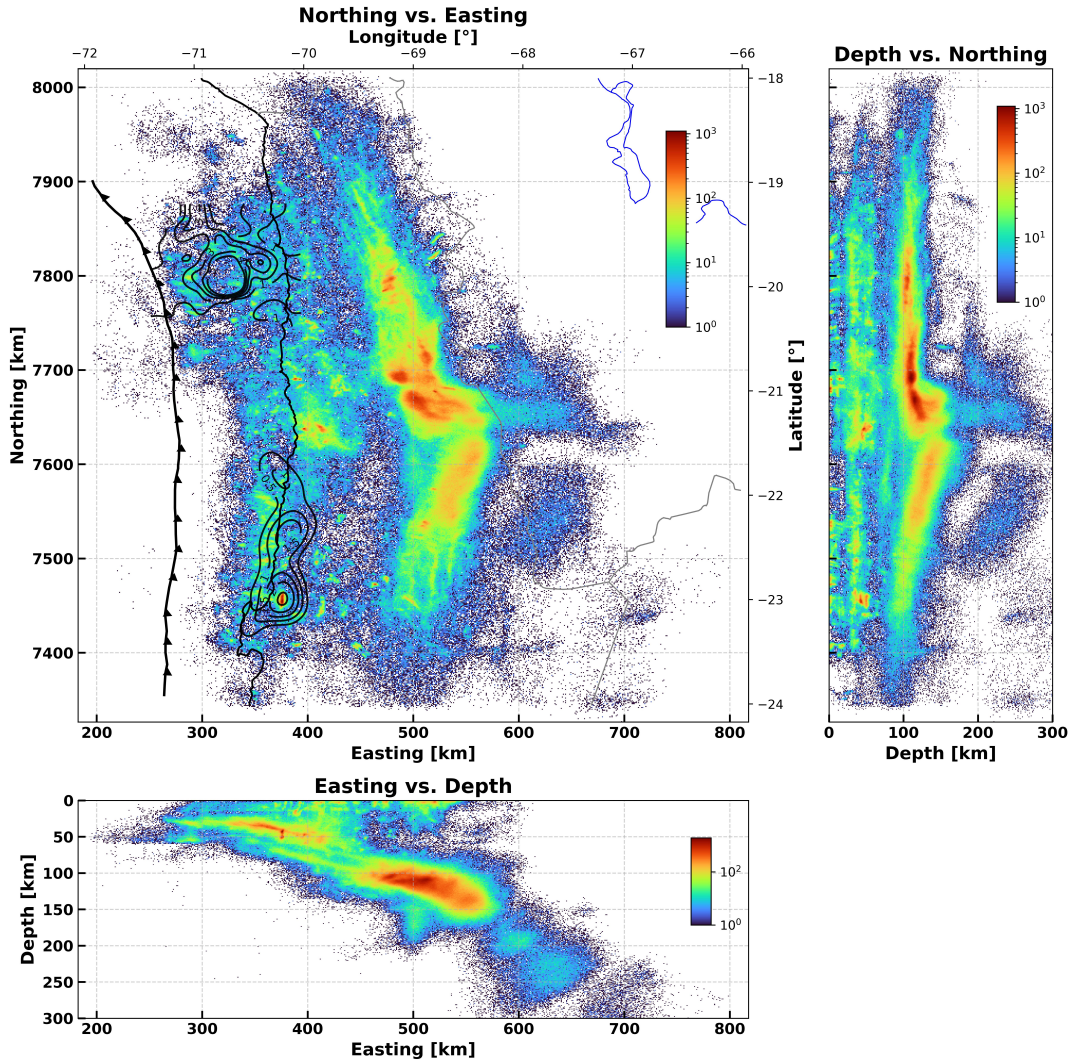


Figure 6: Quality-filtered earthquake density cross-sections for Northern Chile (2007–2023; $N = 1,902,077$). Only events classified as simul2023 quality classes A–D are shown. Colors indicate earthquake density on a logarithmic scale. (*Top left*) Map view (northing vs. easting, UTM projection), illustrating the spatial distribution of seismicity across the forearc and along the subduction margin. The trench is indicated by a barbed line, and black contours outline coseismic slip distributions of the 2007 Tocopilla (every 0.5 m; from Schurr et al., 2012) and 2014 Iquique earthquakes (every 1 m; from Duputel et al., 2015). (*Top right*) Depth vs. northing cross-section highlighting the landward-dipping Nazca slab and shallow upper-plate seismicity. (*Bottom*) Easting vs. depth section showing the overall subduction geometry and the development of a pronounced intermediate-depth seismicity band, including features consistent with a double seismic zone between approximately 80 and 160 km depth.

Alt text: Map view plot as well as E-W and N-S profile projection of seismicity density for the entire obtained earthquake catalog. Visible features include the landward-dipping Nazca slab beneath Northern Chile, which shows a strong concentration of seismicity at depths around 90–150 km, as well as shallower forearc seismicity in the upper plate and along the plate interface.

TABLE 1. : Annual breakdown of seismicity in northern Chile (2007–2023), including the number of operating stations, phase picks used for phase association, and the number of events retained after relocation with simul2023 and hypoDD.

Year	# Stations	P Picks Used	S Picks Used	# Events after PyOcto	after simul2023	after hypoDD
2007	45	2,233,744	1,987,312	179,830	175,845	173,623
2008	48	3,391,507	2,493,138	201,117	194,924	190,331
2009	33	1,923,343	1,674,174	161,701	159,556	156,333
2010	63	3,374,811	3,015,082	209,028	205,711	201,711
2011	98	3,775,415	3,288,120	213,779	210,737	207,024
2012	85	2,087,802	1,849,997	168,338	165,126	159,201
2013	70	2,327,535	2,092,595	172,467	167,481	158,112
2014	76	4,762,634	4,205,796	257,608	246,380	233,710
2015	71	3,366,518	3,091,064	199,107	191,101	180,016
2016	42	1,854,147	1,712,076	153,668	148,188	140,910
2017	35	1,734,711	1,596,477	151,175	147,146	140,674
2018	39	1,287,127	1,175,916	124,456	122,013	117,838
2019	32	889,976	808,267	102,585	100,212	97,754
2020	30	976,972	906,707	116,114	114,345	110,782
2021	29	795,223	738,657	96,732	94,915	92,221
2022	29	568,920	527,200	73,748	72,914	72,120
2023	25	400,493	372,945	58,697	53,522	53,085
Total		45,716,009	41,251,384	2,592,696	2,279,226	2,269,867

Tectonic classification relative to the slab

To interpret the spatial distribution of seismicity in the Northern Chile subduction zone, we assigned each earthquake to a tectonic domain based on its spatial relationship with the top of the slab. The slab geometry is taken from the slab surface model of Sippl et al. (2018), and the events are classified according to their depth relative to the top of the slab as well as their longitude, latitude and depth. The spatial criteria were slightly modified from those of Sippl et al. (2018), and are summarized in Table 2. Earthquakes are divided into six tectonic domains: (i) plate interface (P1), (ii) upper-plane (P2), (iii) lower-plane (P3), (iv) upper-plate (UP), (v) intermediate-depth (ID) and (vi) not classified (NN). The classification criteria are different north and south of 21°S, in order to account for the sudden offset of slab seismicity visible in the map view (Table 2). Events that fall outside the defined spatial limits or do not satisfy any of the classification conditions are assigned to the NN category. Different from Sippl et al. (2023), we do not further sub-divide upper plate seismicity to explicitly define mining-related events. The reason for this is that their classification was based on proximity to mapped mining sites, but mining activity in the region has developed significantly over 17 years of catalog time. As we do not have an archive of mining activity evolution through time, we cannot provide an adequate distinction between mining-related and tectonic seismicity.

Figure 8 shows the density cross sections of the classified seismicity along different latitudes. It can be seen that while our classification is a useful first indicator for the tectonic provenance of an earthquake, misclassifications are unavoidable, either due to location uncertainty of events close to a classification boundary or due to an imperfect fit of the simplistic classification criteria to the actual geometry of structures. For instance, it can be seen that parts of the offshore seismicity in the northern profiles, which belong to the 2014 Iquique sequence and therefore should most likely be located on the plate interface, are located deeper into the slab and hence classified as NN. We therefore recommend that users of this catalog who are interested in studying the Iquique earthquake sequence do not limit their analysis to the classes P1 and UP, but also include NN events. Further downdip, the drawn boundary between P2/P3 and ID events is not always exactly in the correct place, and some events that likely belong to class ID are located at too deep or too shallow depths, so that they get classified as NN.

We note that several finer-scale features in the density cross-sections should be interpreted with caution. A deficit in event density between approximately 12 and 20 km depth, visible across all latitude bins, coincides with a velocity discontinuity in the 1D velocity model used by simul2023 at 20 km depth and is considered a relocation artifact predominantly affecting events with weak vertical resolution. A localized subvertical streak below the main slab seismicity in the east–depth profile of Figure 6, also visible in the cross sections d-f of Figure 7, is very likely a location artifact rather than a tectonic structure. This feature occurs outside the optimal station footprint, where azimuthal coverage and depth resolution are reduced, and it is not clearly observed in earlier catalogs of the region. We therefore recommend that this feature not be used for tectonic

273 interpretation. Similarly, the apparent broadening of deeper clusters should be interpreted in light of the increasing location
 274 uncertainty away from the network (Figure 4).

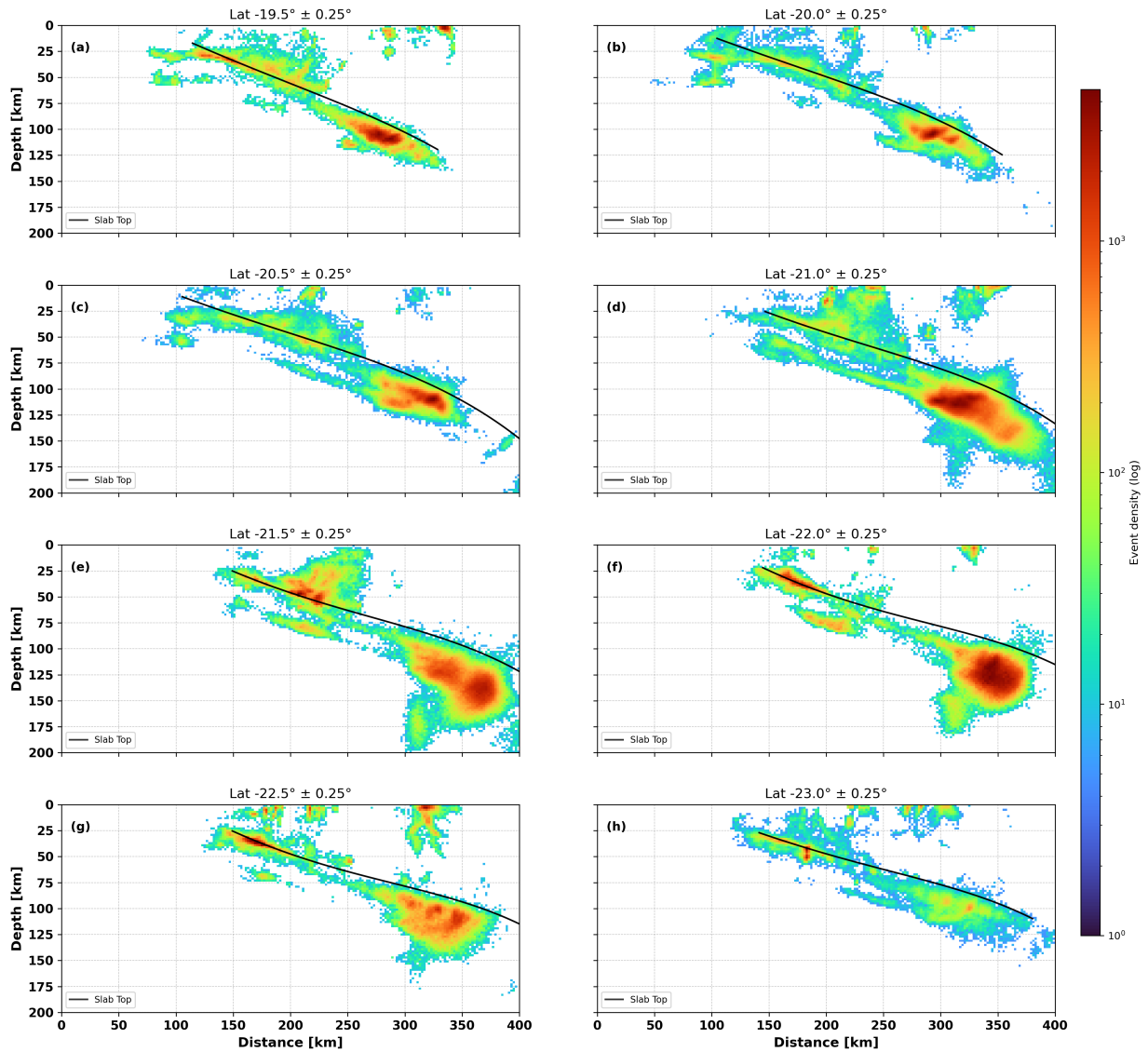


Figure 7: Earthquake density cross-sections along latitude for Northern Chile, derived from the simul2023 quality A–D subset (2007–2023; $N = 1,902,077$). Each panel shows a depth–distance cross-section centered at the indicated latitude (labels in the upper-left corner of each panel). Distance is measured eastward from 72°W (0 km). Colors represent earthquake density (event counts per bin) on a logarithmic scale. The solid black line denotes the slab-top depth model (from Sippl et al., 2018).

Alt text: Eight latitudinal cross-sections showing seismicity density along narrow E–W oriented swaths. Along-strike variations reveal changes in slab dip and seismicity thickness.

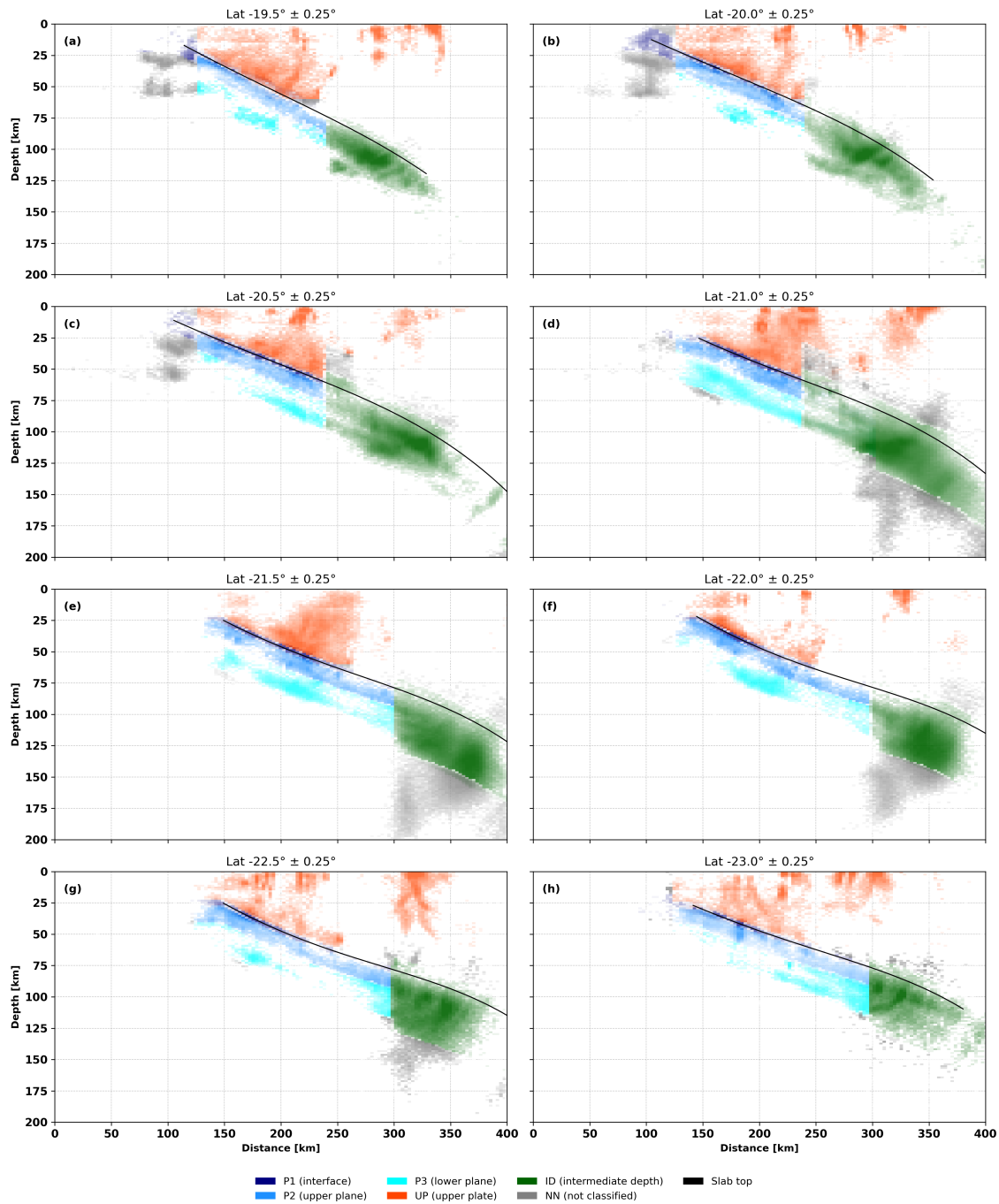


Figure 8: Density cross sections of slab-related seismicity along latitude bands in Northern Chile. Each panel shows earthquake density projected onto a trench-normal cross section within $\pm 0.25^\circ$ of the indicated latitude. Distance is measured eastward from 72°W (0 km). Events are classified relative to the slab top (black line) into plate interface (P1), upper plane (P2), lower plane (P3), upper plate (UP), intermediate depth (ID), and not classified (NN) domains following the spatial criteria in Table 2. Colors represent class-specific event density on a logarithmic scale (darker colors indicate higher density), normalized to the maximum event density for each class.

Alt text: Eight latitudinal cross-sections, with events color-coded by their association to a tectonic unit: plate interface, upper and lower intraslab planes, upper-plate, and intermediate-depth domain. These units were defined by distance relative to the slab top. The geometry reveals a well-developed double seismic zone and clear separation between forearc upper-plate activity and slab-related seismicity.

TABLE 2. : Description of the spatial classification scheme applied to all earthquakes of the IPOC catalog. ST denotes the slab-top depth; distances are given relative to ST (positive values indicate events below the slab top).

Class	Meaning	Color	Areas S of 21°S	Areas N of 21°S
NN	Not classified	Gray	Events south of 23.6°S; east of 68°W; west of 70.8°W and >10 km below slab top (ST)	Events north of 19°S; east of 68°W; west of 70.8°W and >10 km below ST
ID	Intermediate-depth cluster	Dark green	69.1°W–68°W and between 10 km above ST and 50 km below ST	69.7°W–68°W and between 10 km above ST and 50 km below ST
UP	Upper plate	Orange-red	70.8°W–69.1°W and >3 km above ST; 69.1°W–68°W and >30 km above ST; depth ≤ 60 km	70.8°W–69.7°W and >3 km above ST; 69.7°W–68°W and >30 km above ST; depth ≤ 60 km
P1	Plate interface	Navy	70.8°W–69.1°W and ± 3 km around ST; west of 70.8°W and ± 10 km around ST	70.8°W–69.7°W and ± 3 km around ST; west of 70.8°W and ± 10 km around ST
P2	Upper plane	Dodger blue	70.8°W–69.1°W and 3–16 km below ST	70.8°W–69.7°W and 3–16 km below ST
P3	Lower plane	Cyan	70.8°W–69.1°W and 16–40 km below ST	70.8°W–69.7°W and 16–40 km below ST

Temporal evolution and event statistics

Although the 17-year observation period enables the analysis of long-term background seismicity trends, temporal variations in station coverage introduce heterogeneity in detection capability. We summarize the temporal evolution of seismicity in a latitude–time density plot (Figure 9).

The highest seismicity density is consistently observed near 21°S, corresponding to the maximum of intermediate-depth intraslab seismicity shown in Figure 6. In this region, seismicity rates remain broadly stable over time but show a gradual decline in later years. Superimposed on this long-term behavior are shorter-term increases and decreases, particularly during 2010–2012.

Comparison with the on- and off-times of temporary station deployments (second panel in Figure 9) indicates that changes in network density strongly influence the number of detected events.

Figure 9 also shows bursts of seismicity that are related to aftershock sequences of large earthquakes. The most prominent of these are related to the 2007 M_w 7.7 Tocopilla earthquake (e.g. Schurr et al., 2012; Fuenzalida et al., 2013) around 23°S, the 2014 M_w 8.1 Iquique earthquake (e.g. Schurr et al., 2014; Hayes et al., 2014) around 20°S, and the 2020 M_w 6.2 Rio Loa earthquake (Tassara et al., 2022) around 21.5°S. Short-lived increases in event rates corresponding to these sequences are also visible in the cumulative event rate plot. The effect of the Iquique sequence is underestimated here, since part of the offshore events were not classified as plate interface events but were instead assigned to class NN (see above).

The cumulative event rates as well as the provided annual statistics (Table 1) show significant variations in event counts per year, with later years showing clearly lower event rates. This is a consequence of the decreased detection capability of the network at later times, caused by the availability of fewer stations. In Figure 10, we show estimates of the spatial distribution of completeness magnitude for each year, determined with the method of Schorlemmer and Woessner (2008). Detections or non-detections of events are retrieved from the catalog, and the magnitude above which an event is detected at a minimum of 5 stations (assuming P- and S-phase picks at each station, this corresponds to the minimum of 10 picks used for event association) with a probability of 0.99999 is mapped. It is evident that while M_c values below 2 for events within the network

298 footprint were common in early years, with M_c values reaching below 1.5 in the central latitudes, completeness magnitudes
 299 increased in more recent years. Since about 2020, M_c has risen above 2 and approaches 2.5 in large parts of the study area.

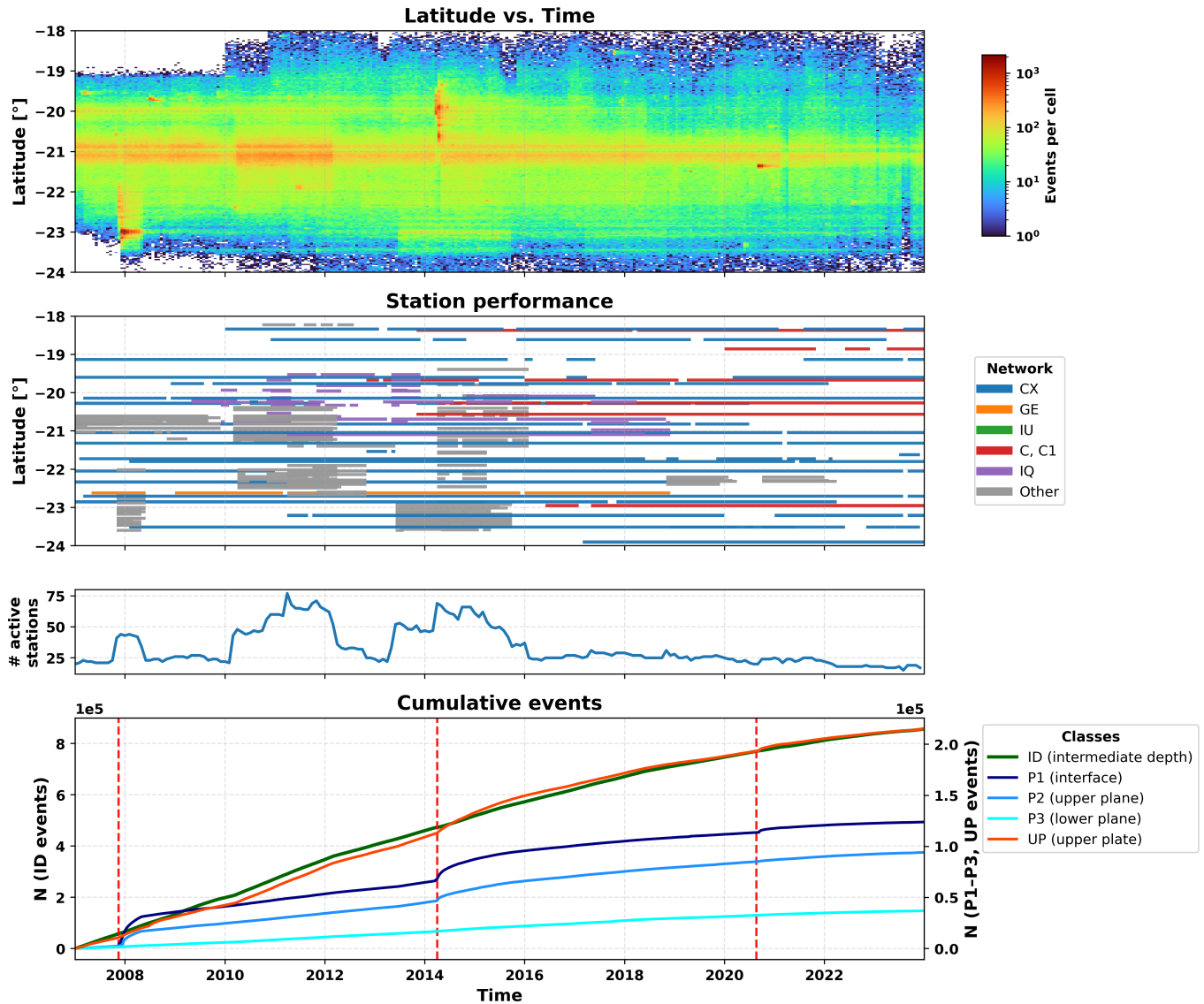


Figure 9: Temporal evolution of seismicity, network coverage, and cumulative event counts for Northern Chile (2007–2023). (Top) Latitude–time earthquake density (events per bin; logarithmic color scale). (Second) Station runtimes; horizontal bars denote months when a station is active (events/month with a pick ≥ 5), colored by network. (Third) Total number of active stations per month. (Bottom) Cumulative number of events by tectonic class; intermediate-depth (ID) events are shown on the left axis and slab/upper-plate classes (P1–P3, UP) on the right axis. Red dashed lines mark times of abrupt changes in cumulative rates in response to the Tocopilla, Iquique and Rio Loa events (see text).

Alt text: Evolution of earthquake density through time, plotted against latitude together with the history of station runtimes. Seismicity rates remain relatively stable in the main intraslab cluster near 21°S over the 17-year analysis period, while sudden increases in event numbers correspond to major earthquake sequences.

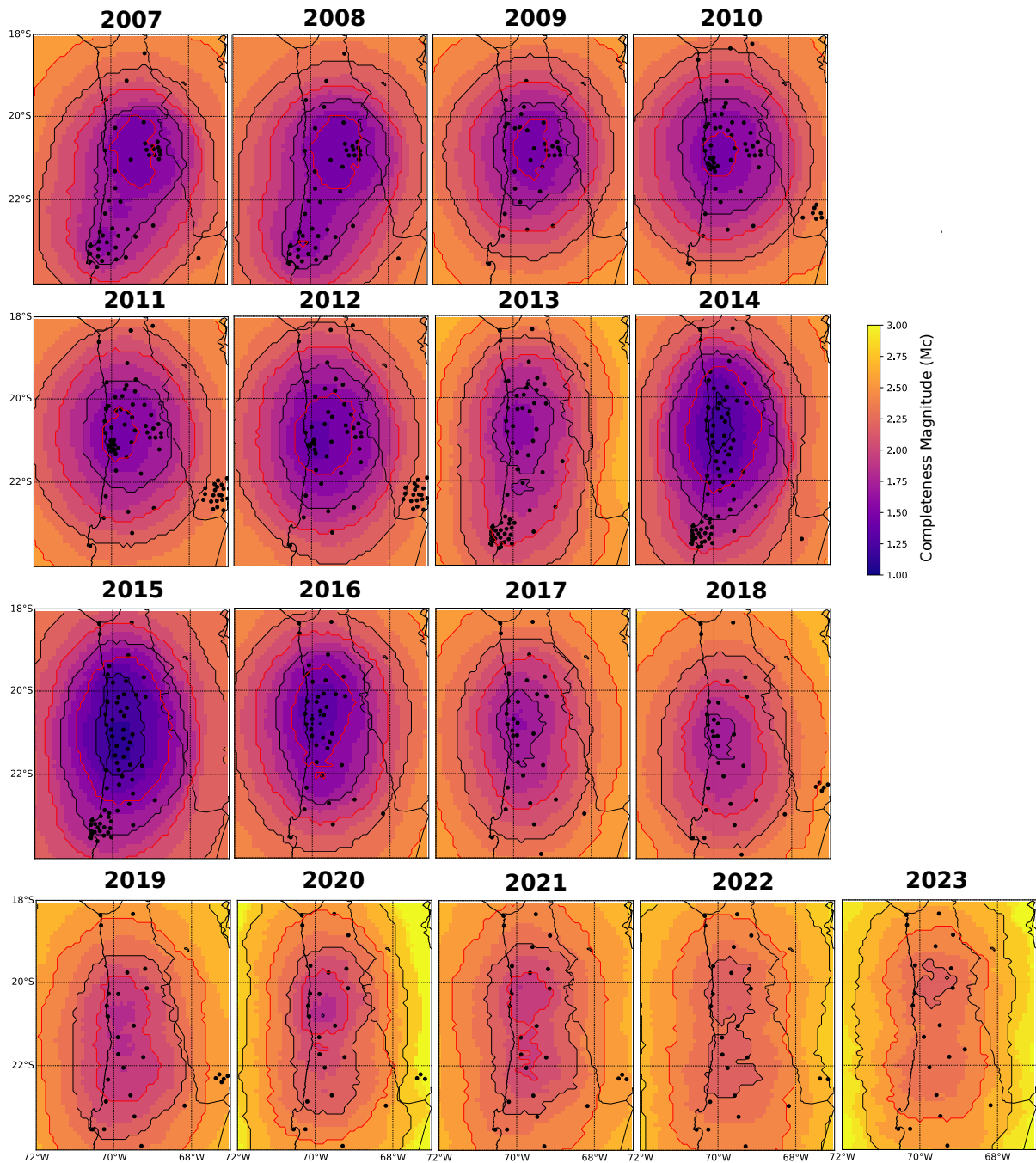


Figure 10: Yearly maps of completeness magnitude M_c estimated using the method of Schorlemmer and Woessner (2008), assuming a hypocentral depth of 50 km and using a probability threshold of 0.99999 for detection at at least five stations. Contour lines are drawn every 0.25 units of M_c , with contours every 0.5 units (i.e. at 1.5, 2, 2.5) in red. Black dots show the locations of stations that were operating for more than 30 days in each year. Note the deterioration of detection capability in later years due to a smaller number of operating stations, which is reflected in lower event numbers retrieved for these years (Table 1).

Alt text: Spatial maps of yearly estimates of completeness magnitude show lower M_c values during periods of dense station coverage and progressively higher M_c in later years as station numbers decline.

Zoom into the 2007 Tocopilla sequence

To provide an example for the spatio-temporal evolution of seismicity during a major subduction earthquake sequence in our catalog, we focus on the 2007 Tocopilla earthquake and its aftershock activity (Figure 11). The M_w 7.7 Tocopilla mainshock occurred on 14 November 2007 at a depth of 53 km beneath the Northern Chilean forearc and ruptured a segment of the downdip part of the plate interface offshore of Tocopilla (Schurr et al., 2012). While the slip distribution, its relation to aftershock seismicity, and many aspects of the Tocopilla sequence have been discussed in detail before (Schurr et al., 2012; Fuenzalida et al., 2013; Sippl et al., 2023), we have now identified an order of magnitude more aftershocks that are summarized in Figure 11, where we distinguish three phases of activity.

Phase 1 comprises the mainshock and its immediate aftershock response in the time between 1 November and 15 December 2007. As the station coverage in the area was sparse before the mainshock, we did not resolve much background seismicity preceding the mainshock. The seismicity during this phase largely outlines the approximate north-south extent of the rupture and is predominantly located at depths between 30 and 70 km. In cross section view, a narrow east-dipping structure of high seismicity density outlines the subducting Nazca plate interface, with the mainshock hypocenter situated at the downdip end of the active area. The plot of the temporal evolution of the seismicity density shows an initial decay in event numbers followed by a sharp increase that corresponds to the installation of the temporary network Y9 (Cesca et al., 2009).

Phase 2 is initiated by the M_w 6.9 Michilla earthquake on 16 December 2007, marked by an orange star in Figure 11. This event occurred in the southern part of the Tocopilla rupture area at a depth of approximately 45 km, and broke vertically through the oceanic crust of the downgoing Nazca slab (Fuenzalida et al., 2013). The event generated its own vigorous aftershock sequence, which significantly exceeded event rates elsewhere in the Tocopilla aftershock area. In our plots, this seismicity shows up as a localized concentration near the Michilla epicenter in map view, as well as a distinct, vertically elongated cluster directly below the plate interface activity in profile view. A sudden decrease in the event rate in May 2008 corresponds to the removal of array Y9, after which the detection capability for the region drops significantly (see Figures 9 and 10).

In mid-2013, the MEJIPE temporary seismic network (8G; Salazar et al., 2013) was installed around the Mejillones Peninsula, once again providing much better coverage of the rupture area starting 5.5 years after the mainshock. We show the operation time of this network as Phase 3 in Figure 11. While the longer recording period results in substantially more background seismicity in the upper plate and downgoing slab appearing in the density distributions, we can clearly distinguish the sharp vertical structure of the Michilla earthquake sequence as an area of still increased seismicity rate more than 5 years after its initiation in both the map view and the cross section plot. This example highlights the advantage of working with a long-term seismicity catalog that includes all available temporary networks. Previous studies that either only looked at

the immediate aftermath of the Tocopilla earthquake (e.g. Schurr et al., 2012; Fuenzalida et al., 2013) or only used permanent seismic stations (e.g. Sippl et al., 2018) did not recognize the longevity of this feature.

To assess whether the enhanced visibility of secondary structures in Phase 3 reflects improved detectability or simply the longer observation period, we repeated the analysis using a uniform magnitude threshold of $M_L \geq 3.0$. The persistence of these structures after applying the threshold indicates that their visibility is primarily controlled by the substantially longer observation window of Phase 3, which allows low-rate background seismicity to accumulate and become apparent in the density distributions (Figure S4).

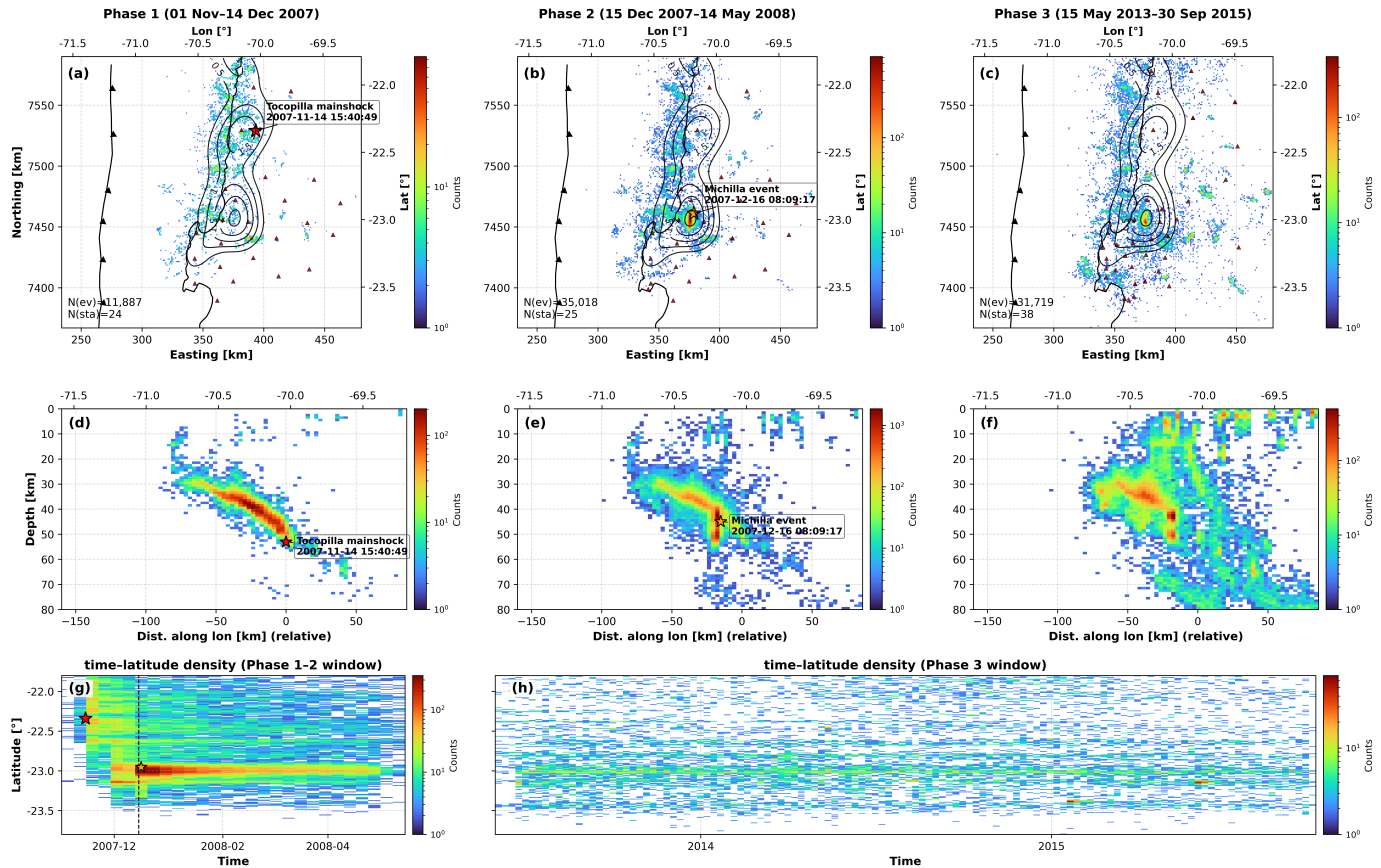


Figure 11: Zoom into the 2007 Tocopilla earthquake sequence. (a–c) Earthquake density maps for the three temporal phases defined in the text (UTM coordinates in km). Triangles indicate seismic stations. Stars mark the dominant event of each phase: the M_w 7.7 Tocopilla mainshock on 14 November 2007 (a; red; Schurr et al., 2012) and the M_w 6.9 Michilla earthquake on 16 December 2007 (b; orange; Fuenzalida et al., 2013). Black lines outline mainshock slip as in Figure 6. (d–f) Longitude-relative distance versus depth density sections highlighting the spatio-temporal evolution of seismicity. (g) Time–latitude density plot for Phases 1 and 2, with the phase boundary indicated by a dashed vertical line; (h) time–latitude density plot for Phase 3. Colors denote event counts per bin on a logarithmic scale.

Alt text: Temporal evolution of the seismicity of the 2007 Tocopilla sequence, shown in map view, profile view and as time against latitude. Plots are separated into three distinct phases with different geometry characteristics.

Conclusions

We present a new high-resolution seismicity catalog for Northern Chile that covers the time period 2007–2023. The catalog comprises more than 2.2 million earthquakes, based on over 45 million P- and 41 million S-phase picks. After relocation with

simul2023 and relative relocation using hypoDD, the dataset achieves increased spatial and temporal resolution compared to previous studies, allowing detailed imaging of the upper plate, plate interface, and subducting Nazca slab.

The catalog resolves first-order tectonic features, including background activity along the plate interface, widespread crustal seismicity in the upper plate, and vigorous intraslab seismicity forming a double seismic zone that grades into a thick seismogenic cluster at ~ 90 km depth. Temporal variations in seismicity reflect both changes in network coverage and major tectonic events such as the 2007 Tocopilla and 2014 Iquique earthquakes. The overall completeness magnitude is estimated to be $M_L \sim 2.3$ in most of the study region, with a sensitivity that extends significantly below $M_L \sim 2.0$ inside the station network during years of dense station coverage.

This catalog is supplied as a research dataset for the seismological and geoscientific community. We expect that it will serve as a basis for a broad range of future research. Potential research avenues could include more detailed investigations of plate interface structure, processes related to the complex geometries outlined by intraslab seismicity, statistical seismology and studies of earthquake clustering or triggering processes, and tomographic imaging of crust, mantle wedge, and downgoing slab.

Data and Resources

The IPOC-Deep earthquake catalog, including relocated hypocenter data and associated P- and S-wave phase picks, is publicly available through GFZ Data Services (Najafipour et al., 2026).

Supplementary material accompanying this article consists of four figures (Figures S1–S4). Figures S1 and S2 provide additional evaluations of the pretrained INSTANCE and fine-tuned EQT-Instance-CJN phase-picking models, Figure S3 presents the distributions of the simul2023 location-quality parameters used for catalog classification, and Figure S4 shows the magnitude-threshold analysis of the three phases of the 2007 Tocopilla earthquake sequence.

Utilized seismic stations were obtained through GEOFON (<https://geofon.gfz.de/waveform/archive/>) and IRIS (<https://ds.iris.edu/ds/nodes/dmc/data/>) data services, and belong to the networks CX (GFZ and CNRS-INSU, 2006), C1 (Universidad de Chile, 2013), C (no DOI), GE (GEOFON Data Centre, 1993), IU (Albuquerque Seismological Laboratory/USGS, 1988), IQ (Cesca et al., 2009), 8F (Wigger et al., 2016), 5E (Asch et al., 2011), XP (West and Christensen, 2010), 8E (Walter et al., 2017), 1U (Pritchard, 2018), ZG (Beck et al., 2010), Y9 (Sobiesiak and Schurr, 2007), 3D (Asch et al., 2014) and 8G (Salazar et al., 2013).

Acknowledgments

C. Sippl has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (ERC Starting grant MILESTONE, StG2020-947856).

Declaration of Competing Interest

The authors acknowledge there are no conflicts of interest recorded.

References

- Albuquerque Seismological Laboratory/USGS (1988). Global Seismograph Network (GSN - IRIS/USGS) [Data set]. International Federation of Digital Seismograph Networks. doi: <https://doi.org/10.7914/SN/IU>.
- Asch, G., F. Tilmann, B. Heit, and B. Schurr (2014). HART-PISAGUA Project Chile [Data set]. GFZ Data Services. doi: <https://doi.org/10.14470/8Q7569558037>.
- Asch, G., F. Tilmann, B. Schurr, and T. Ryberg (2011). Seismic network 5E: MINAS Project (2011/2013). doi: <https://doi.org/10.14470/ab466166>.
- Beck, S., G. Zandt, and L. Wagner (2010). Central Andean Uplift and the Geodynamics of the High Topography [Data set]. International Federation of Digital Seismograph Networks. doi: https://doi.org/10.7914/SN/ZG_2010.
- Bormann, P. (2012). New Manual of Seismological Observatory Practice (NMSOP-2). IASPEI, GFZ German Research Centre for Geosciences, Potsdam. doi: <https://doi.org/10.2312/GFZ.NMSOP-2>.
- Braszus, B., A. Rietbrock, C. Haberland, and T. Ryberg (2024). AI based 1-D P- and S-wave velocity models for the greater alpine region from local earthquake data. *Geophysical Journal International* **237**(2), 916–930. doi: <https://doi.org/10.1093/gji/ggae077>.
- Cesca, S., M. Sobiesiak, A. Tassara, M. Olcay, E. Günther, S. Mikulla, and T. Dahm (2009). The Iquique Local Network and PicArray. doi: <https://doi.org/10.14470/VD070092>.
- Duputel, Z., J. Jiang, R. Jolivet, M. Simons, L. Rivera, J.-P. Ampuero, B. Riel, S. E. Owen, A. W. Moore, S. V. Samsonov, F. Ortega Culaciati, and S. E. Minson (2015). The Iquique earthquake sequence of April 2014: Bayesian modeling accounting for prediction uncertainty. *Geophysical Research Letters* **42**(19), 7949–7957. doi: <https://doi.org/10.1002/2015GL065402>.
- Eberhart-Phillips, D., C. Thurber, A. Rietbrock, B. Fry, M. Reyners, and F. Lanza (2024). Simul2023: a flexible program for inversion of earthquake data for 3-D velocity and hypocenters or 3-D Q. doi: <https://doi.org/10.5281/ZENODO.10695070>.
- Fuenzalida, A., B. Schurr, M. Lancieri, M. Sobiesiak, and R. Madariaga (2013). High-resolution relocation and mechanism of aftershocks of the 2007 Tocopilla (Chile) earthquake. *Geophysical Journal International* **194**(2), 1216–1228. doi: <https://doi.org/10.1093/gji/ggt163>.
- GEOFON Data Centre (1993). GEOFON Seismic Network. doi: <https://doi.org/10.14470/TR560404>.
- GFZ and CNRS-INSU (2006). IPOC Seismic Network: Integrated Plate boundary Observatory Chile - IPOC. doi: <https://doi.org/10.14470/PK615318>.
- Graeber, F. M. and G. Asch (1999). Three-dimensional models of P wave velocity and P-to-S velocity ratio in the southern central Andes by simultaneous inversion of local earthquake data. *Journal of Geophysical Research: Solid Earth* **104**(B9), 20237–20256. doi: <https://doi.org/10.1029/1999JB900037>.
- Hayes, G. P., E. Bergman, K. L. Johnson, A. Sladen, D. Melgar, E. J. Fielding, S. Wei, A. R. Nelson, A. M. Heimsath, and W. D. Barnhart (2014). Continuing megathrust earthquake potential in Chile after the 2014 Iquique earthquake. *Nature* **512**(7514), 295–298. doi: <https://doi.org/10.1038/nature13677>.

- 404 Lomax, A., J. Virieux, P. Volant, and C. Berge-Thierry (2000). Probabilistic Earthquake Location in 3D and Layered Models. In *Advances*
405 *in Seismic Event Location*, pp. 101–134. doi: 10.1007/978-94-015-9536-0_5.
- 406 Michelini, A., S. Cianetti, S. Gaviano, C. Giunchi, D. Jozinović, and V. Lauciani (2021). INSTANCE – the Italian seismic dataset for machine
407 learning. *Earth System Science Data* **13**(12), 5509–5544. doi: <https://doi.org/10.5194/essd-13-5509-2021>.
- 408 Mousavi, S. M., W. L. Ellsworth, W. Zhu, L. Y. Chuang, and G. C. Beroza (2020). Earthquake Transformer—an attentive deep-learning model
409 for simultaneous earthquake detection and phase picking. *Nature Communications* **11**(1), 3952. doi: [https://doi.org/10.1038/s41467-](https://doi.org/10.1038/s41467-020-17591-w)
410 [020-17591-w](https://doi.org/10.1038/s41467-020-17591-w).
- 411 Münchmeyer, J. (2024). PyOcto: A high-throughput seismic phase associator. *Seismica* **3**(1). doi:
412 <https://doi.org/10.26443/seismica.v3i1.1130>.
- 413 Münchmeyer, J., D. Molina-Ormazabal, D. Marsan, M. Langlais, J.-C. Baez, B. Heit, D. González-Vidal, M. Moreno, F. Tilmann, D. Lange,
414 and A. Socquet (2025). Characterizing the Atacama Segment of the Chile Subduction Margin (24°S–31°S) With >165,000 Earthquakes.
415 *Journal of Geophysical Research: Solid Earth* **130**(7), e2025JB031256. doi: <https://doi.org/10.1029/2025JB031256>.
- 416 Münchmeyer, J., J. Woollam, A. Rietbrock, F. Tilmann, D. Lange, T. Bornstein, T. Diehl, C. Giunchi, F. Haslinger, D. Jozinović, A. Michelini,
417 J. Saul, and H. Soto (2022). Which Picker Fits My Data? A Quantitative Evaluation of Deep Learning Based Seismic Pickers. *Journal of*
418 *Geophysical Research: Solid Earth* **127**(1), e2021JB023499. doi: <https://doi.org/10.1029/2021JB023499>.
- 419 Najafipour, N., C. Sippl, J. Kasravi, J. Folesky, and B. Schurr (2026). IPOC-Deep: A New Seismicity Catalog for Northern Chile. doi:
420 <https://doi.org/10.5880/fidgeo.2026.050>.
- 421 Ni, Y., M. Denolle, A. Thomas, A. Hamilton, J. Münchmeyer, Y. Wang, L. Bachelot, C. Trabant, and D. Mencin (2025). A Global-scale
422 Database of Seismic Phases from Cloud-based Picking at Petabyte Scale. *Seismica* **4**(2). doi: <https://doi.org/10.26443/seismica.v4i2.1738>.
- 423 Paszke, A., S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Köpf,
424 E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala (2019). PyTorch: An Imperative
425 Style, High-Performance Deep Learning Library.
- 426 Potin, B., S. Ruiz, F. Aden-Antoniow, R. Madariaga, and S. Barrientos (2025). A Revised Chilean Seismic Catalog from 1982 to Mid-2020.
427 *Seismological Research Letters* **96**(1), 484–498. doi: <https://doi.org/10.1785/0220240047>.
- 428 Pritchard, M. (2018). Uturuncu volcano, Bolivia. International Federation of Digital Seismograph Networks. doi:
429 https://doi.org/10.7914/SN/1U_2018.
- 430 Puente Huerta, J., C. Sippl, J. Münchmeyer, and I. W. McBrearty (2025). Benchmarking seismic phase associators: Insights from synthetic
431 scenarios. *Seismica* **4**(2), 1–19. doi: <https://doi.org/10.26443/seismica.v4i2.1559>.
- 432 Riedel-Hornig, M., C. Sippl, A. Tassara, S. Ruiz, B. Potin, and J. Puente (2026). Seismicity catalogue of the entire Chilean margin (18 to
433 56S) from an automated approach. *Earth System Science Data* **18**, 1–16. doi: <https://doi.org/10.5194/essd-18-1-2026>.
- 434 Ross, Z. E., D. T. Trugman, E. Hauksson, and P. M. Shearer (2019). Searching for hidden earthquakes in Southern California.
435 *Science* **364**(6442), 767–771. doi: <https://doi.org/10.1126/science.aaw6888>.
- 436 Salazar, P., P. Wigger, W. Bloch, G. Asch, S. Shapiro, and J. Kummerow (2013). MEJIPE [Data set]. International Federation of Digital
437 Seismograph Networks. doi: https://doi.org/10.7914/SN/8G_2013.

- Schorlemmer, D. and J. Woessner (2008). Probability of Detecting an earthquake. *Bulletin of the Seismological Society of America* **98**(5), 2103–2117. doi: <https://doi.org/10.1785/0120070105>.
- Schurr, B., G. Asch, S. Hainzl, J. Bedford, A. Hoechner, M. Palo, R. Wang, M. Moreno, M. Bartsch, Y. Zhang, and O. Oncken (2014). Gradual unlocking of plate boundary controlled initiation of the 2014 Iquique earthquake. *Nature* **512**(7514), 299–302. doi: <https://doi.org/10.1038/nature13681>.
- Schurr, B., G. Asch, M. Rosenau, R. Wang, O. Oncken, S. Barrientos, P. Salazar, and J.-P. Vilotte (2012). The 2007 M7.7 Tocopilla northern Chile earthquake sequence: Implications for along-strike and downdip rupture segmentation and megathrust frictional behavior. *Journal of Geophysical Research: Solid Earth* **117**(B5), B05305. doi: <https://doi.org/10.1029/2011JB009030>.
- Si, Z., W. Wang, L. Li, S. Zhong, Z. Liu, Z. Yu, and Y. Zhang (2026). Earthquake catalog in northeastern Tibetan plateau from the large aperture ChinArray-II through deep learning approach. *Geophysical Journal International* **244**(1), ggaf292. doi: <https://doi.org/10.1093/gji/ggaf292>.
- Sippl, C., B. Schurr, G. Asch, and J. Kummerow (2018). Seismicity Structure of the Northern Chile Forearc From >100,000 Double-Difference Relocated Hypocenters. *Journal of Geophysical Research: Solid Earth* **123**(5), 4063–4087. doi: <https://doi.org/10.1002/2017JB015384>.
- Sippl, C., B. Schurr, J. Münchmeyer, S. Barrientos, and O. Oncken (2023). The Northern Chile forearc constrained by 15 years of permanent seismic monitoring. *J. South Am. Earth Sci.* **126**, 104326. doi: <https://doi.org/10.1016/j.jsames.2023.104326>.
- Sobiesiak, M. and B. Schurr (2007). Taskforce Tocopilla 2007 [Data set]. GFZ Data Services. doi: <https://doi.org/10.14470/L47552843299>.
- Tassara, C., S. Cesca, M. Miller, J. Ángel López-Comino, C. Sippl, J. Cortés-Aranda, and B. Schurr (2022). Seismic source analysis of two anomalous earthquakes in Northern Chile. *Journal of South American Earth Sciences* **119**, 103948. doi: <https://doi.org/10.1016/j.jsames.2022.103948>.
- Universidad de Chile (2013). Red Sismologica Nacional. International Federation of Digital Seismograph Networks. doi: <https://doi.org/10.7914/SN/C1>.
- Valenzuela-Malebrán, C., S. Cesca, J. López-Comino, M. Zeckra, F. Krüger, and T. Dahm (2022). Source mechanisms and rupture processes of the Jujuy seismic nest, Chile-Argentina border. *Journal of South American Earth Sciences* **117**, 103887. doi: <https://doi.org/10.1016/j.jsames.2022.103887>.
- Waldhauser, F. and W. L. Ellsworth (2000). A Double-Difference Earthquake Location Algorithm: Method and Application to the Northern Hayward Fault, California. *Bulletin of the Seismological Society of America* **90**(6), 1353–1368. doi: <https://doi.org/10.1785/0120000006>.
- Walter, T., A. Gaete, S. Mikulla, C. Kujawa, J. Salzer, and M. Zimmer (2017). Seismic monitoring at Lascar volcano after 2014 Iquique earthquake [Data set]. GFZ Data Services. doi: <https://doi.org/10.14470/3R7569753098>.
- West, M. and D. Christensen (2010). Investigating the relationship between pluton growth and volcanism at two active intrusions in the central Andes [Data set]. International Federation of Digital Seismograph Networks. doi: https://doi.org/10.7914/SN/XP_2010.
- Wigger, P., P. Salazar, J. Kummerow, W. Bloch, G. Asch, and S. A. Shapiro (2016). West-Fissure- and Atacama-Fault Seismic Network (2005/2012). doi: <https://doi.org/10.14470/3S7550699980>.

471 Woollam, J., J. Münchmeyer, F. Tilmann, A. Rietbrock, D. Lange, T. Bornstein, T. Diehl, C. Giunchi, F. Haslinger, D. Jozinović, A. Michelini,
472 J. Saul, and H. Soto (2022). SeisBench—A Toolbox for Machine Learning in Seismology. *Seismological Research Letters* **93**(3), 1695–1709.
473 doi: <https://doi.org/10.1785/0220210324>.
474 Zhang, M., W. L. Ellsworth, and G. C. Beroza (2019). Rapid Earthquake Association and Location. *Seismol. Res. Lett.* **90**(6), 2276–2284.
475 doi: <https://doi.org/10.1785/0220190052>.
476 Zhu, W. and G. C. Beroza (2018). PhaseNet: a deep-neural-network-based seismic arrival-time picking method. *Geophysical Journal*
477 *International* **216**(1), 261–273. doi: <https://doi.org/10.1093/gji/ggy423>.

Manuscript Received Manuscript Received 1572026

Supplementary Material

IPOC-Deep: a new seismicity catalog for Northern Chile with >2 million events

Nooshin Najafipour, Christian Sippl, Javad Kasravi, Jonas Folesky, and Bernd Schurr

This supplement contains four figures (S1–S4) supporting the main manuscript.

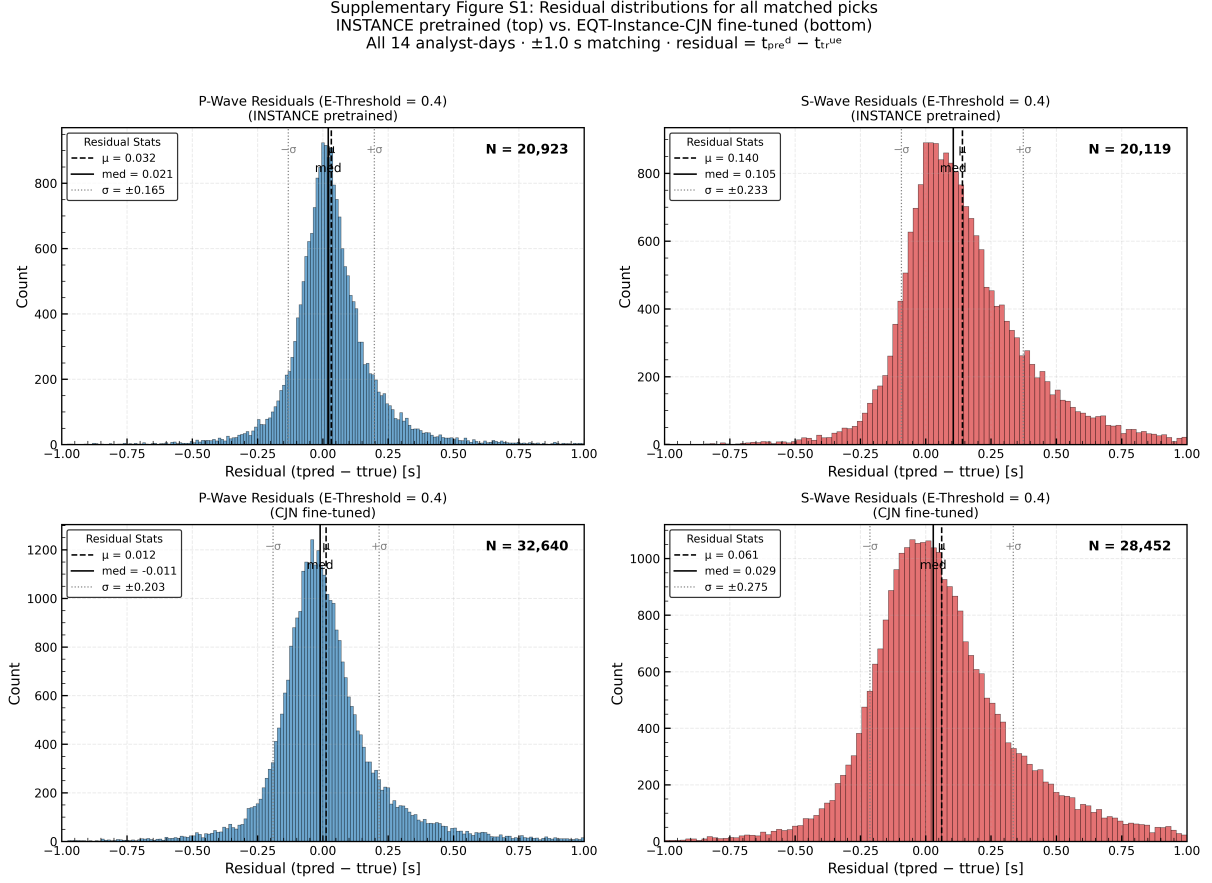


Figure S1: Residual distributions ($t_{\text{pred}} - t_{\text{true}}$) for all matched arrivals in the handpicked reference dataset. The upper panels show results for the pretrained INSTANCE model and the lower panels for the fine-tuned *EQT-Instance-CJN* model. Left panels show P-wave residuals and right panels show S-wave residuals. Dashed, solid, and dotted lines indicate the mean, median, and $\pm 1\sigma$ values, respectively. The fine-tuned model recovers substantially more arrivals than the pretrained model and reduces the systematic positive bias of S-wave picks, although the residual distributions become slightly broader. Because the number of detected arrivals differs between the two models, this comparison reflects both detection performance and picking accuracy; a controlled common-subset comparison isolating picking accuracy alone is provided in Figure S2.

Controlled common-subset comparison: *INSTANCE* pretrained vs. *CJN* fine-tuned
All 14 analyst-days · common subset (both models detected the pick within ± 1.0 s)

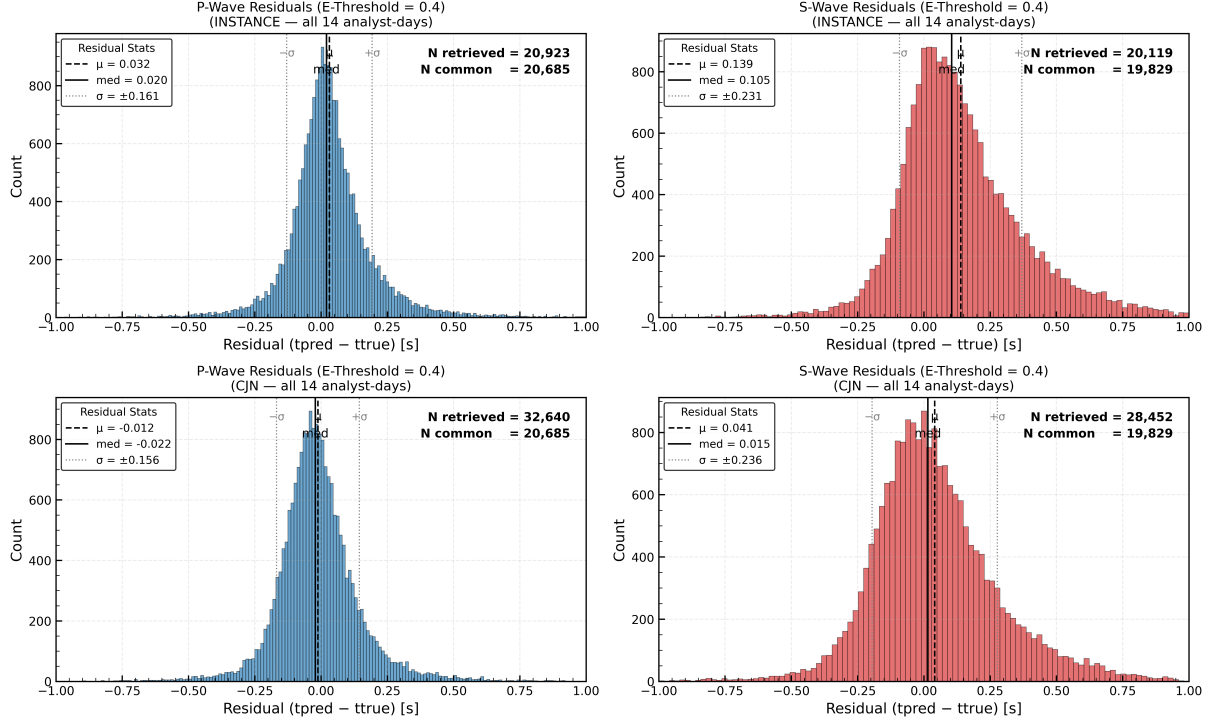
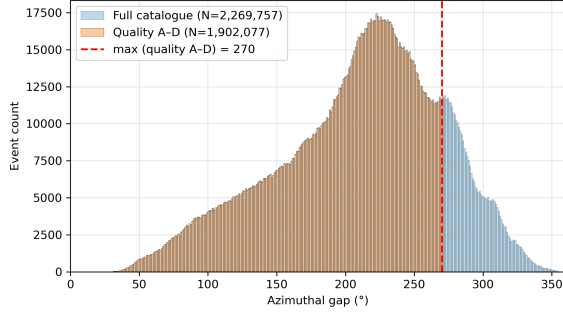
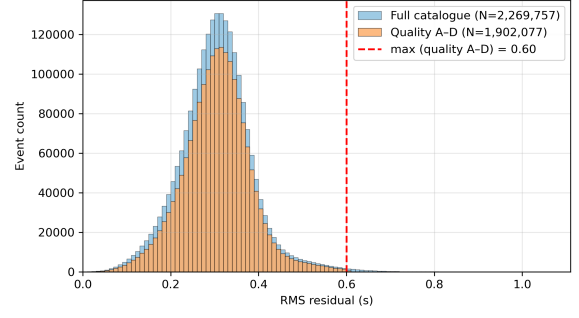


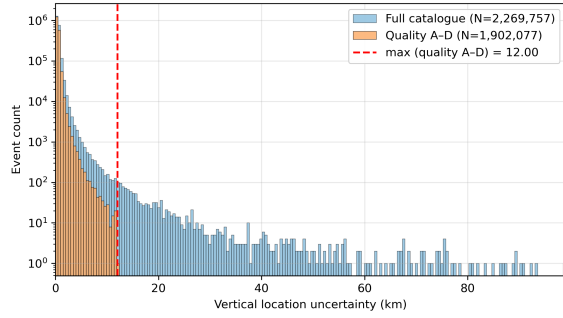
Figure S2: Residual distributions for the pretrained *INSTANCE* model and the fine-tuned *EQT-Instance-CJN* model using all handpicked arrivals from the 14 analyst-days employed during model evaluation. Handpicked arrivals were matched independently to both models using station code, phase type, and a ± 1.0 s time tolerance. Only arrivals detected by both models were retained for the residual comparison, yielding common subsets of 20,685 P-wave picks and 19,829 S-wave picks. The total number of retrieved arrivals for each model is also indicated, illustrating the substantially higher detection rate achieved by the fine-tuned model. Panels show P-wave residuals (left) and S-wave residuals (right) for the pretrained *INSTANCE* model (top) and the fine-tuned *EQT-Instance-CJN* model (bottom). Vertical dashed lines indicate the mean residual, solid lines indicate the median, and dotted lines denote $\pm 1\sigma$. The fine-tuned model substantially reduces the positive S-wave bias while maintaining comparable P-wave precision.



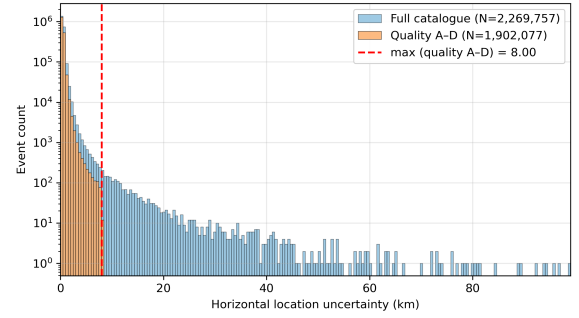
(a) Azimuthal gap



(b) RMS travel-time residual



(c) Vertical location uncertainty (σ_z)



(d) Horizontal location uncertainty (σ_h)

Figure S3: Distributions of simul2023 location-quality parameters for the full earthquake catalog (blue) and the subset classified as simul2023 quality grades A–D (orange). Red dashed lines indicate the threshold criteria separating classes A–D from class E. Panels show (a) azimuthal gap, (b) RMS travel-time residual, (c) vertical location uncertainty, and (d) horizontal location uncertainty.

Tocopilla 2007 sequence — magnitude threshold test
Structures in Phase 3 persist under a consistent $M \geq 3.0$ filter (Phase 3 duration = 868 d, 28× longer than Phase 1).

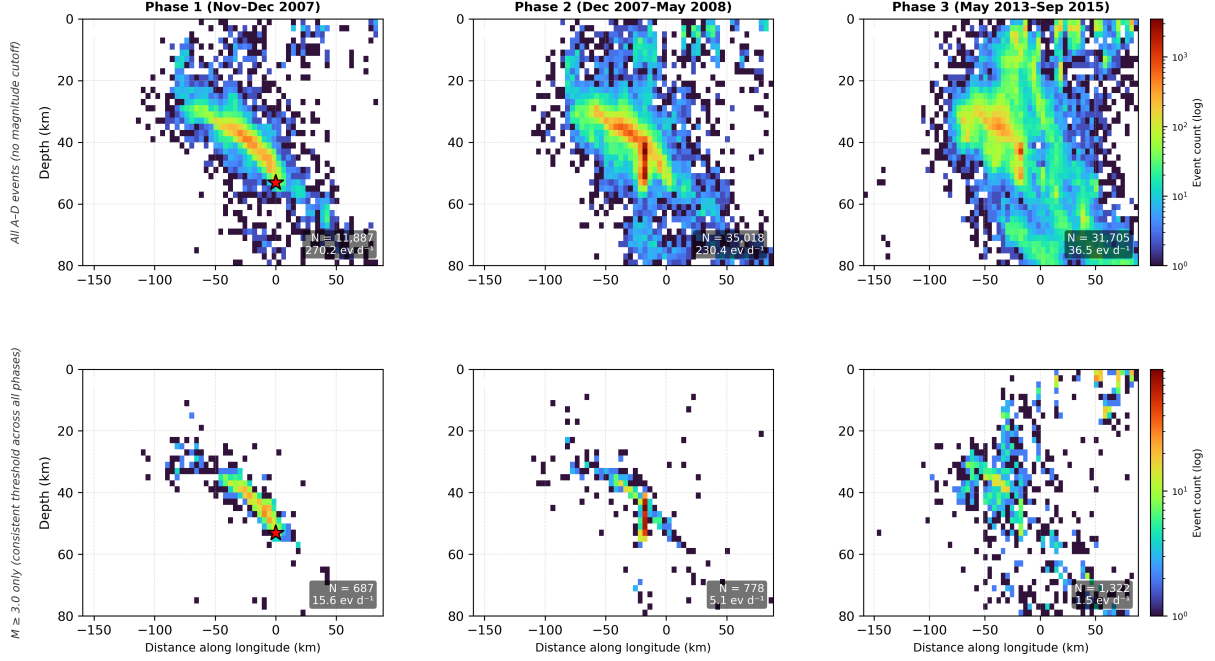


Figure S4: Comparison of seismicity distributions for the three analysis phases of the 2007 Tocopilla earthquake sequence. The upper row shows all quality A–D earthquakes, whereas the lower row includes only earthquakes with $M \geq 3.0$, applying the same magnitude threshold to all three phases. Event numbers and average daily seismicity rates are shown for each panel. Although the magnitude threshold substantially reduces the number of events, the principal secondary structures observed during Phase 3 remain visible. Their persistence demonstrates that these features are not solely the result of improved detection of small earthquakes. Instead, their enhanced expression primarily reflects the substantially longer observation period of Phase 3 (868 days), which allows low-rate background seismicity to accumulate and become apparent.