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Baseline seismic monitoring of the Canning Basin

Interim Report 1

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Table of Contents

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1 Executive Summary

In this interim report, we present the results of the desktop study of the seismic sources through maps using publicly available datasets. Also, we assess the capabilities of the data centre with the first batch of seismic monitoring data coming from the seismic network.

Overall, the desktop study results indicate that the region's seismicity is poorly understood due to the lack of sufficient seismic station coverage and potential impact of the existing infrastructure on man-made signal generation. These results are presented via maps in the report. The newly installed twelve seismic stations by the Geological Survey of Western Australia (GSWA) are currently continuously monitoring the region 24/7. Six out of 12 stations send the data near real-time to the IRIS and Geoscience Australia Repositories, and the data is publicly available. Our initial seismic detection work with multiple algorithms indicates that there are measurable previously undetected events in the region. In addition, the new data from the recently installed seismometers by GSWA is expected to improve the accuracy and detection of the located events.

The project is on time and budget.

1.1 Background

The Canning Basin, in northwest Western Australia, is the largest sedimentary basin in Australia, aside from the Eromanga Basin (subdivision of the Great Artesian Basin) and it contains potential opportunities for developing shale and unconventional gas (Figure 1). Exploration and investigations across large parts of the basin have to date focussed on the prospectivity for oil and gas for which licences for development of facilities have been granted. The regional geology and structure of the basin has been reviewed and summarised in numerous publications by the Western Australia Government Department of Mines, Industry Regulation and Safety.

Australia is often considered a seismically stable continent with no major ongoing tectonic processes apart from the interaction of its boundaries with other tectonic plates. However, in contrast to this, widespread seismicity is observed across the continent (Rajabi et al. 2017). Within the continent, elevated and concentrated levels of seismic activity are found in the SE Australian passive margin, Mount Lofty & Flinders Ranges, SW Western Australia and North West Seismic zone (Hillis et al. 2008) (Figure 1).

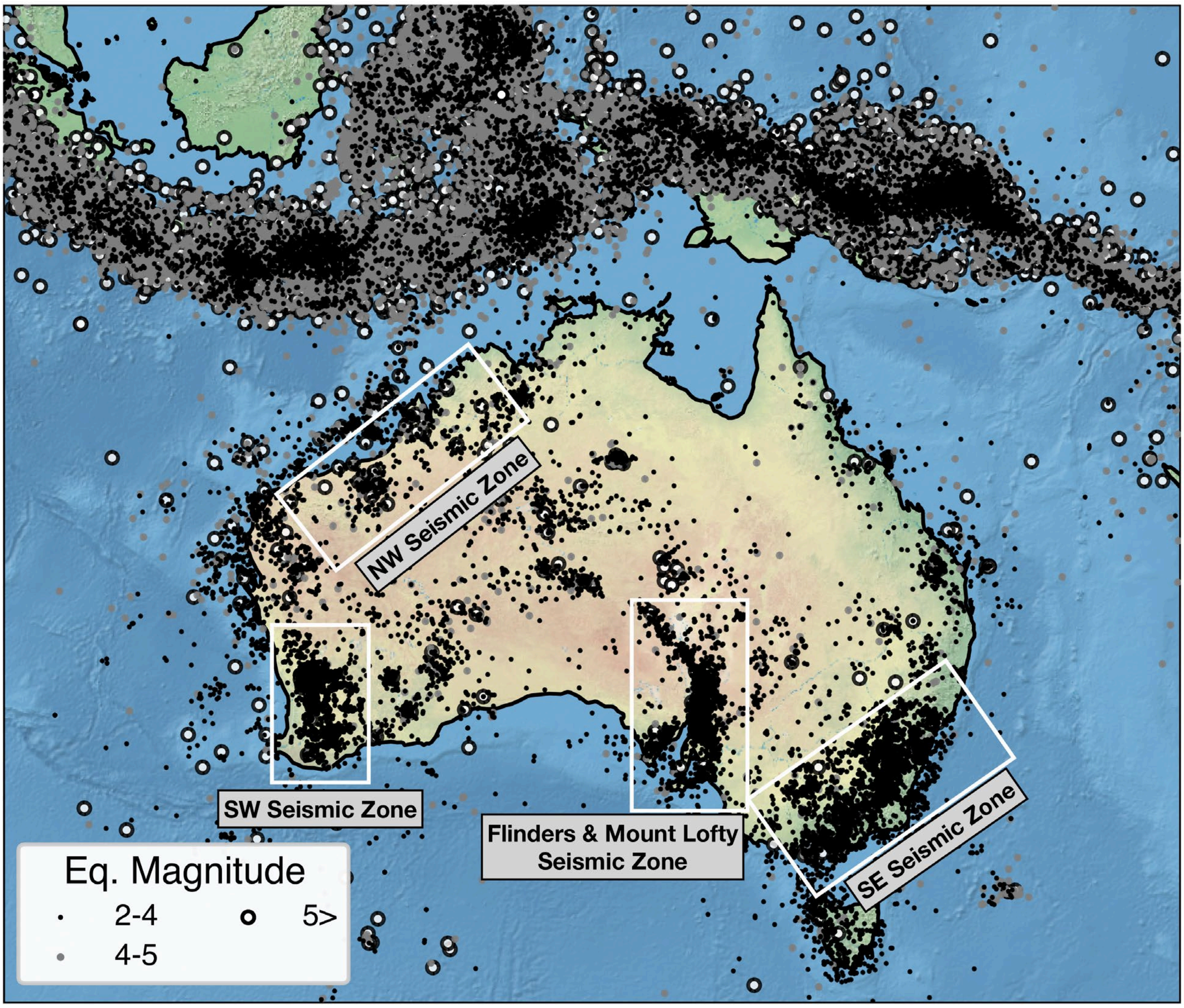

Figure 1: The distribution of earthquakes between 1900 and 2021 with magnitudes larger than 2 across the Australian continent. Four seismic zones are marked on the map. Modified from Rajabi et al. 2017. Source of the earthquakes: Geoscience Australia.

The origin of the natural seismicity in the Canning Basin is associated with the ongoing deformation at the north-eastern margin of the basin (Kennett et al., 2018) with maximum horizontal stress direction oriented NE-SW. Previously seismic activity within the basin is relatively under-constrained due to the lack of seismic monitoring stations in the region (Figure 2A-blue triangles).

1.2 Desktop Study Results

In the desktop study part, we identify the potential sources of seismic activity by using the current and past seismic activity catalogues, mine sites, major roads and any human activity due to the petroleum wells.

The distribution of the seismic monitoring stations was primarily determined by the need to fill the gaps in Geoscience Australia's monitoring stations of the Australian National Seismograph Network (ANSN) prior to the installation of this array (see Figure 2A, blue triangles), logistical needs such as access via public roads (see Figure 2C), the security of the site, and coverage of 4G mobile communication networks, which allows the GSWA team to send data real-time into the National Earthquake Alert Centre at Geoscience Australia in Canberra. There are moderate numbers of operational mines and infrastructure facilities close to the network (Figure 2B). However, generally there are few seismic noise sources and it is expected that the increase in the number of local monitoring stations will result in a decreased monitoring threshold and increase sensitivity to seismic events.

We also looked at the ten-yearly distribution of earthquake activity with all available magnitudes by interrogating the seismic catalogue curated by Geoscience Australia (Figure 3). Overall, the seismic activity is steady in the region with some significant events and their aftershocks, such as the magnitude 6.6 offshore Broome event that occurred on the 14th of July 2019, affecting the total number count (see Figure 3E&F). It is expected that the new network will increase the detection sensitivity to the local seismic activity, especially in the zone between longitudes 121.5°-126 °E and latitudes 19 °-22 °S.

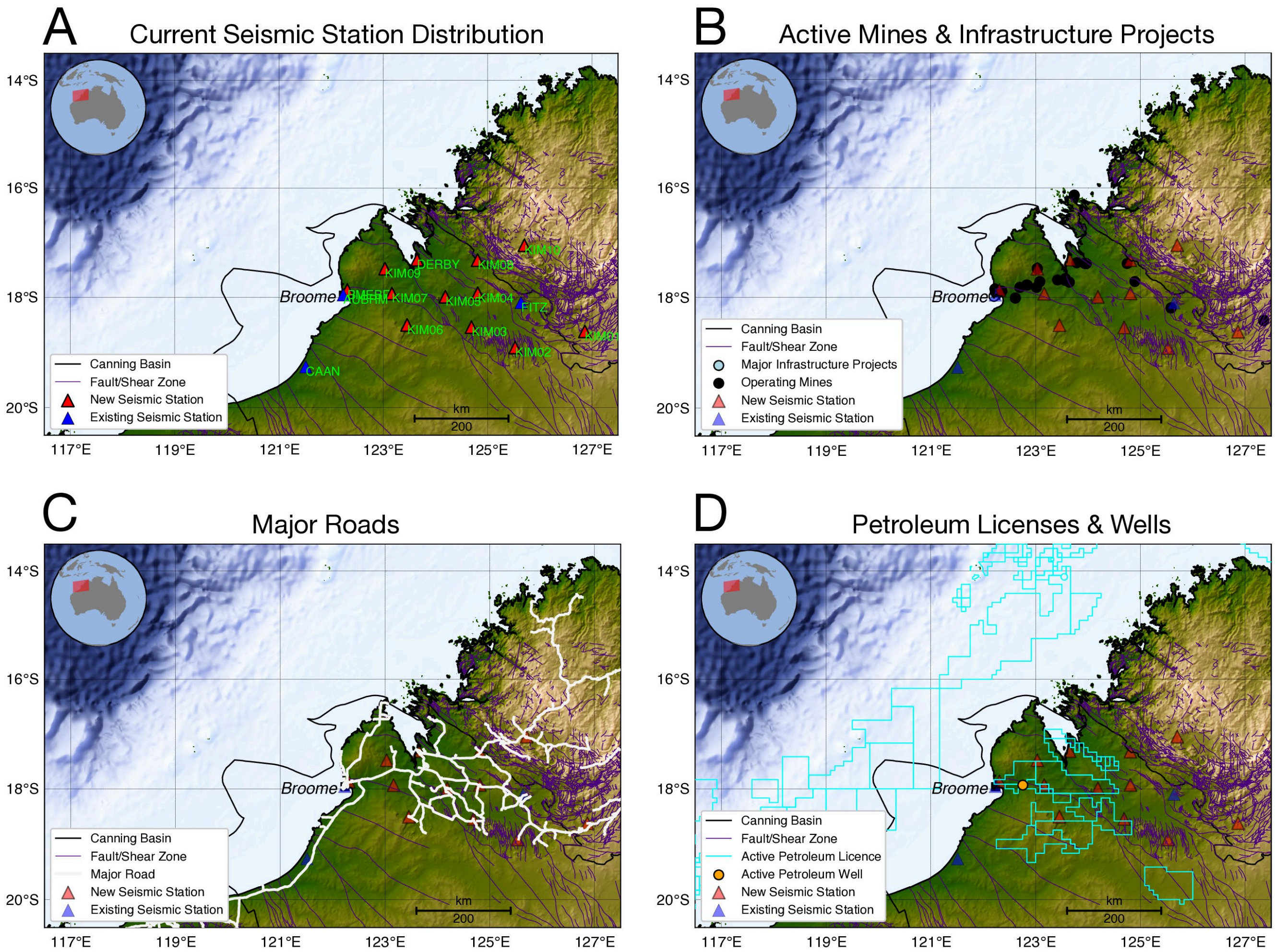

Figure 2: A) Seismic station monitoring network. New stations (red triangles), and existing network (blue triangles). The raw data is freely available from http://ds.iris.edu/mda/AU/. B) Location of operating mines (black circles) and major infrastructure projects (light blue circle), source: GSWA.

C) Major road network, source: Roads (Simplified) (LGATE-195). D) Active petroleum licenses (cyan polygons) and producing wells (orange circle), source: GSWA. In each map, the borders of the Canning Basin are marked with black line, and known fault/shear zones are given with purple lines.

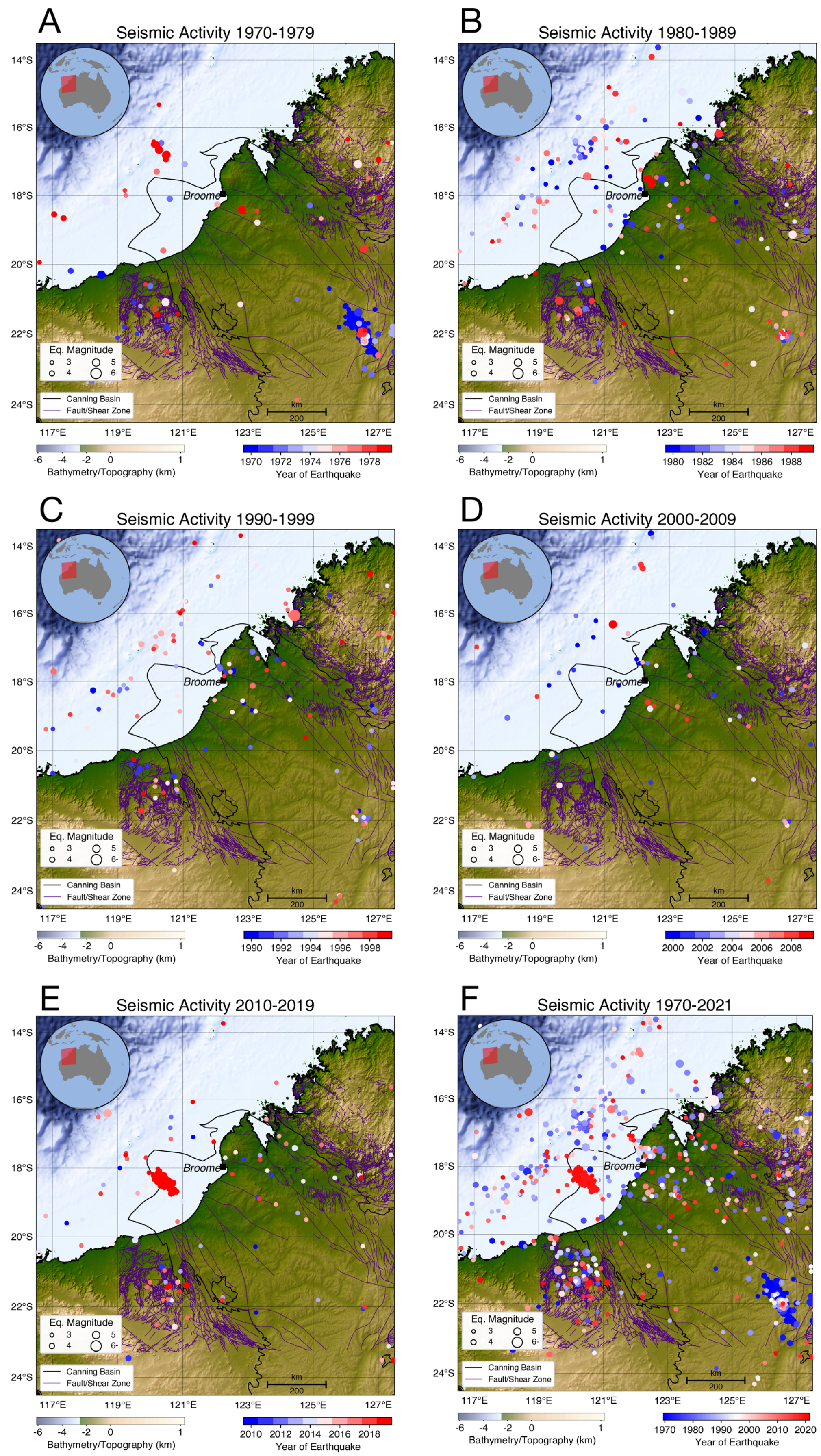

Figure 3: Ten yearly distribution of seismic activity in the region between 1970 and 2021. A) 1970-1979. B) 1980-1989. C) 1990-1999. D) 2000-2009. E) 2010-2019. F) 1970-2021. Each circle is scaled according to the earthquake magnitude and colours indicate the occurrence year of the earthquake. The borders of the Canning Basin are marked with black line, and known fault/shear zones are given with purple line. Earthquake catalogue source: Geoscience Australia. Basin boundaries and fault zones: GSWA.

1.3 Capabilities of the Data Centre

One of the building blocks of the proposed data centre in this project is building a near real-time earthquake detection and location workflow, which will be operating continuously with minimal human intervention. As a part of this, we trialled two automated earthquake detection algorithms. Automatic detection of earthquakes has been developed since the 1970s with the advent of digital seismometry (Allen, 1978; Stewart, 1977). However, these approaches require sensor and location-specific tuning parameters and are prone to produce false detections in more challenging situations such as low SNR, waveforms with emergent arrivals, overlapping events, cultural noise, and sparse station spacing (Yoon et al. 2005). In recent years, significant progress has been made in tackling this problem with the advances in computational resources and machine learning (ML)-based methods.

As a part of this, we first tested the EQTransformer method of Mousavi et al. (2020). This earthquake picker is based on deep learning, where it consists of a multi-task neural network architecture (NN) with one deep encoder, and three separate encoders. The NN generates high level representation of seismic signals preserving their temporal dependencies and later decoders map these features to three sequences of probabilities of earthquake signals and earthquake phases. We tested this picker with multiple probability thresholds, where each choice affects the picking performances.

We also tested PhaseNet of Zhu & Beroza (2019) with the default parameters. In our experience, both pickers are comparable where EQTransformer showed slightly better performance on local earthquakes. This finding is consistent with a recent comprehensive benchmarking study conducted by Münchmeyer et al. (2022), where they compared a number of automatic ML-based pickers with a conventional picker and ranked EQTransformer as the best one. In both of the picker tests, we did not attempt to retrain the neural network with labelled data (timings of the detected earthquake phases) from the region. Recent studies by Tan et al. (2021) and Jiang et al. (2022) successfully used EQTransformer with a default training model to improve earthquake catalogues in Italy and Banda Arc Subduction Zone. However, we plan to retrain these pickers using labelled datasets from Geoscience Australia in the next stages of our project.

We present the detection results of the telemetered data from six stations of Canning Basin Seismic Network (KIM01-06) as well as the existing ones (KIMBA) for selected events. The current distribution of the seismic stations of the network is given in Figure 2A.

1.3.1 Examples of Detected Earthquakes

In this section, we show examples of earthquakes detected using the EQTransformer algorithm that were not listed in the Geoscience Australia earthquake catalogue. However, we need to emphasise that some of the Geoscience Australia detected earthquakes may not be published due to the application of multiple test criteria, e.g., low signal-to-noise ratio (pers. Comm. With Phil Cummins). Between Figures 4 and 8, different examples of detections are given. In summary, EQTransformer works efficiently and detects several events, even in the case of partially missing data due to a sensor problem (see the waveforms from N and E sensors in Figure 8).

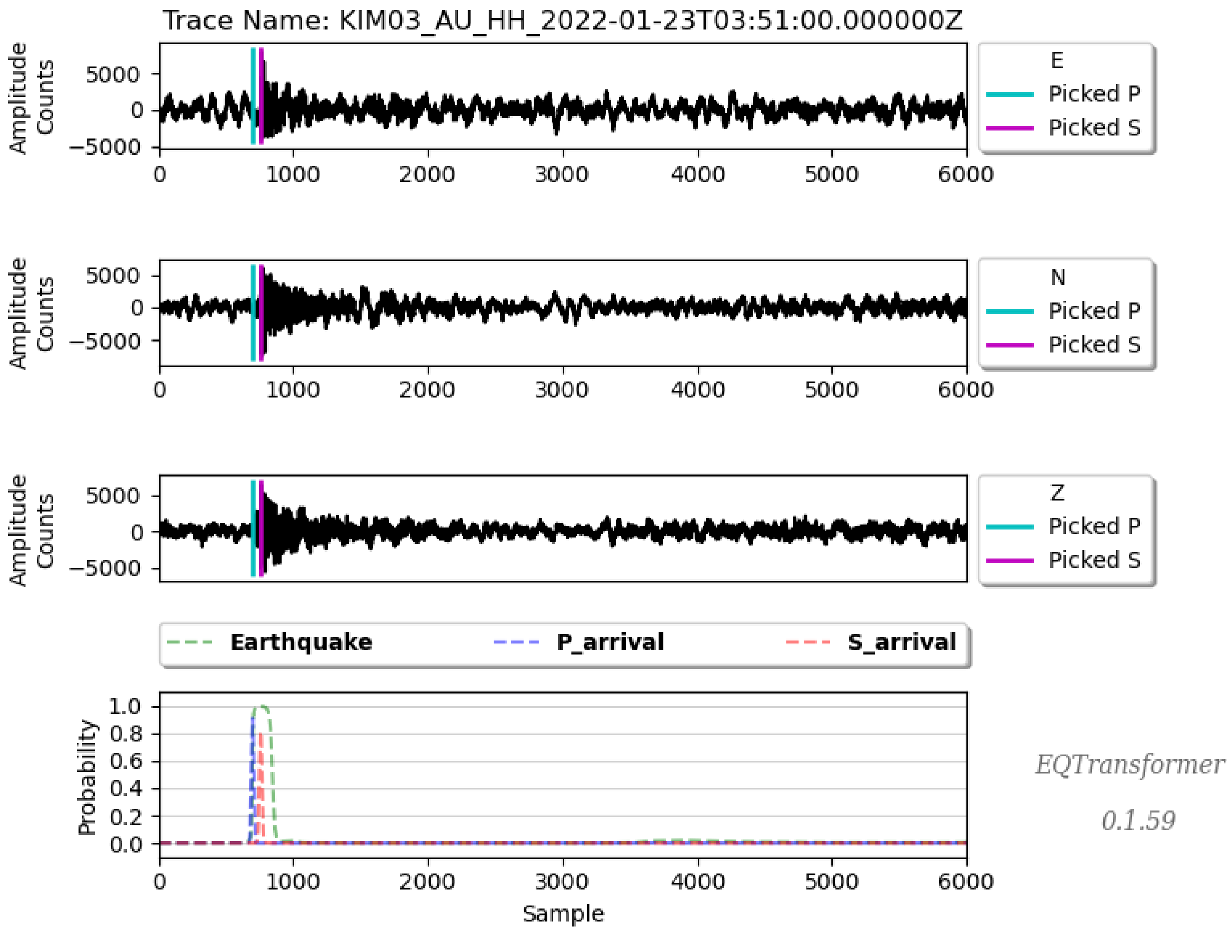

Figure 4: An example of detected seismic activity from 23/01/2022 at 03:51 UTC. The first three rows show time series with length of 60 s, from east-west (E), north-south (N) and vertical components of the seismic station – KIM03. The last row shows the probability of the detections of P and S waves.

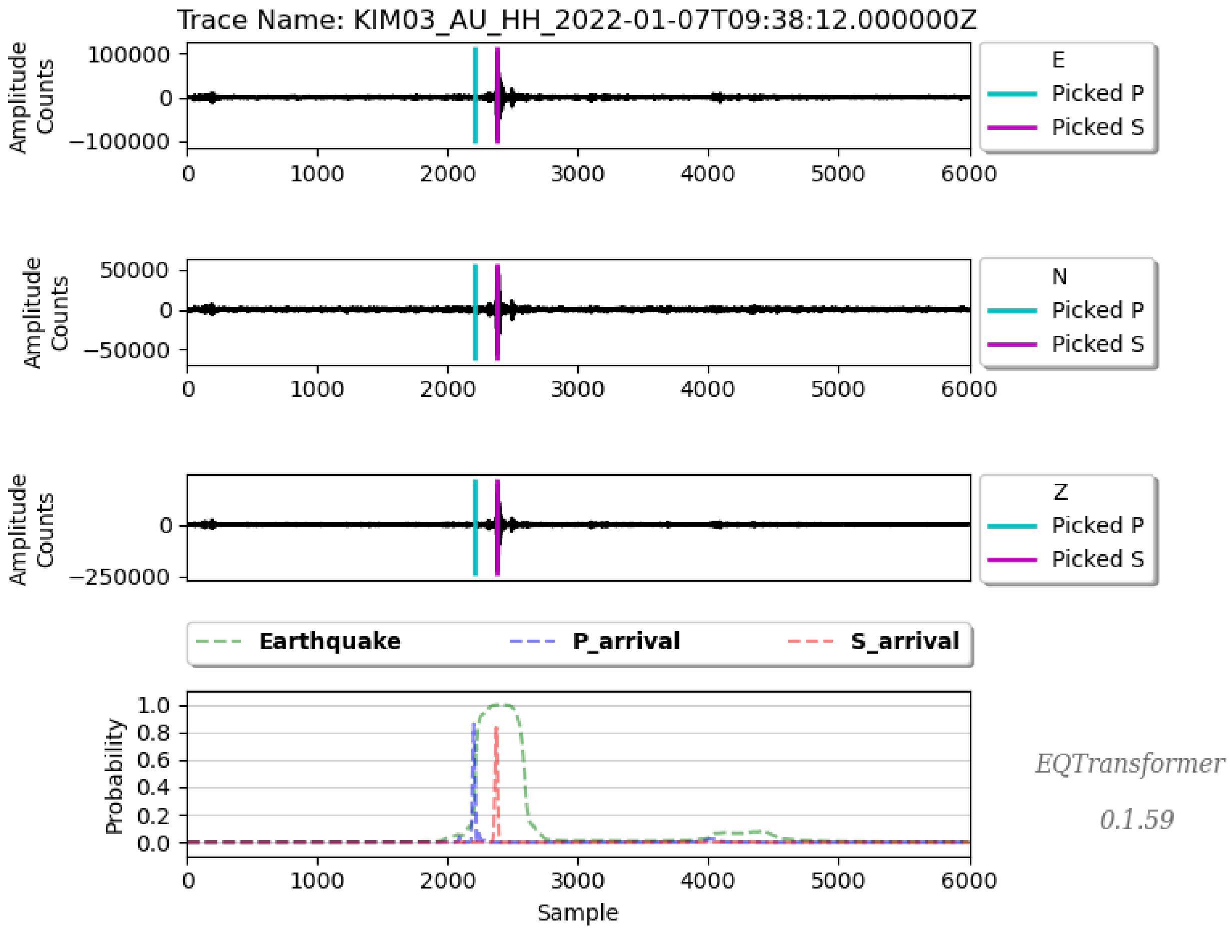

Figure 5: An example of detected seismic activity from 07/01/2022 at 03:51 UTC. The first three rows show time series with length of 60 s, from east-west (E), north-south (N) and vertical components of the seismic station – KIM03. The last row shows the probability of the detections of P and S waves.

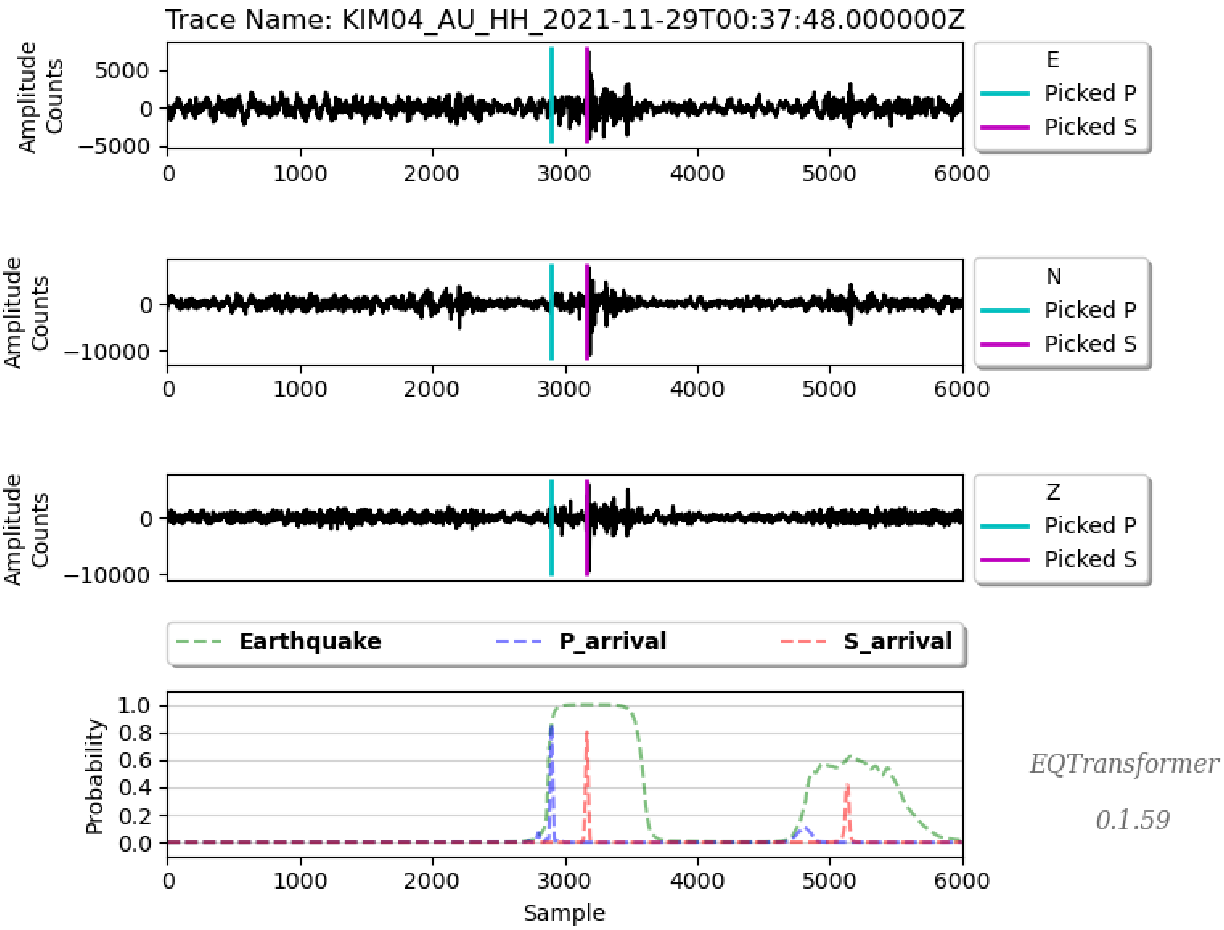

Figure 6: An example of detected seismic activity from 29/11/2021 at 00:37 UTC. The first three rows show time series with length of 60 s, from east-west (E), north-south (N) and vertical components of the seismic station – KIM04. The last row shows the probability of the detections of P and S waves.

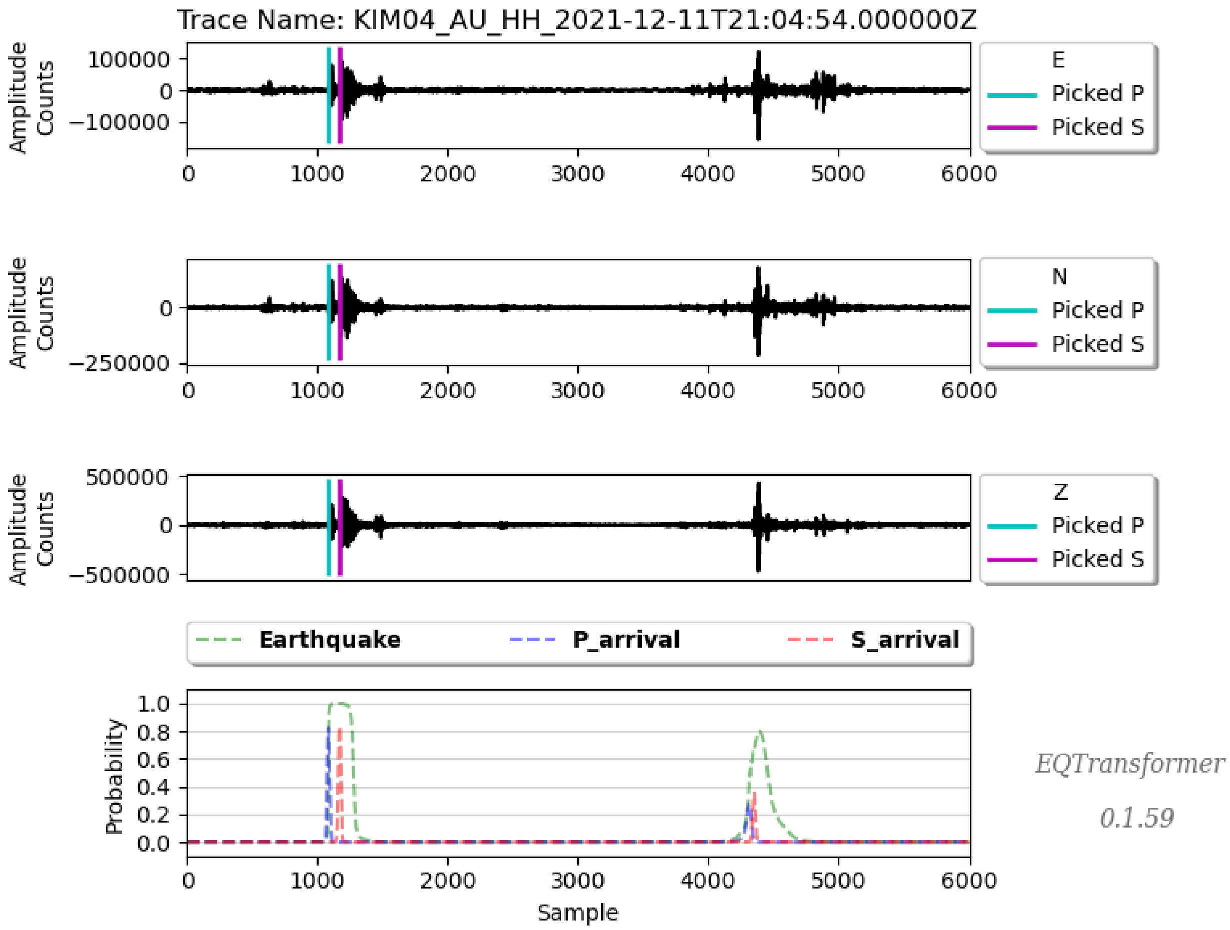

Figure 7: An example of detected seismic activity from 11/12/2021 at 21:04 UTC. The first three rows show time series with length of 60 s, from east-west (E), north-south (N) and vertical components of the seismic station – KIM04. The last row shows the probability of the detections of P and S waves.

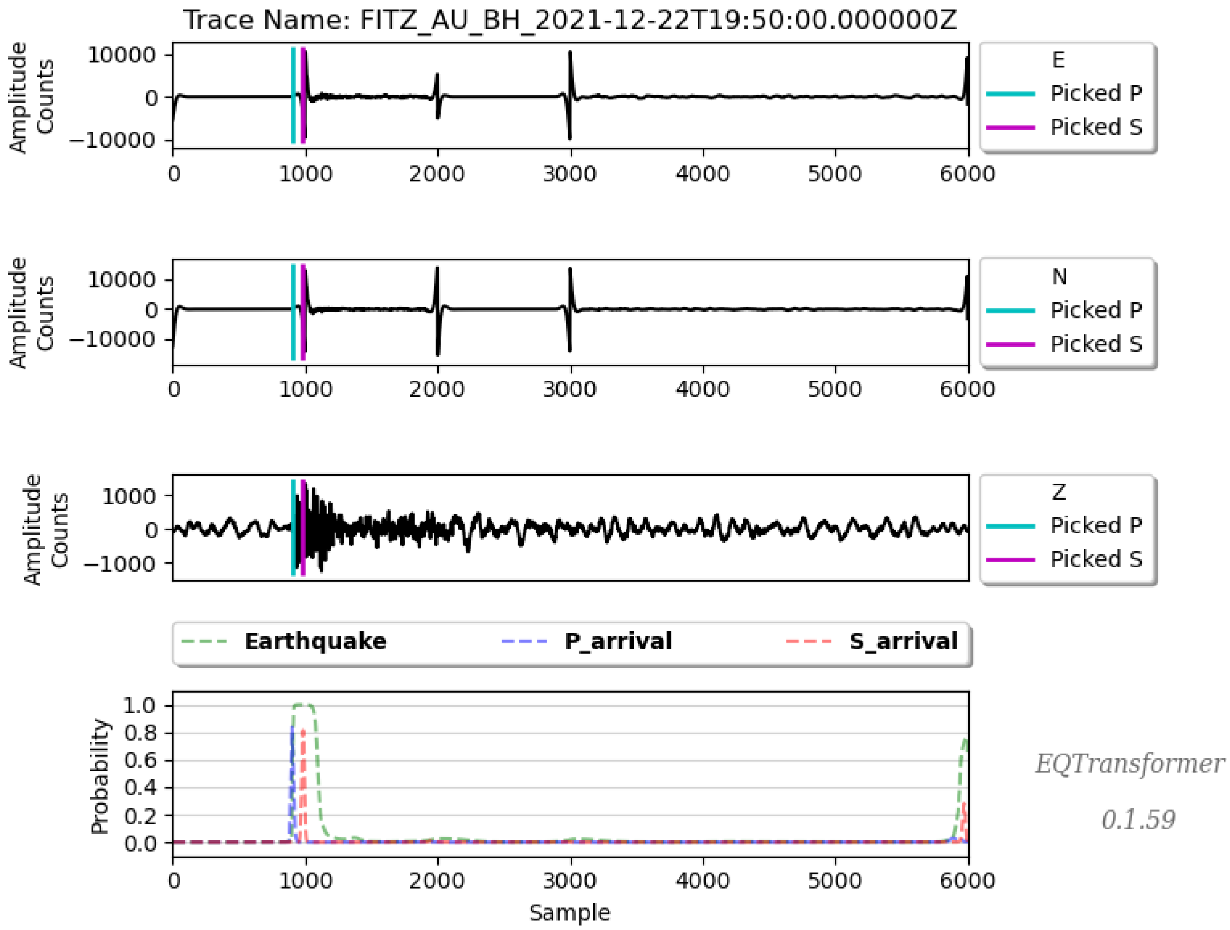

Figure 8: An example of detected seismic activity from 22/12/2021 at 19:50 UTC. The first three rows show time series with length of 60 s, from east-west (E), north-south (N) and vertical components of the seismic station – FITZ. The last row shows the probability of the detections of P and S waves. Despite two channels being faulty (N & E), the detector successfully detected the event just using the data from the vertical component.

1.4 Next Steps

We outline the immediate next steps that we will carry out to finalise the detection & location component of the project.

- We will continue improving the performance of the detector by fine tuning the probability parameter.
- We will run the EQTransform with the remaining data from the first six stations and newly added stations and incorporate the location step.
- We will retrain the picking algorithm with a labelled dataset and repick the data outlined in step 2.
- We will refine the local geological model to fine tune the location estimates.

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