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Establishing Baseline Groundwater and Natural Seismicity levels across the Northern Perth Basin with Passive Seismic Data – Interim Report 1

Baseline Groundwater and Seismicity of Northern Perth Basin

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1 Outline

The northern Perth Basin stretches about 450 km from north to south and up to 90 km from west to east. The basin covers about 35,000 km^2, making up three-quarters of the onshore Perth Basin (Department of Water, 2017). In this interim report, we provide progress for groundwater monitoring and baseline natural seismicity levels in the North Perth Basin, using seismic data from a dense seismic array recently deployed by the Geological Survey of Western Australia (GSWA). From the analysis using passive data, we found that the seismic velocity of shear waves decreases during winter (raining season) and is inversely correlated to groundwater depths. The good agreement between velocity changes and the hydraulic head highlights the promise of using existing seismometers in Western Australia for monitoring groundwater levels. We also conducted machine-learning based analysis for earthquake detection and phase picking, and found several clusters of earthquakes.

2 Groundwater monitoring using passive seismic waves

2.1 Introduction

The energy and mining sectors demand significant volumes of water annually, which places considerable strain on existing water resources and can lead to conflicts between these sectors and farmers. A report by McKinsey & Co (Delevingne et al., 2020) forecasts that by 2040, several regions including parts of northern Perth Basin may experience water stress with varying degrees. Therefore, it is imperative to establish observation methods and report values in preparation for the anticipated surge in activity.

The traditional method for monitoring groundwater tables is through hydraulic head measurements, which directly gauge the water levels in specific aquifer layers. However, these point-scale head measurements are often too sparse in time and space to adequately capture variations in highly non-uniform aquifer systems (Mao et al., 2022). While drilling boreholes is a common approach, it is both invasive and expensive. Seismic waves recorded with seismograph arrays offers a cost-effective non-invasive approach to monitor time dependent variations of the water level at different depths. In essence, there is a robust correlation between fluctuations in seismic velocity that have been observed and variations in the depth of the water table. These fluctuations primarily arise from changes in pore pressure and bulk density within the near-surface materials.

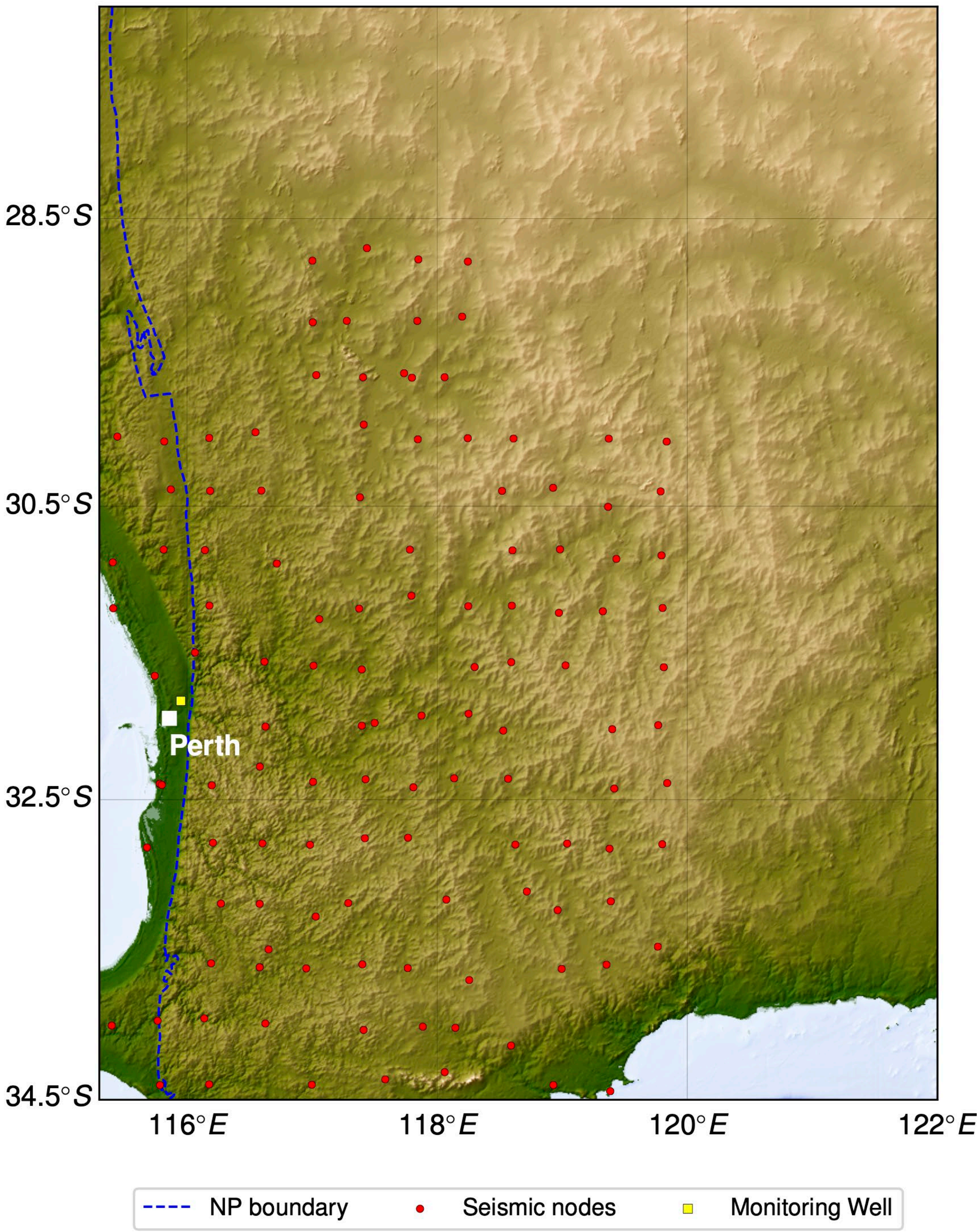

Figure 1. The survey map. The red dots are the seismic nodes from the WAArray, with available data from November 2022 to December 2023. The yellow square is one monitoring well used for measuring groundwater level (hydraulic head, mAHD). The dashed blue line is the boundary of the Perth Basin.

2.2 Data & Ambient Noise Interferometry

We used the seismic ambient noise recorded by the dense seismic network WAArray. The data is available from November 2022 to December 2023. The survey contains 129 nodes. Figure 1 shows the location of the seismic nodes. Since in this study, our main interest is in the North Perth Basin, we select nodes in the range with longitude lower than 118° and latitude larger than -32°.

For the data processing, we detrended and down-sampled the vertical component of the data from 100 Hz to 20 Hz with anti-aliasing filtering. The ambient noise data were then filtered to the frequency band 0.02 – 1 Hz. 1-bit normalization was applied to the data in the time domain. We divided the recordings of ambient noise into daily-long segments. The daily Green's function (seismic waves travelling between arbitrary two seismic stations/nodes) were then reconstructed by computing cross correlations for all the pairs of stations within 60 km distance using the segmented noise data. The maximum time lag for cross correlation was 120 s and selective stacking was used for stacking cross correlation functions within the daily segments. We further stacked over 7 days of the daily cross correlation functions to improve the signal to noise ratio. The stacked weekly data was the monitoring data. To obtain the reference/baseline data, we stacked all the weekly data.

Figure 2 shows the obtained cross correlation functions using ambient noise recorded by the seismic nodes. The dashed red line is the travel time moveout for a velocity of 3 km/s. The data is of good quality and suitable for monitoring of shear-wave velocity changes.

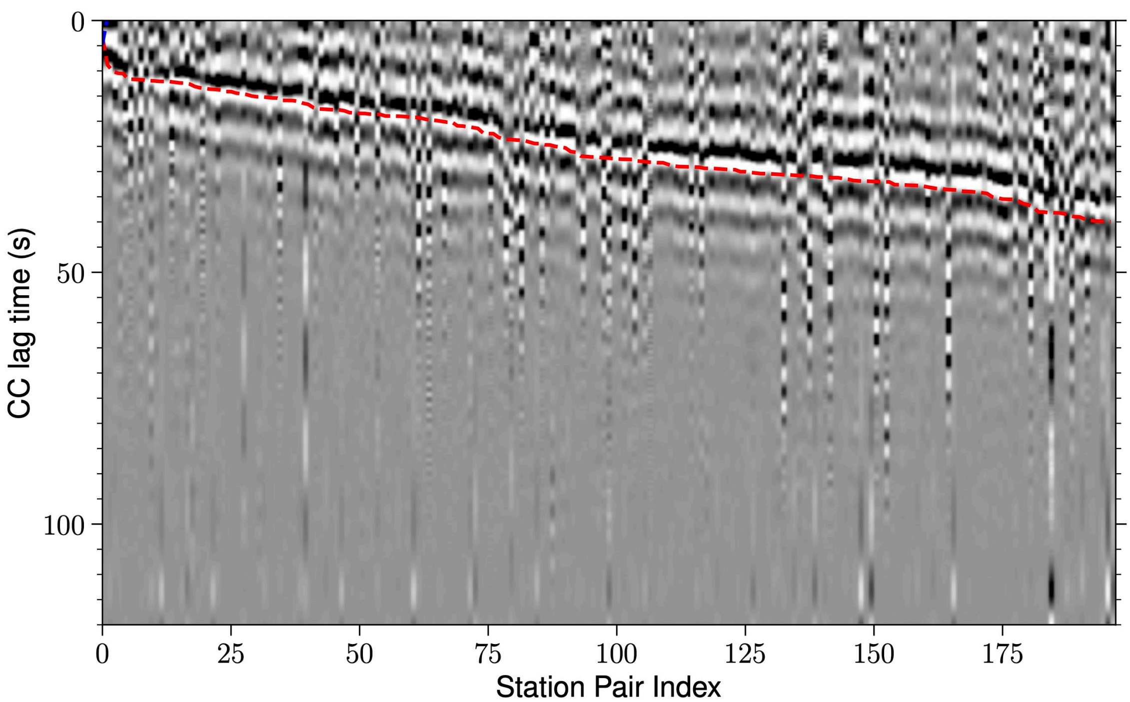

Figure 2. The cross-correlation functions, i.e., an approximation to the Green's function. The station distance is within 60 km. The dashed red line is the time moveout of velocity 3 km/s. The main signal is surface waves as expected.

2.3 Monitoring

Temporal changes in subsurface properties, such as seismic wave speeds, can be monitored by measuring phase shifts in the coda of seismic waveforms. The temporal seismic velocity variations provide insights for groundwater level changes. From rock-physics measurement, the shear-wave velocity decrease with increasing water saturation in the rock formations (for example, during raining season in the winter) and increase with decreasing water saturation during the dry seasons.

Using the continuous monitoring data from 11/2022 to 12/2023 and the reference/baseline data, we used a wavelet-domain trace stretching method (Yuan et al., 2021; Guo et al., 2024) to measure the shear-wave velocity changes from the coda of the monitoring and reference data.

Figure 3a shows the measured velocity changes (dv/v) from all the station pairs, which are in the range of -0.2 to 0.2% and consistent with similar studies in other regions of the world. Figure 3b shows mean velocity variations (black dots), along with groundwater level measurement (mAHD) from borehole (blue line, location shown in Figure 1). We also smoothed the mean velocity changes using a Gaussian filter, with the standard deviation of the Gaussian kernel to be 4. The smoothed velocity changes are reported in red in Figure 3b. We found that there is a clear pattern of shear-wave velocity decrease between July to October of 2023 (black dots and red line), which is the raining season in Perth with higher groundwater level. The decreases in seismic velocity gradually healed from October of 2023 towards the end of year, consistent with decreasing groundwater levels. Moreover, positive velocity changes, especially between March and May of 2023, are observed. Overall, the velocity changes are inversely correlated to groundwater levels. Therefore, the non-invasive, environmentally friendly and cost-effective ambient noise monitoring method provides a complementary solution to the traditional point-based borehole measurement. The good agreement between dv/v and the hydraulic head highlights the promising potential of using existing seismometer arrays in Western Australia for monitoring groundwater levels.

So far, we have shown that velocity changes can be measured continuously in time, with high sensitivity (at the order of 0.01%) and low cost. On the other hand, the extracted Green's function (Figure 2) from ambient noise could be further improved and noisy traces can be identified and removed, to reduce the fluctuations in the velocity change measurements (Figure 3). In the next steps, more data processing will be attempted to reduce the noise in the data and improve the velocity measurement accuracy. We will also map the velocity changes into the space domain to infer more detailed information for a spatio-temporal monitoring (Guo et al., 2024) of groundwater level in the North Perth Basin.

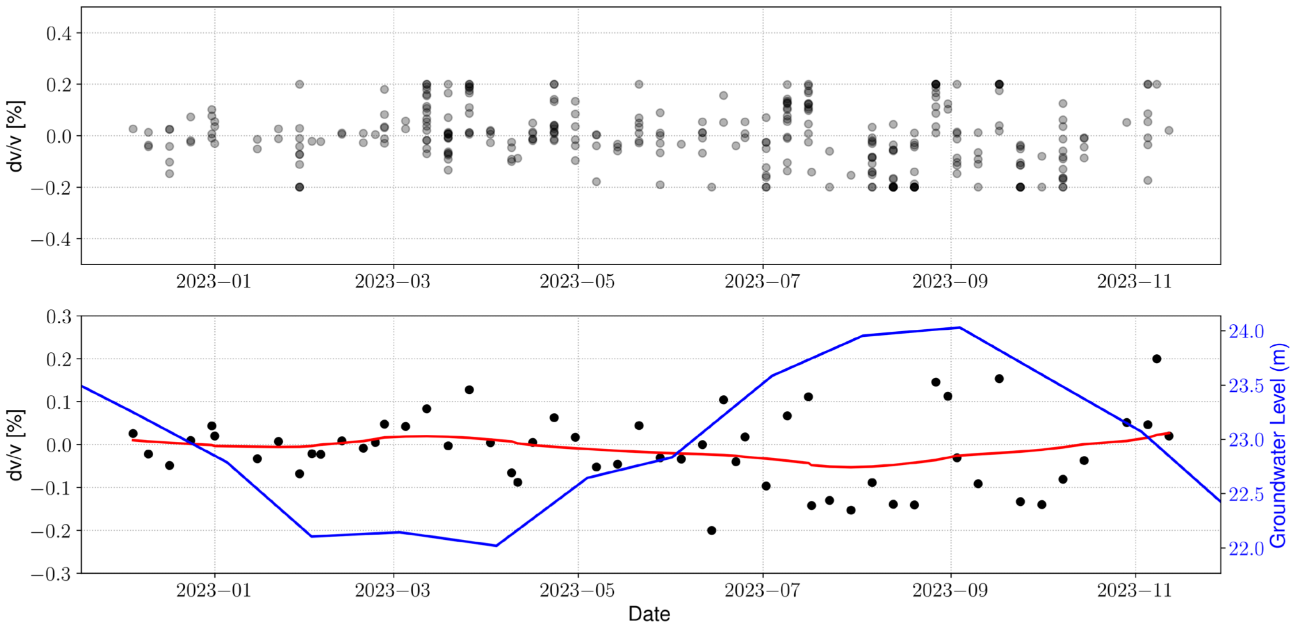

Figure 3. The measured relative seismic velocity changes (dv/v) in time during the passive monitoring period from November 2022 to December 2023. (a) shows the individual measurements from all the available station pairs. (b) shows the mean velocity changes (black dots) from passive monitoring versus groundwater level (hydraulic head, blue line) measurement from Borehole. The red line is the mean velocity changes after Gaussian smoothing. The standard deviation for the Gaussian kernel is 4.

3 Seismicity Detection and Phase Picking

3.1 Introduction

Seismicity refers to the occurrence, distribution, and behaviour of earthquakes within a specific region. It encompasses the measurement of seismic activity and the study of how earthquakes—ground shaking and fault movements—occur over time. Seismicity can vary between locations and is influenced by factors such as tectonic plate boundaries, geological conditions, and entropic activities such as resource exploration. It is typically monitored using seismometers (seismic stations), which record ground motion.

In the case of the North Perth basin, seismicity remains poorly documented due to the limited historical coverage of seismic stations. However, with the recent deployment of seismic arrays by the Geological Survey of Western Australia (GSWA), we expect substantial improvements in seismic monitoring. Miller et al. (2023) showed a significant increase in the detection of small magnitude events in Southwest Western Australia following the installation of a temporary seismic array. However, seismic station coverage still remains sparse in the northern Perth Basin.

This project aims at addressing this gap by leveraging dense seismic data from GSWA to create a baseline catalogue of natural seismic activity. A seismic catalogue is a comprehensive list of earthquakes detected in a given region over time, including information such as location, depth, magnitude, and origin time. This catalogue will serve as a foundation to produce seismic hazard maps, assess earthquake risks, and improve our understanding of the Earth's internal structure and the forces driving earthquakes. Seismicity is typically expressed in terms of earthquake magnitude and frequency. Areas with higher seismicity are more prone to earthquakes, making an understanding of seismicity crucial for earthquake preparedness and risk mitigation.

Governments can use seismicity data to assess hazards that may impact infrastructure projects and guide new developments.

3.2 Steps to Build a Seismic Catalogue

The process to build a seismic catalogue typically involves the following steps:

- Assuming data is collected by setting up a network of seismometers (seismic stations), the first step in the process of building an earthquake catalogue is to detect and pick seismic phases recorded by the network.
- The next step will be earthquake association which refers to the process of linking detected seismic signals to specific earthquake events. This involves identifying whether a signal recorded by multiple seismic stations originates from the same earthquake and distinguishing it from other sources like explosions or noise. The goal is to accurately associate individual seismic waves with specific earthquake occurrences to improve earthquake detection, location, and characterization.
- Then, the last step consists in calculating the accurate coordinates (latitude, longitude, depth) and the origin time of the earthquake and measuring the amplitude of seismic waves at different stations to estimate the earthquake's magnitude.

Parts of this section present the results related to earthquake detection and phase picking, as well as the initial estimation of earthquake locations. The steps for relocation (accurate location) and magnitude calculation will be covered in the next interim report.

3.3 Phase detection and Picking

Detection involves recognising earthquake signals among a range of non-earthquake signals and background noise recorded by a seismic sensor. Phase picking, on the other hand, refers to the process of identifying the arrival times of distinct seismic phases, such as the P-wave and S-wave, within an earthquake signal, which are then used to determine the earthquake's location.

We used a new deep-learning model, the EQTransormer model (Mousavi et al., 2020), for simultaneous detection of earthquake signals and picking first P and S phases. This model is highly efficient in detecting and characterising more and smaller seismic events. The EQTransformer model generates results when at least one phase, either P or S, has a probability exceeding a user-defined threshold within a time window that has a high likelihood of representing an earthquake. Here we used threshold values of 0.01, 0.01, and 0.1 for detection, P-picking, and S-picking respectively. Applying the model with the chosen probability thresholds on all available data recorded on WAArray between November 2022 and 31 of December 2023 resulted in ~1.3 million picks. Some examples of event detection and phase picking are shown in Figure 4 to Figure 6.

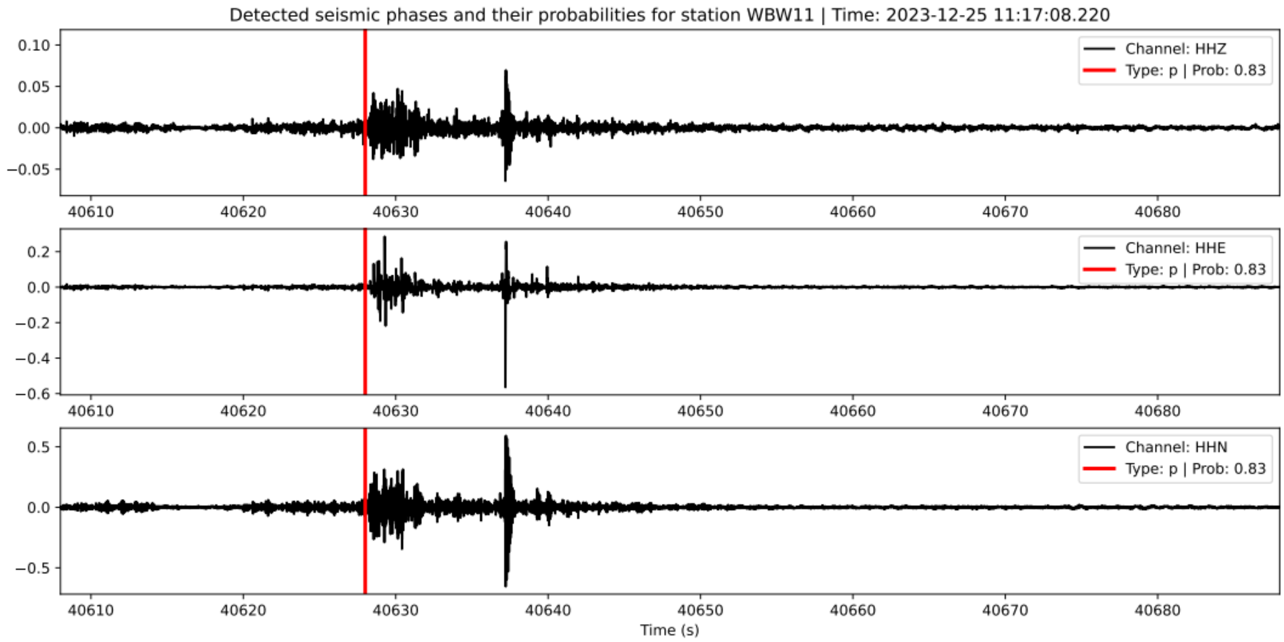

Figure 4. An example of detection and P-phase picking with a 83% probability of being classified as an earthquake.

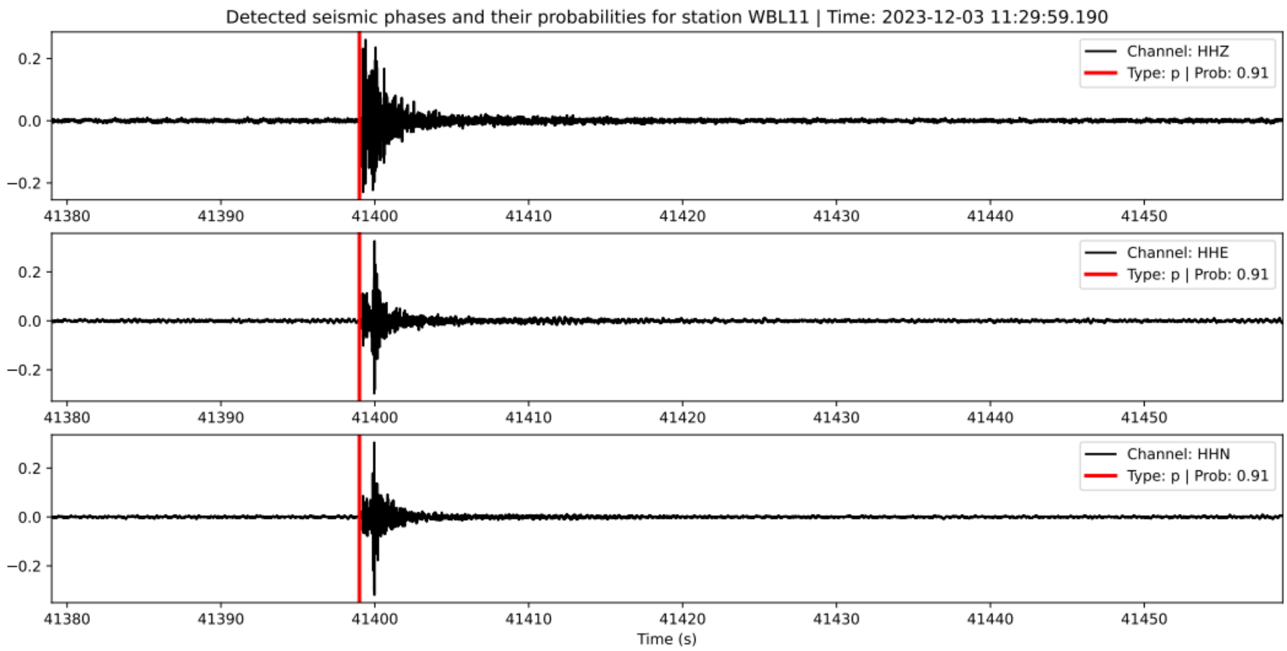

Figure 5. An example of detection and P-phase picking with a 91% probability of being classified as an earthquake.

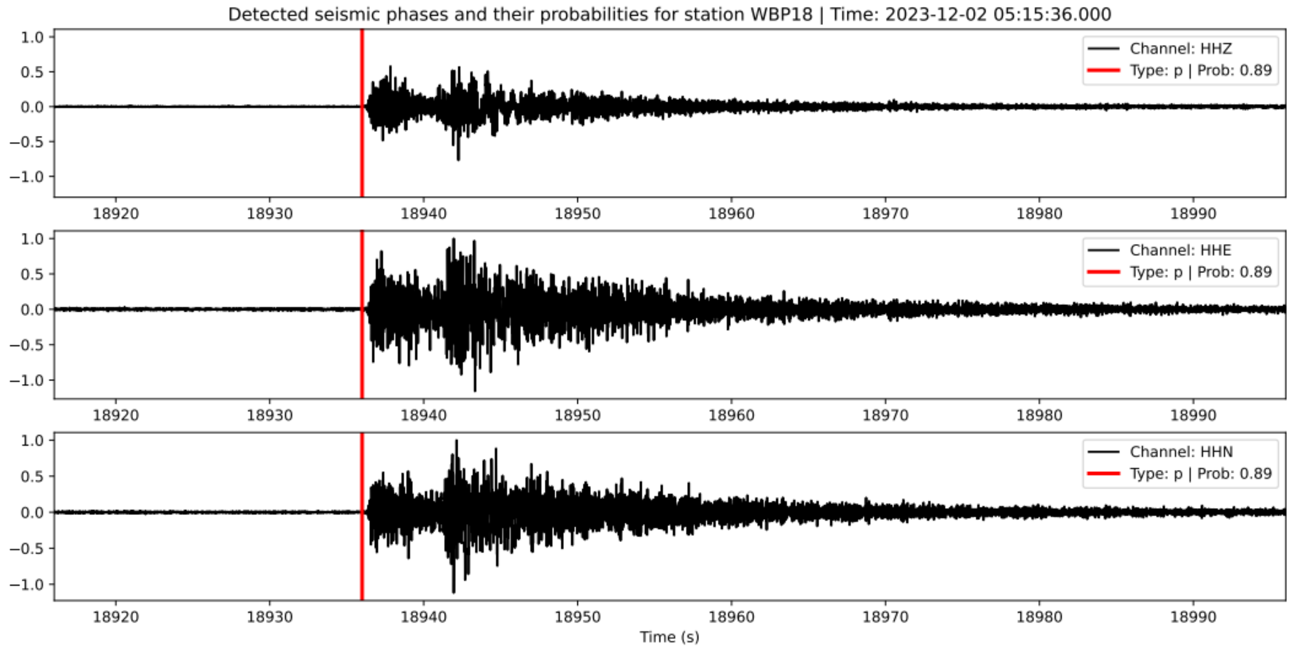

Figure 6. An example of detection and P-phase picking with a 89% probability of being classified as an earthquake.

3.4 Phase Association and Initial Estimates of location of earthquakes

We filtered all detected and picked seismic phases that have a probability threshold greater than 0.5 (50%) for being an earthquake and used these picks in the phase association and initial estimation of earthquake locations steps. Phase association in seismology refers to the identification and linkage of seismic phases (e.g., P-waves, S-waves) recorded at different seismic stations to a same seismic event, such as an earthquake. The goal is to determine which seismic picks (arrival times of different phases) across multiple stations belonging to the same earthquake. By checking the consistency of the time differences between the P- and S-wave arrivals at different stations, one may associate these picks with a common event.

Phase association is a prerequisite for earthquake location. Without correctly associating the phases, an accurate earthquake location estimation is impossible. Earthquake location estimation is the process of determining the epicenter, depth, and origin time of a given earthquake event, based on the arrival times of different seismic phases (typically P- and S-waves) at multiple stations. The goal in this step is to pinpoint where (location and depth) and when (origin time) the earthquake occurred. The inputs to location estimation are the phase picks (arrival times of P- and S-waves) from multiple stations, which are correctly associated with the earthquake through phase association. Location estimation typically uses methods like triangulation, inverse modelling, or grid search algorithms that depend on the travel time of seismic waves between the earthquake source and the stations. Seismologists use velocity models (such as homogeneous, 1D or 3D Earth models) to calculate the travel times.

For phase association and initial location estimation, we use PyOcto (Münchmeyer, J., 2024), an innovative Python-based associator inspired by the Octotree data structure. PyOcto works by dividing space-time into potential origin points, achieving fast performance by focusing only on promising regions. This makes it a high-throughput phase associator. The core concept is to mimic a grid-search associator while limiting the search to 'useful' grid cells. At this stage, a homogeneous velocity model (Vp = 7 km/s, Vs = 4 km/s) with a tolerance of 2.5 km/s is employed to estimate the initial and preliminary locations and depths of potential earthquakes. In total, 644 events were identified in the region, focusing only on those with a high probability of being actual earthquakes. Figure 7 shows the initial catalogue, illustrating the preliminary earthquake locations (longitude, latitude, and depth). Several clusters of earthquakes are observed in the area. For example, several clusters of earthquakes are evident in the Southwest Seismic Zone (SWSZ), located about 150 km to the east of Perth in southwestern Australia which is one of the most seismically active areas in Australia. As another example several clusters of earthquakes are clearly found around Arthur River between Darkan and Wagin. These earthquakes often occur in swarms. Region in the east and southeast of Wagin (bounded by longitudes 117°-118° and latitudes 33°-34°30S) also seems to be seismically active region in the Western Australia.

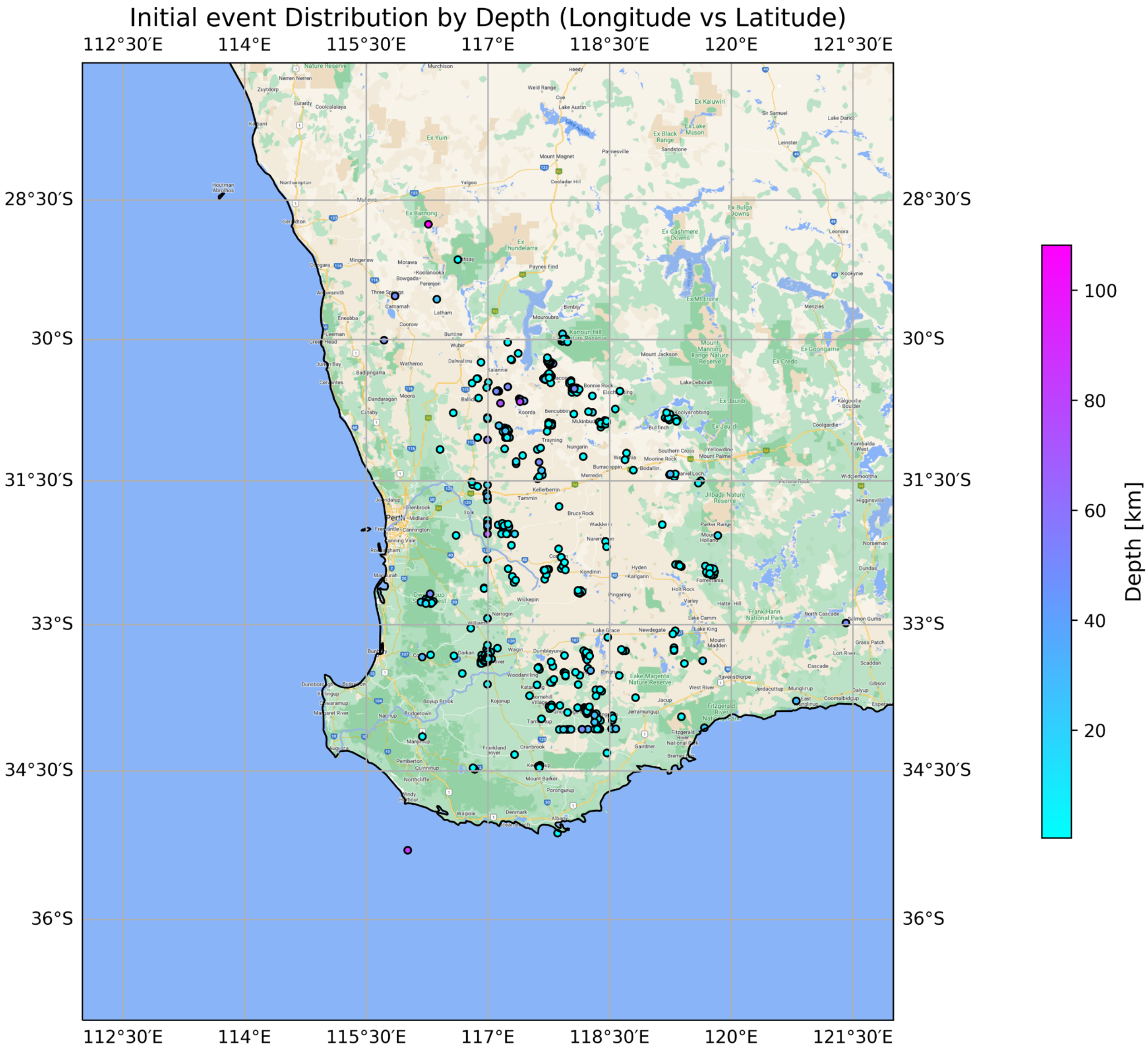

Figure 7. The initial catalogue for the North Perth Basin and immediate surroundings regions.

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