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Integrating a Convolutional Neural Network with Antelope to Locate Earthquakes

Increased Analyst Efficiency and Earthquake Catalogue Completeness

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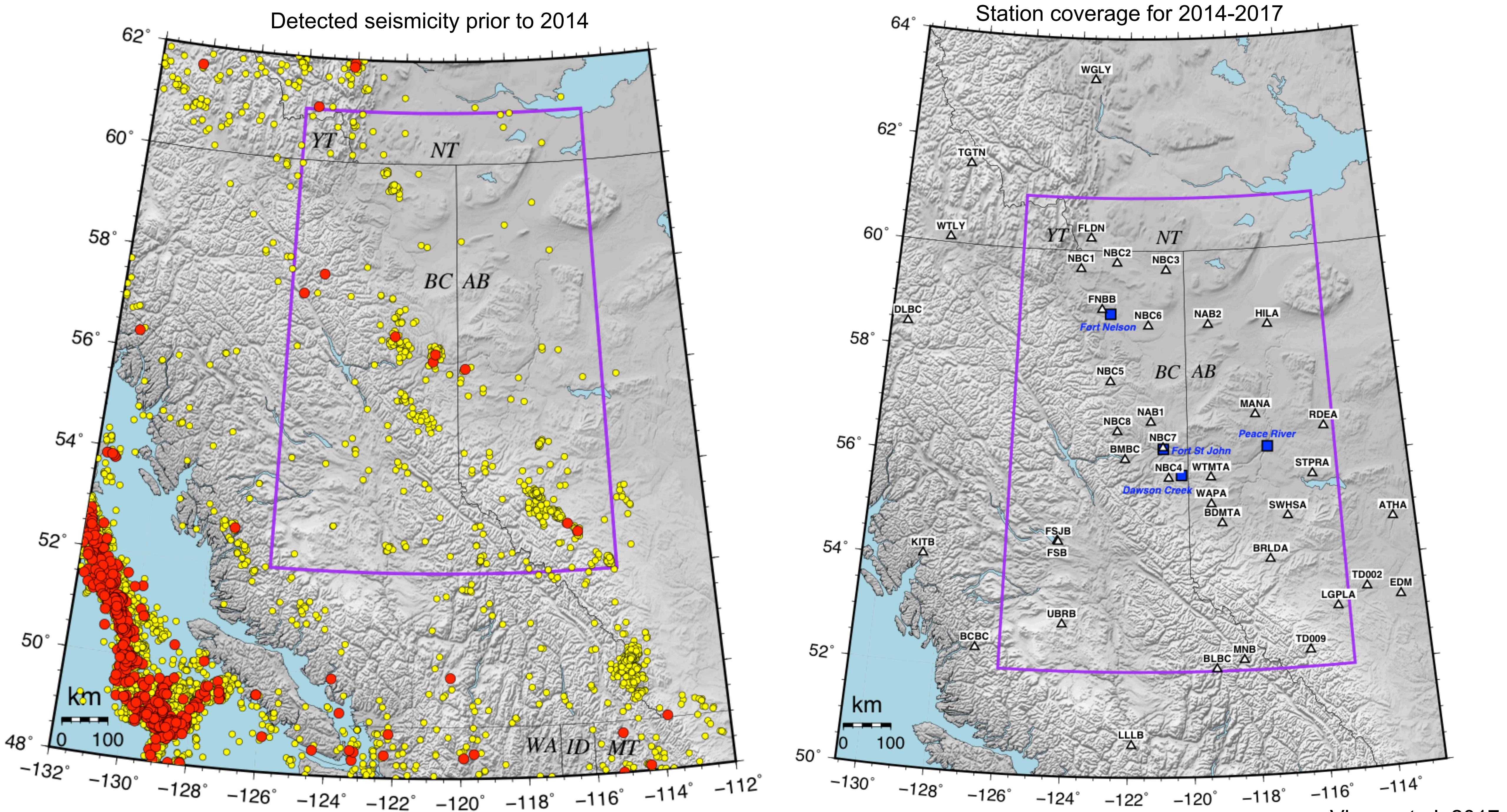
Primary objective of the Induced Seismicity Research Project (ISR):
To identify and fill critical knowledge gaps on the seismogenesis of induced earthquakes.

Other Objectives:
To create an earthquake catalogue that is as complete as possible with limited analyst resources.

Potential Solutions:
1) Improving earthquake detection threshold throughout our study area.
- Increase seismic station density. (Increases number of waveforms and analyst must look at)

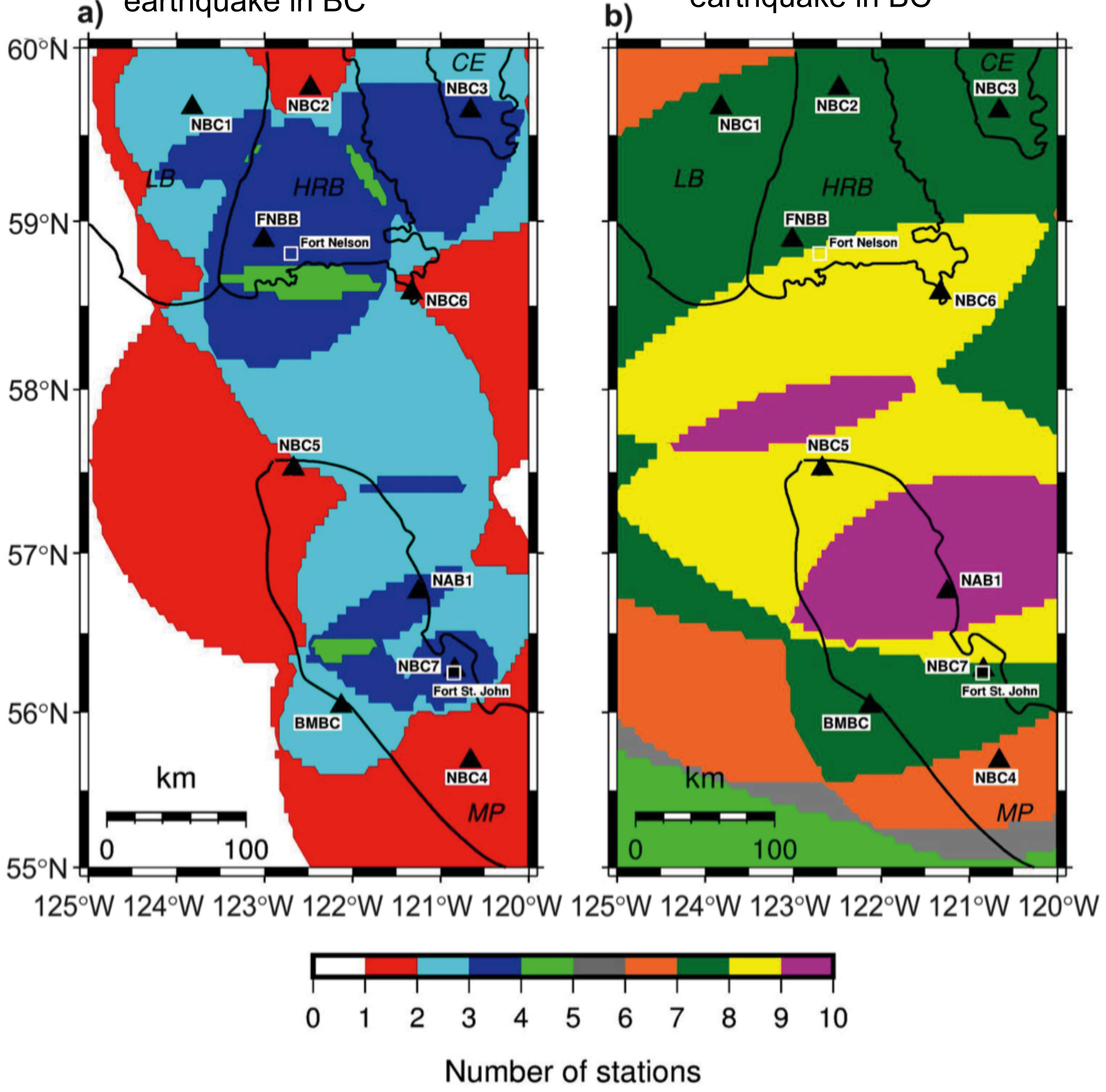
2) Maximizing analyst efficiency.
- Develop tools to help analyst locate earthquakes more efficiently.
    - Automate earthquake detections to increasing consistency of arrival detections and decreasing the amount of time required by analysts.



Visser et al, 2017

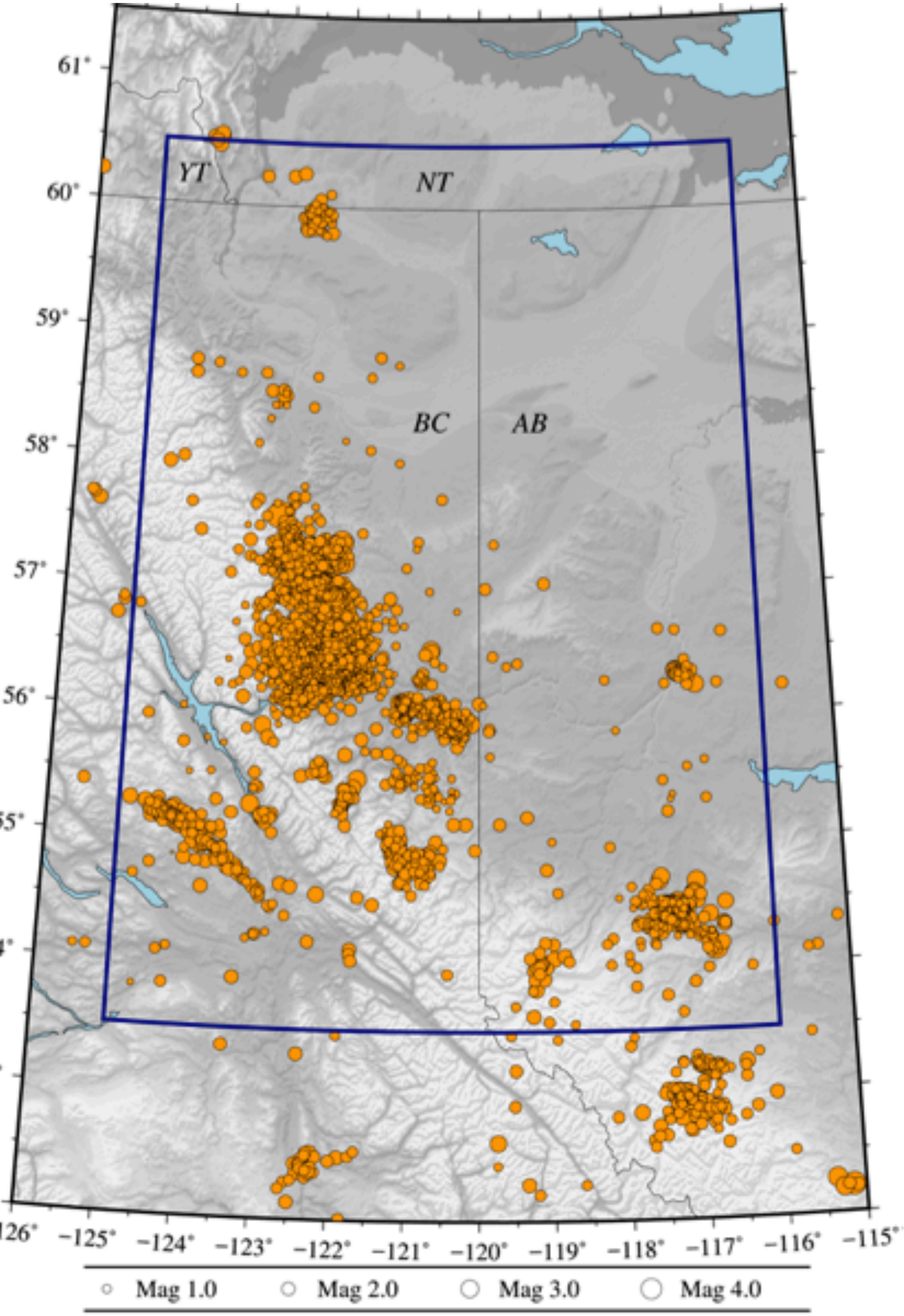
Map of the number of stations able to detect a magnitude 1.6 earthquake in BC

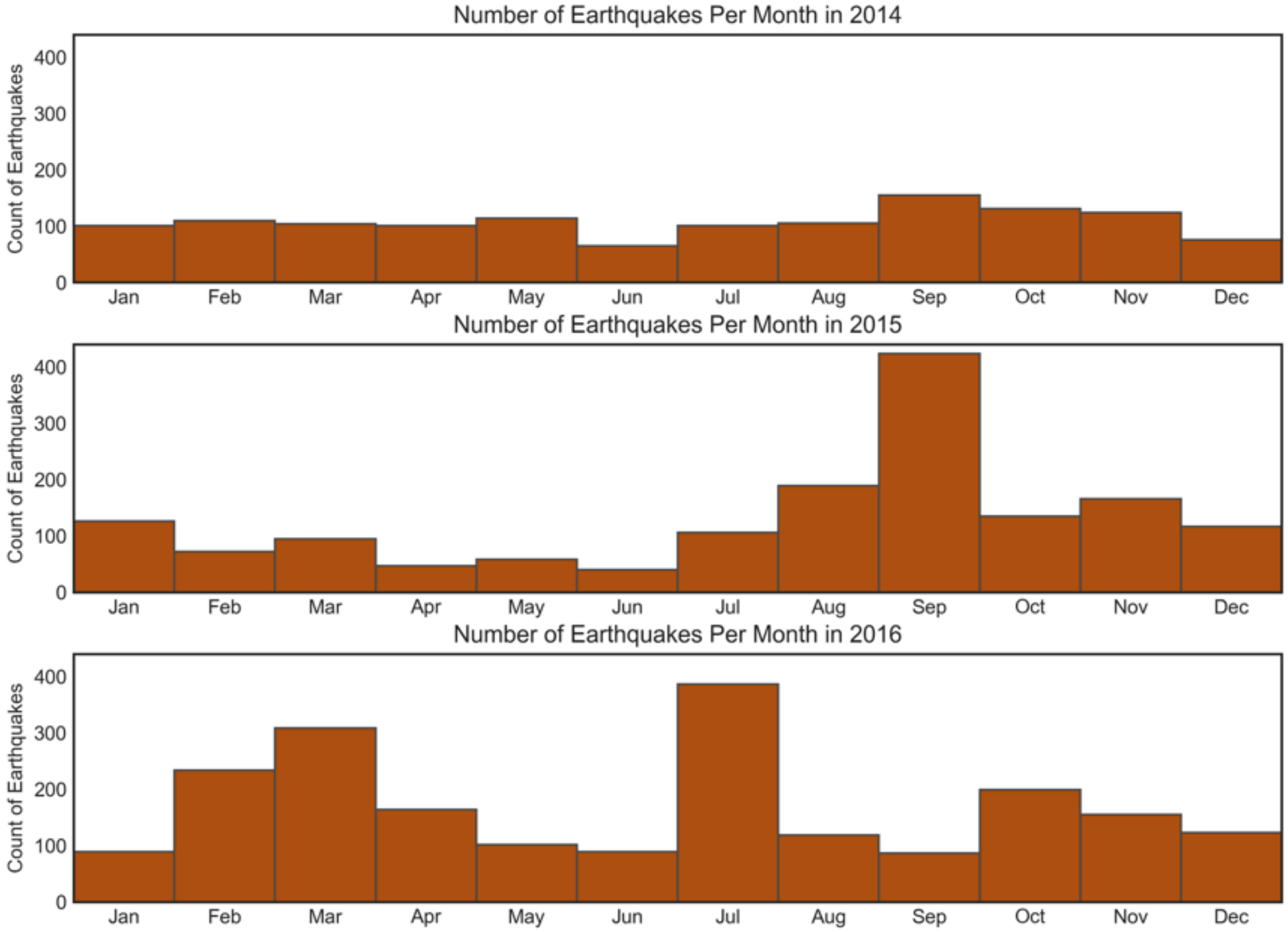
Map of the number of stations able to detect a magnitude 2.6 earthquake in BC



Mahani et al, 2016

Earthquakes located in northeastern British Columbia and western Alberta for 2014-2016.





Visser et al, 2017

Analyst phase detections:

- Eyes can get tired
- May occasionally miss small earthquakes
- Slow relative to convolutional neural network

Convolutional Neural Network (CNN) phase detections:

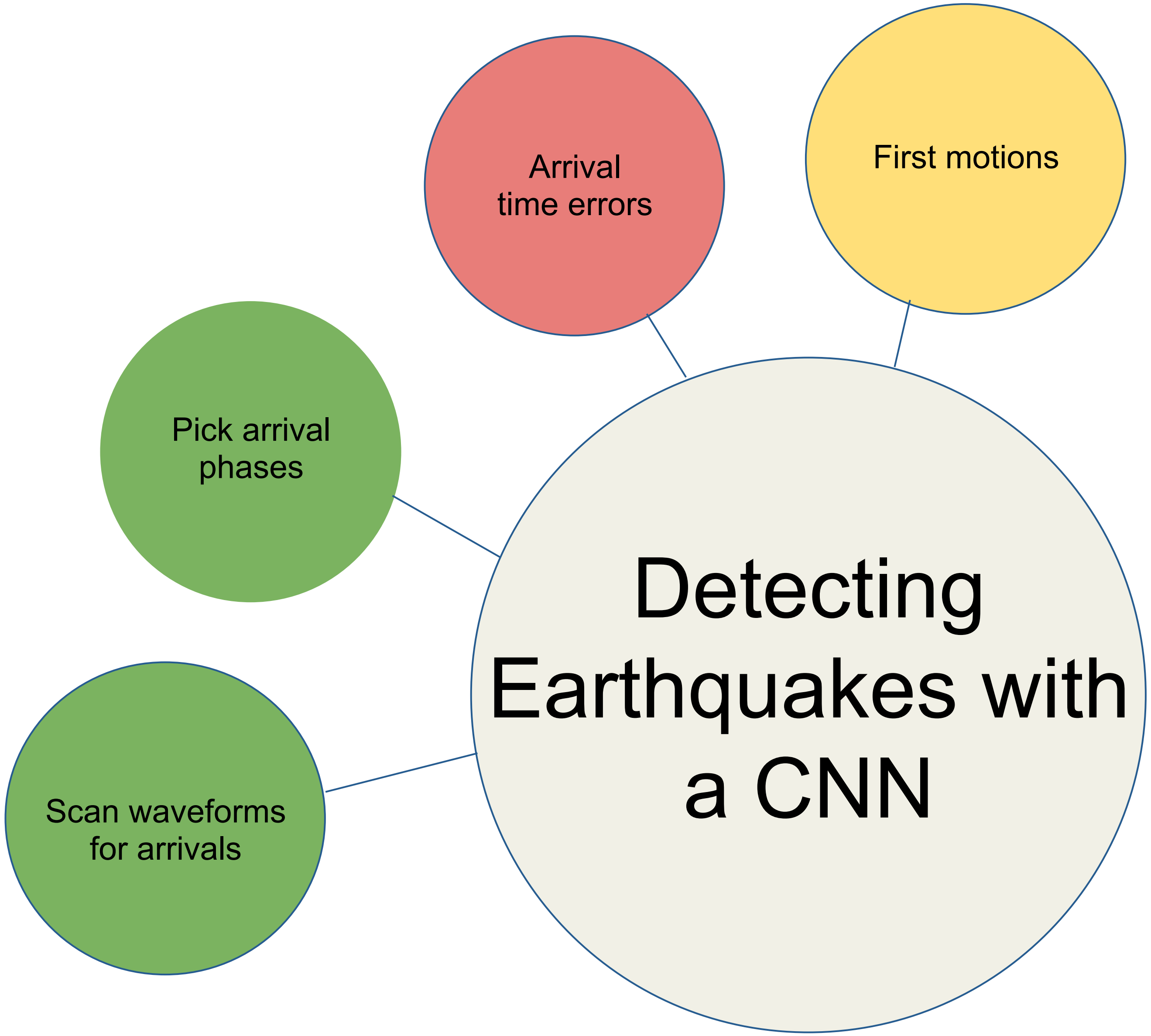
- Never gets tired
- Has nowhere else to be
- Detects earthquake arrivals consistently for training set
- May miss earthquakes not in training set
- Fast relative to analyst
- Doesn’t tell puns

What is a CNN?

- A CNN is an algorithm that mimics biological neurons

- The CNN is given images with some information about them, different neurons will fire allowing the CNN to make connections between the image and its information

- Once a CNN has been trained it should be able to recognize certain images, in our case the CNN is able to recognize time windows which include phase arrivals


Arrival time errors
First motions
Pick arrival phases
Detecting Earthquakes with a CNN
Scan waveforms for arrivals

Our CNN

- The CNN is trained on waveforms with phases that have been picked by a human analyst

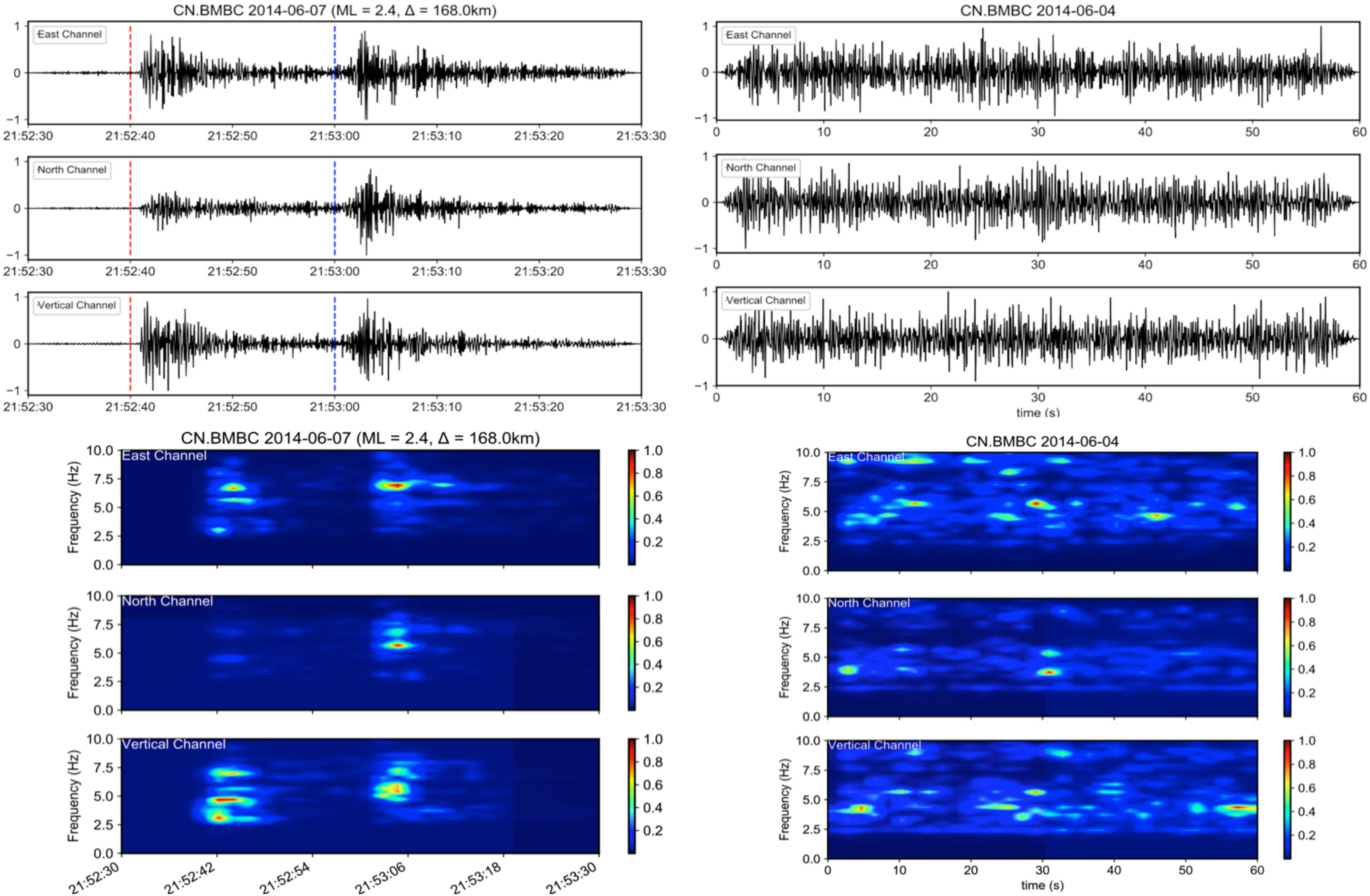
- ~98.5% accuracy on training dataset

- As the catalogue is developed the training dataset may be expanded

- A specialized training dataset for a specific region is optimal

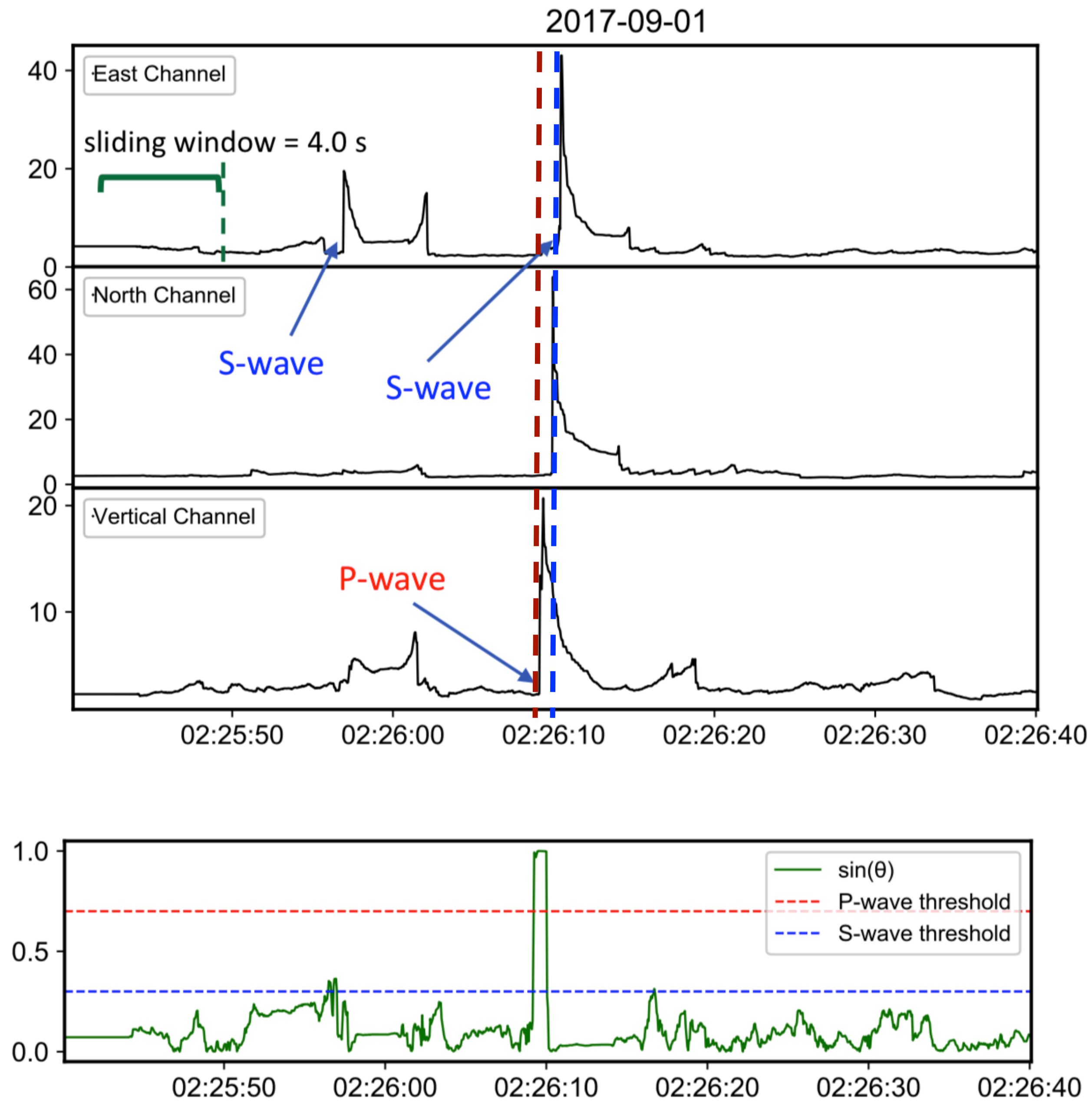
- Only runs on three channel stations, hence the need to use dbdetect on single channel stations

- Produces a table of arrivals that is Antelope readable

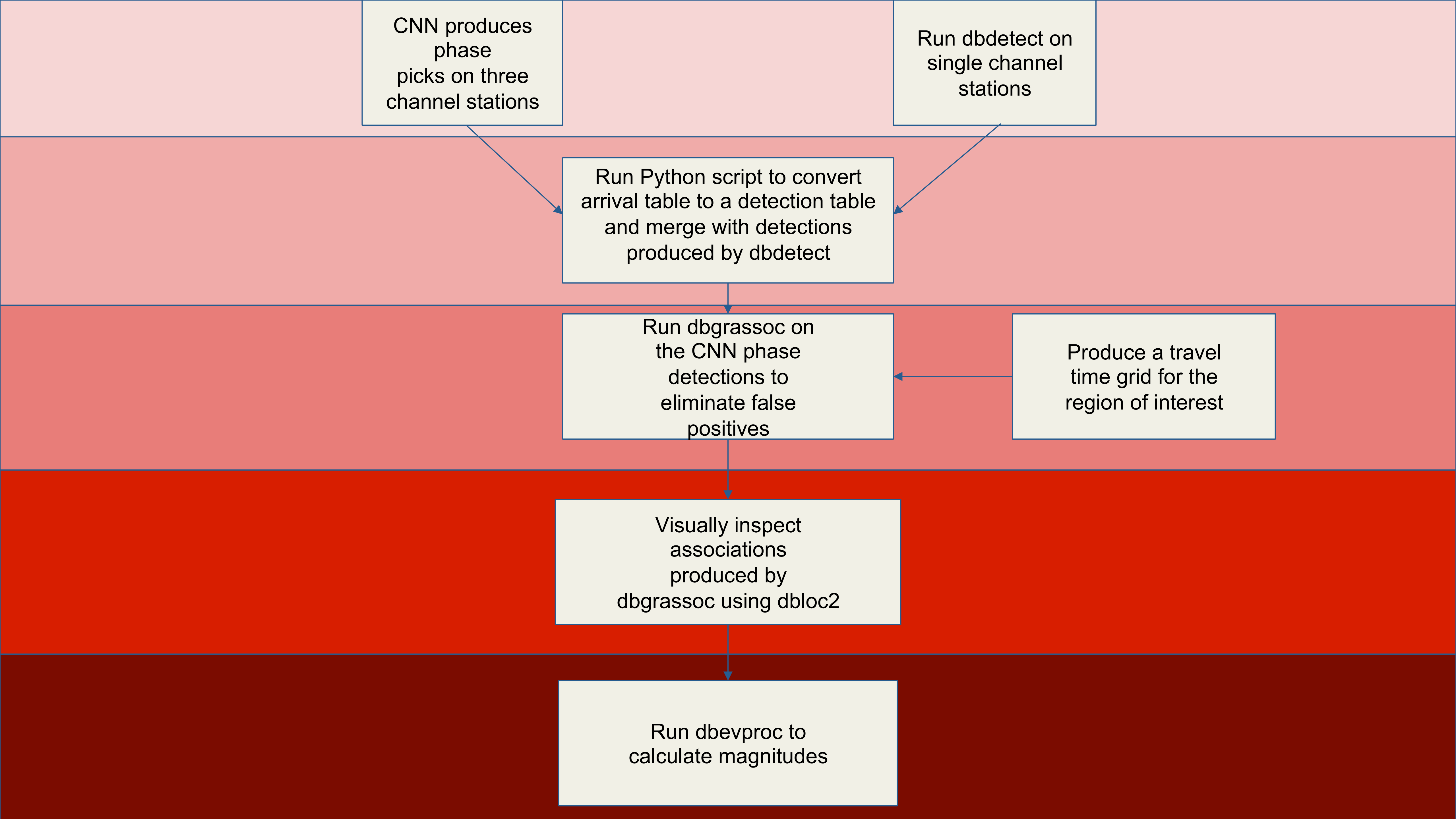


Dokht and Kao, 2018

Kurtosis functions



Modified after Dokht and Kao, 2018


CNN produces phase picks on three channel stations
Run dbdetect on single channel stations
Run Python script to convert arrival table to a detection table and merge with detections produced by dbdetect
Run dbgrassoc on the CNN phase detections to eliminate false positives
Produce a travel time grid for the region of interest
Visually inspect associations produced by dbgrassoc using dbloc2
Run dbevproc to calculate magnitudes

dbgrassoc

- dbgrassoc is used to eliminate many false positive detections

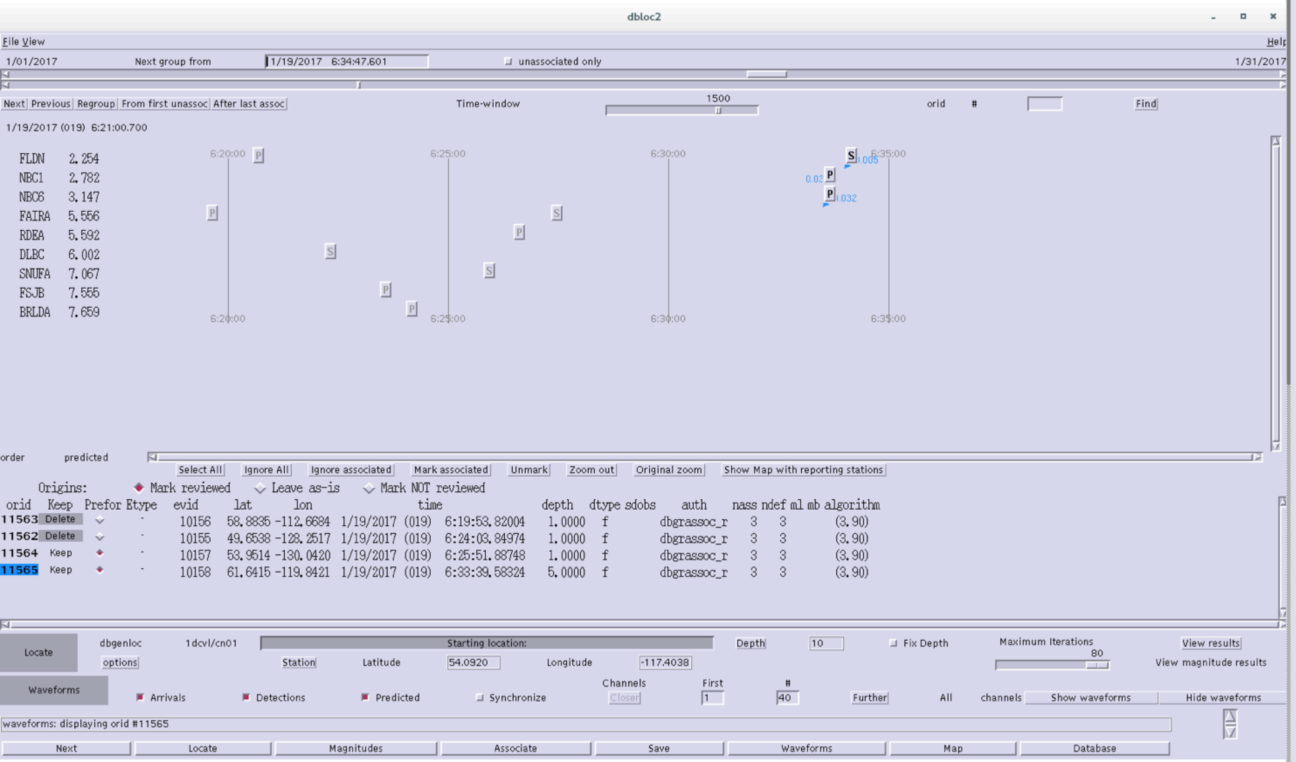
- Provides us with a preliminary location of real events

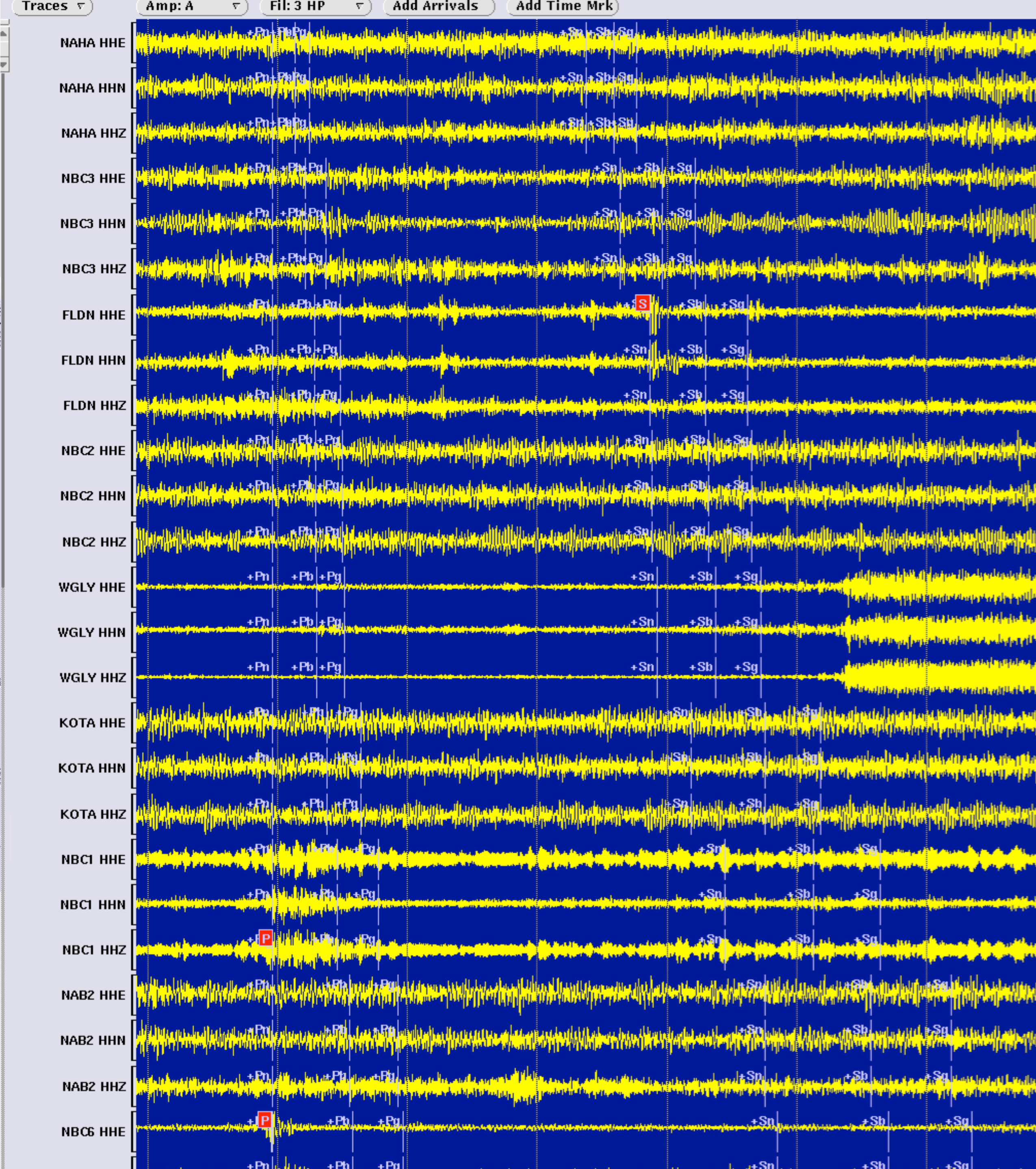
- In the parameter file, we set a table using a distance variable station threshold as well as trying both S and P phases for each detection.

- It currently takes several hours for dbgrassoc to run for one month of data

- A false positive that remained after running dbgrassoc is shown in the next slide

Example of a false positive event





Visual Inspection

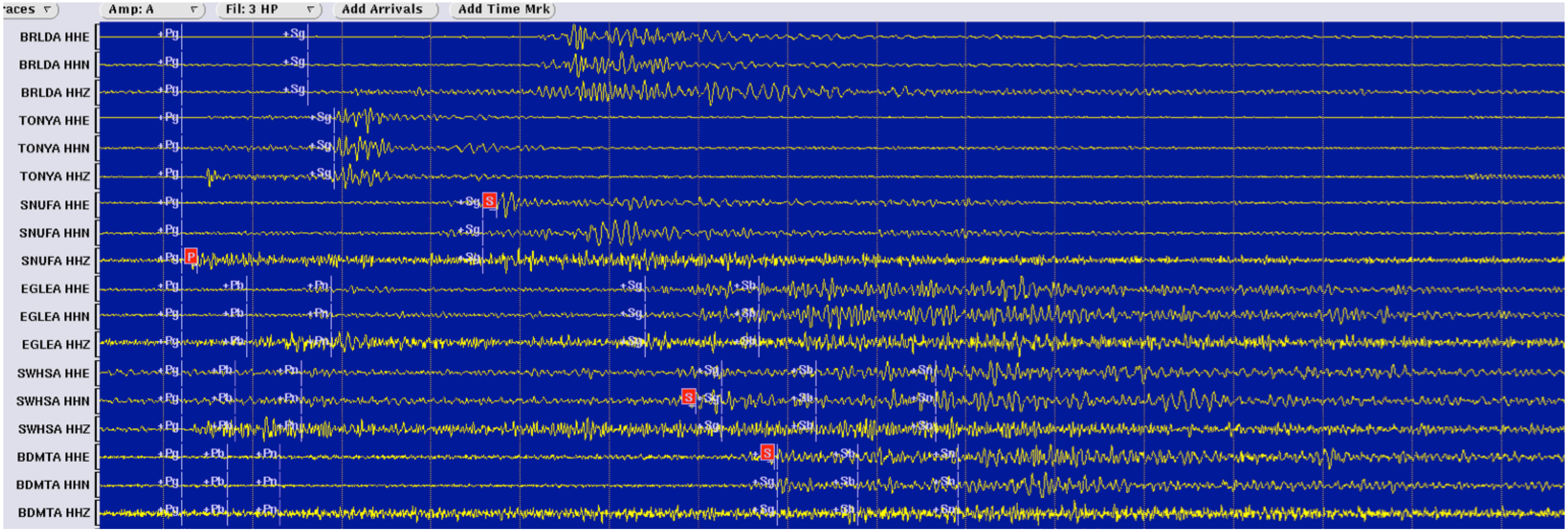
- This is the most time consuming process

- We use dbpick through dbloc2 to visually inspect the associations produced by dbgrassoc

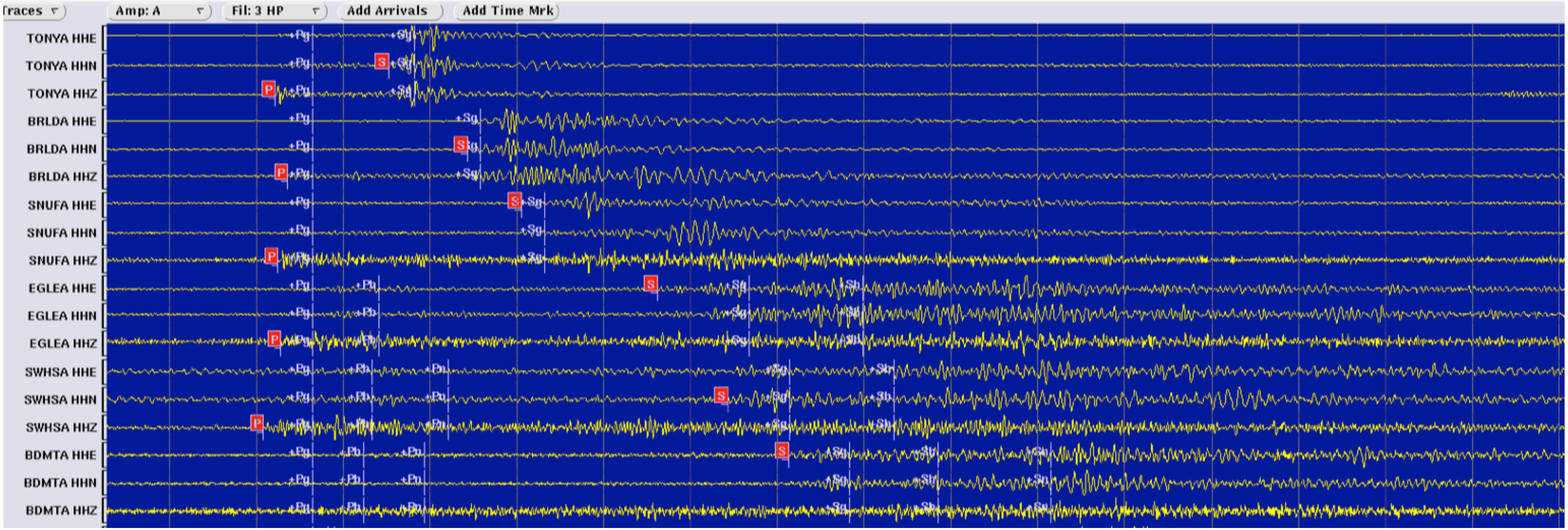
- After running dbgrassoc there are still several false positive events

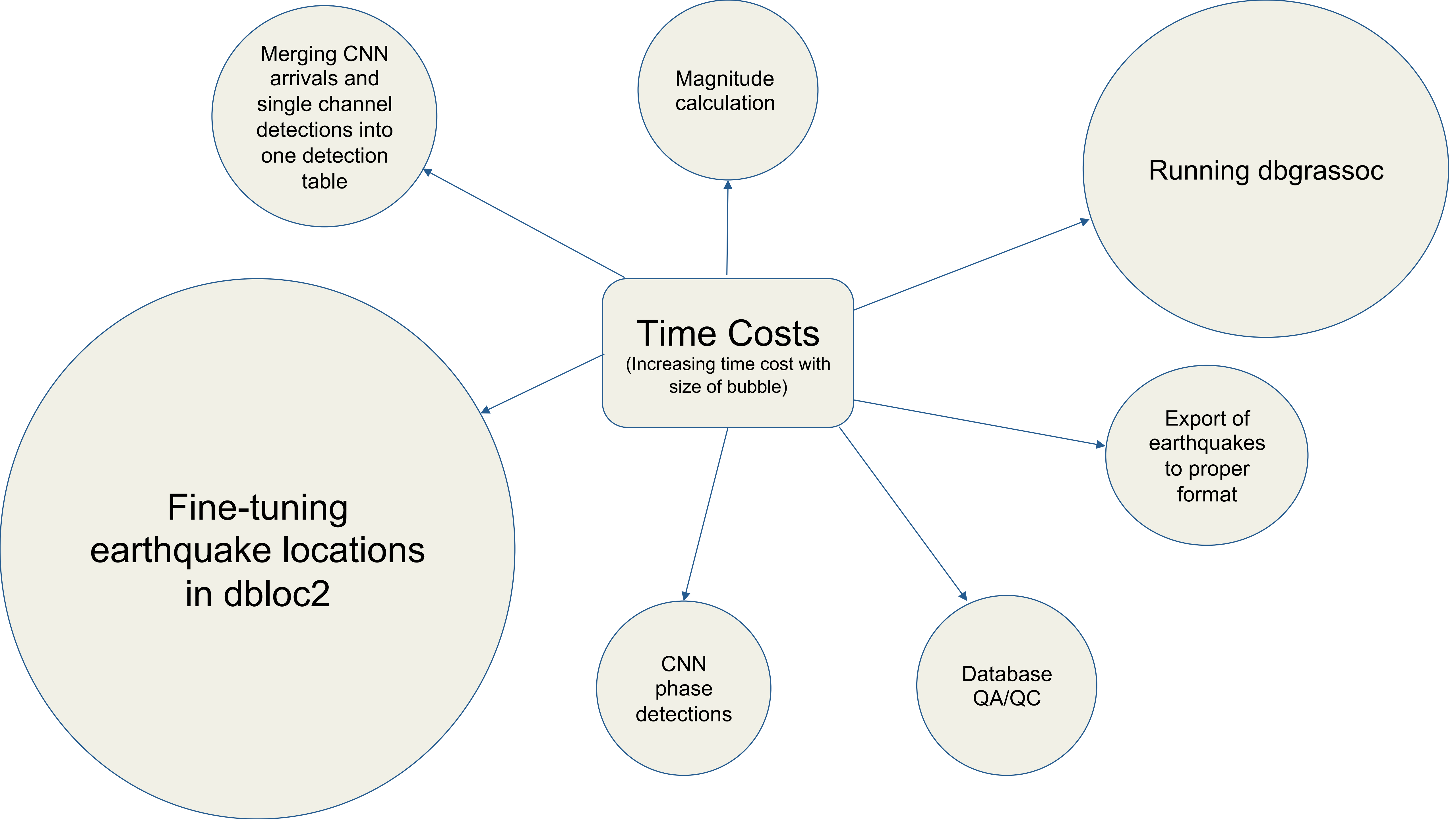
- There is an example of an event before and after visual inspection on the following slides

Before Visual Inspection



After Visual Inspection




Merging CNN arrivals and single channel detections into one detection table
Magnitude calculation
Running dbgrassoc
Time Costs
(Increasing time cost with size of bubble)
Fine-tuning earthquake locations in dbloc2
Export of earthquakes to proper format
CNN phase detections
Database QA/QC

Results

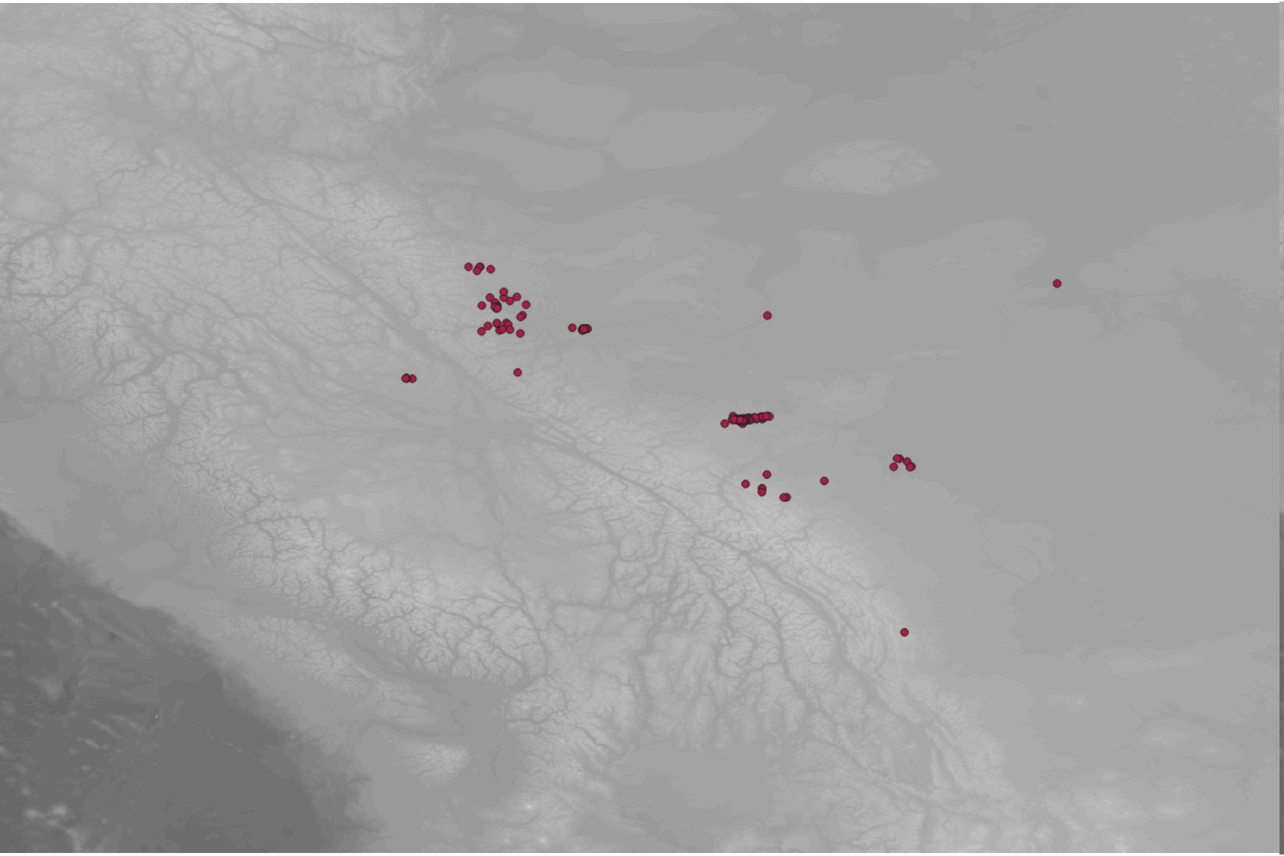
- More consistent at detecting seismic events: This method with the CNN found 13% more events than a human analyst over a 19 day period

- We are able to more thoroughly scan sections of the waveform with possible events

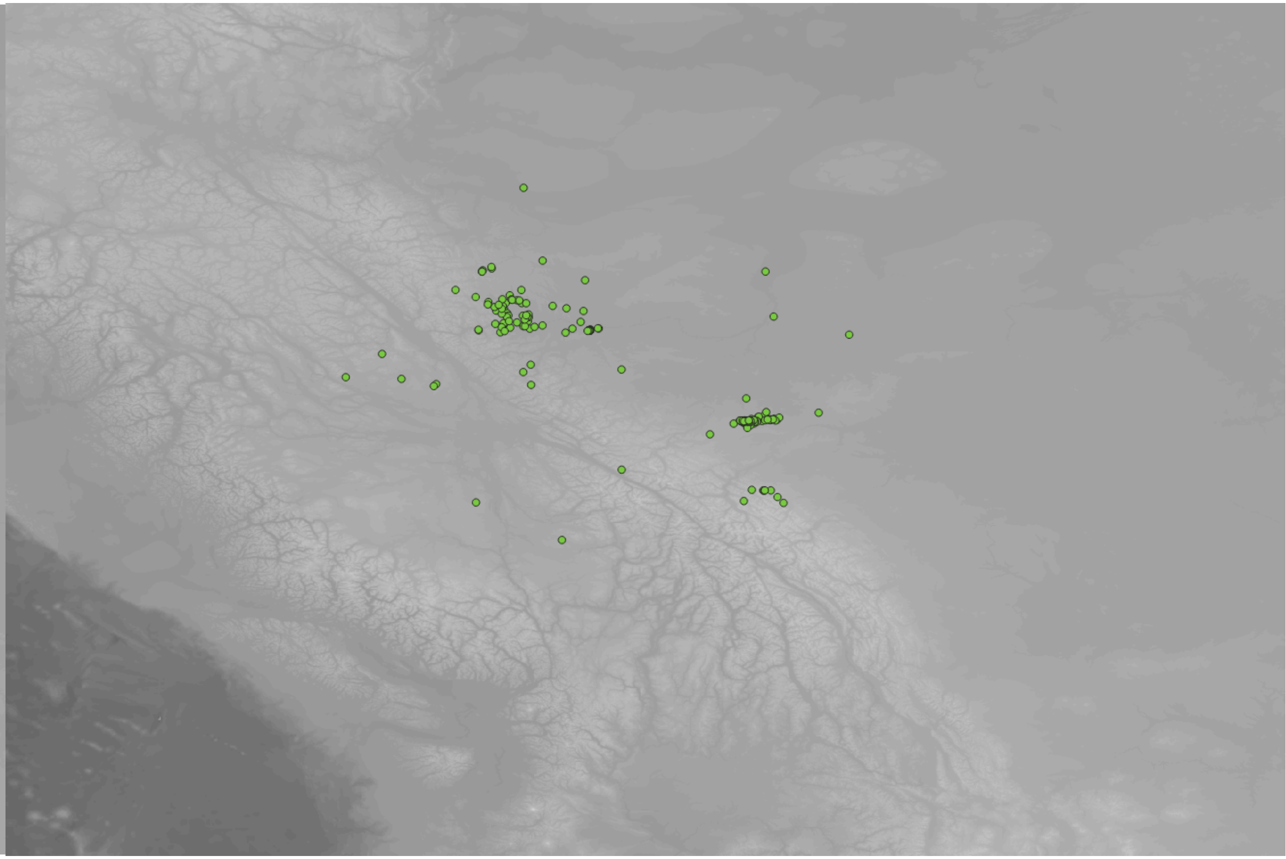
- We are able to process 286 earthquakes in 3 work weeks

- Not much faster: Roughly 87% of origins output from dbgrassoc are false positives which takes time to scan and review.

Analyst Detected
(241 events)



CNN Detected
(272 events)



Future Possibilities

- Developing a more mature training dataset should improve the number of events detected as well as increasing the quality of the phase picks

- We are working on optimizing our dbgrassoc settings so that we will have less false positives and more accurate initial locations

- The ability for the CNN to produce arrivals on single channel stations should decrease the amount of false positives

Comments/Suggestions?

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