MicroBayesLoc: A Bayesian Approach for Locating Microseismic Activity

CASIS 2014

May 21st, 2014

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LLNL-PRES-654642

This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

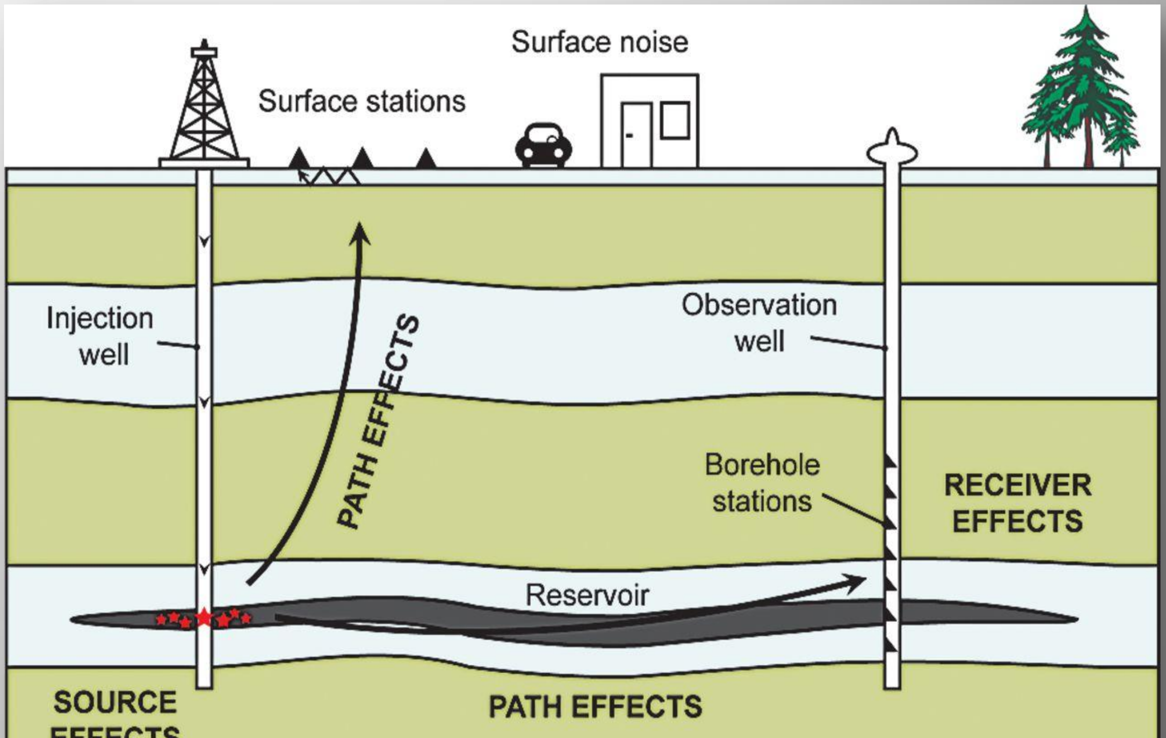
Locating Microseismic Activity

Setup

Focus on seismic activity due to hydraulic fracturing

Main Goal

Provide probabilistic characterization of the origin of the ongoing seismic activity



Source: http://tle.geoscienceworld.org

Approach

Bayesian inversion using imperfect seismic earth model and noisy observations --- leveraging previous work at the regional/global scale

From Origin to Observed Arrivals

- Given origin locations (sources), s_i, compute model-based travel times

  $$F_w(s_i, r_j;\theta)$$

  to station (receiver) r_j for phase w

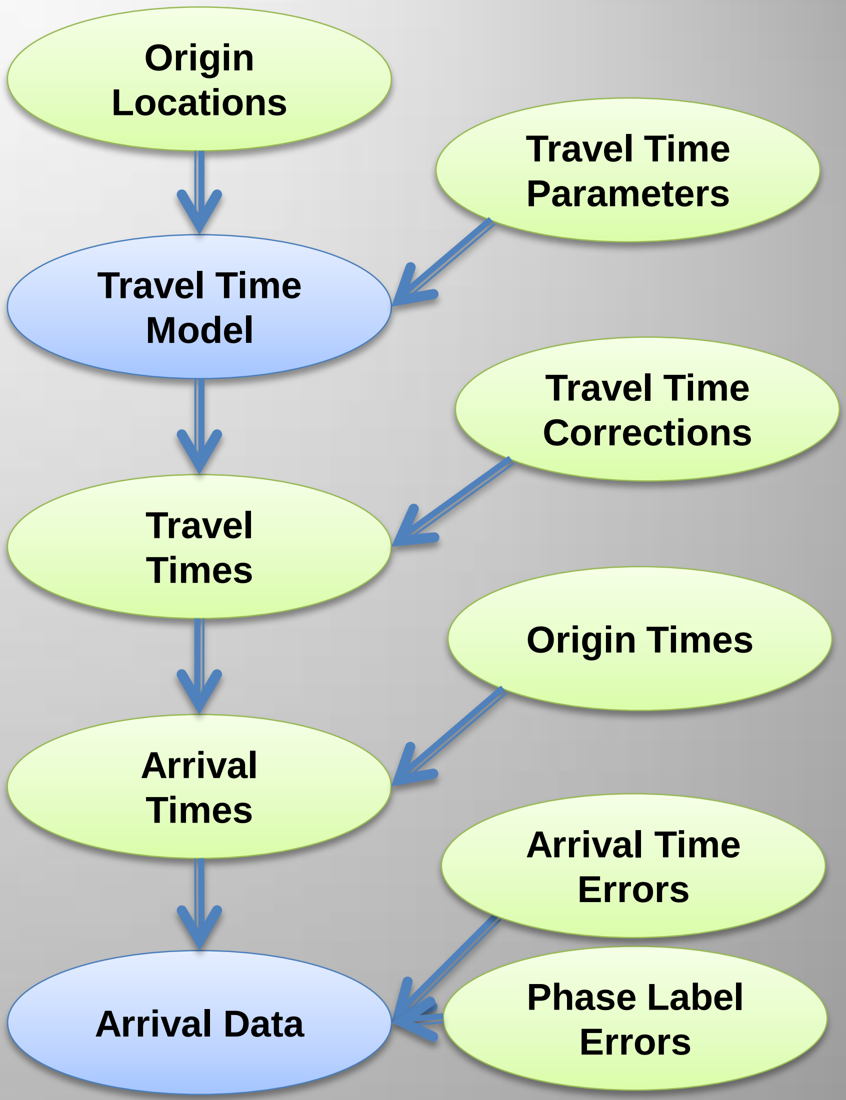
- From imperfect model-based travel times to corrected travel times

  $$T_w(s_i, r_j) = F_w(s_i, r_j;\theta) + (\text{correction})$$

- Compare picked arrival times, a_{wij}, to expected arrival times

  $$a_{wij} = A_w(s_i, r_j) + (\text{noise})$$

  where $A_w(s_i, r_j) = o_i + T_w(s_i, r_j)$ and o_i is the origin time



Other Sources of Observations

In addition to observed arrival times, we have two other potential sources of data

- **Differential Arrival Data**
  - The time difference between the arrivals of two or more events to the same station
  - Estimated by waveform cross-correlation
  - More accurate than absolute arrival picks
  - The expected differential time is less impacted by travel time model errors
- **Azimuth and Angle of Incidence**
  - Information of where the seismic wave came from
  - Not considered at this point

The Travel Time Model

Many Options…

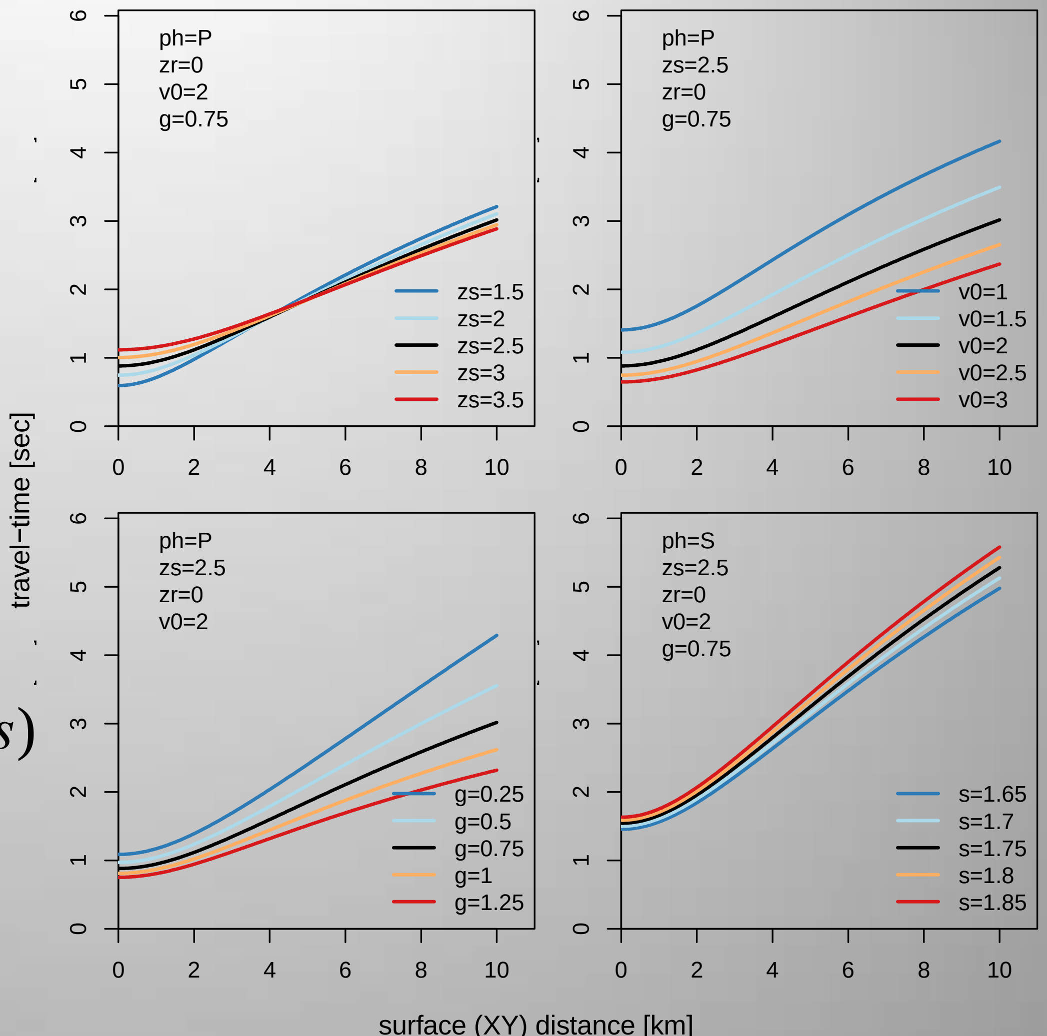
- Just assume a simple travel time model determined by
  - Surface velocity (v_0)
  - Velocity gradient (g)
  - P/S scaling parameter (s)
- Analytic solution

$$F_P(s_i, r_j; q) = F(s_i, r_j; v_0, g)$$

$$F_S(s_i, r_j; q) = F(s_i, r_j; v_0 / s, g / s)$$

$$q = (v_0, g, s)$$

- But can "plug-in" any travel time model

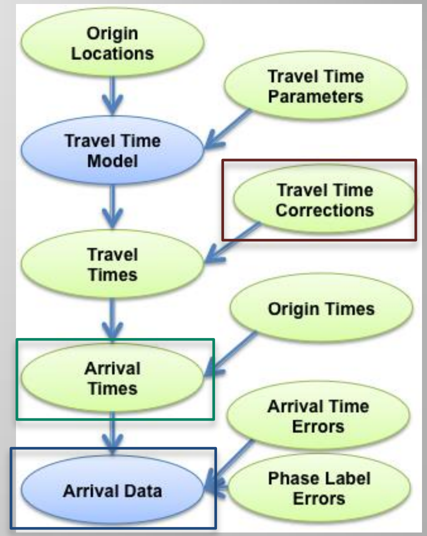


Bayesian Hierarchical Model (I)

Observation Model

$$\boxed{a_{wij}} \sim \mathrm{Gau}(\boxed{A_w(s_i,r_j)}, (k_w^a k_i^a k_j^a)^{-1})$$

$$d_{wi_1i_2j} \sim \mathrm{Gau}(A_w(s_{i_1},r_j) - A_w(s_{i_2},r_j), (\kappa_w^d \kappa_{i_1}^d \kappa_{i_2}^d \kappa_j^d)^{-1})$$



The Expected Arrival Time

$$\boxed{A_w(s_i,r_j)} = o_i + F_w(s_i,r_j;q) + \boxed{d_w(s_i,r_j)}$$

With spatially-correlated travel time corrections

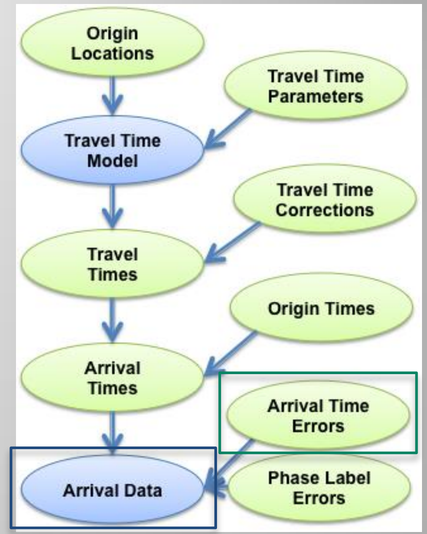
$$\delta_w(s_i,r_j) = \delta_w(r_j)$$

$$\delta_w(\cdot) \sim \mathrm{GauProc}(0, \tau_w^2 K(\cdot,\cdot;\rho_{xy},\rho_z))$$

$$\tau_w^2 \sim \mathrm{InvGam}(\cdot,\cdot),\ \rho_{xy} \sim \mathrm{Gam}(\cdot,\cdot),\ \rho_z \sim \mathrm{Gam}(\cdot,\cdot)$$

Bayesian Hierarchical Model (II)

Observation Model



$$\boxed{a_{wij}} \sim \mathrm{Gau}(A_w(s_i, r_j), \boxed{(k_w^a k_i^a k_j^a)^{-1}})$$

$$d_{wi_1i_2j} \sim \mathrm{Gau}(A_w(s_{i_1}, r_j) - A_w(s_{i_2}, r_j), (\kappa_w^d \kappa_{i_1}^d \kappa_{i_2}^d \kappa_j^d)^{-1})$$

Observation Precision Model

For the main phase-specific precision parameters

$$\kappa_w^a \sim \mathrm{Gam}(\cdot, \cdot)$$

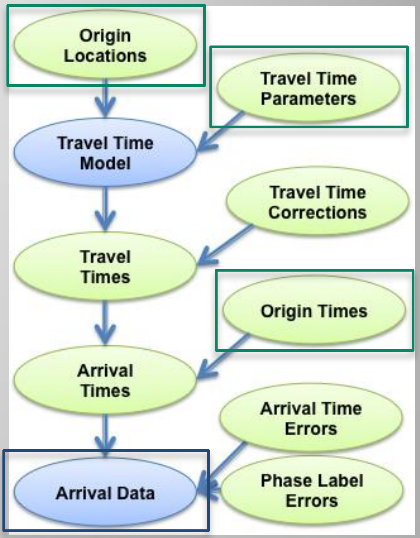
with relatively vague ("flat") prior for each phase

But treat the event- and station-specific factors as "random-effects"

$$\kappa_j^a \sim \mathrm{Gam}(\lambda, \lambda) \text{ with } \lambda \sim \mathrm{Gam}(\cdot, \cdot),$$

such that $\mathrm{mean}(\kappa_j^a) = 1$ and $\mathrm{var}(\kappa_j^a) = 1/\lambda$

Bayesian Hierarchical Model (III)



Observation Model

$$\boxed{a_{wij}} \sim \mathrm{Gau}(A_w(\boxed{s_i}, r_j), (k_w^a k_i^a k_j^a)^{-1})$$

$$d_{wi_1i_2j} \sim \mathrm{Gau}(A_w(s_{i_1}, r_j) - A_w(s_{i_2}, r_j), (\kappa_w^d \kappa_{i_1}^d \kappa_{i_2}^d \kappa_j^d)^{-1})$$

Priors on the Origin and Travel-Time Model Parameters

In general just non-informative ("flat") priors for the origin parameters

However, if we have events with known or partly known origins

$p(o_i) = \mathrm{Gau}(o_i \mid \cdot, \cdot)$ and similarly for the other origin parameters

And for the travel time model parameters

$$v_0 \sim \mathrm{Gau}(\cdot, \cdot),\ g \sim \mathrm{Gau}(\cdot, \cdot),\ s \sim \mathrm{Gau}(\cdot, \cdot)$$

MCMC for Posterior Inference

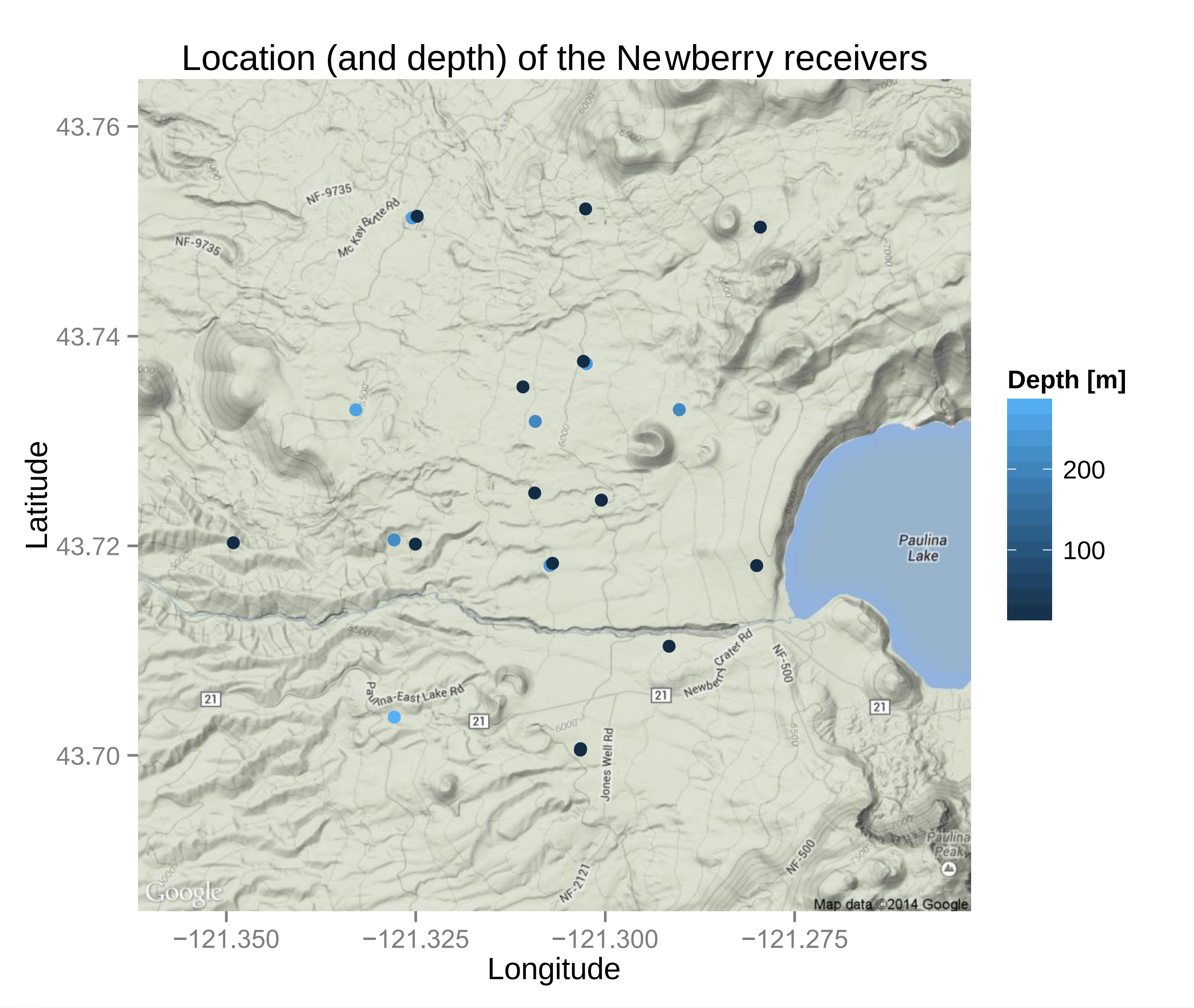
- **Yields a Posterior Sample of All Unknowns**
- **Various “Samplers” Used**
  - Adaptive Metropolis-Hasting for origin and travel time model parameters
    - — Learn posterior covariance matrices from past realizations
    - — Use the gradient of the travel time model to yield efficient samplers
  - Gibbs samplers for travel time corrections and precision parameters

Application to the Newberry Site

Data

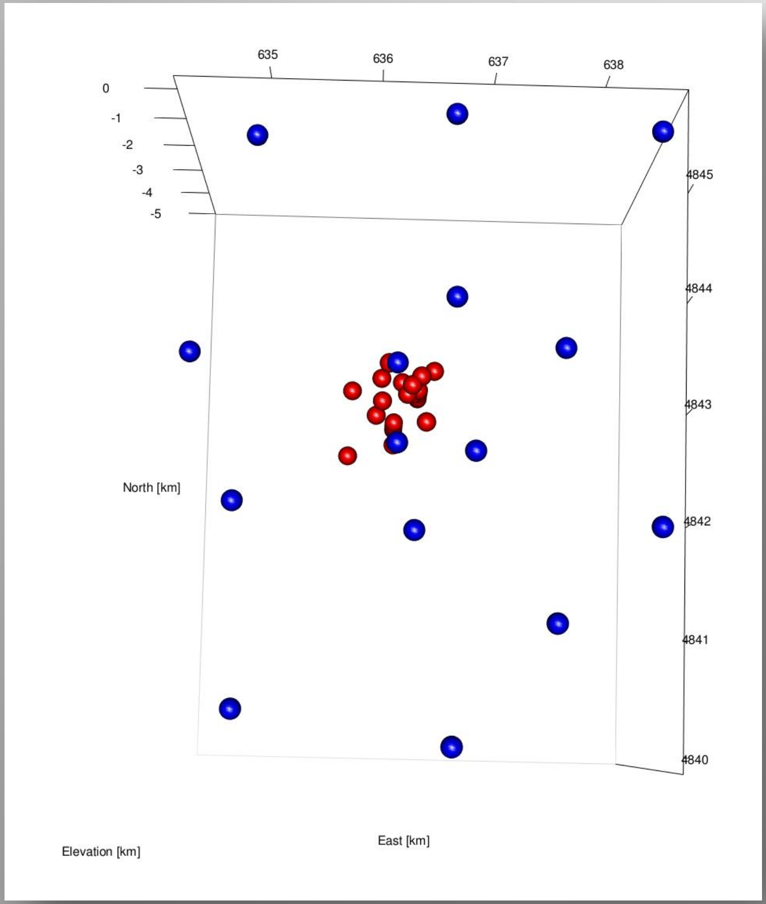
- 15 receivers
- 188 events
- 2527 arrivals
  - 1358 P
  - 1169 S

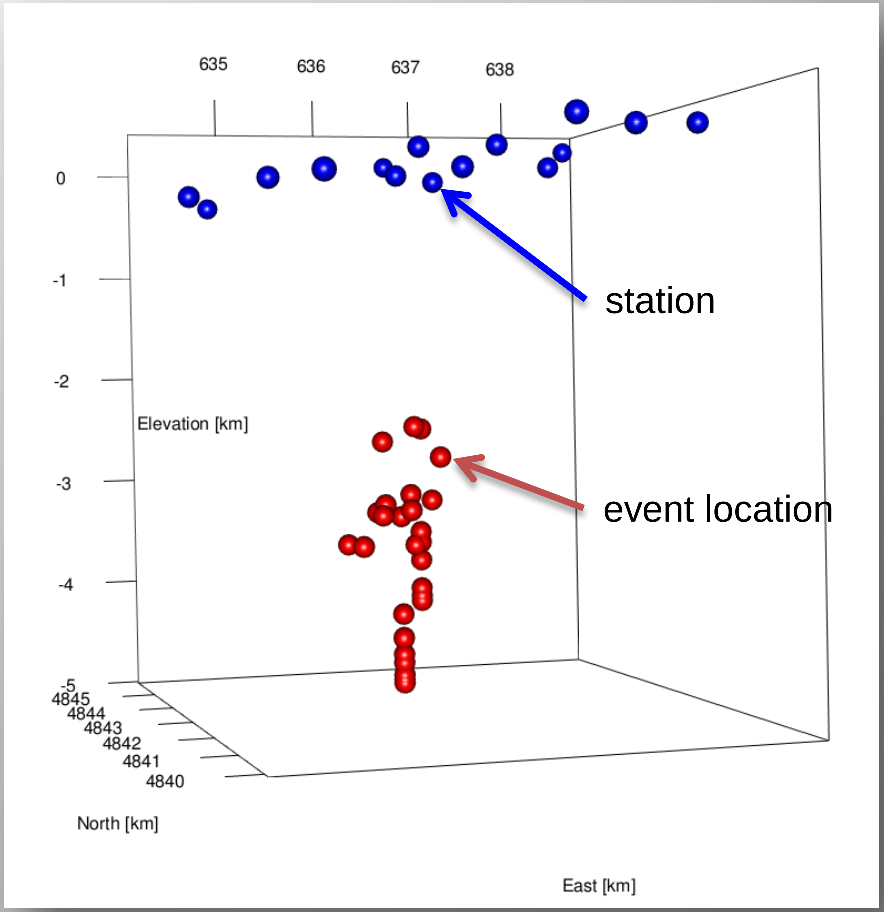
Use synthetic arrival data in addition to real data



Application 1: Synthetic Data

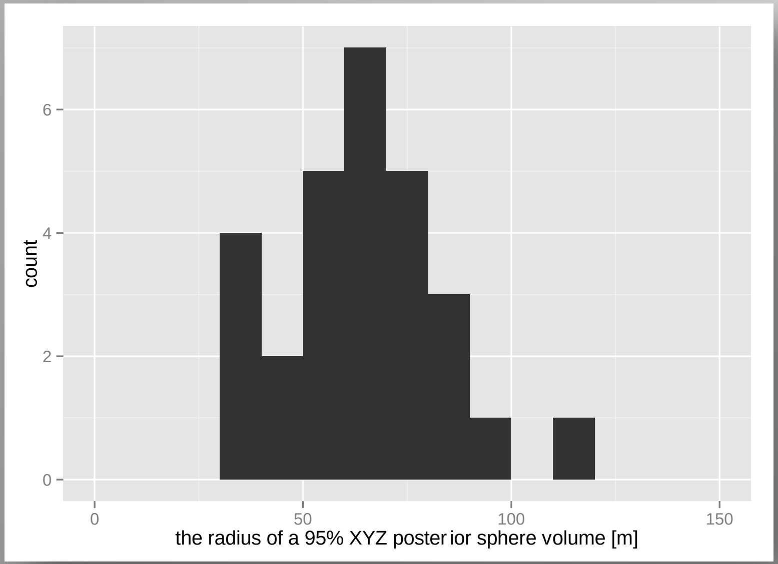
28 known events with 377 synthesized arrivals according to a known travel time model

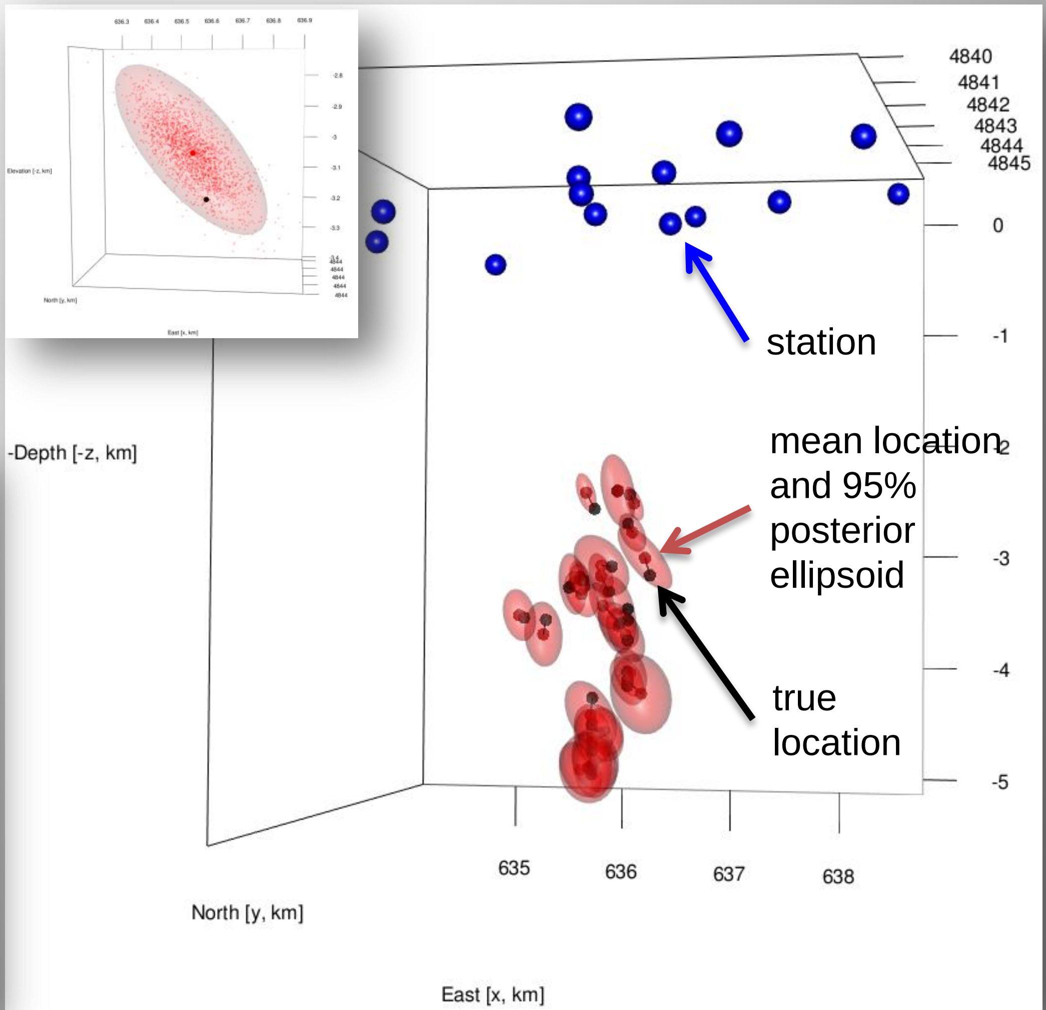




Application 1: Synthetic Data
Known Travel Time Model

A Best-Case Scenario
Assume a known travel time model and only estimate precision parameters

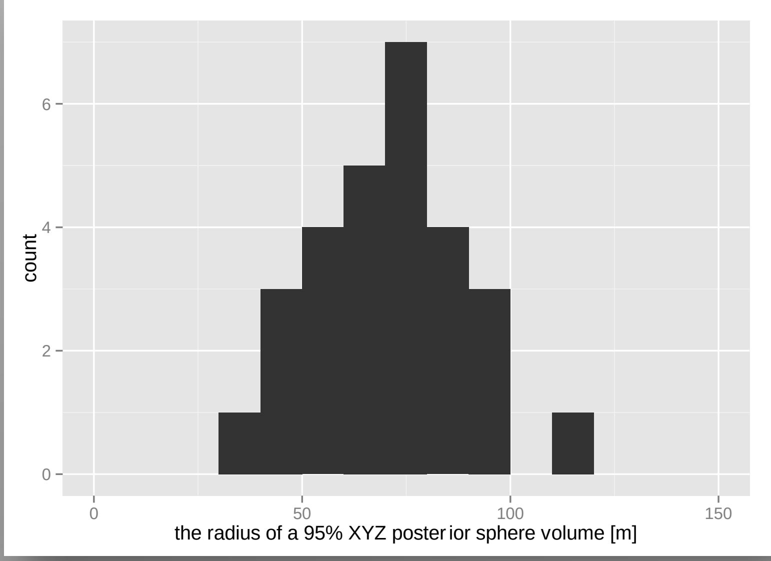


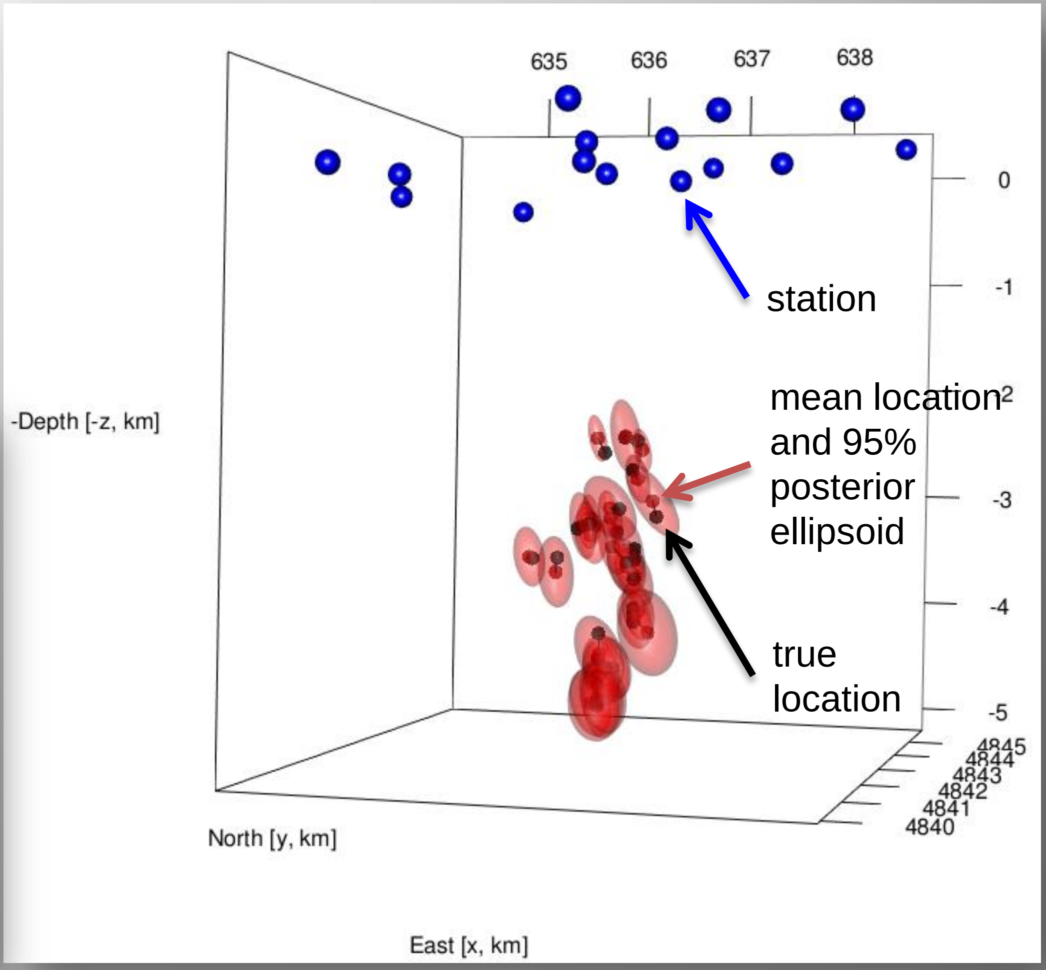


Application 1: Synthetic Data
Unknown Travel Time Model

Estimate (sample) the three unknown parameters of the travel time model

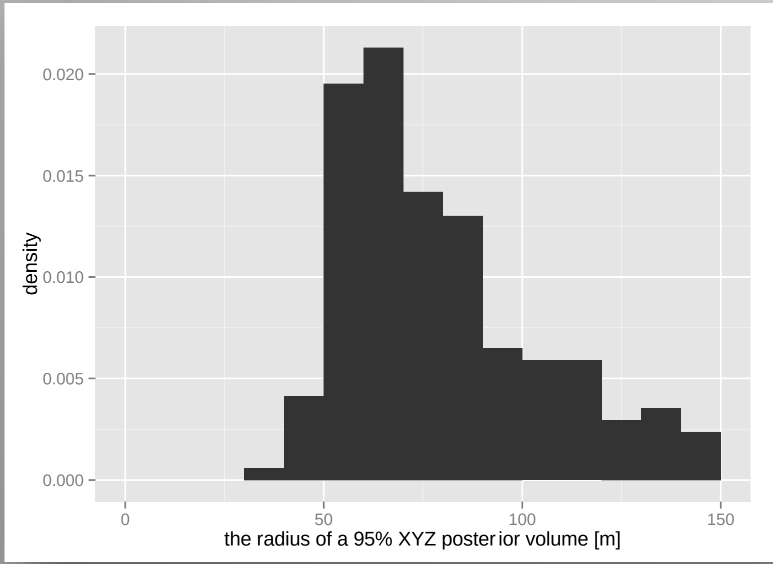
Slightly wider posterior distributions for the locations

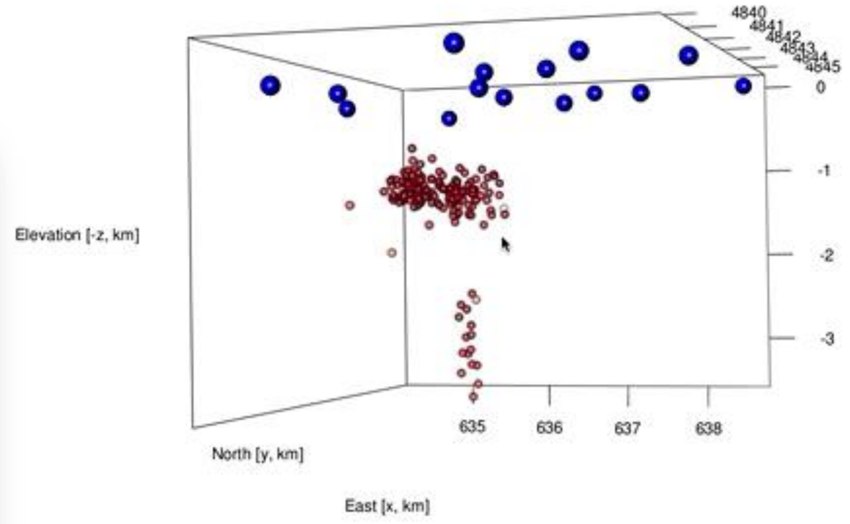




Application 2: Newberry Data (I)
Estimate travel time model and Precision Parameters

Estimate (sample) the three unknown parameters of the travel time model, along with phase-, station-, and event-specific precision parameters





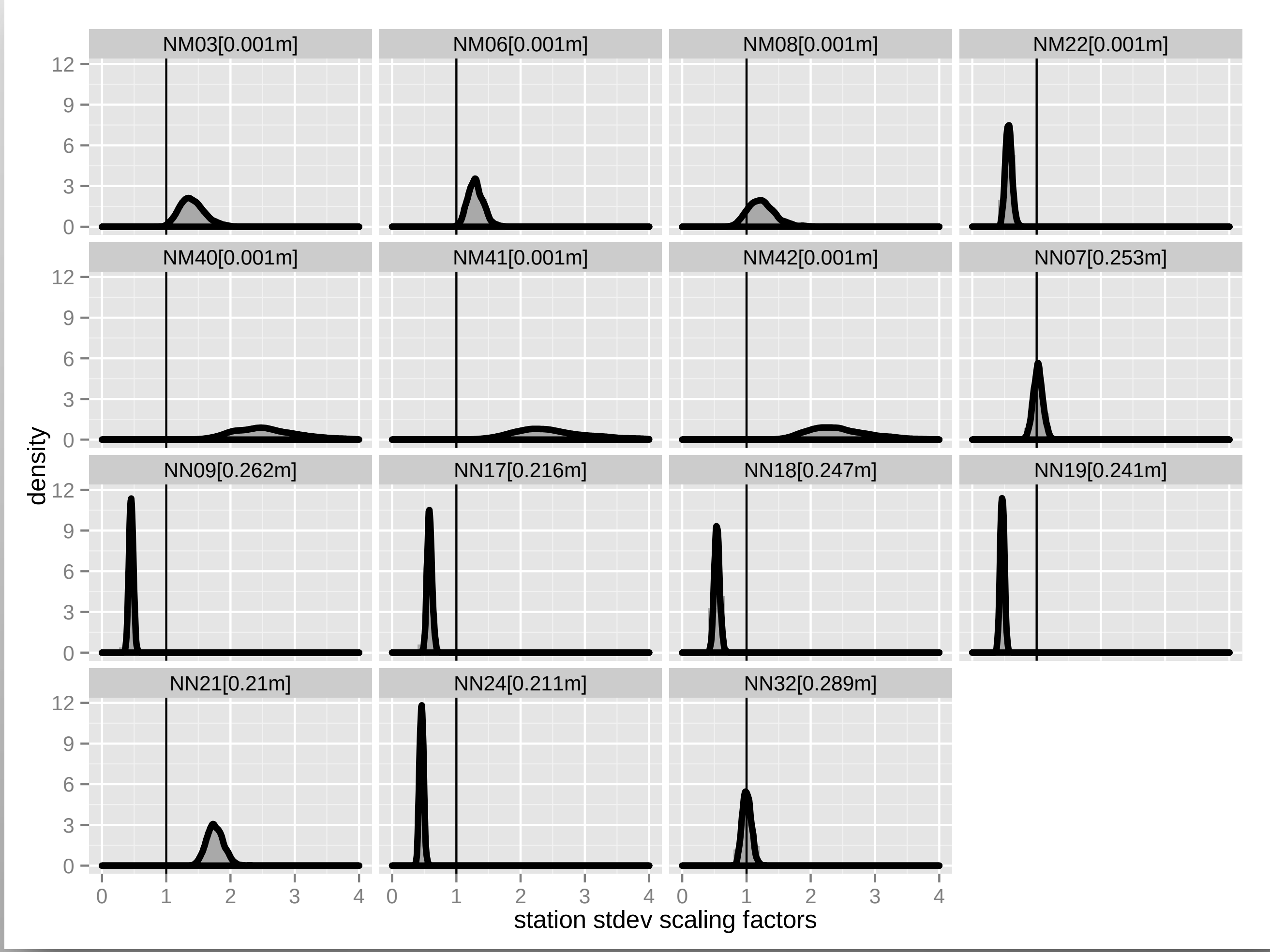
Application 2: Newberry Data (II)

Estimate travel-time model and Precision Parameters

The posterior density of the station standard deviation scaling parameters

$$1/\sqrt{\kappa_j}$$

Stations at or near the surface are in general "down-weighted"



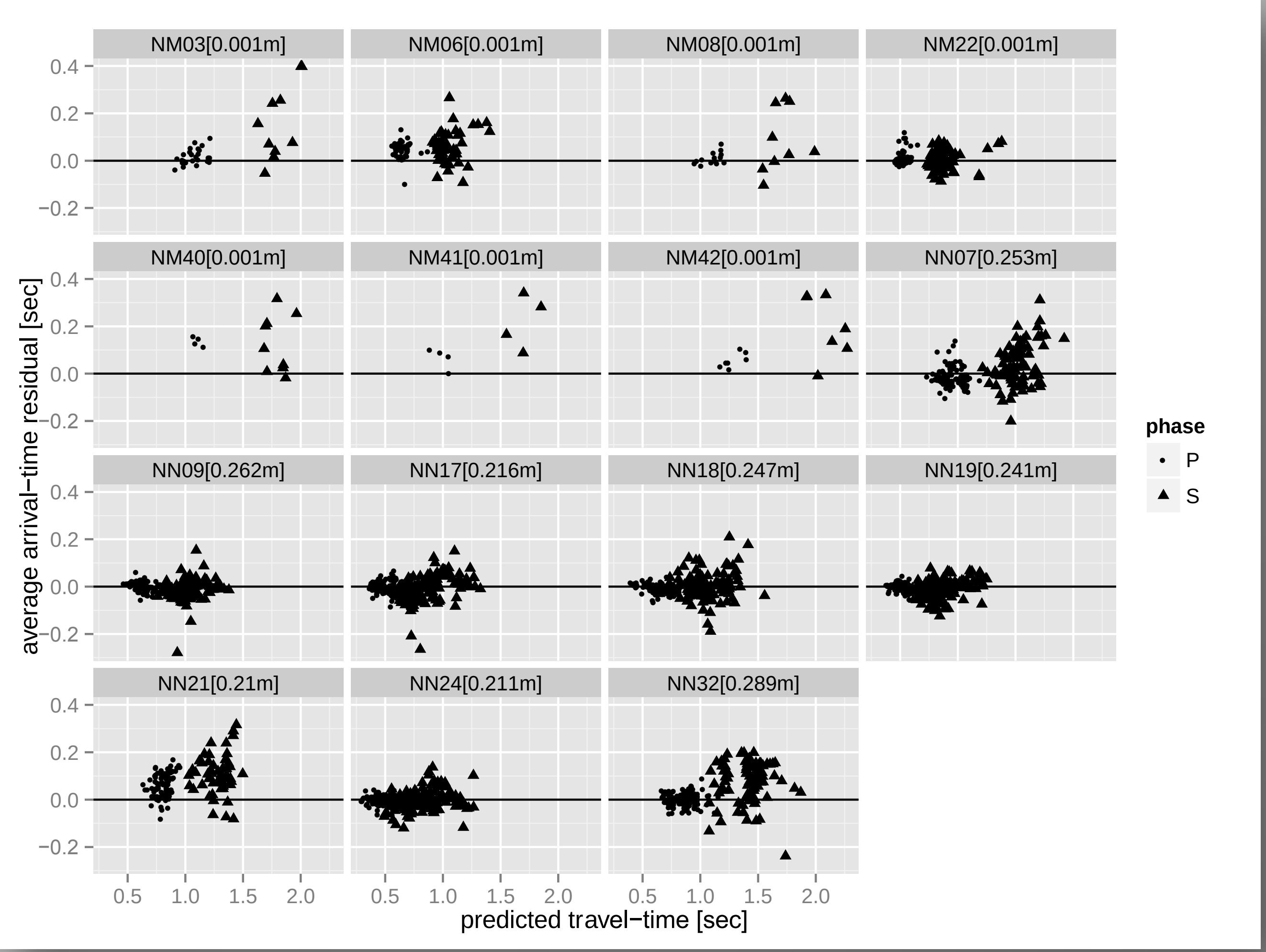
Application 2: Newberry Data (III)

Estimate travel-time model and Precision Parameters

A look at the arrival time residuals versus predicted travel times

Again, near-surface stations tend to have larger residuals

Some evidence for the need for travel time corrections



Few Final Remarks

- Good initial results for absolute arrival times
- The need for better travel time model
  - Resulting in smaller statistical travel time corrections
  - And more accurate locations
- Add (real) differential arrival data
  - Yields better relative locations
  - Challenge for the MCMC sampler

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