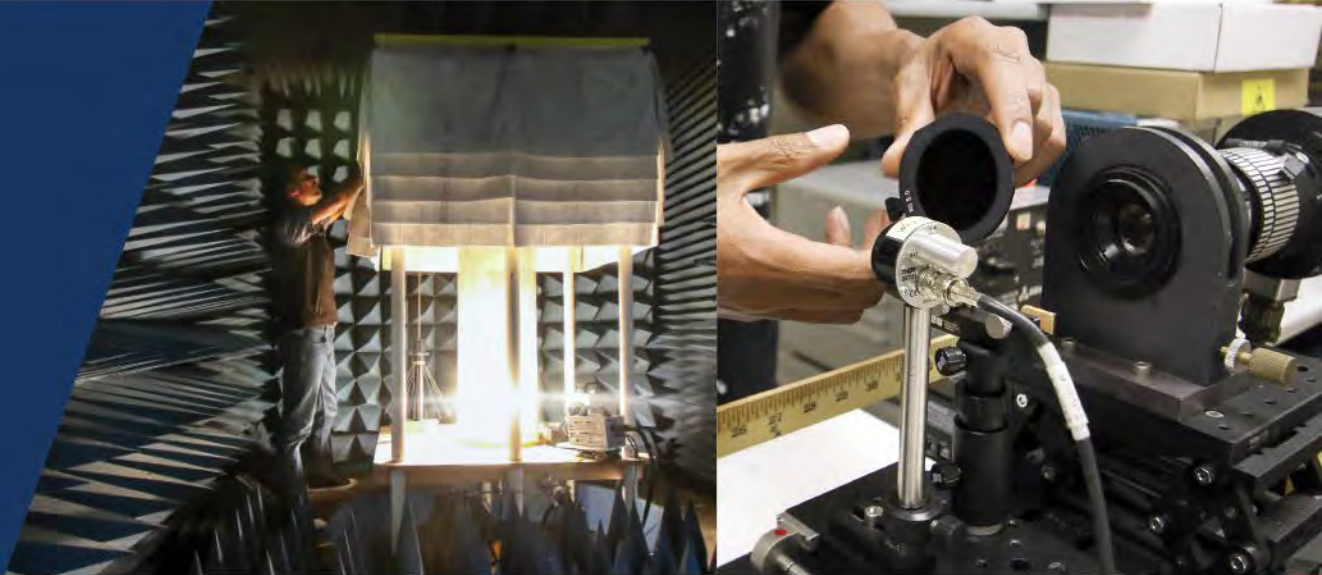




Indirect Measurement of Underground Facility Expansion/Extent through the Multi-Modal Use of Cyber Metadata (Traceroutes) and Physics-Informed Models Applied to Pre-Post Digital Surface Mapping

Project #: NLV-012-21

Year 2 of 3



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Estimation of the size and expansion of an underground facility

- *The estimation of the size and/or expansion of an underground facility is a challenging analysis problem that is of relevance to the non-proliferation community.*
- Direct measurements are infrequently a feasible option and unintended emissions are minimized (geospatial intelligence (GEOINT), human source intelligence (HUMINT)/surveys, electronically-gathered intelligence (ELINT))
- Combining weaker signals and indicators of facility size/expansion from multiple modalities:

Current FY Focus

- **Cyber** – High-resolution latency measurements and traceroutes
- **GEOINT** - Stochastic surface growth/decay from subsidence and/or accumulation of excavated material as indicated via Digital Surface Model(DSM)/Digital Elevation Model (DEM) data
- **Seismic** – 3D localization records from an array of seismic sensors

Current FY Focus

- **Measurement combination:** In this work we have a specific goal to combine facility size estimates from the modalities/methods above to create a more-informed estimate with multimodal robustness in a meta-analysis capability.
- Deliverables:
 - **Cyber-based scale estimation capability from traceroutes**
 - **DSM/DEM stochastic surface growth/decay capability**
 - **Variable bandwidth Kernel Density Estimation (KDE) for spatial-temporal localization results Geometric Dilution of Precision (GDOP)**
 - **Meta-analysis measurement combination analytic**

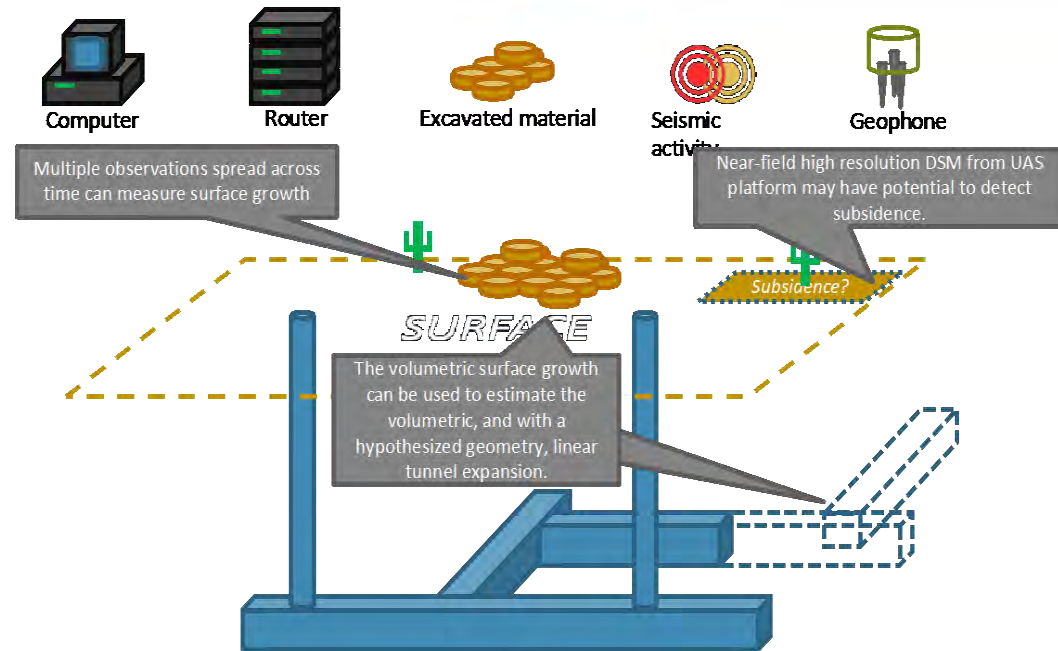
Innovation

► Input opportunities for the measurement combination analytic

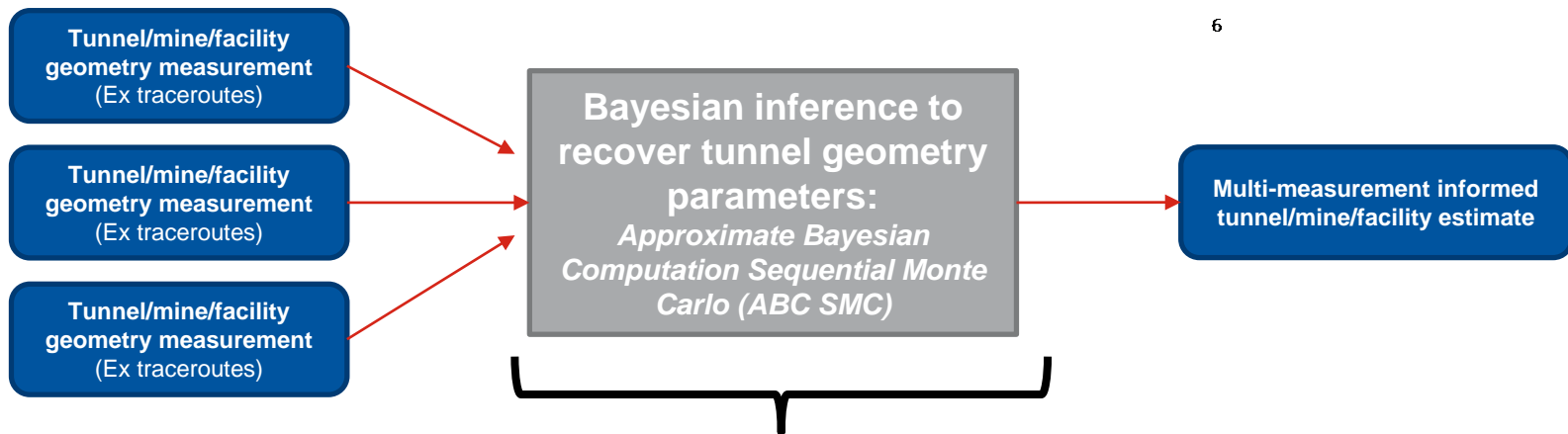
- Traceroute/latency-based measurement
- Seismic localization-based measurement

DSM/DEM-based measurement:

Measurement development began and matured in FY21, focus area of Q1 and Q2 FY22



► Simple workflow:



“Measurement Combination Analytic”

Technical Approach (Current Year)

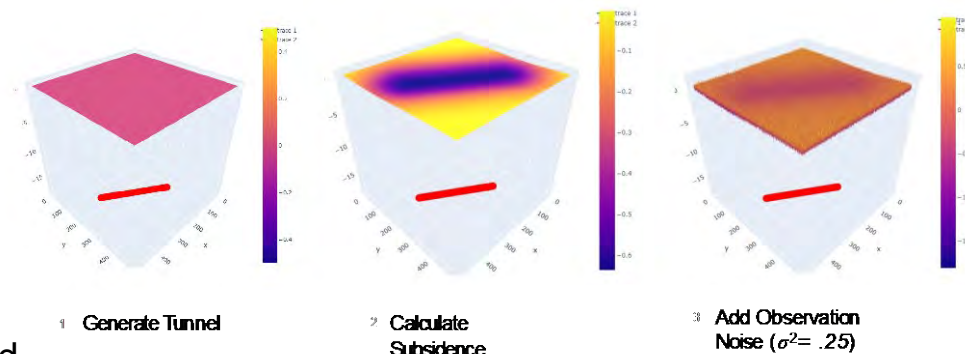
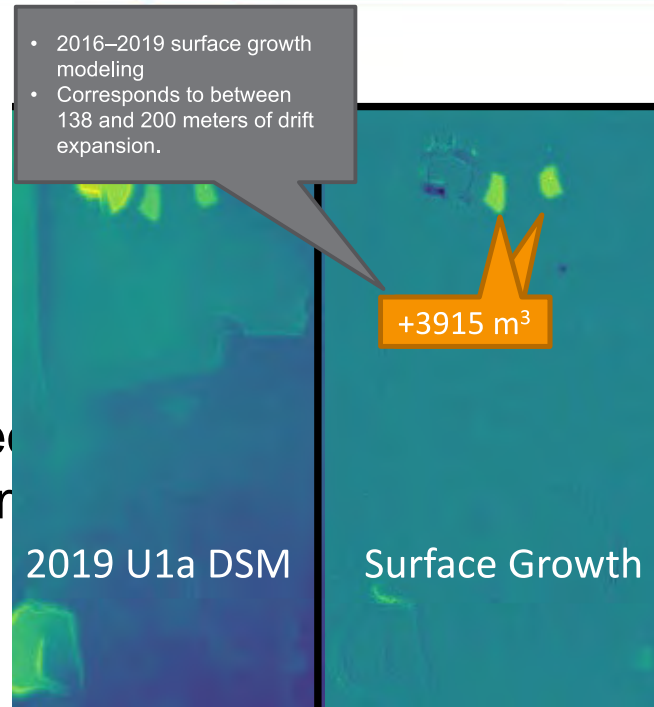
Subsidence-based inference and measurement combination analytic

- **Year 1:** Assessed stochastic surface growth (excavated material deposits on surface) for tunnel/mine expansion
- **Year 2:** Bayesian inference to recover tunnel geometry based on observed data and alternate measurement priors (traceroute, seismic localization).
- Parametric subsidence model

- Parametric subsidence models are available for **some** geophysical environments and mining methods

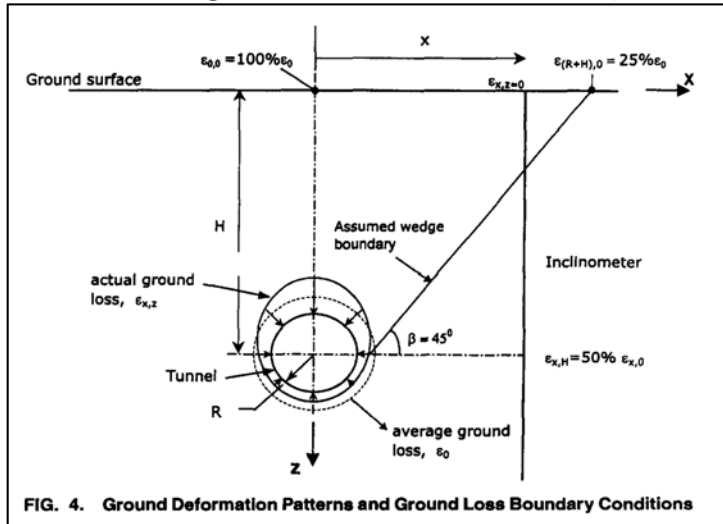
- Ex: Alluvium clay: Loganathan, N., H. G. Poulos. 1998. "Analytical Prediction for Tunneling-Induced Ground Movements in Clays." *J Geotech Geoenviron Eng.* **124**(9): 846-856.

- Non-parametric subsidence model
- Subsidence model = forward simulation based on geophysics
- Inference where the model is a simulation



Results: Parametric Subsidence Model

- “Analytical Prediction for Tunneling-Induced ground Movements in Clays” by Loganathan and Poulos (1998).



Assuming $\delta = 0$ for the undrained condition, and substituting (6) in (11), the modified formula for the prediction of the horizontal ground movements around a tunnel may be given as

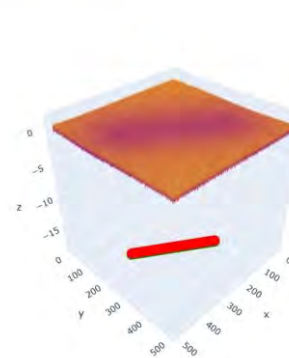
$$U_x = -R^2 x \left[\frac{1}{x^2 + (H - z)^2} + \frac{3 - 4\nu}{x^2 + (H + z)^2} - \frac{4z(z + H)}{(x^2 + (H + z)^2)^2} \right] + \frac{4gR + g^2}{4R^2} \exp \left\{ - \left[\frac{1.38x^2}{(H + R)^2} + \frac{0.69z^2}{H^2} \right] \right\} \quad (12)$$

R -radius, H -depth, z -original surface, δ -distance from tunnel, ν -Poisson's ratio, g -gap parameter

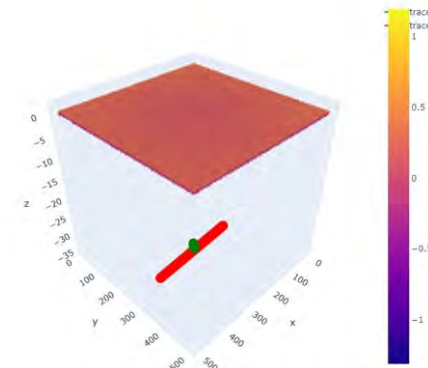
Sampling/Inference

- 1 Start with flat surface ($z=0$)
- 2 Randomly generate tunnel (depth, radius, angle, length)
- 3 Calculate subsidence
- 4 Make noisy observation
- 5 Use L-BFGS for prediction

Synthetic Subsidence Surface



Synthetic Subsidence Surface



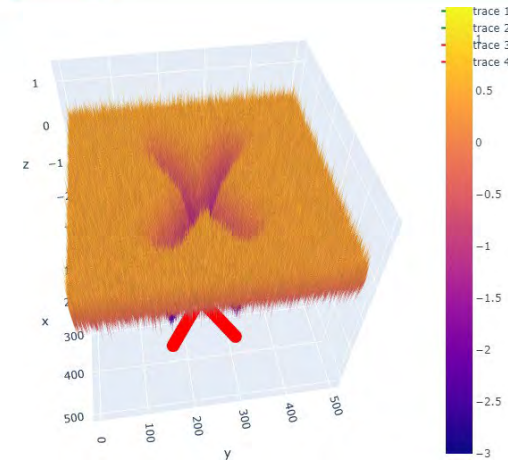
Real: $H = 188.44$, $R = 9.47$, $\theta = 2.58$, $L = 300.72$
Pred: $H = 186.22$, $R = 12.31$, $\theta = 2.58$, $L = 300.33$

Real: $H = 339.85$, $R = 3.14$, $\theta = 0.94$, $L = 22.94$
Pred: $H = 353.08$, $R = 2.99$, $\theta = 0.09$, $L = 313.81$

Results: Parametric Subsidence Model

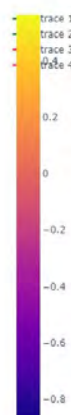
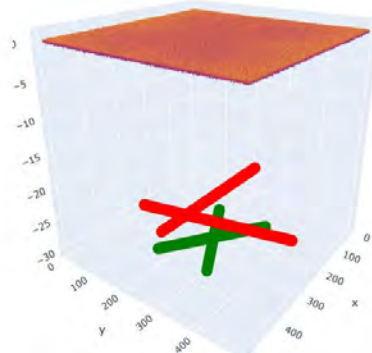
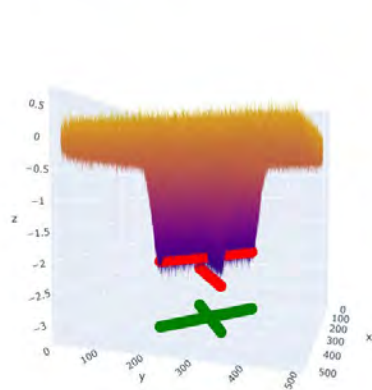
Early attempts at extending to multiple tunnel segments

- Take a surface with multiple tunnel segments below it, predict as if just one segment exists.
- Subtract the effect of this tunnel from the surface observations and repeat.
- Add back in the first predication and subtract the second prediction and keep repeating.



Synthetic Subsidence Surface

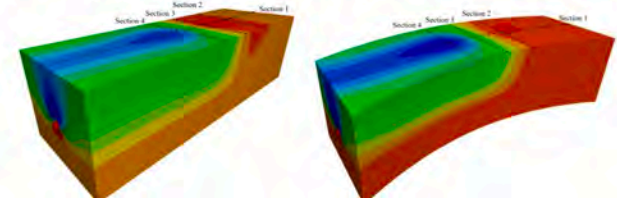
Synthetic Subsidence Surface



- Piecewise Linear Tunnel Subsidence: Couldn't find in literature
- Tunnel Intersection Subsidence
 - "Three-Dimensional Numerical Analyses of Perpendicular Tunnel Intersections" (Chortis & Kavvas)
 - No mention of subsidence, everything is Numerical.
- Twin Tunnel Subsidence:

$$U_z = U_{max} \left[\exp \left\{ -\frac{x_A^2}{2i^2} \right\} + \exp \left\{ -\frac{x_A^2 - d}{2i^2} \right\} \right]$$

- "Ground loss model for analyzing shield tunneling-induced surface settlement along curve sections" Deng et al.



Challenges led to the consideration of a non-parametric subsidence model that could natively represent multiple/complex mine geometries.

Results: Non-Parametric

Parameter	Symbol
Mass node position, velocity, acceleration	$R = [R_x, R_y, R_z], V, A$
Spring lattice topology (adjacency matrix)	A_{LSM} (sparse)
Non-linear spring lattice parameters	$L_0, L(t), K_0, K'_0 \quad \kappa = \frac{K_0}{L_0} \cdot \left(\frac{L_0}{L}\right)^{K'_0}$

- Sparse Linear Algebra
LSM force computations

$$D_x = \text{diag}(R_x)$$

$$\Delta X = D_x \cdot A_{LSM} - A_{LSM} \cdot D_x$$

$$\Delta L^2 = \Delta X^2 + \Delta Y^2 + \Delta Z^2$$

$$\vec{F} = \left[\frac{\Delta L}{L} \cdot \Delta X \cdot \kappa \quad \frac{\Delta L}{L} \cdot \Delta Y \cdot \kappa \quad \frac{\Delta L}{L} \cdot \Delta Z \cdot \kappa \right]$$

New workflow

- Create a physics based model for Subsidence
 - 1 Voxel Simulation
 - 2 Finite Element methods
 - 3 Spring Mass Lattice
- Model Based Statistical Inference: Approximate Bayesian Computation

- Contemporary/proprietary methods exist that do not allow for machine iteration and large quantities of trials (for simulating subsidence).
- The ABC approach can be demonstrated even with low complexity simulations: Spring lattice simulations
 - A lattice of non-Hookean springs with spring coefficients determined by elastic modulus estimates for the medium
 - Fast computation:
 - Excise a tunnel or tunnels
 - Integrate the dynamical system of springs
 - Subsidence estimated from lattice surface
- Lattice Spring Model (LSM)-based forward simulations have many other applications (e.g. shock physics) that can be used to develop the inference capability in a lower dimensional application.
 - Particles colliding with a target object (1D)
 - Inference recovers ballistic particle velocities (1D)
 - Subsidence from excavated tunnel (3D)
 - Inference recovers tunnel radius, length, position, orientation.

ABC SMC Algorithm

1. Initialize Thresholds $\varepsilon_1 > \varepsilon_2 > \dots > \varepsilon_T$

Sequence of more accurate acceptance thresholds

2. Set $t = 1$

Accept "Close" Simulation Shock Problem:

- Average diff in Velocity
- Average diff in Elevation

■ For $i = 1, \dots, N$

■ Until $\rho(x, x_{obs}) < \varepsilon_1$

• Sample $\theta_i^{(1)} \sim p(\theta)$

• Simulate $x \sim p(x | \theta_i^{(t)})$

• Set $w_i = 1/N$

Sample Parameters Shock Problem:

- Velocity profile of particles
- Radius, Length, Depth

3. For $t = 2, \dots, T$

■ Until $\rho(x, x_{obs}) < \varepsilon_t$

• Pick θ_i^* from $\theta_j^{(t-1)}$ with probabilities $w_j^{(t-1)}$

• Sample $\theta_i^{(t)} \sim K_t(\theta_i^{(t)} | \theta_i^*)$

• Simulate $x \sim p(x | \theta_i^{(t)})$

• Set new weights

$$w_i = \frac{p(\theta_i^{(t)})}{\sum_j w_j^{(t-1)} K_t(\theta_i^{(t)} | \theta_i^{(t-1)})}$$

Run Simulation

Use smaller tolerance for better samples

Use "Best" samples from previous round

■ Normalize weights

Sample parameters near the previous best

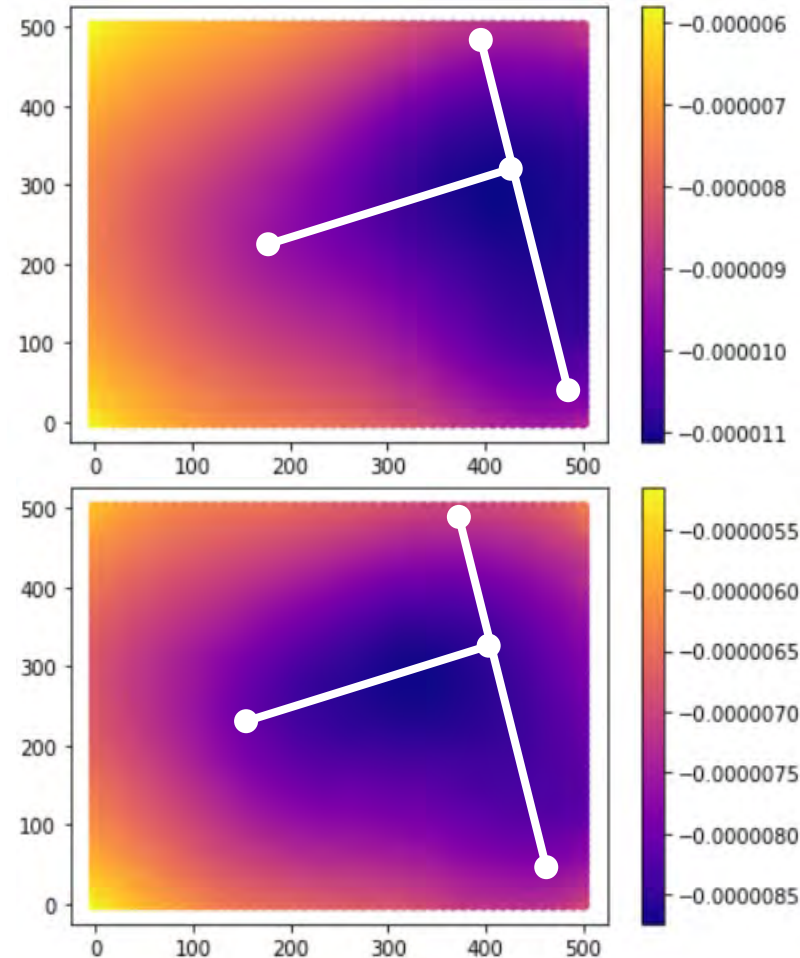
Rank quality of new samples

Results:

LSM-Based Forward Simulation

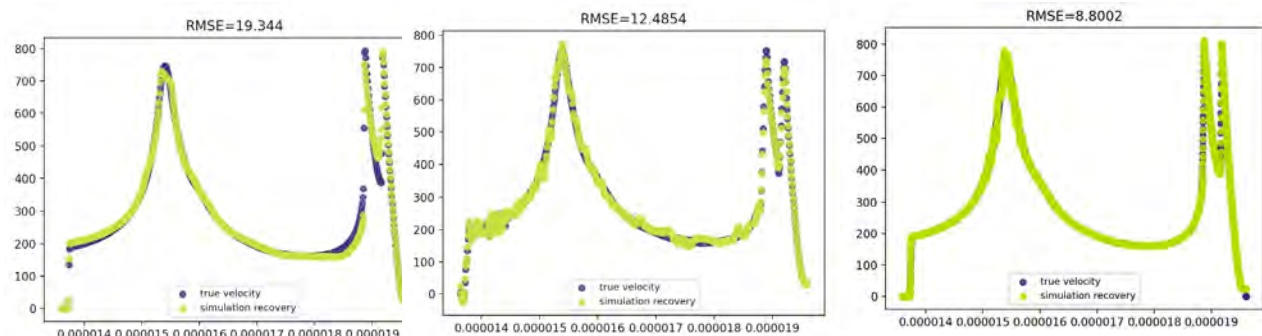
Subsidence with multiple tunnels

- LSM with 50×50×50 mass nodes and over 2,000,000 springs connecting them
- Subsidence forward model details:
 - Tunnel 1:
 - Depth: -200 units
 - Radius: 7.996 units
 - Start point: (486.08, 9.25) “bottom right blob in picture”
 - End point: (397.34, 499.15) “top right blob in picture”
 - Tunnel 2:
 - Depth: -200 units
 - Radius: 7.816 units
 - Start point: (130.64, 216.99) “bottom left blob in picture”
 - End point: (365.37, 331.44) “top left blob in picture”
- This example has some properties of what the surface subsidence should look like; however, the subsidence should be more discrete so this tells us that we need to tune parameters of the LSM to match the soil and to simulate for a longer window of time.
- 10-15 minute computation time, 10k integration time steps, 0.8 seconds per integration time step.



Summary of Results, Path Forward

- ▶ Simulation based statistical inference provides a flexible framework for parameter estimation that is compatible with multiple-measurement applications.
- ▶ A fast low-fidelity surrogate simulator is crucial to allow for high iteration count and large quantities of simulations.
- ▶ Project developed a python-based forward simulation capability that can be used for a wide variety of materials and geophysical environments (namely: Alluvium, LiF, Sn, Ta, Al).
- ▶ 1D test problems have shown successful recovery of large parameter quantities (inference on particle velocities as opposed to particle displacements).
 - 1000 particle velocities recovered from a 1D lattice with 20k mass nodes.
 - 1D lattice => shock physics applications
 - Began a shock physics collaboration with Lawrence Livermore National Laboratory (LLNL) using LSM based inference.
- ▶ **Underway:** 3D subsidence inference using ABC SMC. What we have found:
 - Validation of 3D lattices is challenging, 1D is easy (great place to start exercising inference capabilities).
 - **Lesson:** Find a 1D test problem to rapidly develop the methods.



- ▶ New collaboration started with LLNL Design Physics on LSM-based statistical inference for momentum diagnostics.
- ▶ Paper in preparation: 1D LSM-based statistical inference to recover particle parameters of shocked lithium fluoride.
- ▶ Seismic localization analytic enhancements for Advanced Data Analytics for Proliferation Detection (ADAPD) Defense Nuclear Nonproliferation Research and Development (DNN R&D) joint venture (FY20)

Backup slides

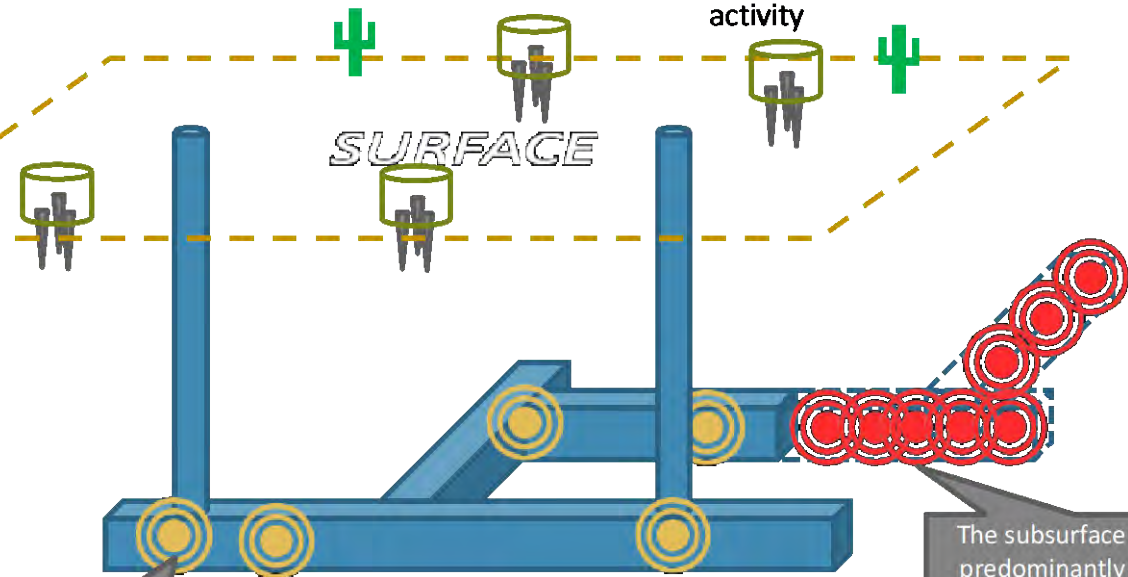
- ▶ FY21 work: seismic localization based measurement
- ▶ FY21 work: traceroute/latency based measurement

Seismic Localization-Based Tunnel Geometry Estimation



Seismic-based measurement:

Measurement development began and matured in FY21, ground truth, validation experiments, and new application areas in FY22



A localization analytic developed by the NNSS ADAPD researchers in 2019/2020 searches the multivariate time series generated by the geophone array for source locations.

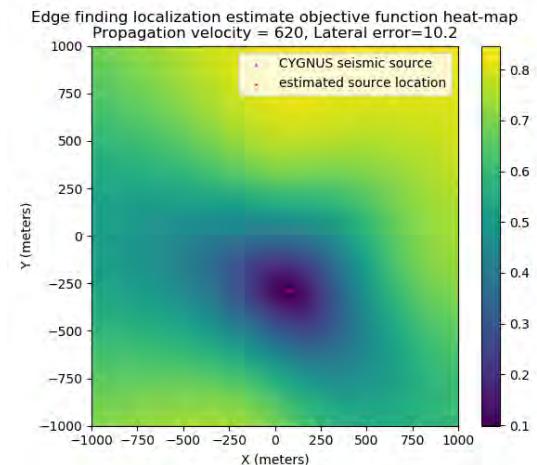
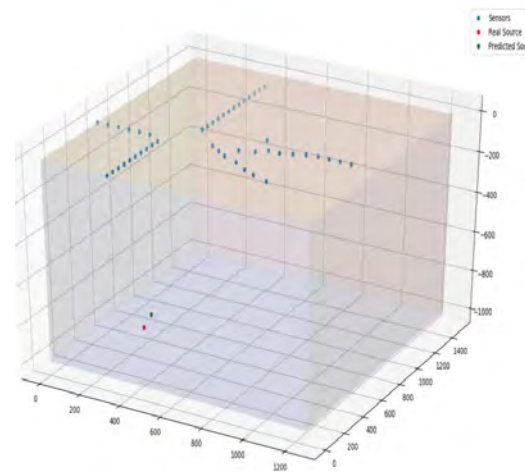
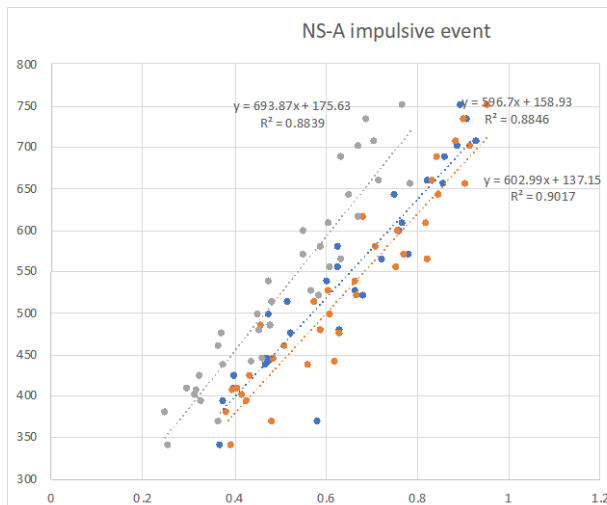
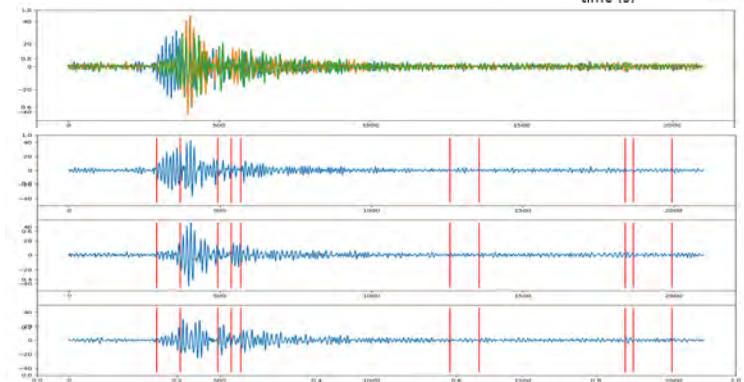
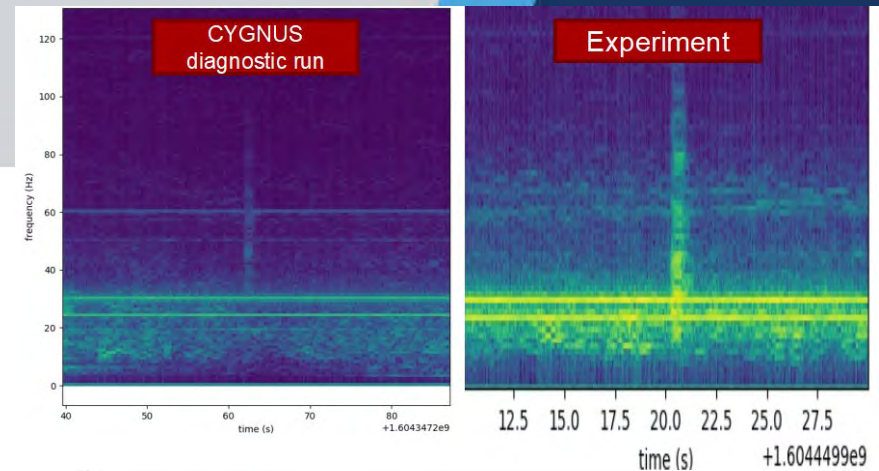
ADAPD was predominantly interested in surface acoustic-propagation localization results for pattern-of-life analysis. The subterranean localization capabilities are a bonus this SDRD was happy to utilize.

The subsurface signals are predominantly impulsive, and required development of a refined propagation velocity model and edge-finding analytic in cooperation with ADAPD.

Technical Approach and Results (Past Years)

Seismic localization data

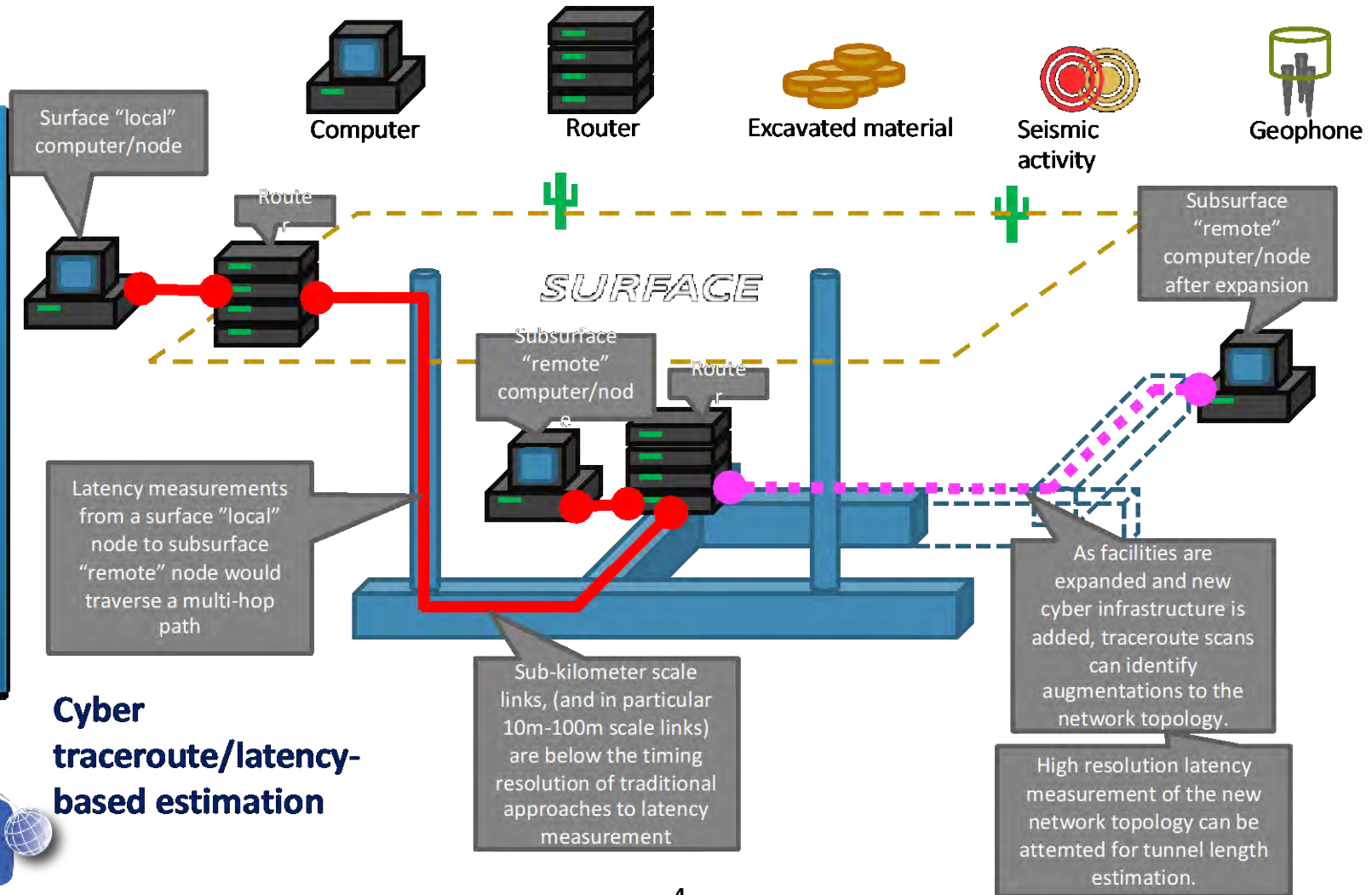
- ▶ Fall 2020 and Spring 2021: Investigations revealed ground truth matched impulsive events in seismic data (upper left)
- ▶ U1a seismic propagation velocity model development (lower left, lower right)
 - Joint UA + NNSS + Sandia collaboration FY21
- ▶ NNSS Summer Intern Program + UA-developed edge-finding automatic time-picking algorithm (mid and lower right).
 - Multivariate Bayesian offline change point detection algorithm
- ▶ UA: GP-bootstrapping signal simulator localization analytic testing (lower-right)



Traceroute/Network Latency Tunnel Length Estimation

Cyber-based measurement:

Measurement development began in FY21, continues through to the present...

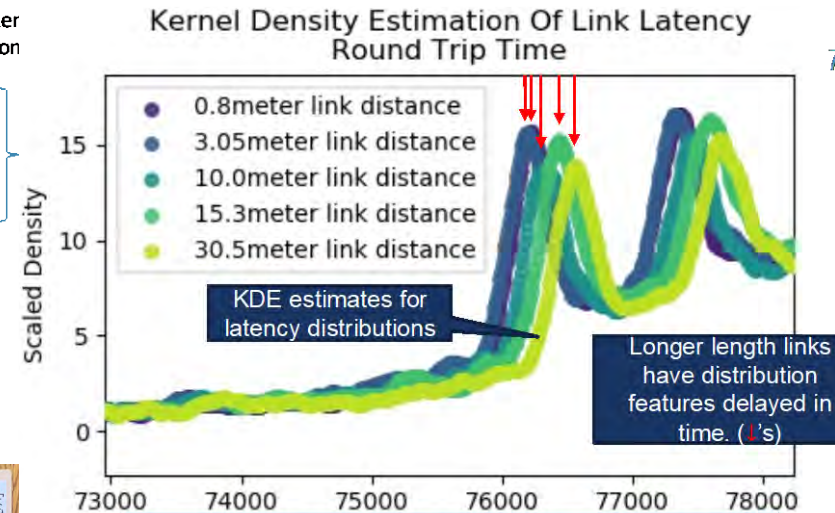
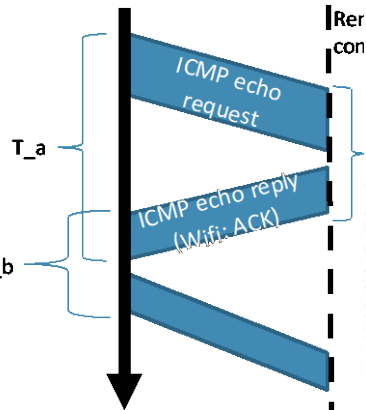


Cyber traceroute/latency- based estimation

Technical Approach and Results (Past Years)

Traceroute/Latency

- Analytic improvements and further experimentation on the cyber latency testbed have resulted in a 42.4 ns accuracy latency measurement capability (24x improvement over clock resolution) T_a that has been applied and validated under controlled conditions.
- This corresponds to a distance measurement accuracy in Cat5e/Cat6/optical fiber of $\approx 4.2\text{ m}$ T_b
- Innovations/progress points:
 - Packet-level timing (abandon OS timing)
 - Variable bandwidth KDE within the noise-assisted subsample signal detection analytic.
 - Estimation of the unobservable “remote delay” through the use of a designed experiment utilizing a second probing computer.



When we compute the time shifts corresponding to the KDE features that are correlated to link length we can compute high accuracy link lengths:

