

Centers 8900, 1400, 5500, 8700 upporting 42 team members

Sandia Strengths

- •Uncertainty Quantification
- •Earth Systems Modeling
- •Risk-Based Analysis for
- Complex Systems
- •Atmospheric Sciences
- •Remote Sensing
- •Information Sciences

CLDERA Positions SNL for Roles in Climate Security

- •Advancing climate science
- Analyzing climate impacts
- •Motivating sound climate actions

Exceptional

service

in the

national

interest

Analytics for Climate and Earth Sciences (ACES) AMUNITY OF PRACTICE



CLDERA is enabling multi-step attribution in the climate by developing quantitative relationships between a climate forcing and its downstream impacts. CLDERA aims to improve climate risk assessments and decision-making through its transformation in approaches for climate attribution.

NEED

Climatic impacts (like drought, flooding, or crop yield) are driving national security, legislative and legal foci.

> Complex coupling between processes obscure the relationships between sources and downstream impacts.

> > Traditional attribution connects a source to a primary climate variable in a single step.

The technical challenge is to draw quantitative relationships in a multi-step attribution framework.

Tiered Verification

Develop data sets of increasing complexity with key characteristics of the multi-step attribution problem to explore sensitivities, establish viability, and prove usefulness of advanced methods/tools.

Data & Model complexity (dimensionality of data, number & interaction between processes, ...)





Simulated Pathways

Random Forest Regression (RFR): Generate feature pathway networks using multi-variate RFR (full pairwise analysis of input features).

- $W_t = \epsilon_{W_t}$ $X_t = 0.5W_{t-1} + 0.2X_{t-1} + \epsilon_{X_t}$ $Y_t = -0.5W_{t-1} + \epsilon_{Y_t}$ $Z_t = 0.3X_{t-1} + 0.5Y_{t-1} + \epsilon_{Z_t}$ Synthetic Dataset
- Feature Importances
- 2 X -1 W 1.497059 W 0.467647 2 3 Y-1 W 1.497059 X 9.658824 5 6 X_-1 X 4.291176 6 7 Y_-1 • X 0.100000

Profiling: Dynamically trace pathways through the E3SM software as the software executes (in-situ).



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Tracing: Add active and passive tracers to E3SM to enable model evaluation and pathway identification.

Signature-Based Clustering: Find & track non-stationary variable clusters for use as features in pathway identification.

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Space-time varying cluster identification in response to Mt. Pinatubo source.

CLDERA - CLimate impact: Determining Etiology thRough pAthways Leadership Team: Diana Bull, Kara Peterson, Laura Swiler, Lyndsay Shand, Irina Tezaur **A**M

sandia.gov/cldera

APPROACH

Develop quantitative representations of the pathway, e.g. the spatio-temporally evolving chain of physical processes, between a source and its downstream impacts.

Pathways combine multiple variables to strengthen the connection between source and impact.

Pathways enable new methods to address variability

- rank source importance
- constrain attribution approaches

Demonstrate computational approaches on simulations and observations of the 1991 eruption of Mt. Pinatubo in the Philippines





OUTCOMES

Tools to discover and represent pathways, and analyses to establish pathway robustness to changing conditions. Cross-validation using simulated and observed pathways will inform areas for model improvement and new measurements.

Contributory ranking of sources to an impact using pathways. Capability enables robust risk analysis and offers the potential to guide future climate actions.

Attribution of source characteristics using inverse optimization methods. Will provide credible methodology to deter unilateral development of climate interventions.

Beginning-to-end attribution in the climate system Tracing evolving chains of physical processes to enable attribution of climate impacts from a localized source.

Energy Exascale Earth System Model (E3SM)

Prognostic Aerosol Modeling: Simulate stratospheric volcanic aerosol in E3SM from SO₂ emissions.

Evaluate E3SM's Stratosphere: Characterize biases and understand what physical processes can be captured.

Establish climate variability surrounding Mt. Pinatubo: Characterize signal-to-noise for detection & attribution.

Sensitivity Analyses: Determine pathway robustness to altered: eruption characteristics and model parameterizations.



Attribution

Enhanced Fingerprinting: Investigate advanced principal component analyses (tensor based, non-negative, etc.) and employ multiple nodes in the pathway to sharpen the signal-to-noise ratios and enable downstream impact attribution. - 260 - 240 - 220 **Non-Negative EOF** aditional EOF 0.0x Pinatubo 0.5x Pinatubo 1.0x Pinatubo — 1.5x Pinatubo Ensemble Mean Ensemble Memembers Weylandt, Swiler. Beyond PCA: Additional Dimension Reduction Techniques to Consider for Climate Data. To be submitted **Inverse Optimization**: Identify source characteristics by developing deep operator neural networks (DONNs) to model parts of E3SM for PDEconstrained optimization. $\dim = O(10^{5})$ $\dim = O(10^{5})$ Driginal Concentration, Time = 32.0 riginal Concentration, Time = 16.0 Evolution Operator Ten years of ERA5 reanalysis presented as a functional PCA PCA time series. Before and after Surrogate Operator Reconstruct Projection Mt. Pinatubo eruption. Compressed Representation Tucker, Yarger, Functional Changepoint time step k+1 **Detection**, Environmetrics $(\dim = O(10))$ **Causal Modeling:** Develop causal discovery method for spatially nonstationary and transient relationships; use directed graphs to represent causal networks. **Application of (adjusted) permutation** $W_t := \eta_{W_t}$ feature importance on echo state network $X_t := 2 \times W_{t-2} + \eta_{X_t}$ trained on MERRA2 reanalysis data. $Y_t := 0.5 \times W_{t-1} + \eta_{Y_t}$ Variable importance shows increased importance of AOD immediately following $Z_t := 0.6 \times X_{t-1} + \eta_{Z_t}$ Pinatubo. 0.4 auto-MCI (nodes)