Approaches for Estimating Radioxenon Background Variations, Anomalies, and Explosion Signals in Modeled and Measurement Data

Presenter: Donald Lucas[*]

Team (alphabetical order)

Ted Bowyer[+], Paul Eslinger[+], Nipun Gunawardena[*], Lee Glascoe[*], Donald Lucas[*], John Lucas[^], Lucas Reilly[^], John Roberts[^], and Ramesh Sarathi[+]

Motivated by the First Nuclear Explosion Signal Screening Exercise and Intercomparison

* Lawrence Livermore National Laboratory

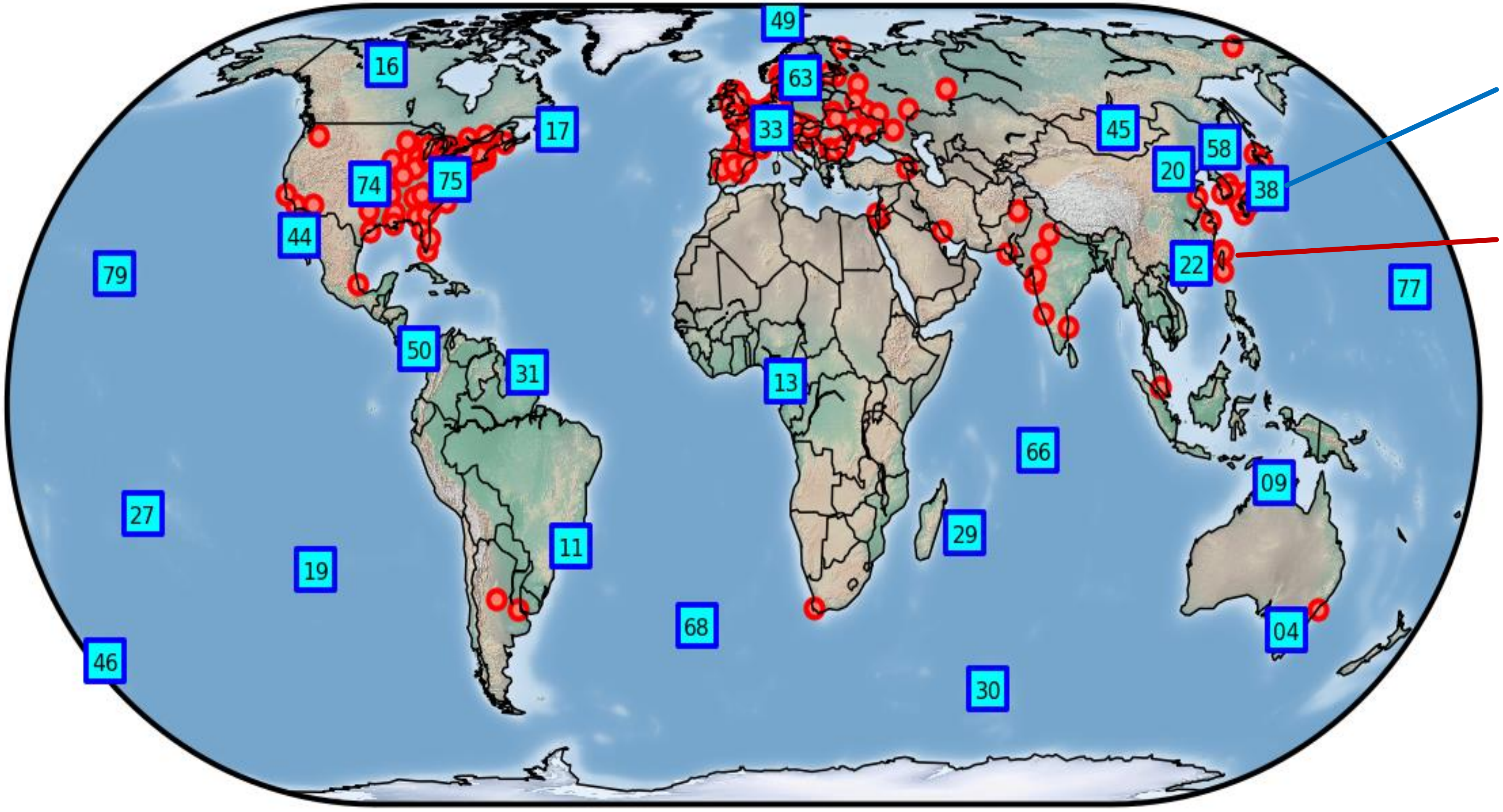
+ Pacific Northwest NATIONAL LABORATORY

^

LLNL-PRES-835765

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

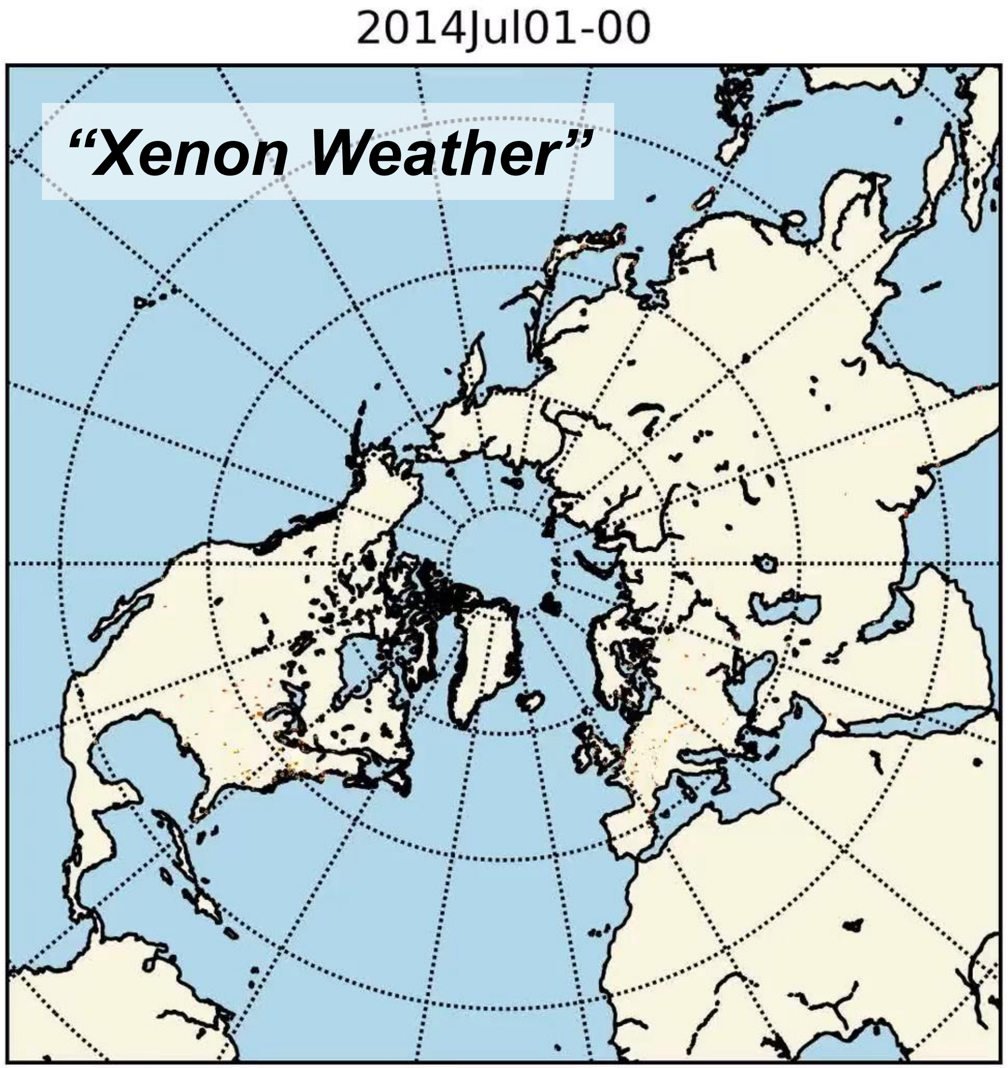
Background Radioxenon is Highly Variable in Space and Time



RN stations

Potential background xenon sources (nuclear power plants, research reactors, and medical isotope facilities)

Background Radioxenon is Highly Variable in Space and Time



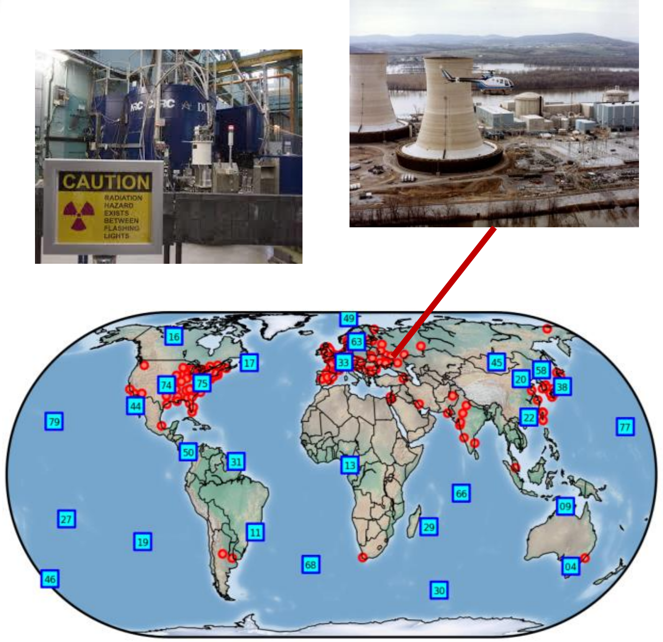
Movie of Xe-133 released from 200 facilities on 2014 July 01 and tracked for two weeks. Colors show near-surface logarithmic activity concentrations.

Extracting nuclear test signals from the radio-xenon background is like finding a needle in a haystack.

Advances in modeling and algorithms may help find the needle.

Atmospheric Models Can Be Used to Estimate Background Xenon

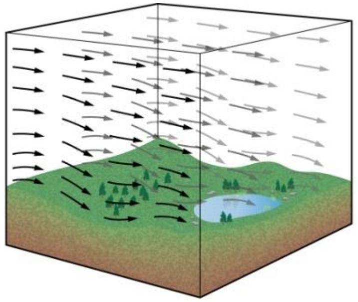
Xenon Sources



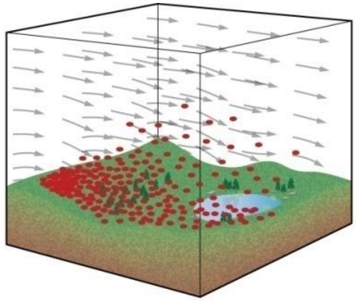
Xenon emission rates at facilities are typically not measured and can represent a large source of model uncertainty.

Atmospheric Models

Meteorology



Atmospheric transport



ECMWF

EUROPEAN CENTRE FOR MEDIUM RANGE WEATHER FORECASTS

NATIONAL CENTERS FOR ENVIRONMENTAL PREDICTION

NCEP

HYSPLIT

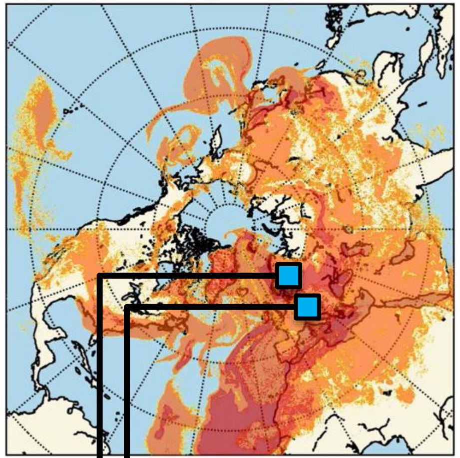
AIR RESOURCES LAB

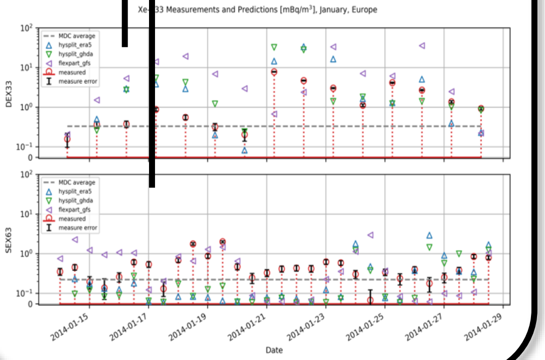
GFS

Global Forecast System

FLEXPART

Xenon Signals

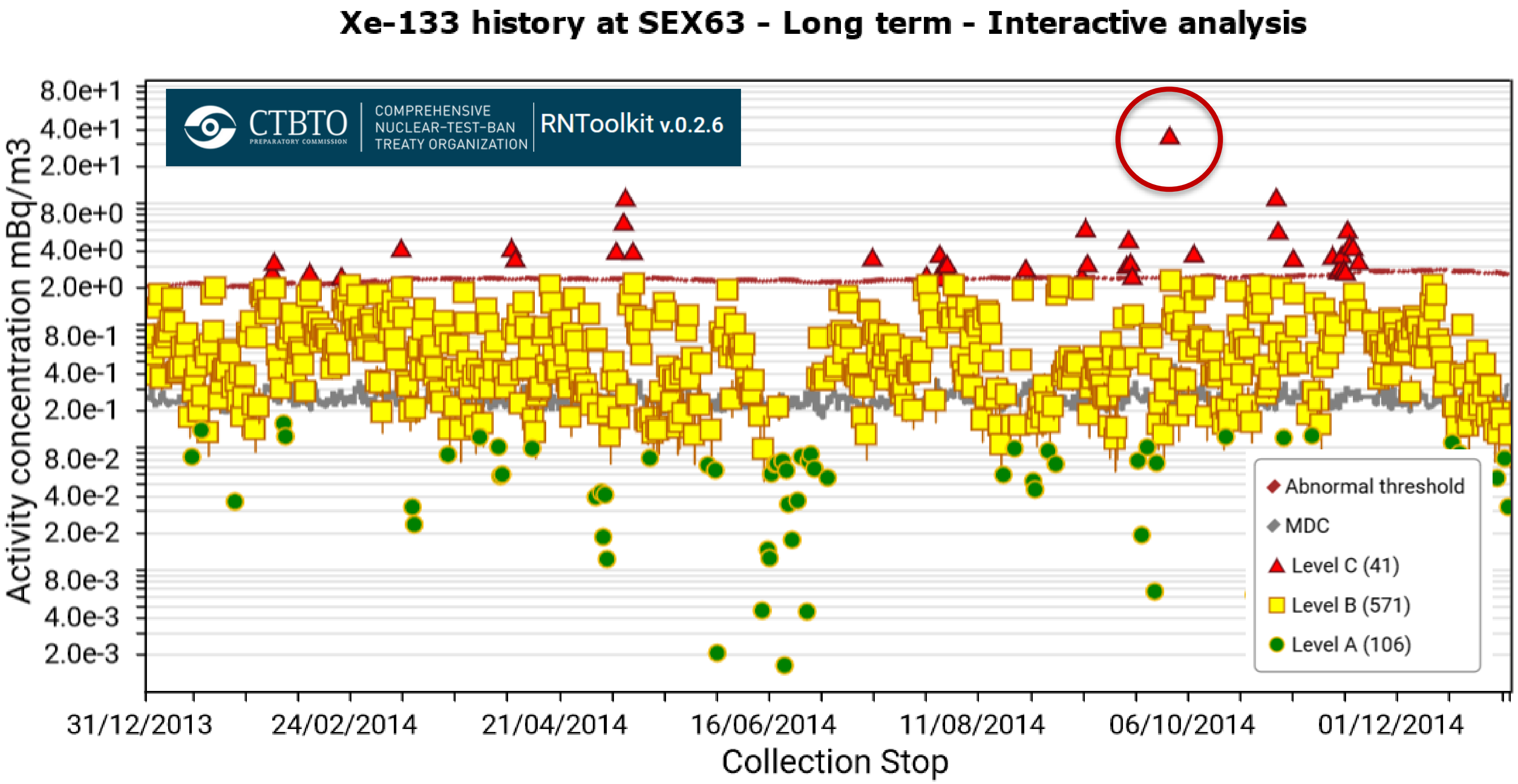




Inverse Modeling

LLNL-PRES-835765

Identifying Xenon Anomalies in Measurements



To distinguish explosion signals from background sources, it is important to quantify the size and frequency of xenon anomalies.

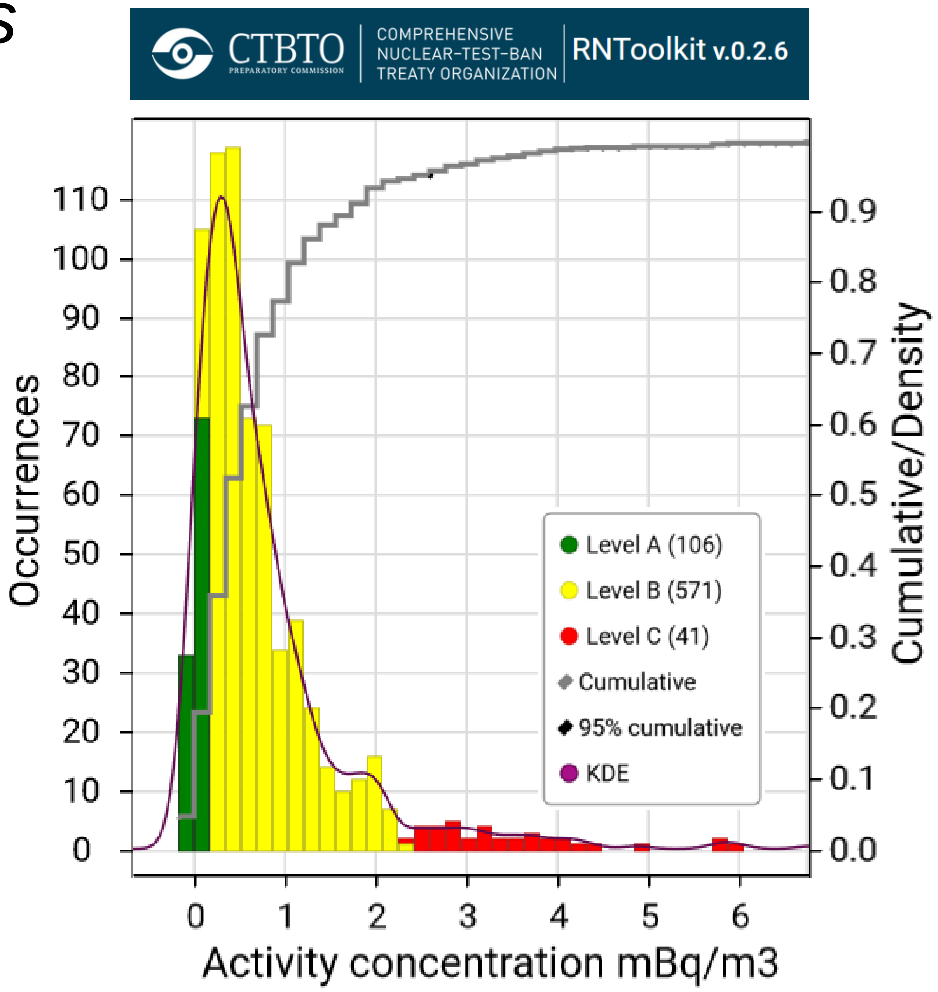
Identifying Xenon Anomalies in Measurements

Anomalies can occur in multiple dimensions

- One or more Xe isotopes
- One or more IMS stations

Quantile Scores

- Empirical and easy to compute in one dimension, but challenging in higher dimensions



Outlier/Novelty Detection Algorithms

- Time series methods
- Machine learning approaches
  - Local Outlier Factor
  - Random Isolation Forest

Identifying Xenon Anomalies in Measurements

Anomalies can occur in multiple dimensions

One or more Xe isotopes

One or more IMS stations

Quantile Scores

Empirical and easy to compute in one dimension, but challenging in higher dimensions

Outlier/Novelty Detection Algorithms

Time series methods

Machine learning approaches

Local Outlier Factor

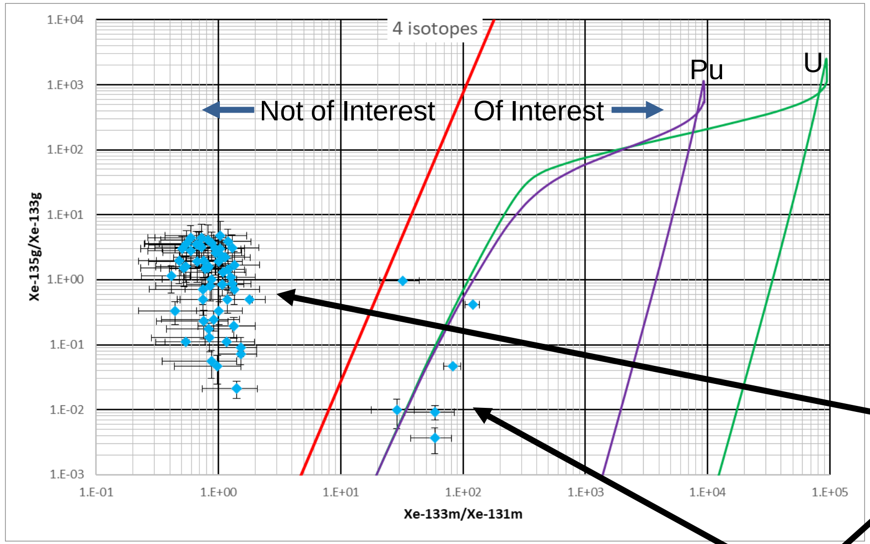
Random Isolation Forest

Example of Identifying Xe-133 Signal Injections in January 2014

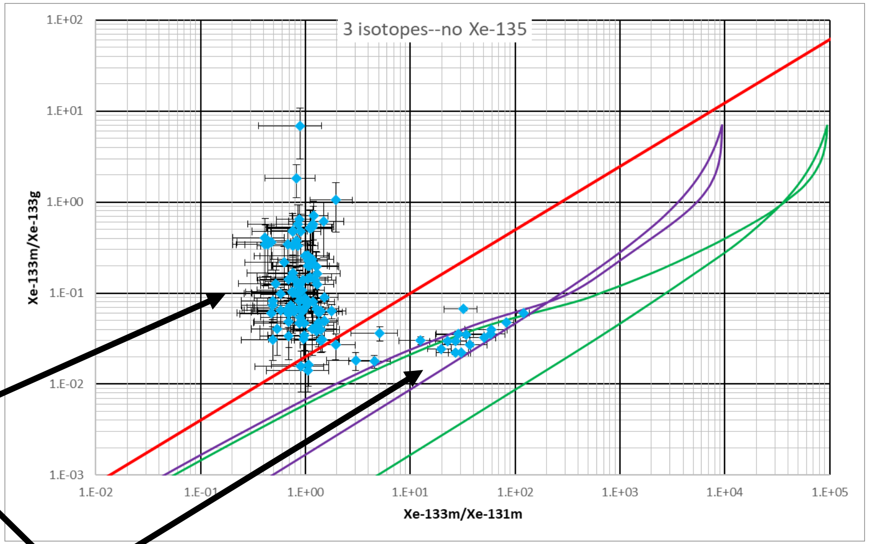
	true positive rate	false positive rate
q50	0.924	0.115
q75	0.847	0.066
q90	0.784	0.036
q95	0.72	0.017
q96	0.716	0.015
q97	0.686	0.011
q98	0.657	0.008
q99	0.623	0.004

There is a tradeoff between true positives and false positives versus the quantile threshold.

Identifying Xenon Anomalies in Measurements

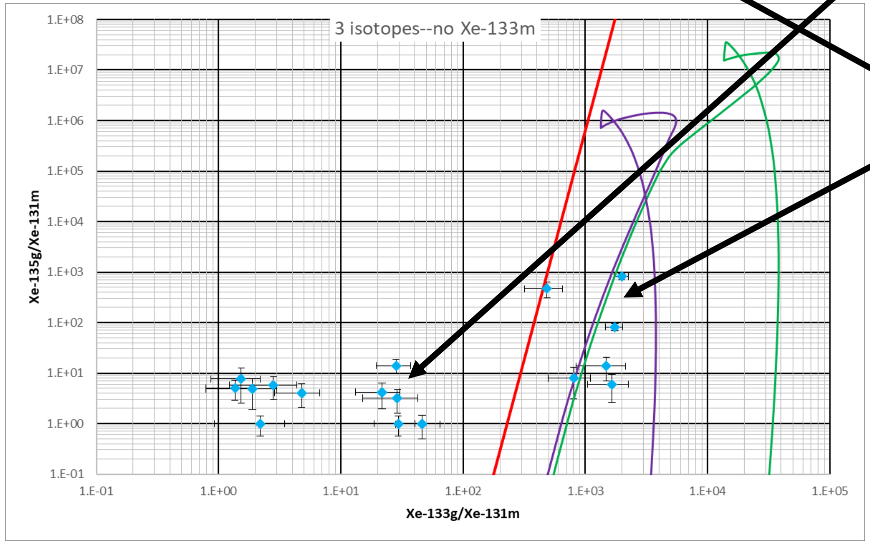


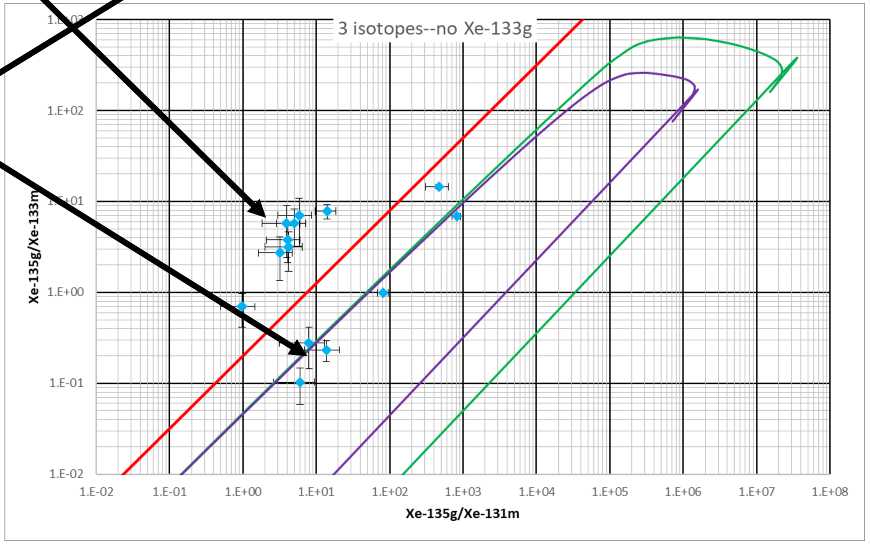
Xenon Ratios help identify anomalies



Xenon Samples not of interest

Xenon Samples of interest





Requires detecting multiple isotopes

With fewer isotopes can use MDC

Identifying Xenon Anomalies in Measurements

Anomalies can occur in multiple dimensions

- One or more Xe isotopes
- One or more IMS stations

Quantile Scores

- Empirical and easy to compute in one dimension, but challenging in higher dimensions

Outlier/Novelty Detection Algorithms

- Time series methods
- Machine learning approaches
  - Local Outlier Factor
  - Random Isolation Forest

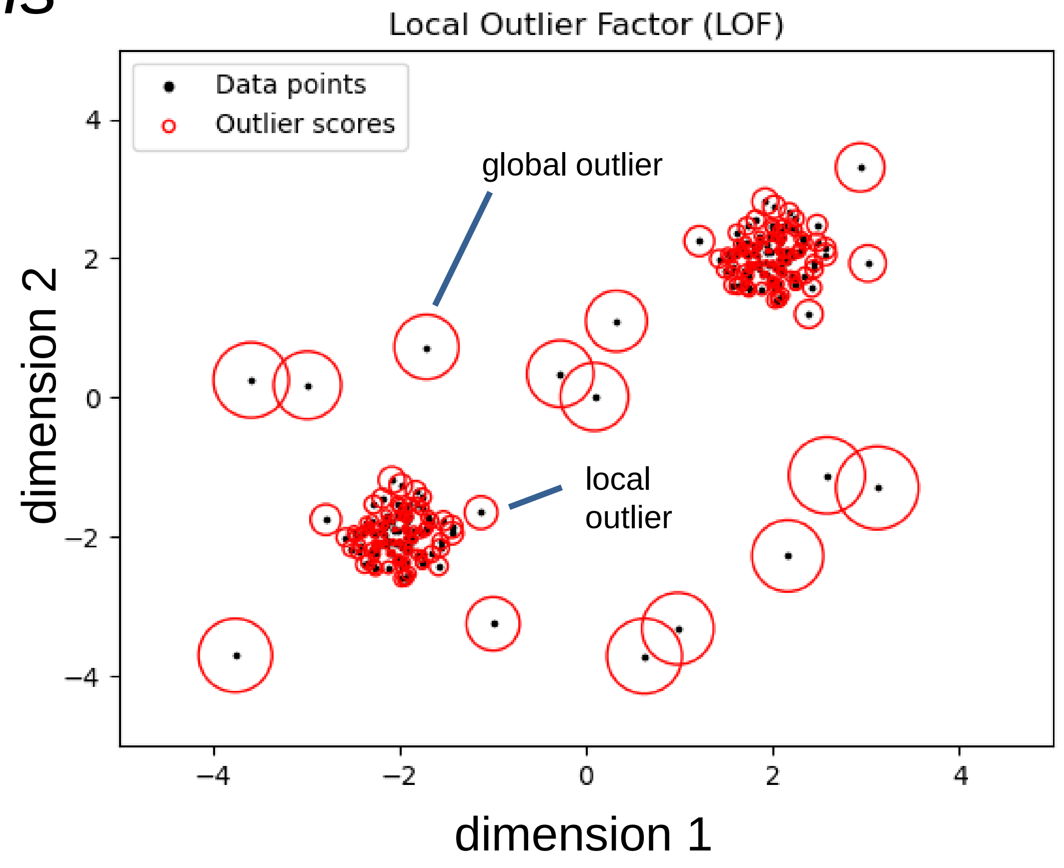


Image modified from scikit learn

Identifying Xenon Anomalies in Measurements

Anomalies can occur in multiple dimensions

One or more Xe isotopes

One or more IMS stations

Quantile Scores

Empirical and easy to compute in one dimension, but challenging in higher dimensions

Outlier/Novelty Detection Algorithms

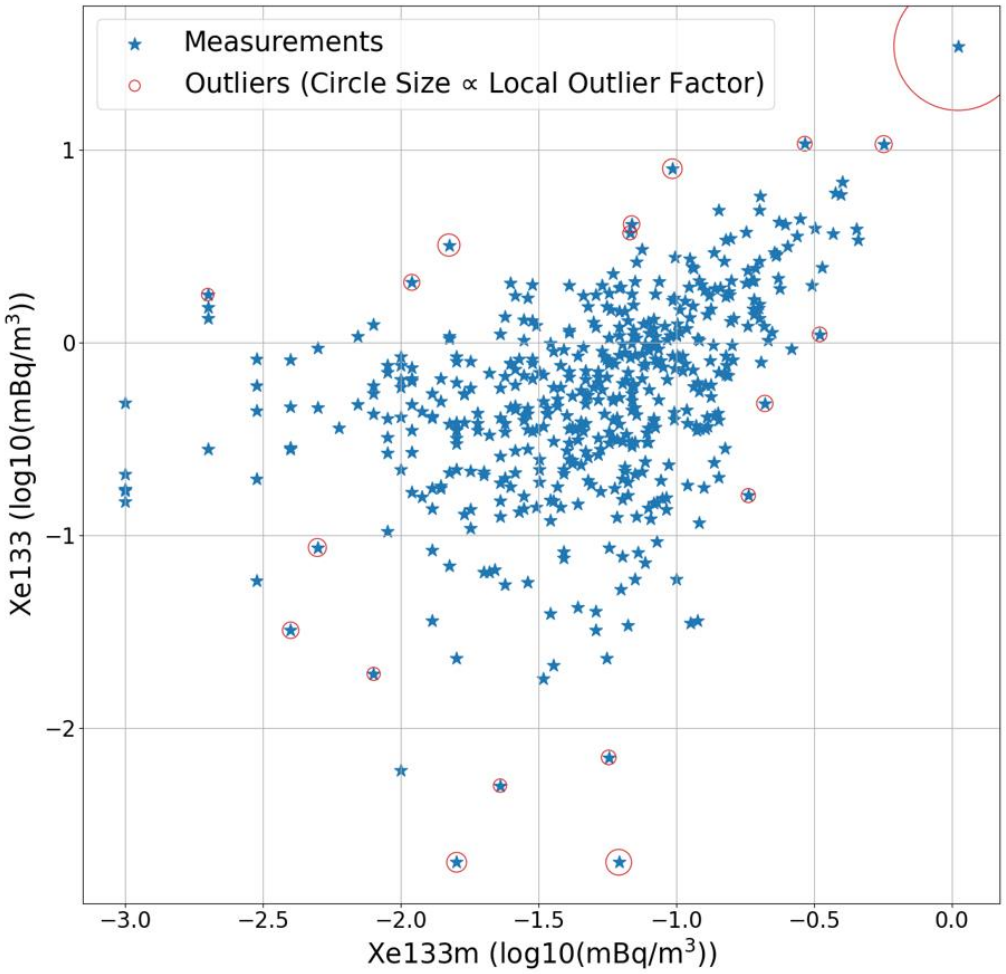
Time series methods

Machine learning approaches

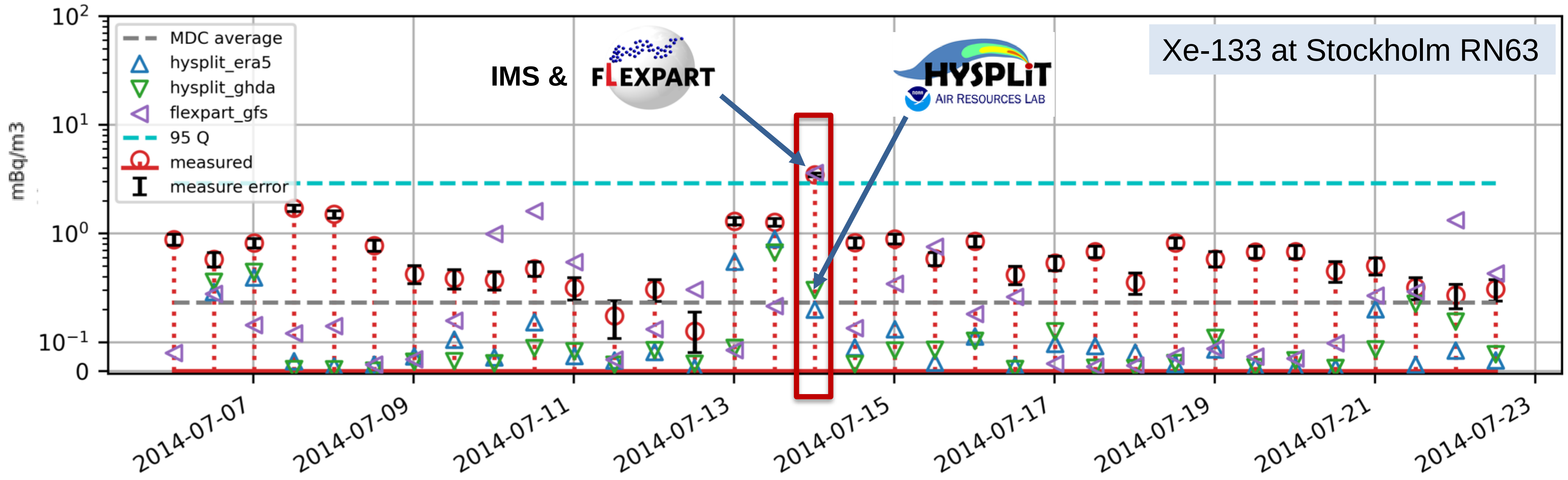
Local Outlier Factor

Random Isolation Forest

LOF applied to Xe-133 and Xe-133m at RN63 for 2014



Identifying Anomalies With Measurements & Atmospheric Models



- Both models tend to underpredict Xe-133 during this period.
  - A case of low emissions or a bias in the atmospheric models?
- There was an elevated collection on 14 July at the 97th percentile.
- FLEXPART matches the elevation, HYSPLIT does not.
- Is the elevated collection an anomaly of interest?

Identifying Anomalies With Measurements & Atmospheric Models

Regression methods can be used to combine ensembles of models, correct for model biases and errors, and provide predictions of IMS collections with uncertainty.

$$Y_{IMS} = F(Hysplit_1, Hysplit_2, \ldots, Flexpart_1, Flexpart_2, \ldots)$$

Train on data for previous periods ➔ Apply to collections of interest

Other predictors can be incorporated, like collections from different IMS stations, environmental variables, categorization levels, etc.

Identifying Anomalies With Measurements & Atmospheric Models

Bayesian Ridge Regression for Xe-133 at RN63

Robust to outliers, easy to train, and provides uncertainty estimates.

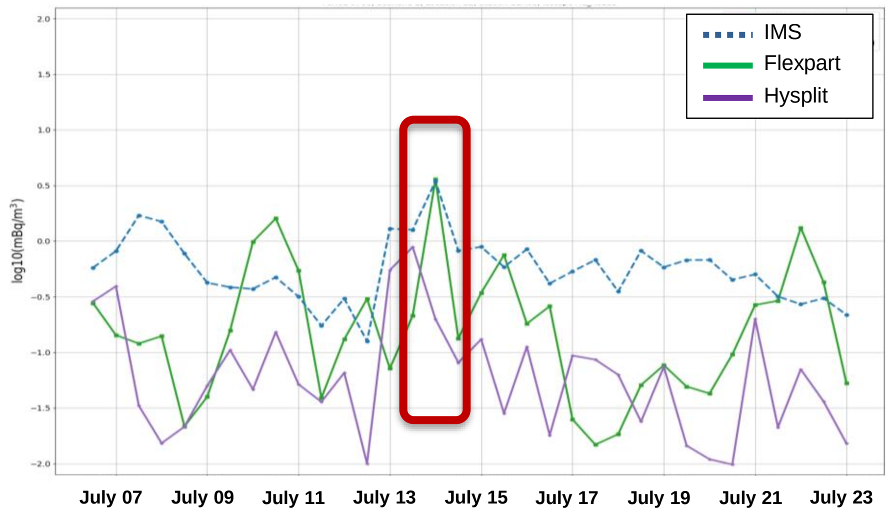
Elevated collection on 13-14 July lies within the regression prediction uncertainty.

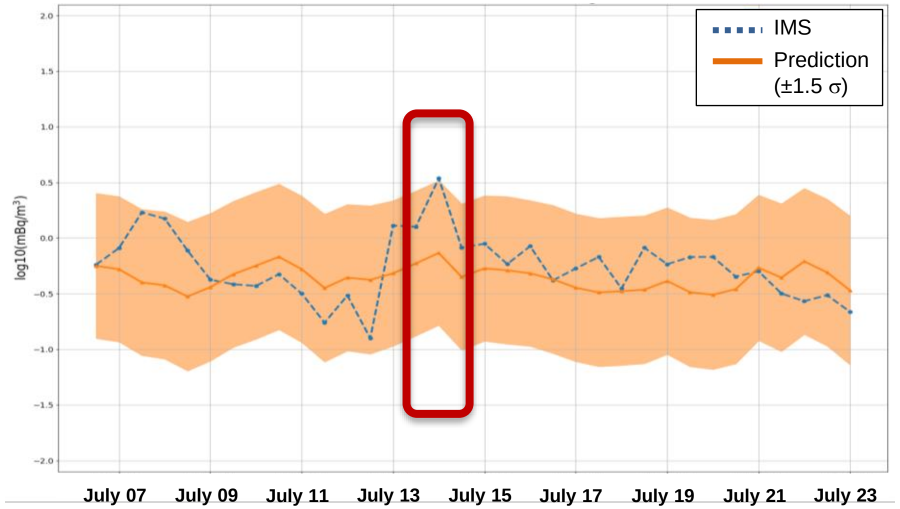
Injected signal on 19-21 July is detected as an anomaly.

Regression Inputs/Targets

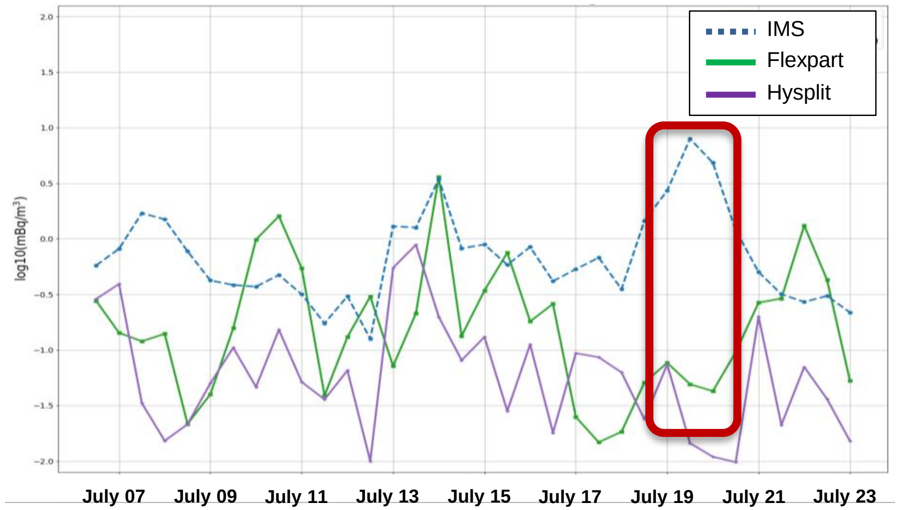
Regression Predictions

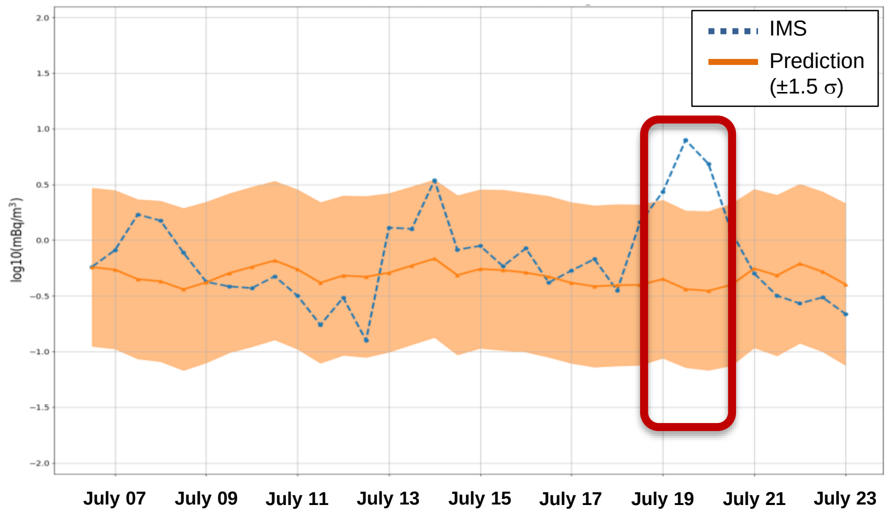
No Injection





With Injection





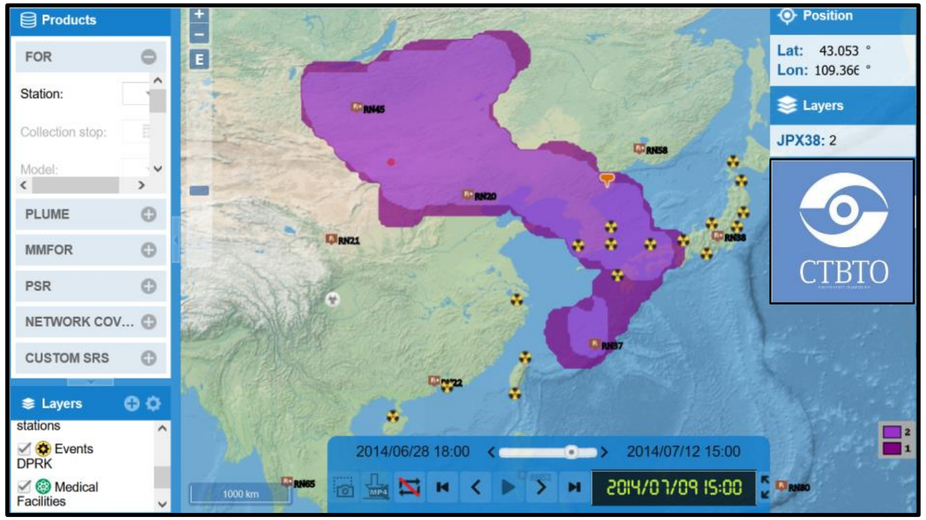
Identifying the Origin of Anomalies

Backwards Modeling

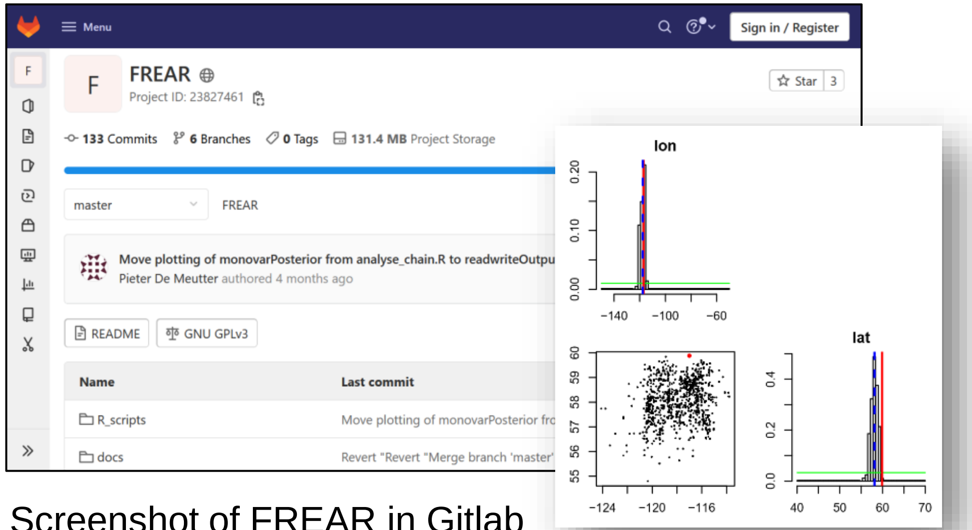
- Field of Regard (FOR)
- Possible Source Region (PSR)

Probabilistic Methods

- *Forensic Radionuclide Event Analysis and Reconstruction* Tool (FREAR)
- Eslinger's likelihood scores
- *Machine Learning Approach*
  - Forward model runs are used to create synthetic detections/non-detections for training data and testing.
  - Once trained, millions of alternate source locations can be quickly evaluated.
  - Previously presented at WOSMIP and INGE.

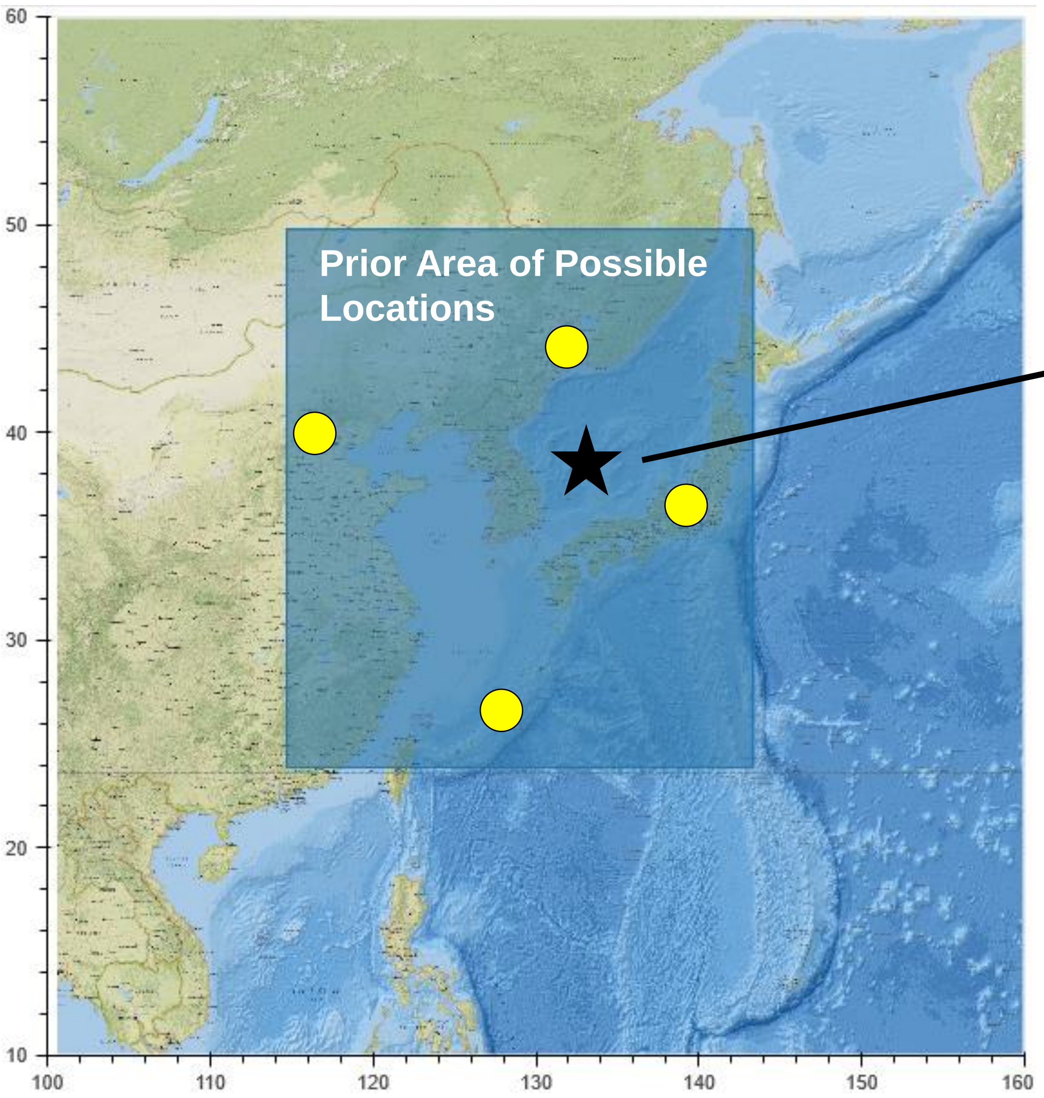


3-day multi-model field of regard for JPX38 for collection for sample ID 2862643 using Web-Grape



Screenshot of FREAR in Gitlab and test results.

Identifying the Origin of Anomalies

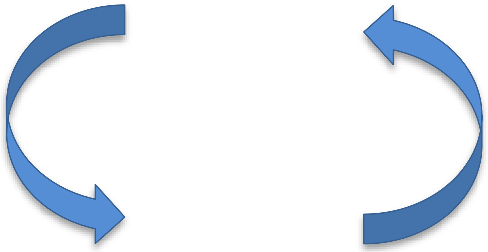


Machine Learning Example

Values to Generate Synthetic Observations

Latitude	Longitude	Start Hours	Duration Hours	Amount
38.1336	132.8962	65.4873	3.0234	896.9242

Forward Atmospheric Simulation

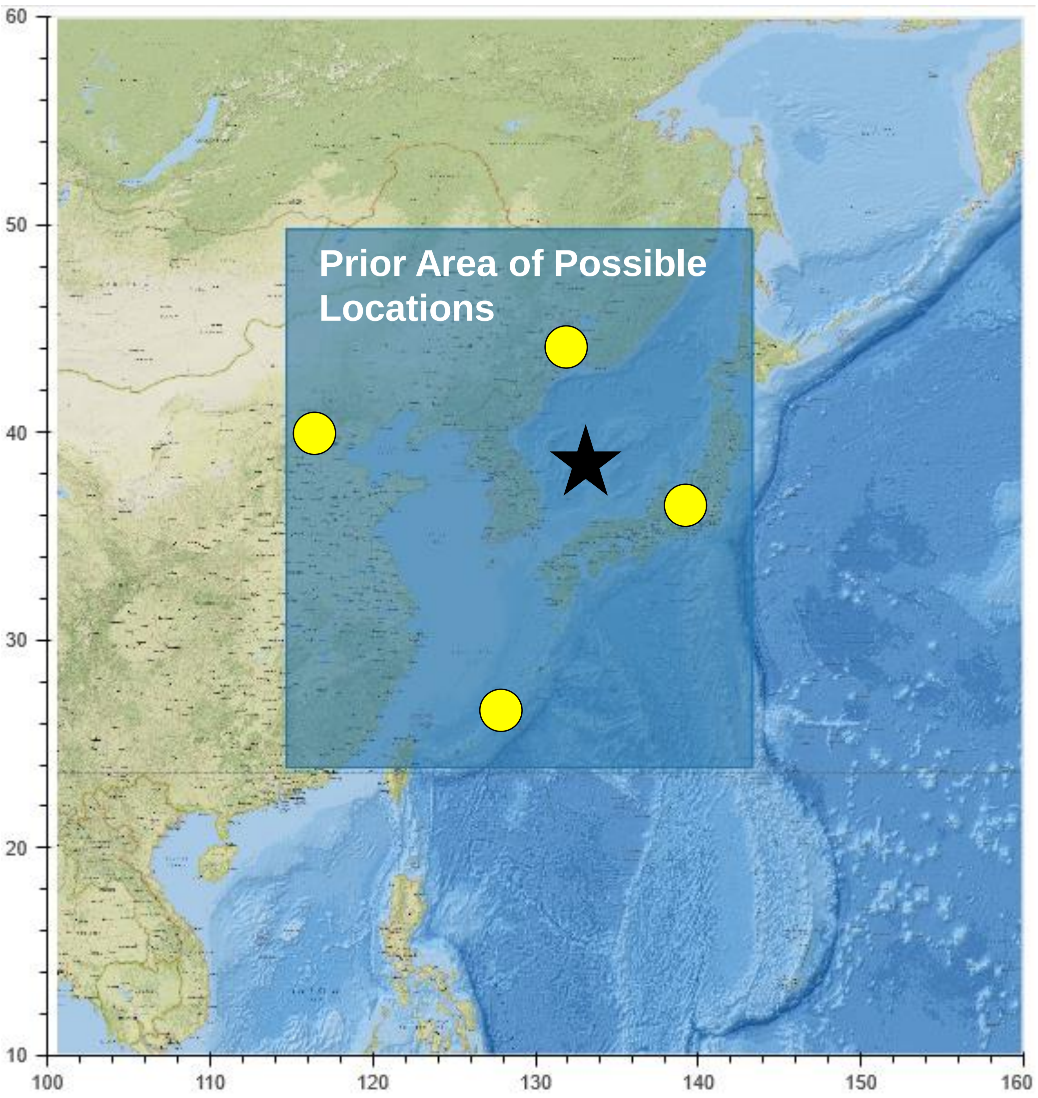


Machine Learning Backwards

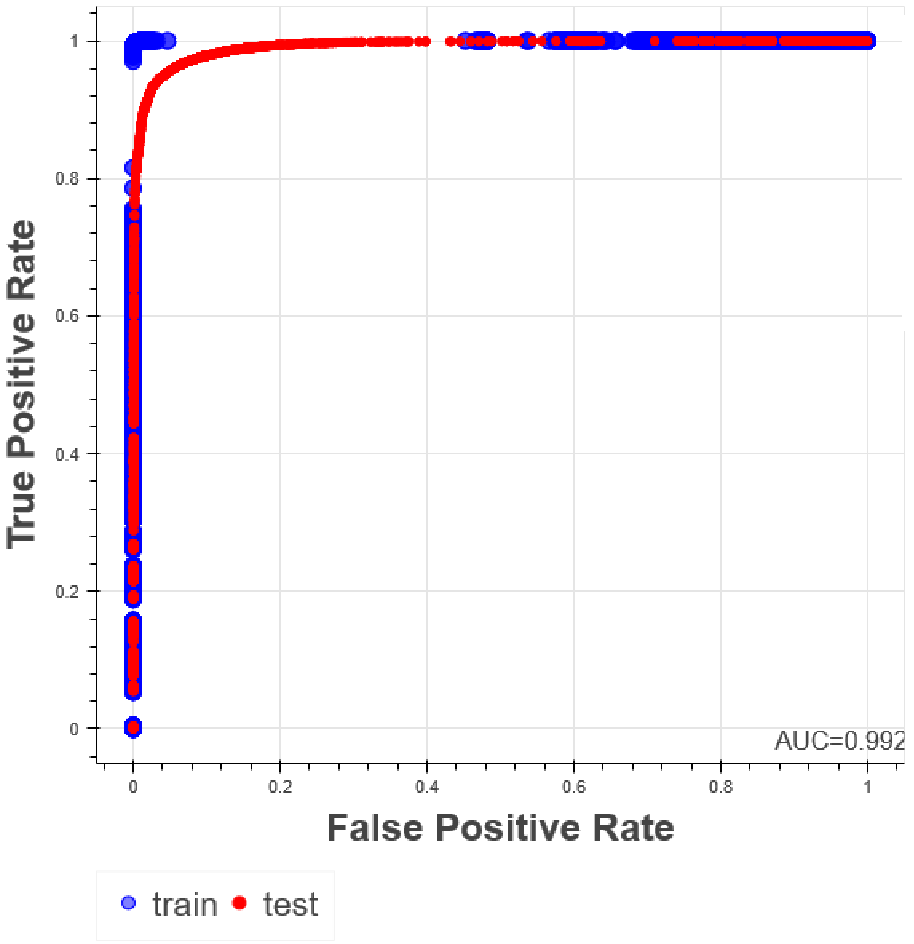
Site Name	Oct 09	Oct 10	Oct 11	Oct 12	Oct 13	Oct 14	Oct 15
RN20	0	0	0	0	0	0	0
RN37	0	0	0	0	0	0	1
RN38	0	0	0	0	1	1	1
RN58	0	0	0	0	0	0	0

= non-detect   = detect

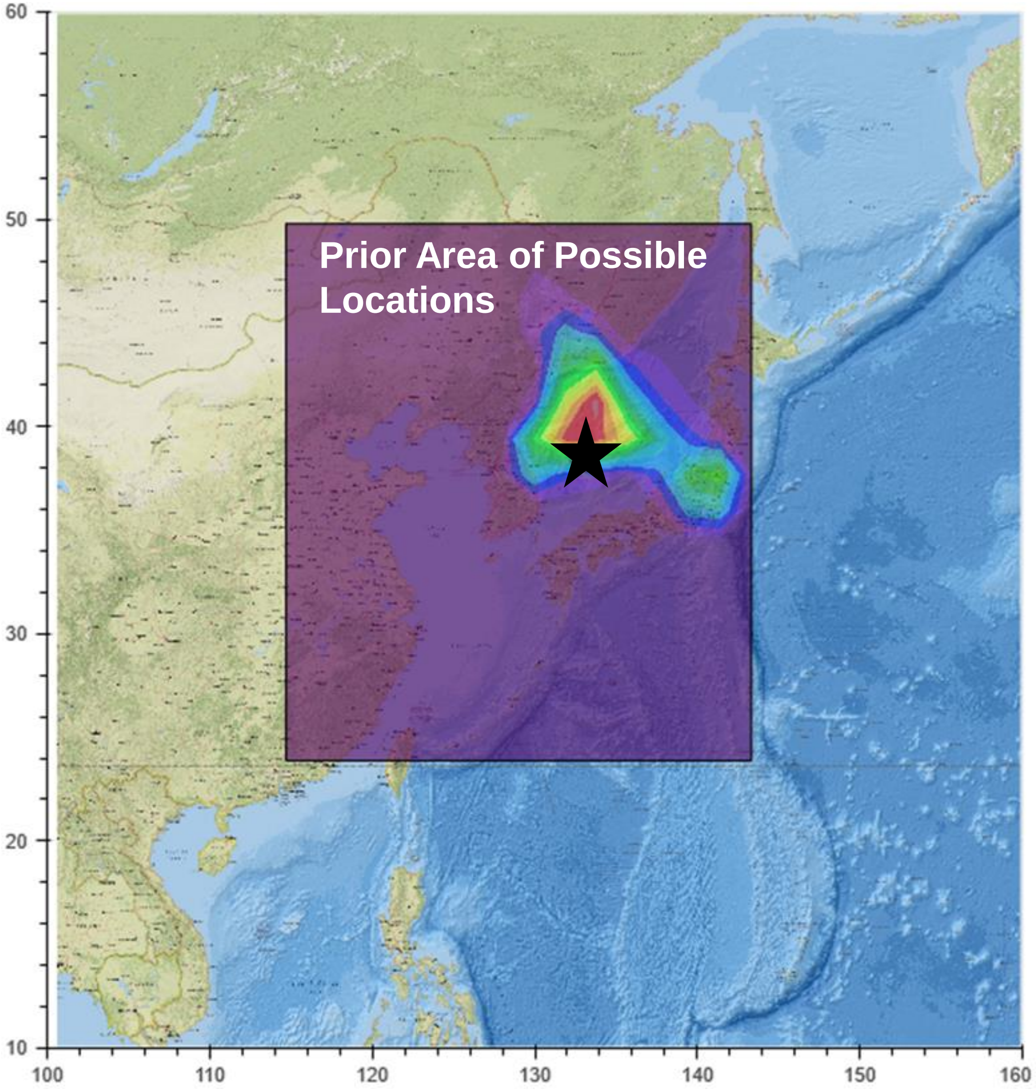
Identifying the Origin of Anomalies



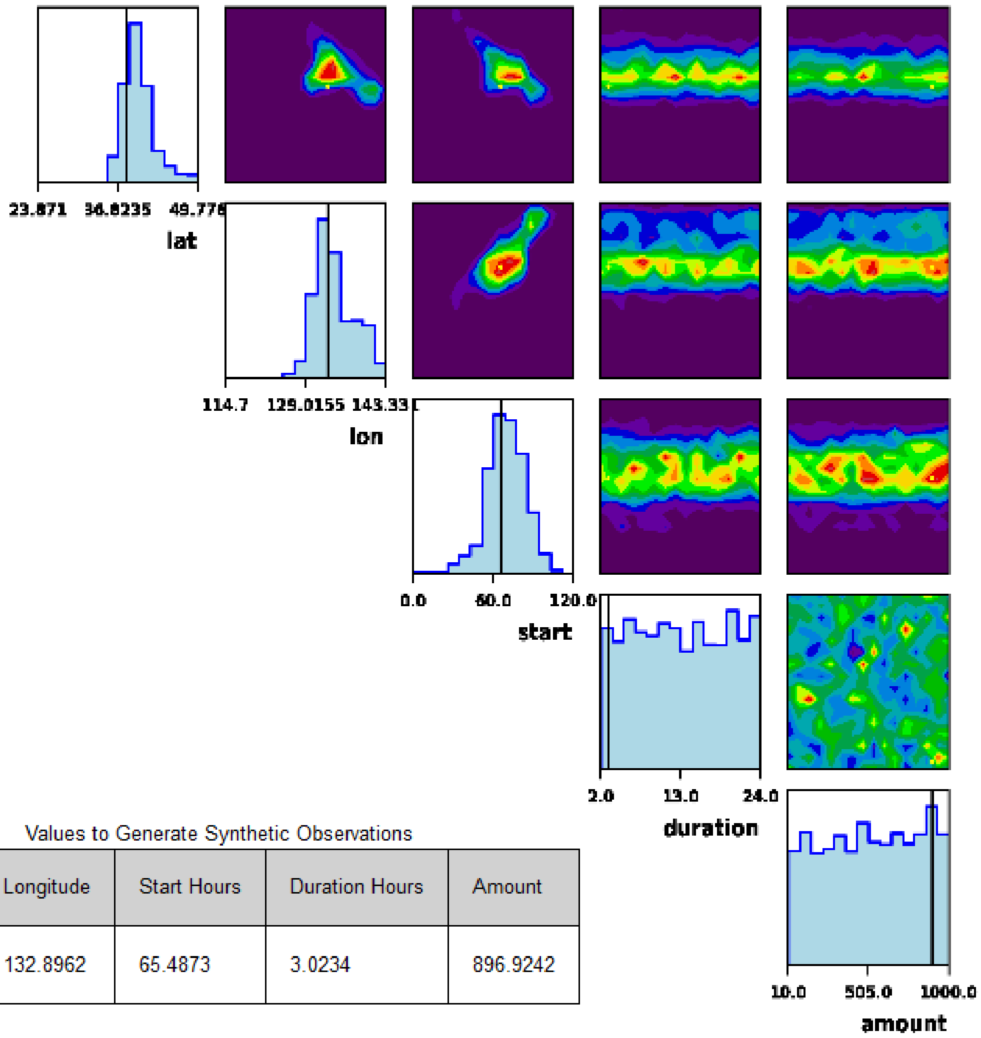
Machine Learning Example



Identifying the Origin of Anomalies



Machine Learning Example



Values to Generate Synthetic Observations

Latitude	Longitude	Start Hours	Duration Hours	Amount
38.1336	132.8962	65.4873	3.0234	896.9242

Summary

- Xenon isotopes used for nuclear monitoring are highly variable in space and time due to
  - changes in weather.
  - the presence of many, widely distributed background industrial sources.
- Advanced methods using atmospheric modeling and statistical analysis are needed to
  - identify xenon anomalies of interest.
  - attribute the anomalies to background sources or nuclear testing.
  - determine the origin of detections.
- Through a collaborative effort, we
  - ran multiple atmospheric models to simulate xenon signals across the global IMS network in 2014.
  - developed and tested outlier and novelty detection methods using quantile approaches and unsupervised machine learning algorithms.
  - used supervised Bayesian regression algorithms to combine multi-model predictions and IMS collections for detecting anomalies with uncertainty.
  - applied probabilistic algorithms to locate the origin of suspected anomalies.