LA-UR-17-30580

Title: Building a Predictive Capability for Decision-Making that Supports MultiPEM

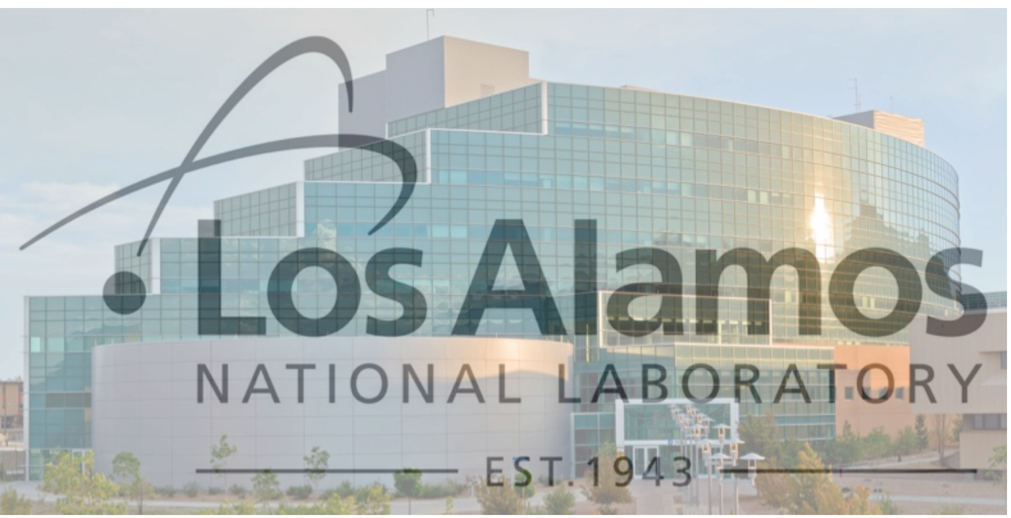
Author(s): Carmichael, Joshua Daniel
Nemzek, Robert James

Intended for: Report

Issued: 2017-12-05 (rev.1)

Building a Predictive Capability for Decision-Making that Supports MultiPEM

Application to Seismic, Acoustic and Radio Emissions that Signal Near Surface Explosions



Joshua D. Carmichael
Robert J. Nemzek

13-Nov-2017

Multi-Phenomenological Explosion Monitoring (MultiPEM)

What is the Objective of MultiPEM?

Multi-Phenomenological Explosion Monitoring (MultiPEM)

What is the Objective of MultiPEM?

- *Multi-phenomenological explosion monitoring (multiPEM) is a developing science that uses multiple geophysical signatures of explosions to better identify and characterize their sources.*
- *MultiPEM researchers seek to integrate explosion signatures together to provide stronger detection, parameter estimation, or screening capabilities between different sources or processes.*
- ***This talk** will address forming a **predictive capability** for screening waveform explosion signatures to support multiPEM*

Multi-Phenomenological Explosion Monitoring (MultiPEM)

What is the Objective of MultiPEM?

- *A **predictive capability** means that if a hypothetical explosion of an anticipated size/yield occurs, we can quantify how well we can detect, associate, screen, locate, or characterize the signatures or parameters of that source with uncertain data*

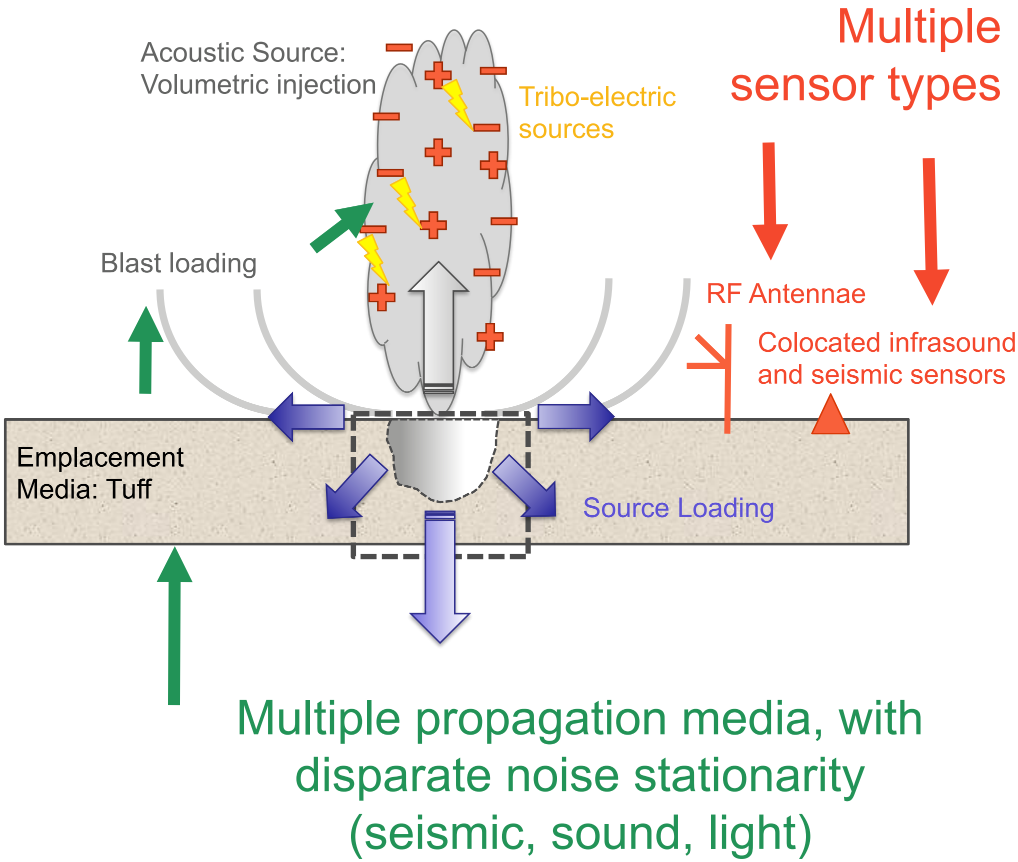
Focus: Waveform Signature Detection

Example Explosion Signatures

Aboveground explosion signatures include **radio**, **acoustic**, and **seismic** waveforms. These waveforms give data on source size and emplacement

What is our Predictive Capability?

A hypothetical explosion of a given size occurs. How well we can **detect** signatures of that source with uncertain data?



Monitoring Detection Problems that Require a Predictive Capability

This Talk Answers Three Research Challenges

1. Does **mean** predicted detector performance match **mean** observed performance?

2. Does observed versus predicted detector performance exceed day-to-day observed variability? That is, does predicted performance assembled on day $\boldsymbol{A}$ match observations from day $\boldsymbol{A}$ better than observations assembled on day $\boldsymbol{B}$?

3. What is the range in observed versus predicted magnitude discrepancies? That is, if a detector predictively identifies explosions of magnitude m with probability Pr_D, what is the observed, absolute range Δm the detector identifies explosions for that Pr_D?

Decision Theory Statement for Any Signature

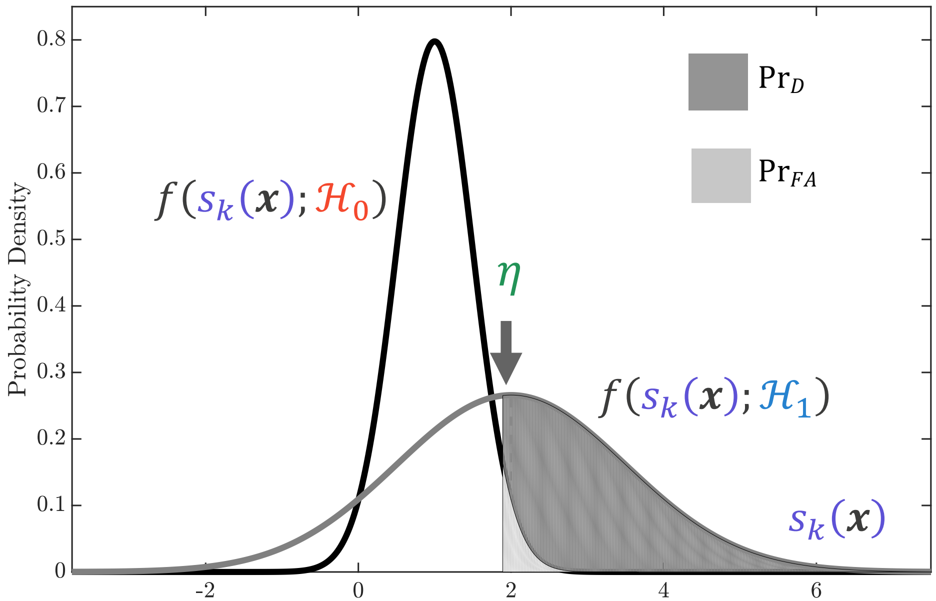
Binary Testing on Two Source Types

Building a Detector (1/2)

- A waveform detector is a decision rule that compares a statistic $s_k(\boldsymbol{x})$ with a threshold $\boldsymbol{\eta}$ to test if data $\boldsymbol{x}_k$ that records signature k is evidence for a target signal (hypothesis $\mathcal{H}_1$) or not (hypothesis $\mathcal{H}_0$):

$$s_k(\boldsymbol{x}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta$$

- The statistic $s_k(\boldsymbol{x})$ has PDFs that depend on the presence ($f_S(s_k(\boldsymbol{x}); \mathcal{H}_1)$) or absence ($f_S(s_k(\boldsymbol{x}); \mathcal{H}_0)$) of that target signal
- The probability Pr_D of correctly deciding a target signal is present compared with the false-alarm probability Pr_{FA} quantifies the detector's performance



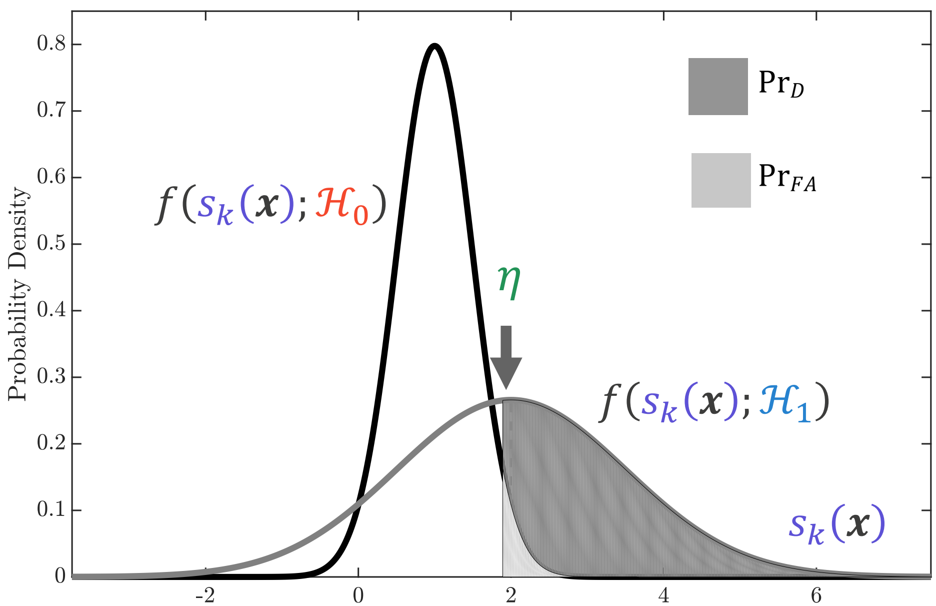
Building a Detector (2/2)

- A waveform detector is a decision rule that compares a statistic $s_k(\boldsymbol{x})$ with a threshold $\boldsymbol{\eta}$ to test if data $\boldsymbol{x}_k$ that records signature k is evidence for a target signal (hypothesis $\mathcal{H}_1$) or not (hypothesis $\mathcal{H}_0$):

$$s_k(\boldsymbol{x}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta$$

Examples: *STA/LTA, correlation, subspace, SNR, spectrogram, cone*

- The statistic $s_k(\boldsymbol{x})$ has PDFs that depend on the presence ($f_S(s_k(\boldsymbol{x}); \mathcal{H}_1)$) or absence ($f_S(s_k(\boldsymbol{x}); \mathcal{H}_0)$) of that target signal
- The probability $\Pr_D$ of correctly deciding a target signal is present compared with the false-alarm probability $\Pr_{FA}$ quantifies the detector's performance

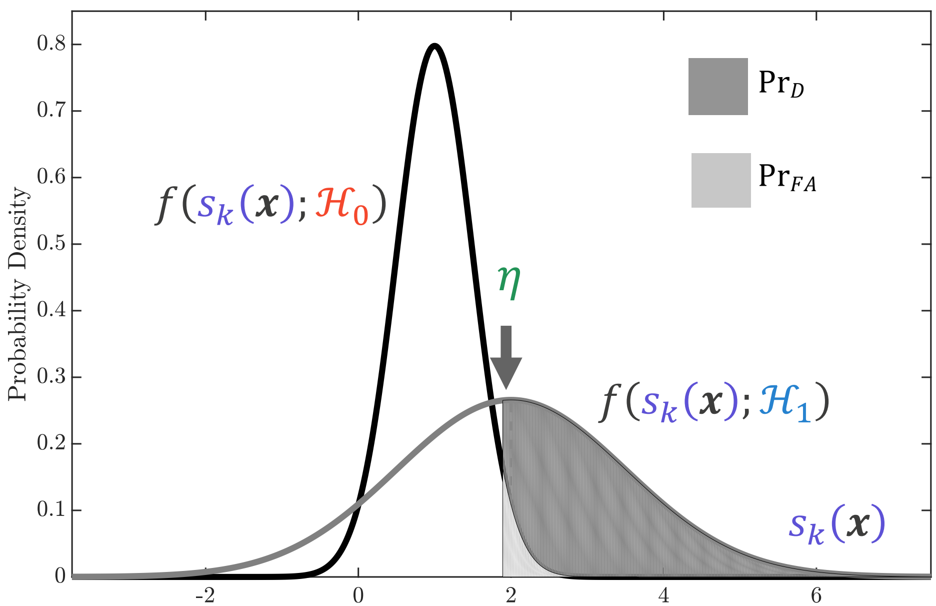


Building a Detector's Predictive Capability (1/2)

- A waveform detector is a decision rule that compares a statistic $s_k(\boldsymbol{x})$ with a threshold $\boldsymbol{\eta}$ to test if data $\boldsymbol{x}_k$ that records signature k is evidence for a target signal (hypothesis $\mathcal{H}_1$) or not (hypothesis $\mathcal{H}_0$):

$$s_k(\boldsymbol{x}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta$$

- The statistic $s_k(\boldsymbol{x})$ has PDFs that depend on the presence ($f_S(s_k(\boldsymbol{x}); \mathcal{H}_1)$) or absence ($f_S(s_k(\boldsymbol{x}); \mathcal{H}_0)$) of that target signal
- The probability Pr_D of correctly deciding a target signal is present compared with the false-alarm probability Pr_{FA} quantifies the detector's performance



Problem Statement

Challenge: If a hypothetical event produces signature k and statistic $s_k(\boldsymbol{x})$, can we predict the probability Pr_D of detecting that event?

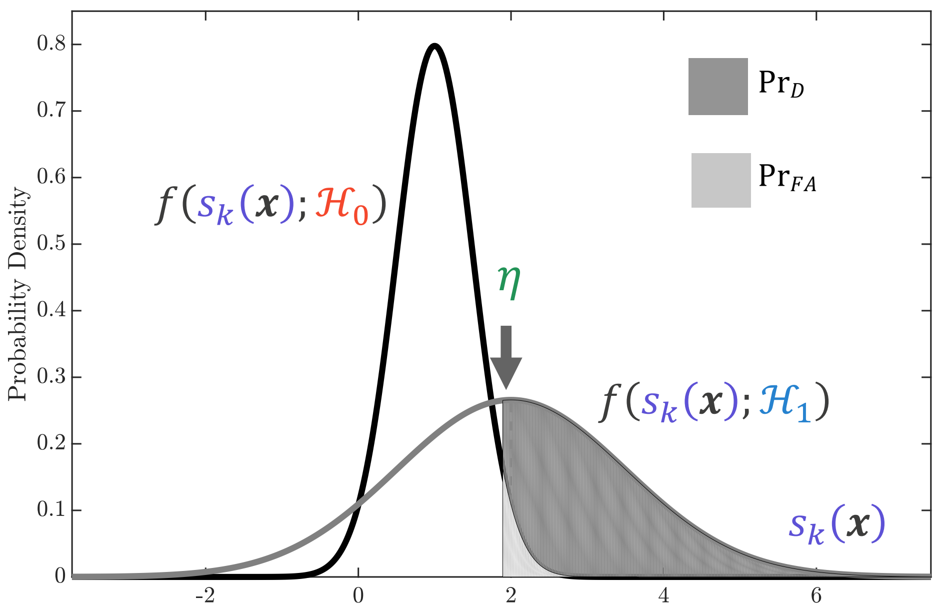
Equivalently, what is the predictive capability of that detector?

Building a Detector's Predictive Capability (2/2)

- A waveform detector is a decision rule that compares a statistic $s_k(\boldsymbol{x})$ with a threshold $\boldsymbol{\eta}$ to test if data $\boldsymbol{x}_k$ that records signature k is evidence for a target signal (hypothesis $\mathcal{H}_1$) or not (hypothesis $\mathcal{H}_0$):

$$s_k(\boldsymbol{x}) \underset{\mathcal{H}_0}{\overset{\mathcal{H}_1}{\gtrless}} \eta$$

- The statistic $s_k(\boldsymbol{x})$ has PDFs that depend on the presence ($f_S(s_k(\boldsymbol{x});\mathcal{H}_1)$) or absence ($f_S(s_k(\boldsymbol{x});\mathcal{H}_0)$) of that target signal
- The probability Pr_D of correctly deciding a target signal is present compared with the false-alarm probability Pr_{FA} quantifies the detector's performance



Problem Statement

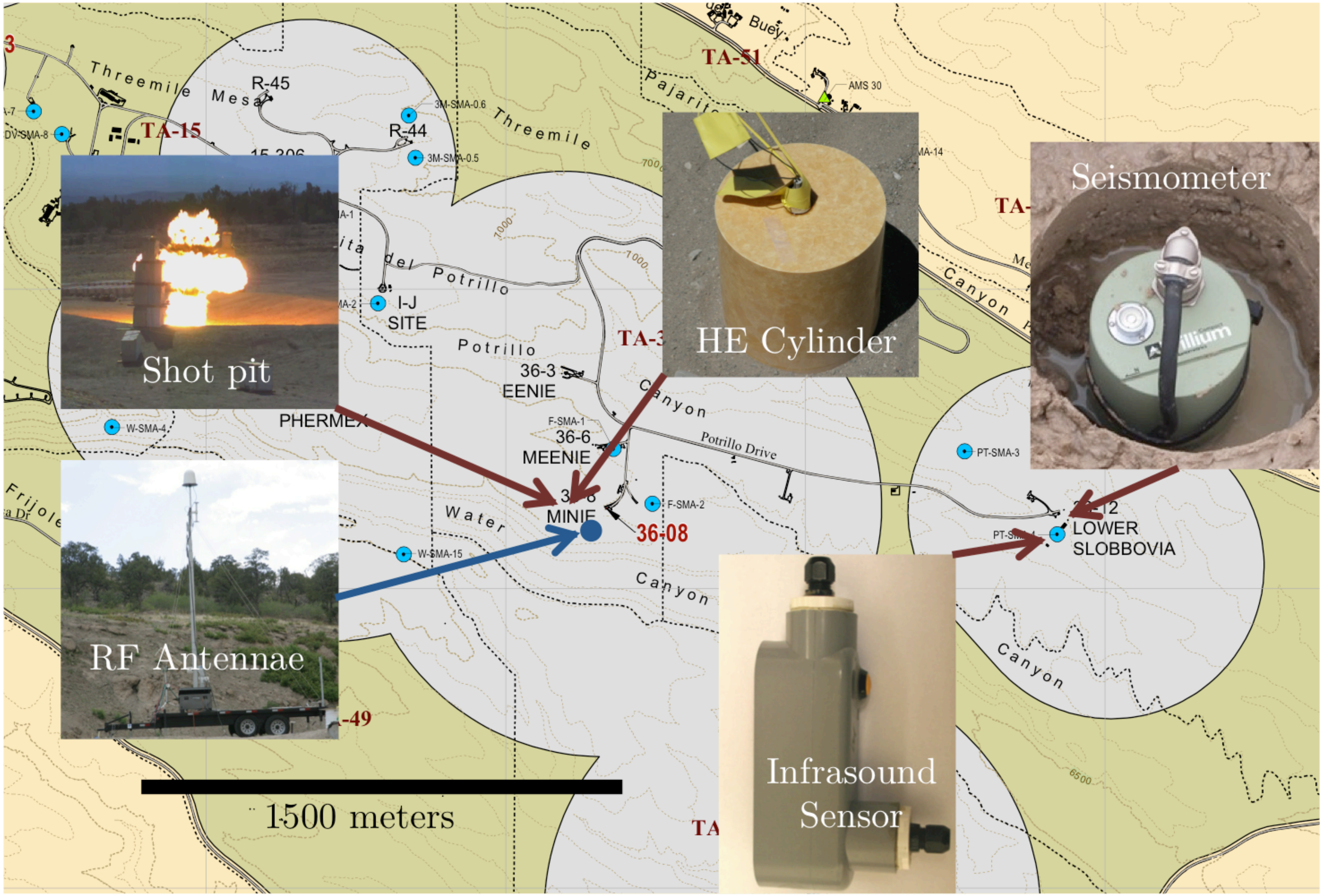
Method: PDF $f_S(s_k(\boldsymbol{x});\mathcal{H}_1)$ is effectively parameterized by the magnitude m of the hypothetical event that produces statistic $s_k(\boldsymbol{x})$.

We will compare observed detector counts with predicted counts

Predicting the Capability of a Radio Emission, SNR Detector

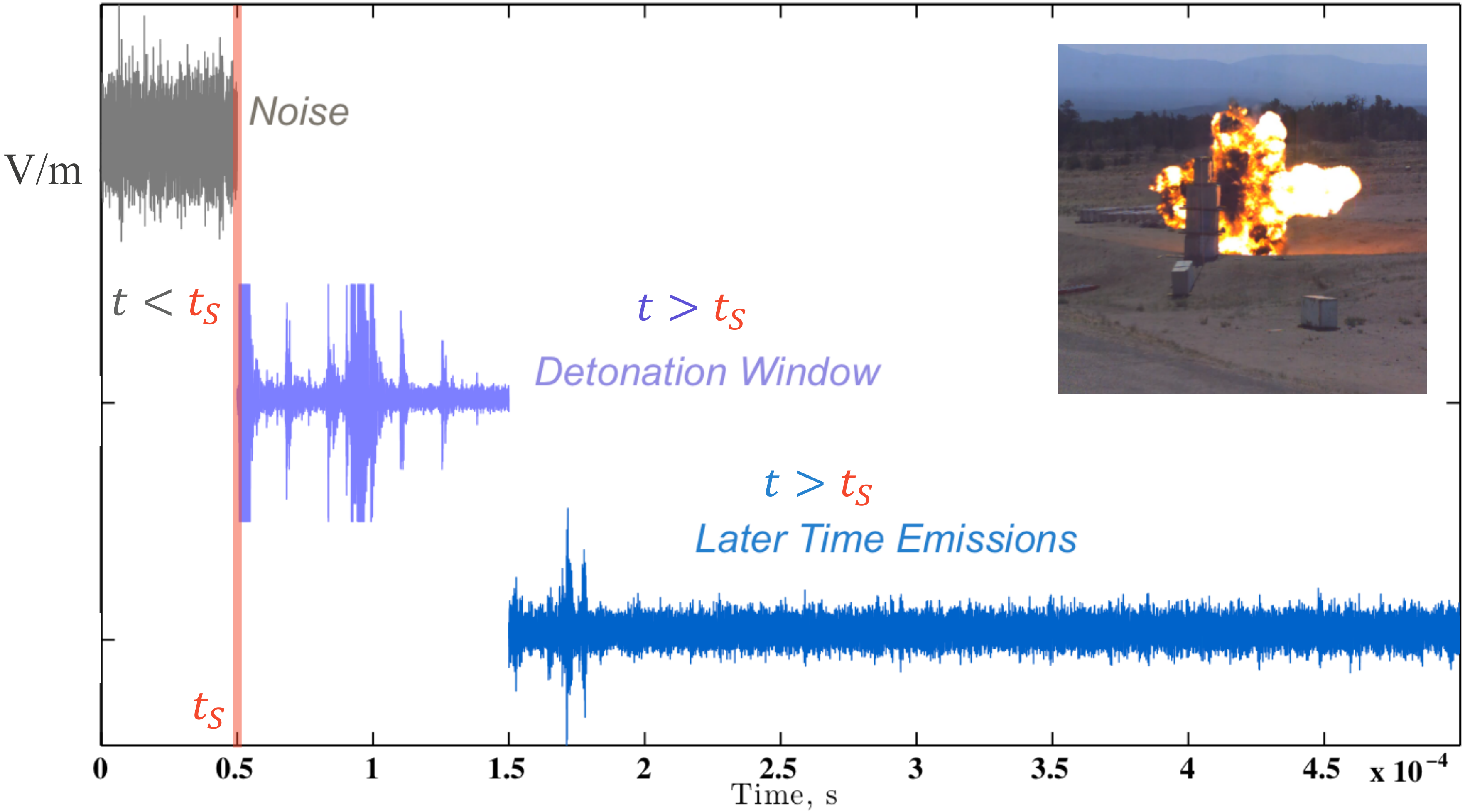
Binary Testing on Two Source Types

Minie Data Collection: 70 Charge Shots



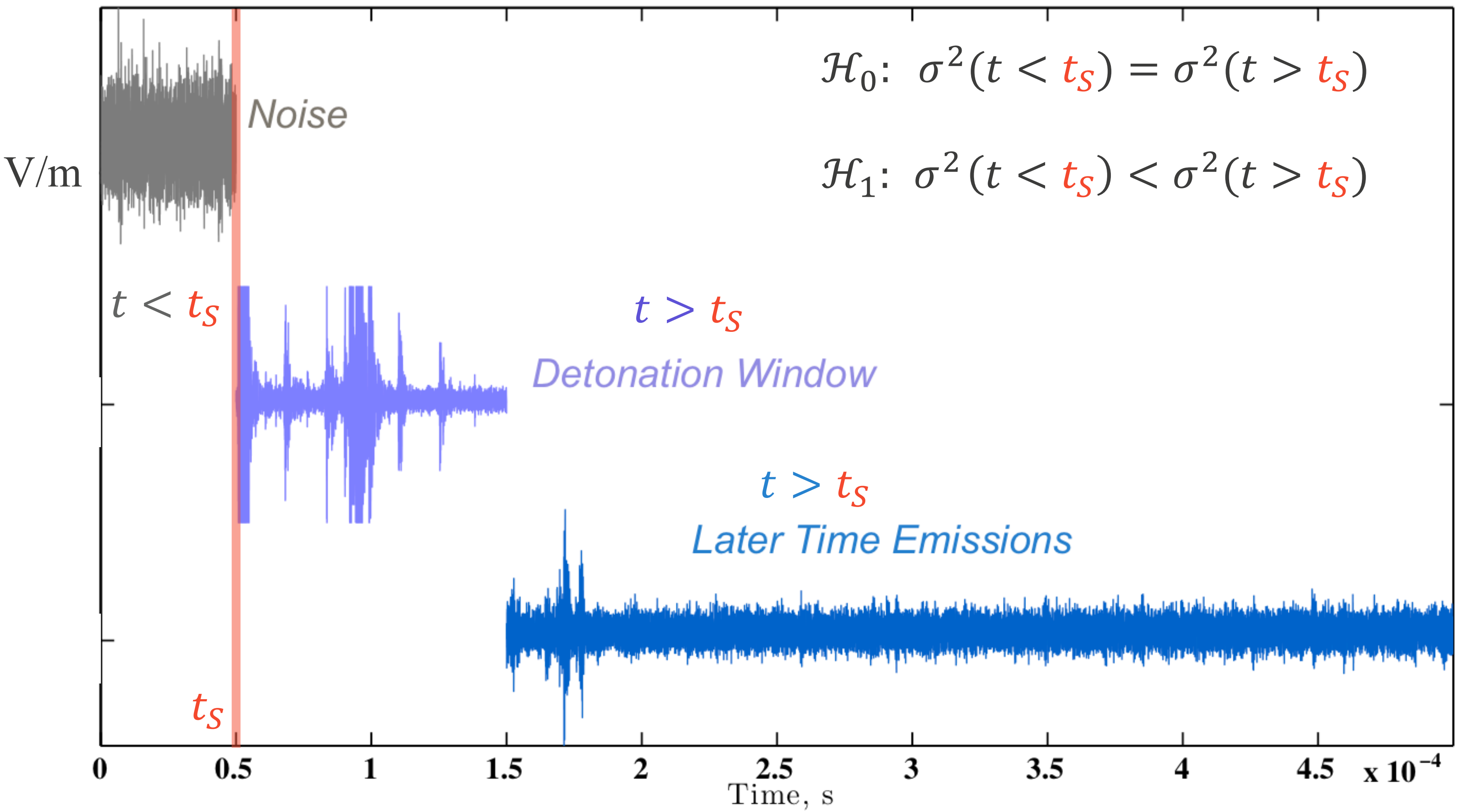
Radio Emissions from Explosions (1/6)

***Hypothesis Test*: Source 0:** No Explosion. **Source 1:** An Explosion



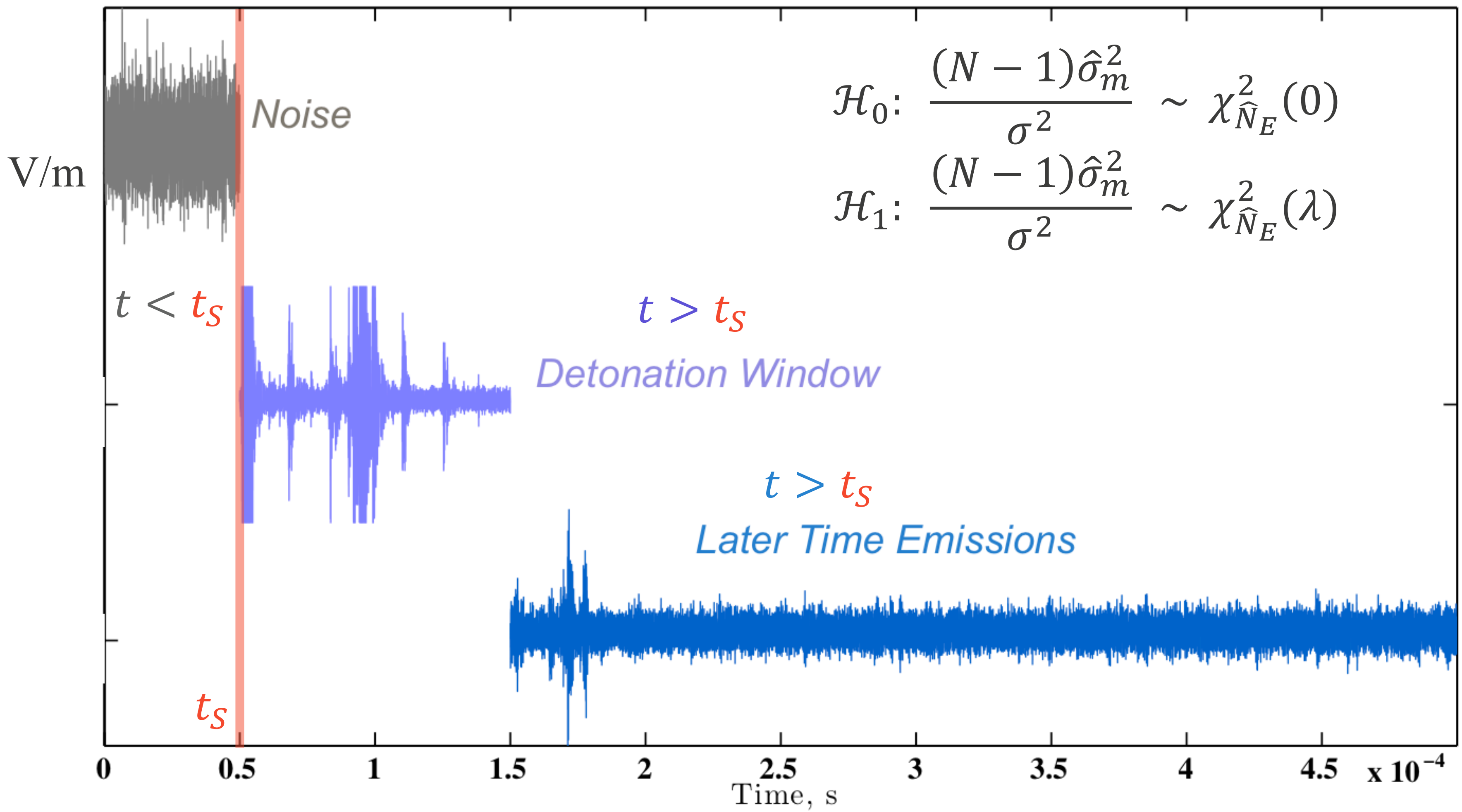
Radio Emissions from Explosions (2/6)

***Hypothesis Test*: Source 0:** No Explosion. **Source 1:** An Explosion



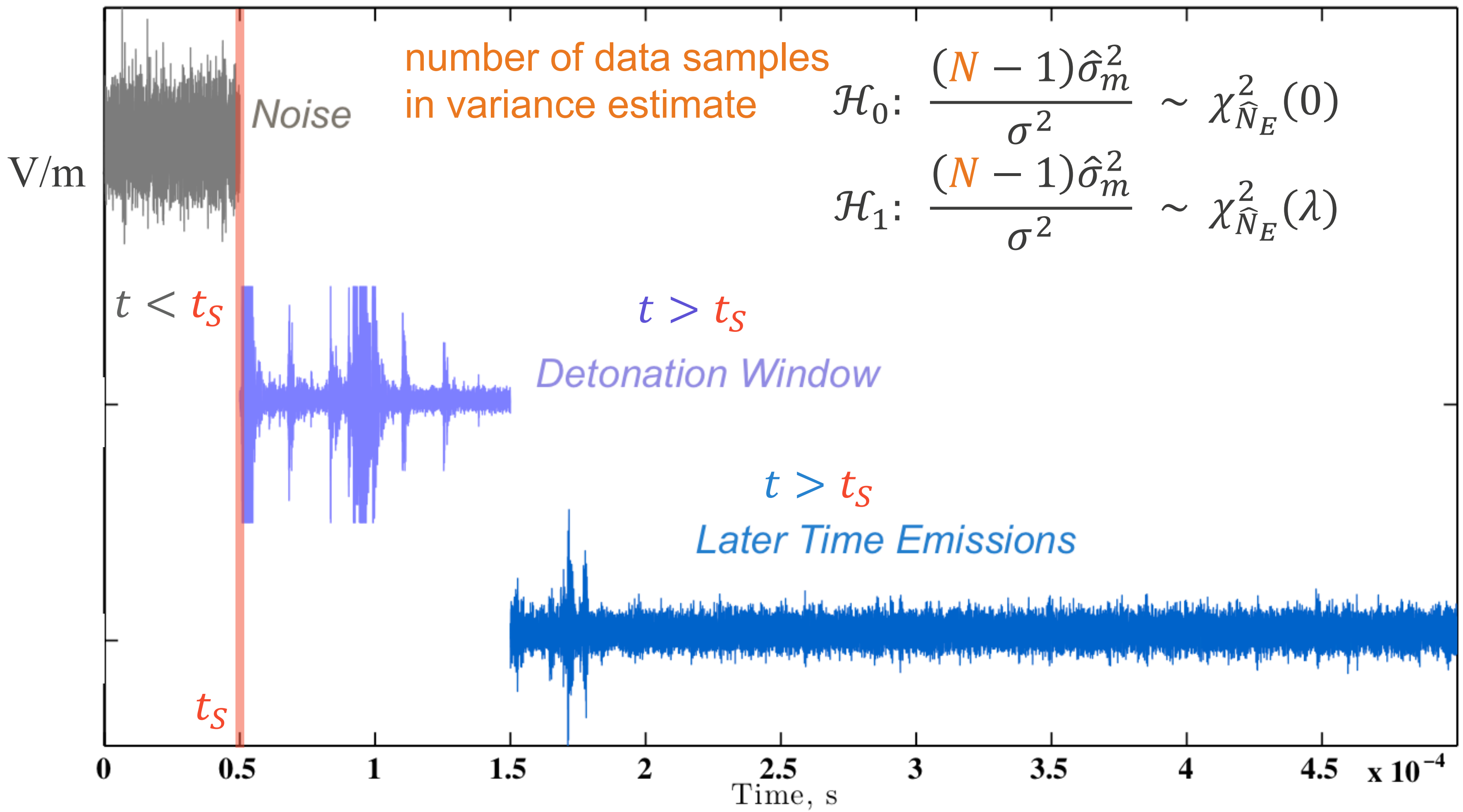
Radio Emissions from Explosions (3/6)

***Hypothesis Test*: Source 0:** No Explosion. **Source 1:** An Explosion



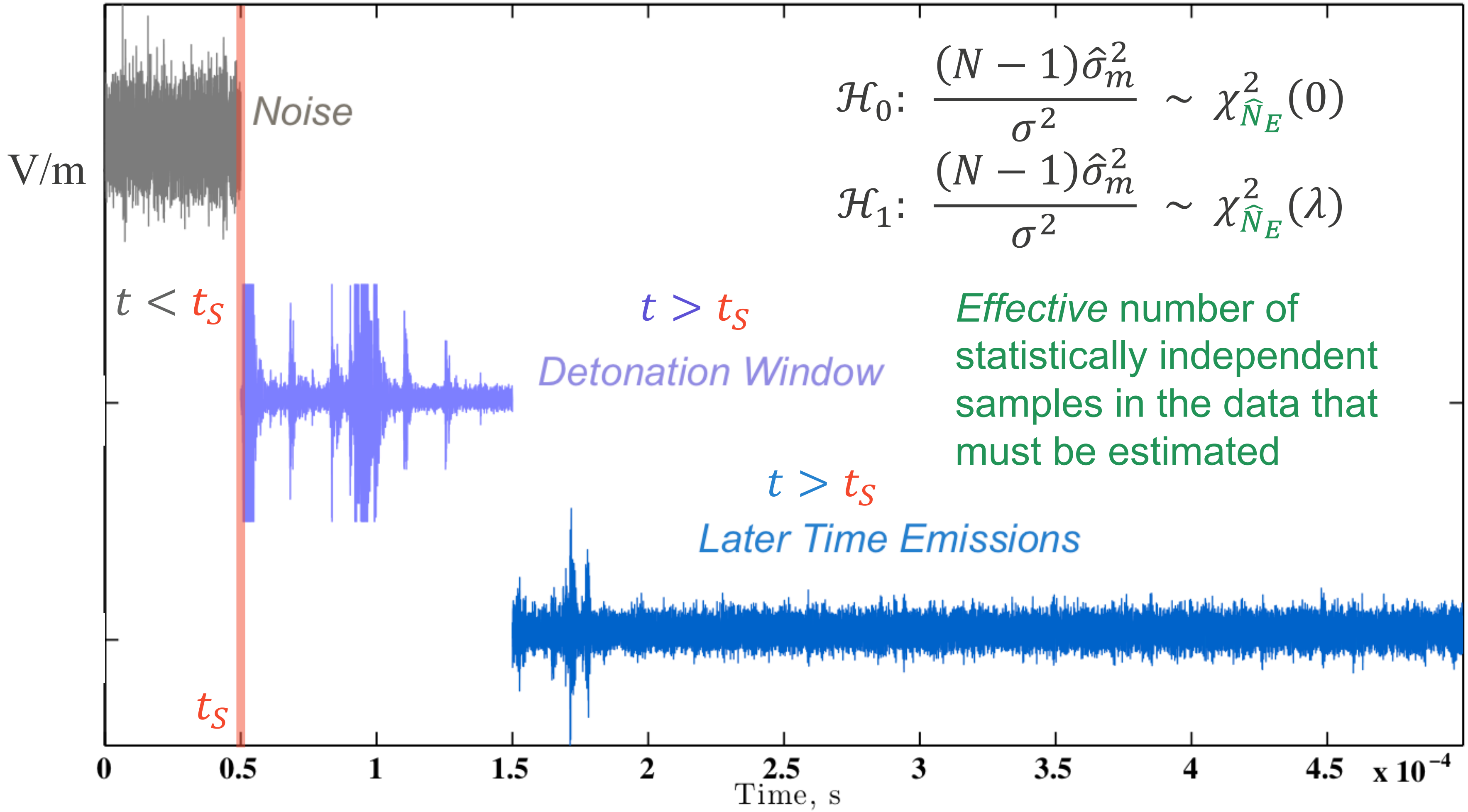
Radio Emissions from Explosions (4/6)

***Hypothesis Test*: Source 0:** No Explosion. **Source 1:** An Explosion



Radio Emissions from Explosions (5/6)

Hypothesis Test: **Source 0:** No Explosion. **Source 1:** An Explosion



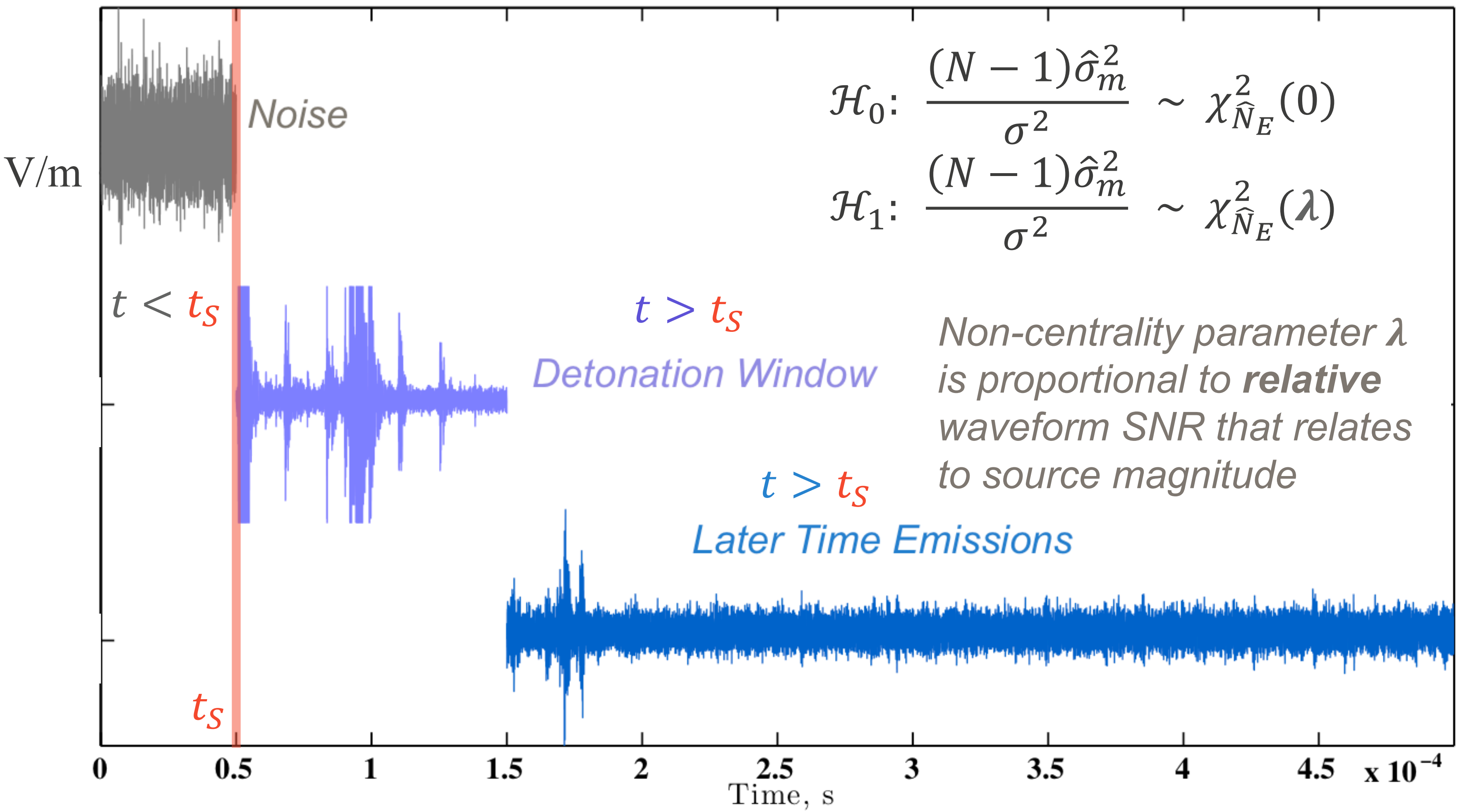
$$\mathcal{H}_0: \frac{(N-1)\hat{\sigma}_m^2}{\sigma^2} \sim \chi^2_{\hat{N}_E}(0)$$

$$\mathcal{H}_1: \frac{(N-1)\hat{\sigma}_m^2}{\sigma^2} \sim \chi^2_{\hat{N}_E}(\lambda)$$

Effective number of statistically independent samples in the data that must be estimated

Radio Emissions from Explosions (6/6)

***Hypothesis Test*: Source 0:** No Explosion. **Source 1:** An Explosion



$$\mathcal{H}_0: \frac{(N-1)\hat{\sigma}_m^2}{\sigma^2} \sim \chi^2_{\hat{N}_E}(0)$$

$$\mathcal{H}_1: \frac{(N-1)\hat{\sigma}_m^2}{\sigma^2} \sim \chi^2_{\hat{N}_E}(\lambda)$$

Non-centrality parameter $\boldsymbol{\lambda}$ *is proportional to* ***relative*** *waveform SNR that relates to source magnitude*

Observed versus Predicted "ROC Curves"

Observed ROC Curves

- Scale **template waveform** of amplitude A_0 recording **template source** with magnitude m_0 to amplitude A consistent with a signal triggered by source of magnitude $m = m_0 + \Delta m$

$$A = 10^{\Delta m} A_0$$

- Repeatedly infuse scaled waveform into real, recorded noise sampled from multiple times and days

- Process noisy waveforms with radio emission, SNR detector over days and Δm. Dynamically adjust detector threshold η to maintain constant 10^{-8} false alarm rate

Predicted ROC Curves

- Estimate **parameters** that shape "explosion signal present" PDF during detector processing

- Construct temporally variable PDF curves and compute detection probabilities at each Δm value

- Integrate area right of concurrent detection threshold η to estimate detection probability $\Pr_D$.

- Scale probability by the true number of infused waveforms to estimate expected number of counts $N \cdot \Pr_D$.

Detector Parameters of $f_S(s_k(\boldsymbol{x}); \mathcal{H}_1)$ (1/2)

Parameter that separates $f_S(s_k(\boldsymbol{x}); \mathcal{H}_1)$ and $f_S(s_k(\boldsymbol{x}); \mathcal{H}_0)$ curves

Noncentrality Parameters

Radio, SNR Detector

- $\lambda = 10^{2\Delta m} \frac{A_0^2 N}{\sigma^2}$
- $\hat{\lambda} = \widehat{N}_E \cdot 10^{\frac{e}{10}}$

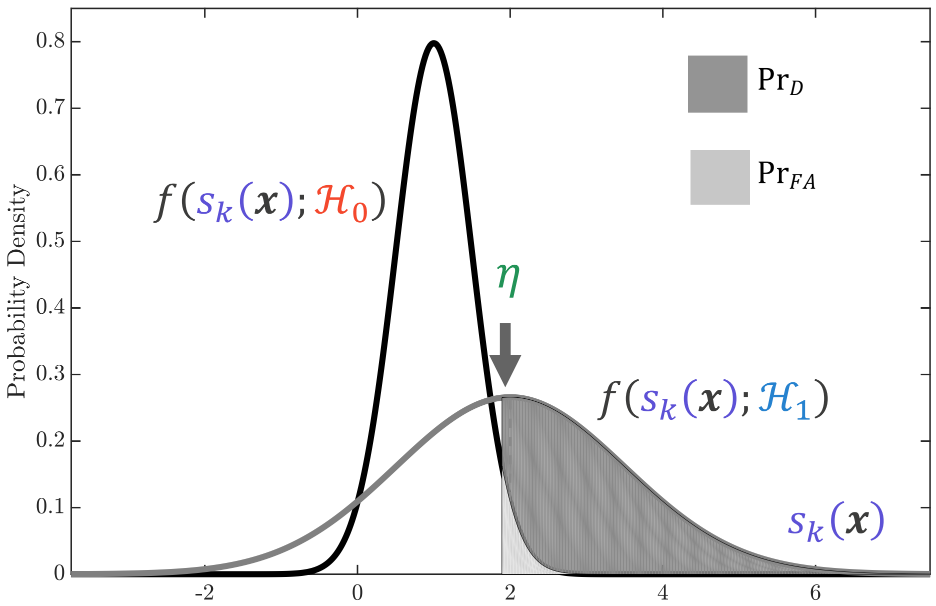
Acoustic Power Detector

- $\lambda = \mathrm{SNR}\left(\frac{N_2}{N_1}\right)(N_2 - 2) - N_1$
- $\hat{\lambda} = Z \cdot \left(\frac{\widehat{N}_1}{\widehat{N}_2}\right)(\widehat{N}_2 - 2) - \widehat{N}_1$

Seismic Correlation Detector

- $\lambda = (N-1)\left(\frac{\rho^2}{1-\rho^2}\right)$
- $\hat{\lambda} = (N-1)\left(\frac{\hat{\rho}^2}{1-\hat{\rho}^2}\right)$

Competing PDFs



Detector Parameters of $f_S(s_k(x);\mathcal{H}_1)$ (2/2)

Parameter that separates $f_S(s_k(x);\mathcal{H}_1)$ and $f_S(s_k(x);\mathcal{H}_0)$ curves

Noncentrality Parameters

Radio, SNR Detector

- $\lambda = 10^{2\Delta m} \frac{A_0^2 N}{\sigma^2}$
- $\hat{\lambda} = \hat{N}_E \cdot 10^{\frac{e}{10}}$

Acoustic Power Detector

- $\lambda = \mathrm{SNR}\left(\frac{N_2}{N_1}\right)(N_2 - 2) - N_1$
- $\hat{\lambda} = Z \cdot \left(\frac{\hat{N}_1}{\hat{N}_2}\right)(\hat{N}_2 - 2) - \hat{N}_1$

Seismic Correlation Detector

- $\lambda = (N-1)\left(\frac{\rho^2}{1-\rho^2}\right)$
- $\hat{\lambda} = (N-1)\left(\frac{\hat{\rho}^2}{1-\hat{\rho}^2}\right)$

Parameter Dependencies

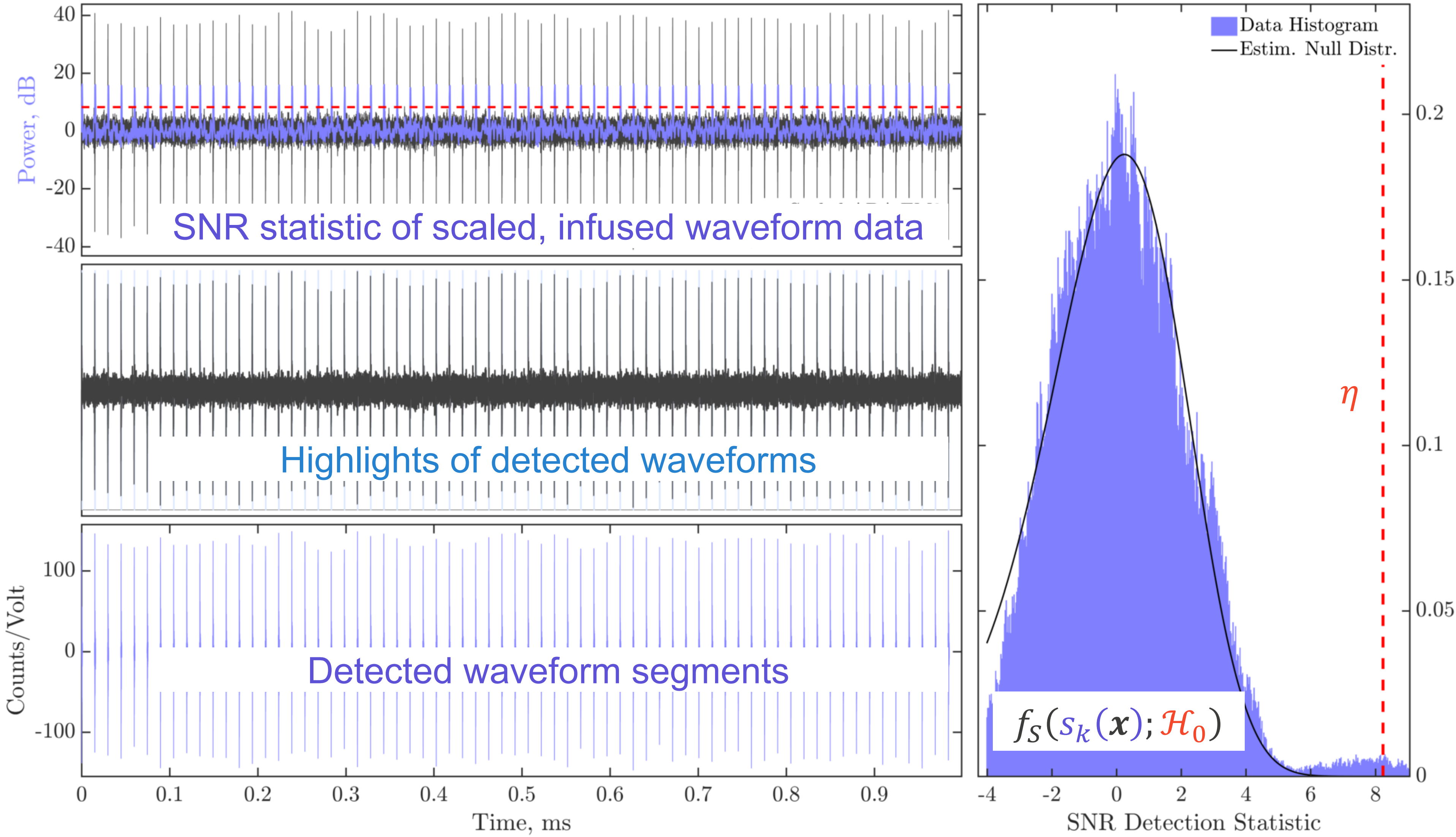
N samples in window, noise variance σ^2, waveform amplitude A_0^2, source magnitude Δm, e is the SNR (dB) statistic at detection, hats $\hat{}$ are estimates of their arguments

N_1 samples in STA window, N_2 samples in LTA window, SNR is the waveform signal to noise ratio, Z is the STA/LTA statistic at a detection, hats $\hat{}$ are estimates of their arguments

N samples in the, ρ is the cross-correlation coefficient and hats $\hat{}$ are estimates of their arguments

Operation of the Radio Emission, SNR Detector

Detect Scaled Waveforms Infused into Real, Recorded Radio Noise



Quantifying the Predictive Capability of a Radio Emission, SNR Detector

Estimate Magnitude Differences between Predicted and Observed ROC Curves

Process over 12 Days, $-2.3 \leq \Delta m \leq 0$

ROC Curve Comparison

Three Research Challenges

1. Does **mean** predicted detector performance match **mean** observed performance?

2. Does observed versus predicted detector performance exceed day-to-day observed variability? That is, does predicted performance assembled on day $\boldsymbol{A}$ match observations from day $\boldsymbol{A}$ better than observations assembled on day $\boldsymbol{B}$?

3. What is the range in observed versus predicted magnitude discrepancies? That is, if a detector predictively identifies explosions of magnitude m with probability Pr_D, what is the observed, absolute range Δm the detector identifies explosions for probability Pr_D?

Solution Method

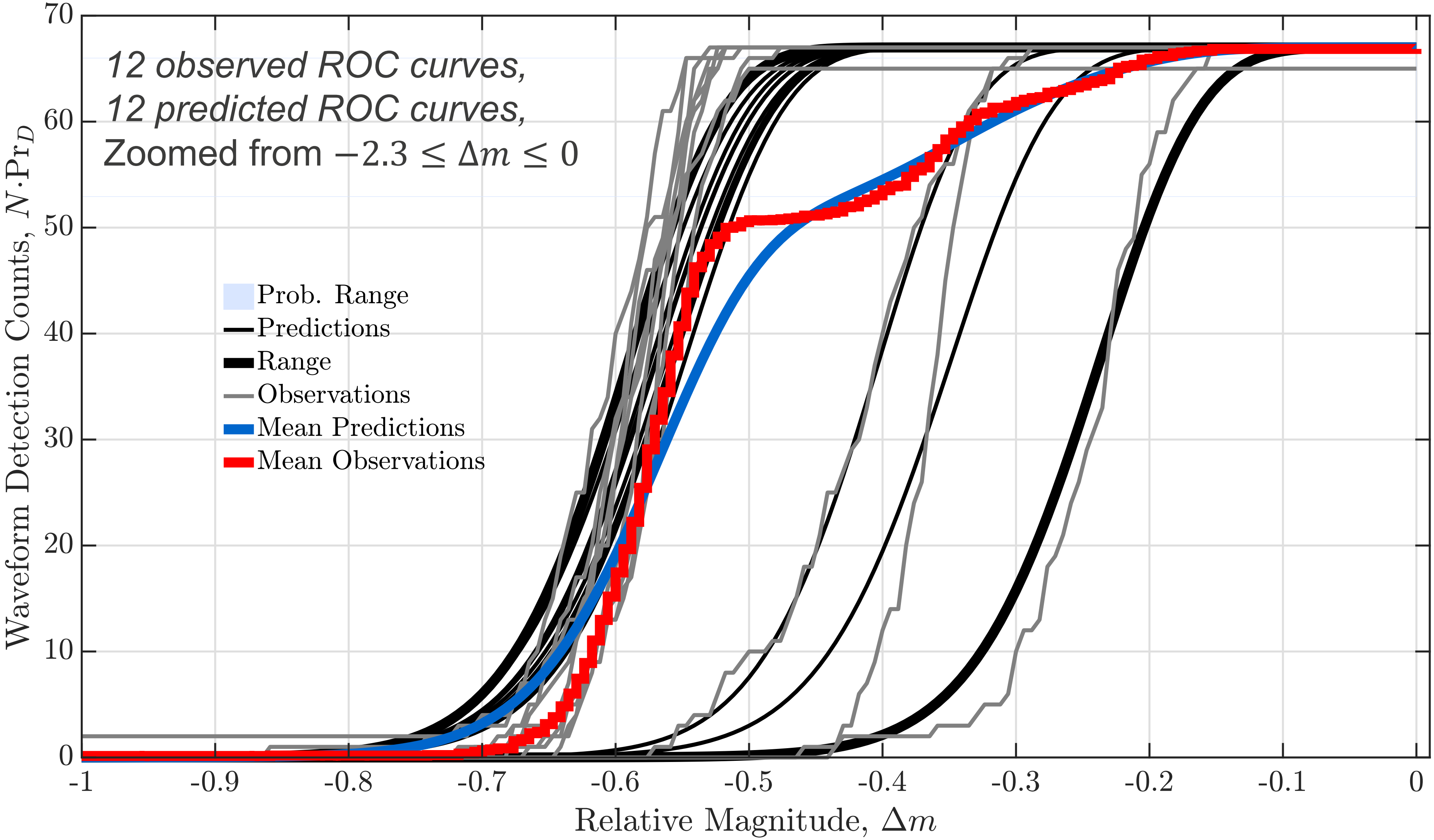
1. Compute predicted and observed ROC curves over a magnitude grid, then average both of over time, and compare

2. Compare predicted ROC curves for each day to observed ROC curves for all days; then compare observed ROC curves against observed ROC curves on other days

3. Introduce ROC "magnitude discrepancy": (i) select a probability interval; (ii) find probability $\mathrm{Pr}_D^{\mathrm{max}}$ in that interval with the max magnitude range across mean observed versus predicted ROC curves; and (iii) estimate the mag range between ROC curve pairs at $\mathrm{Pr}_D^{\mathrm{max}}$.

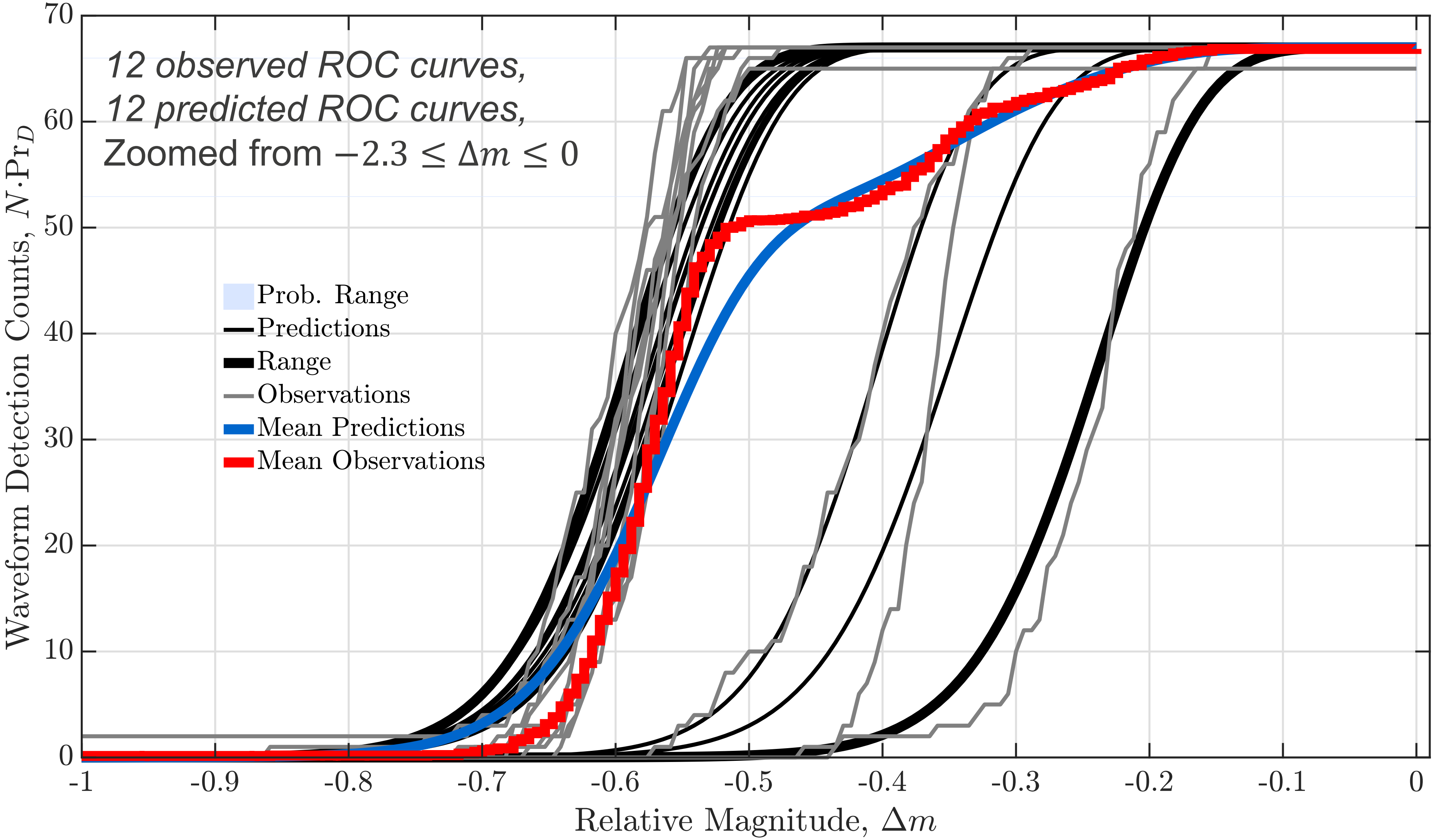
Radio Emissions from Explosions (1/2)

Predicted versus Observed ROC Curves for an SNR Detector



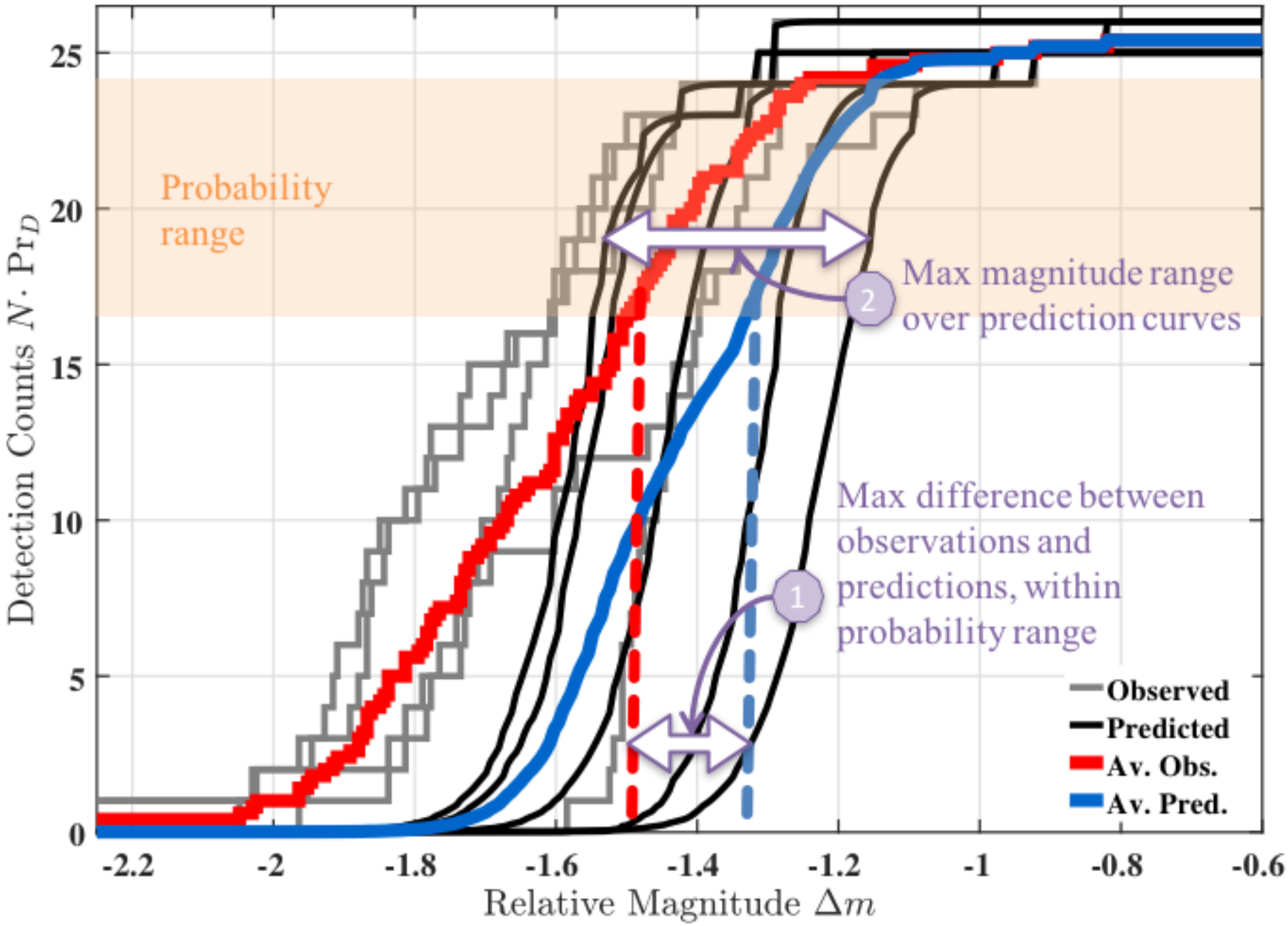
Radio Emissions from Explosions (2/2)

How do we Quantify our Predictive Capability?



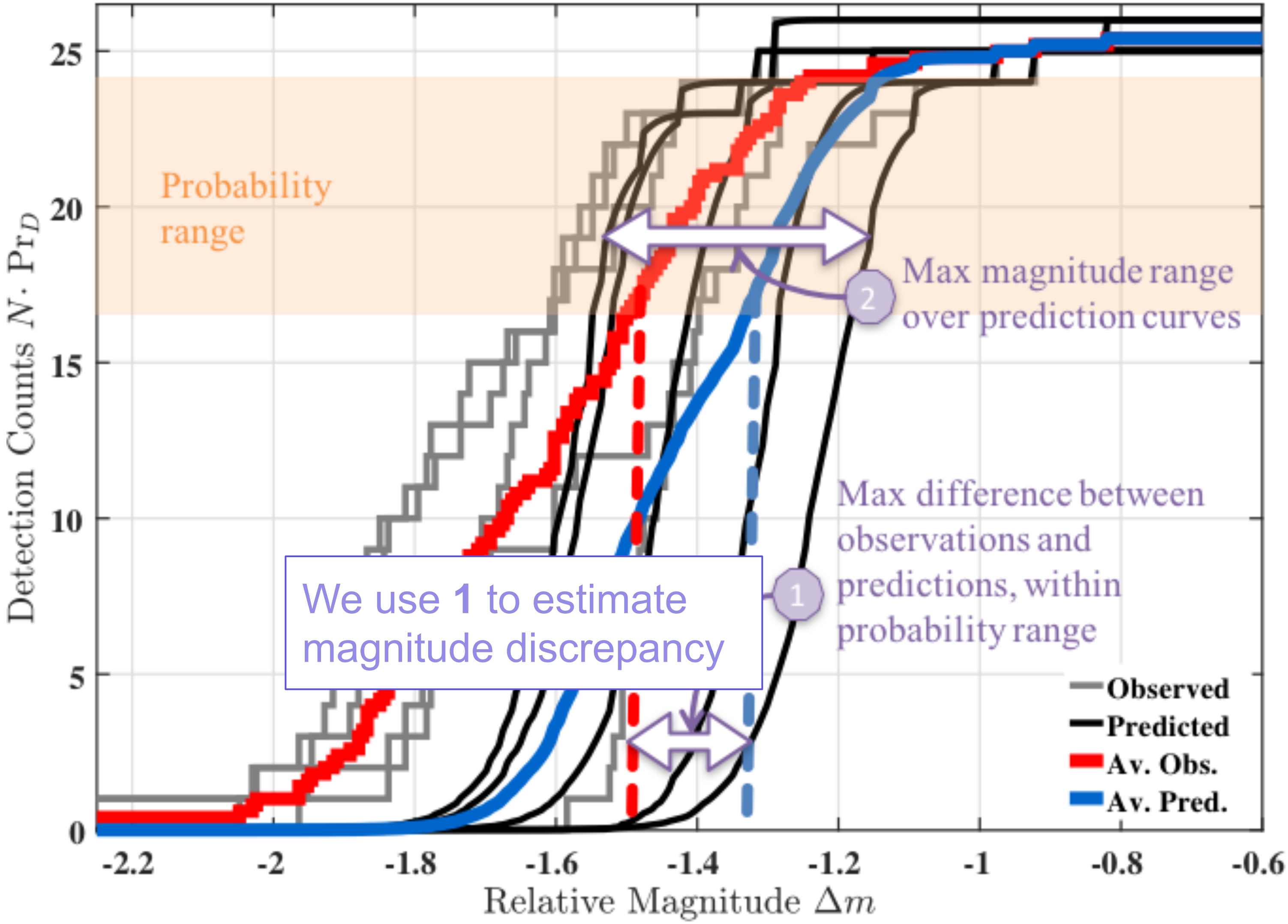
Defining Magnitude Discrepancy (1/2)

Magnitude difference between predicted and observed ROC curves, at constant probability (*different ROC curves here, for illustration*)



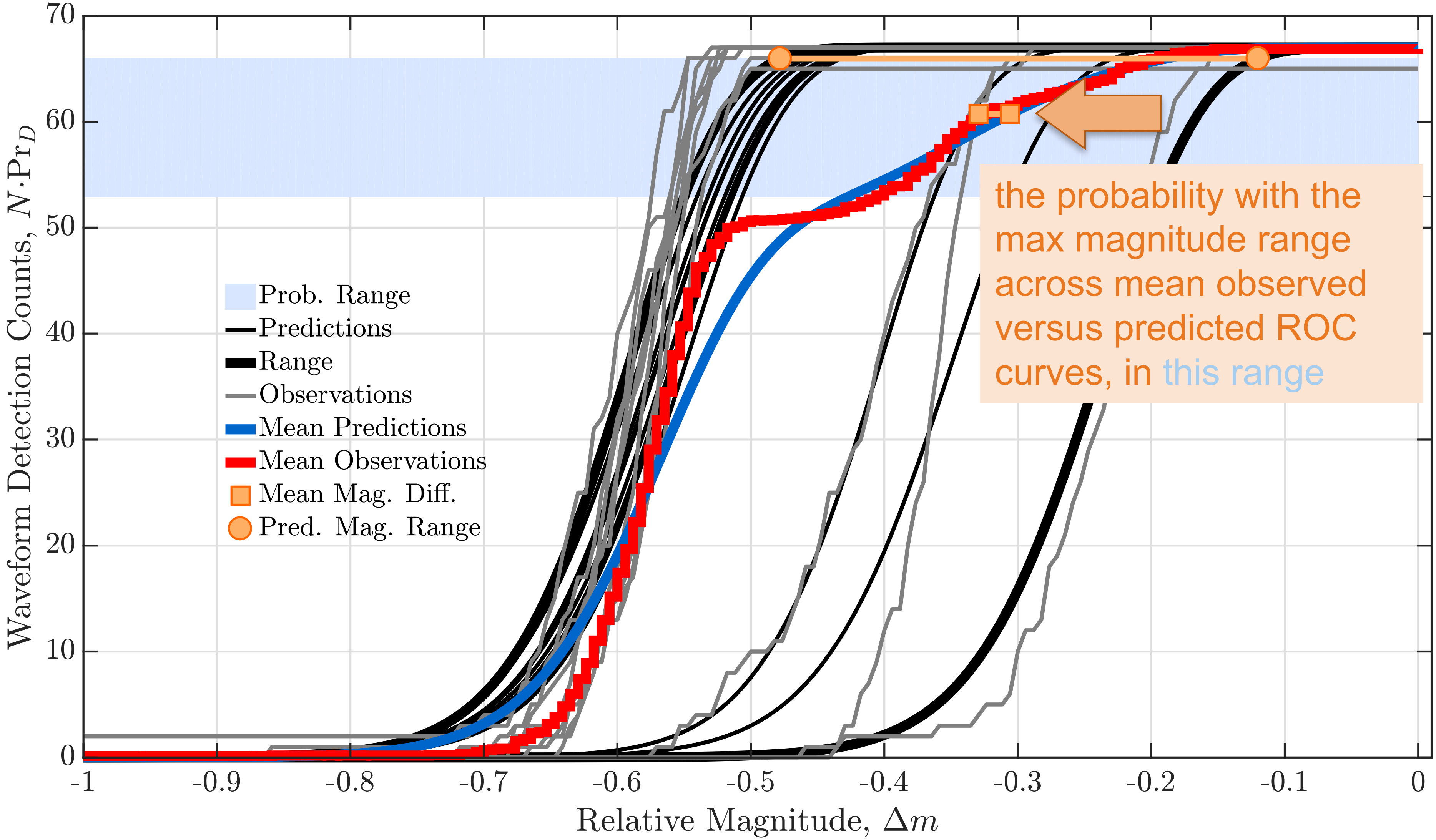
Defining Magnitude Discrepancy (2/2)

Magnitude difference between predicted and observed ROC curves, at constant probability (*different ROC curves here, for illustration*)



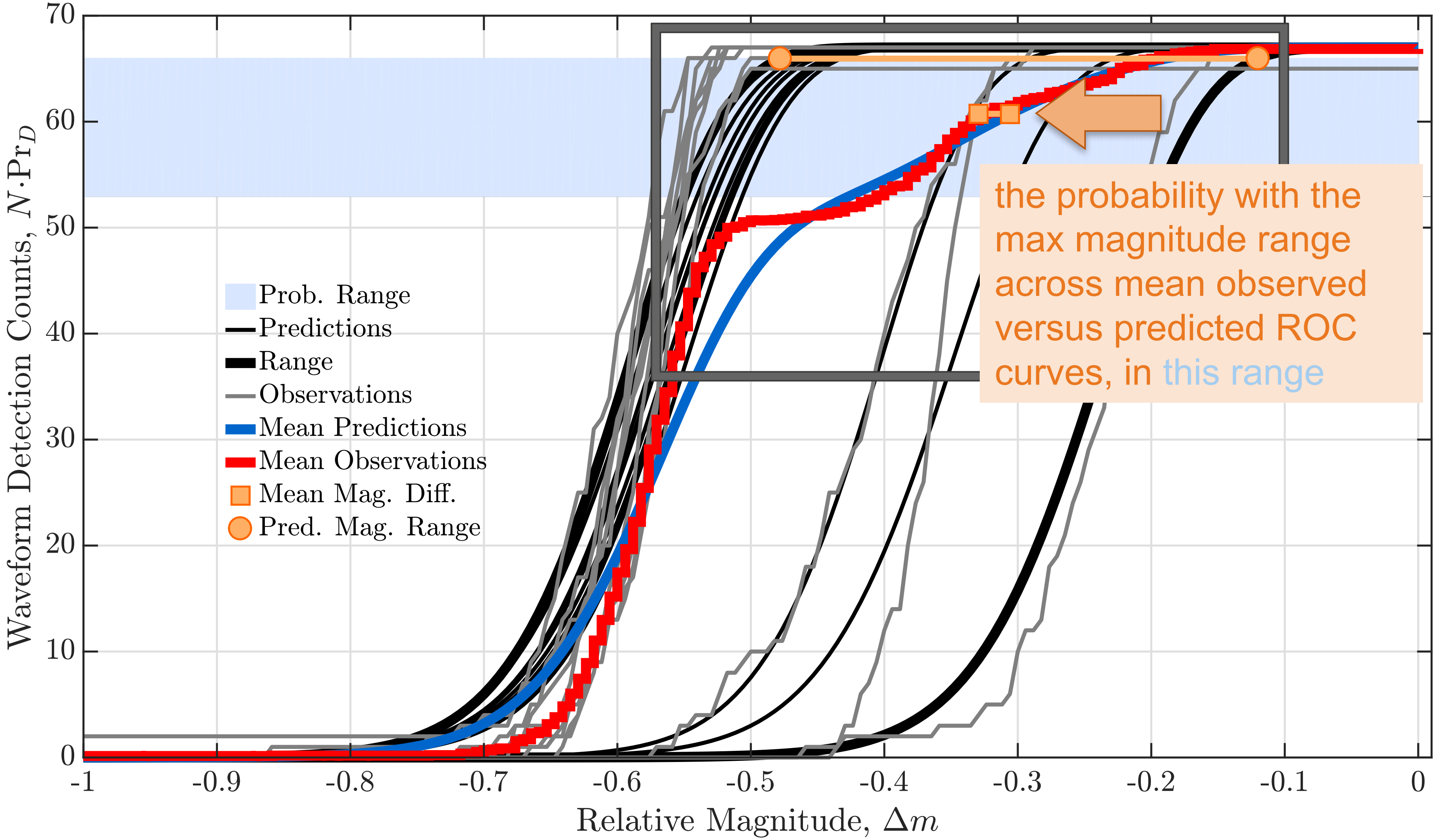
Radio Emissions from Explosions (1/2)

***Hypothesis Test*:** **Source 0:** No Explosion; **Source 1:** An Explosion



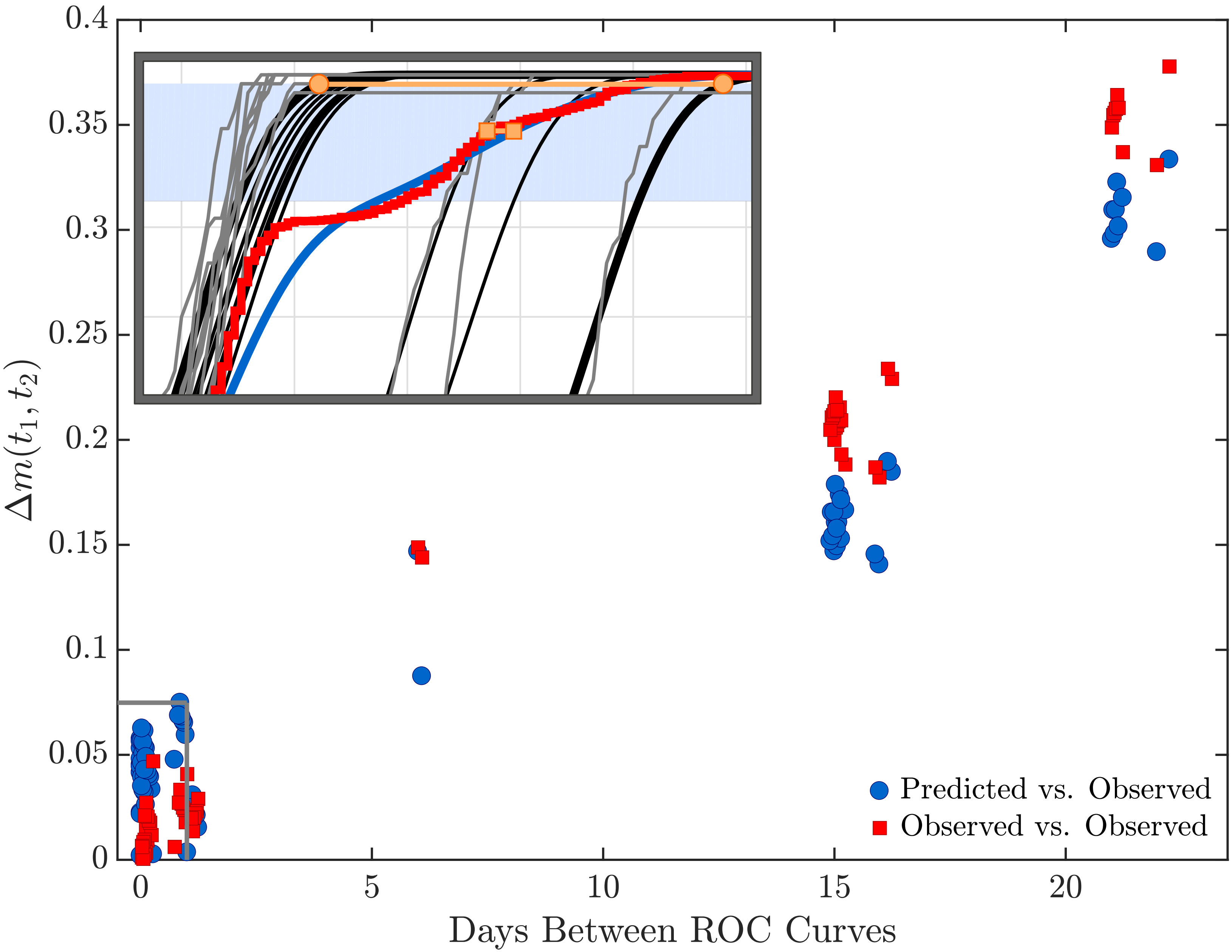
Radio Emissions from Explosions (2/2)

Hypothesis Test: **Source 0:** No Explosion; **Source 1:** An Explosion



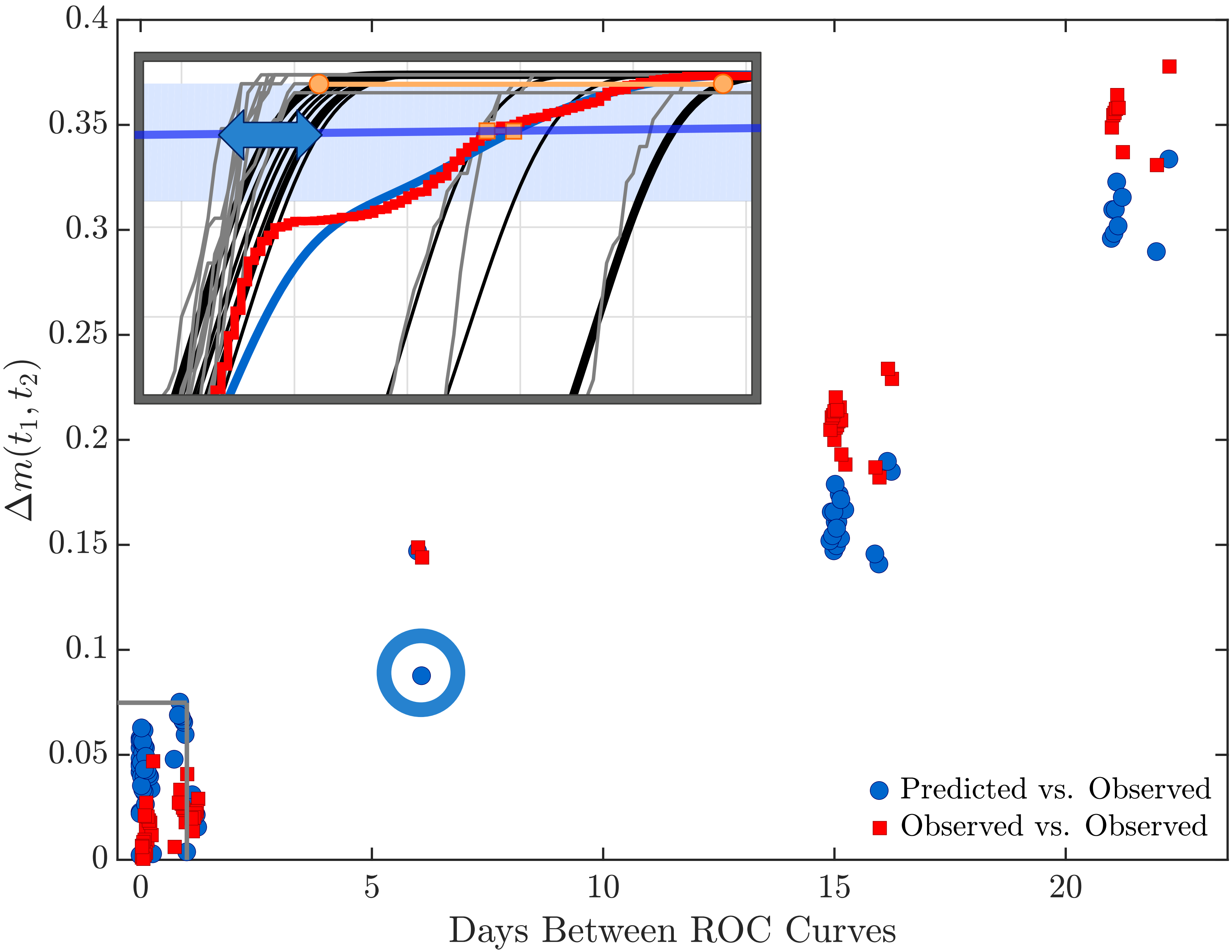
Magnitude Difference at Max Range Probability (1/5)

Radio Emissions



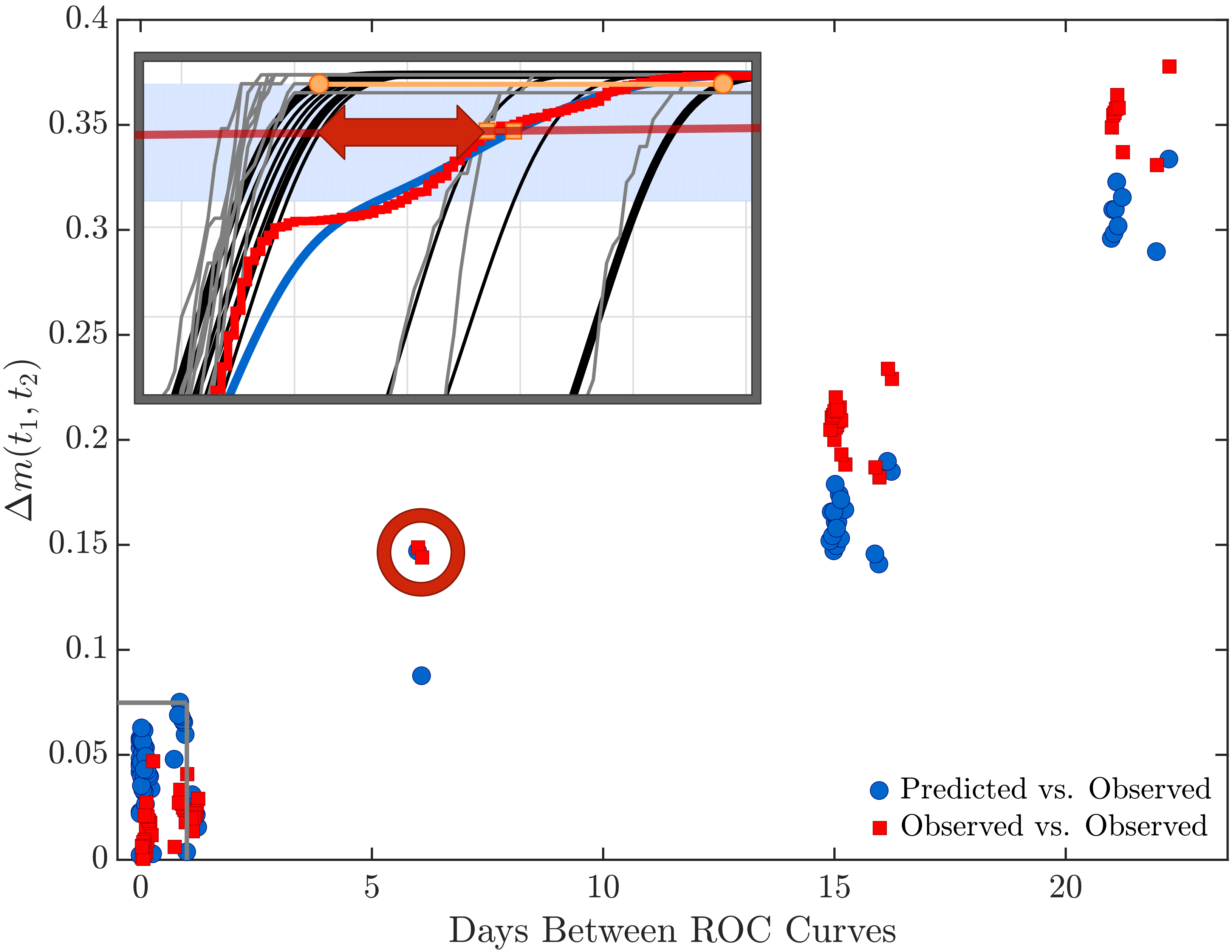
Magnitude Difference at Max Range Probability (2/5)

Radio Emissions

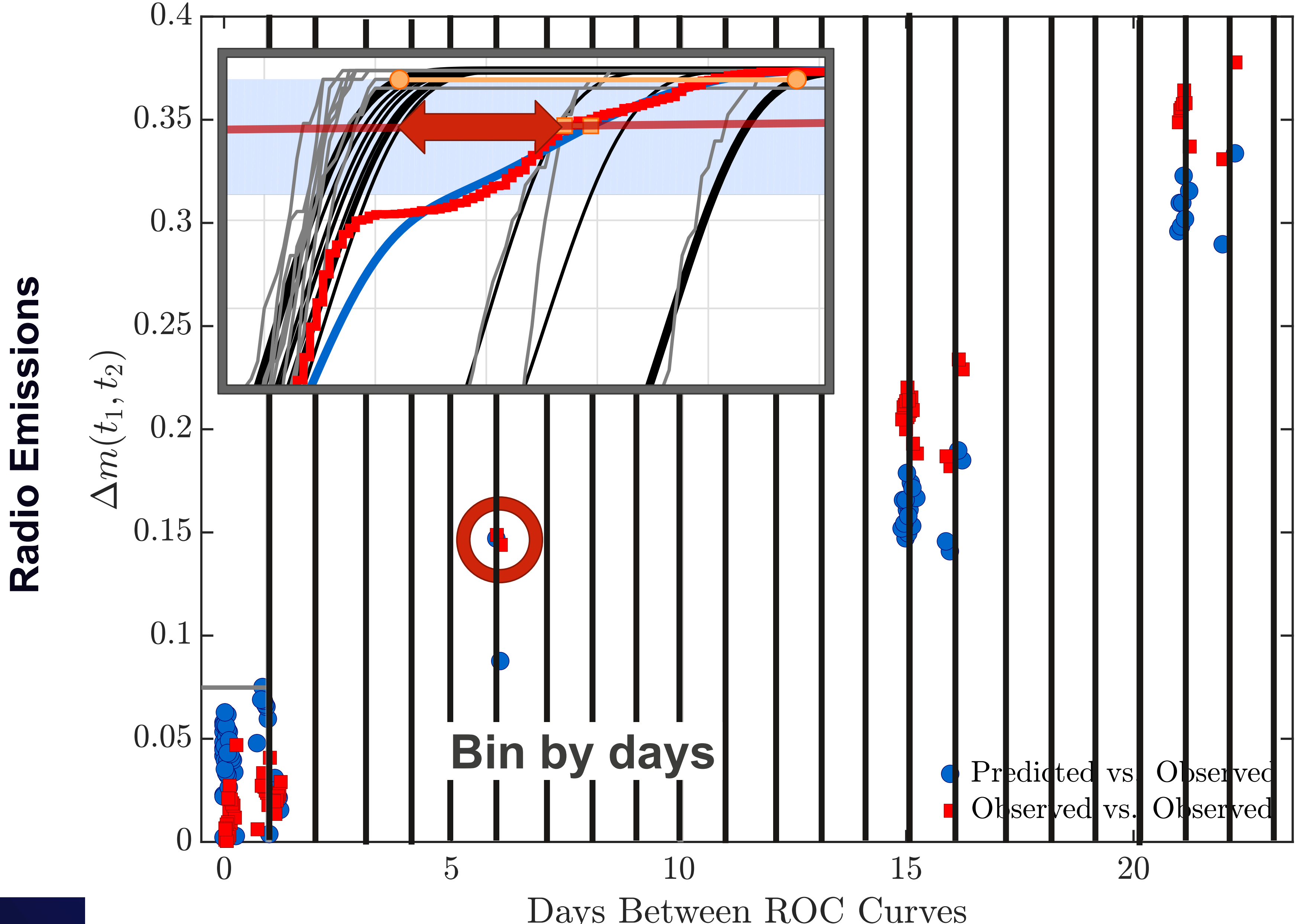


Magnitude Difference at Max Range Probability (3/5)

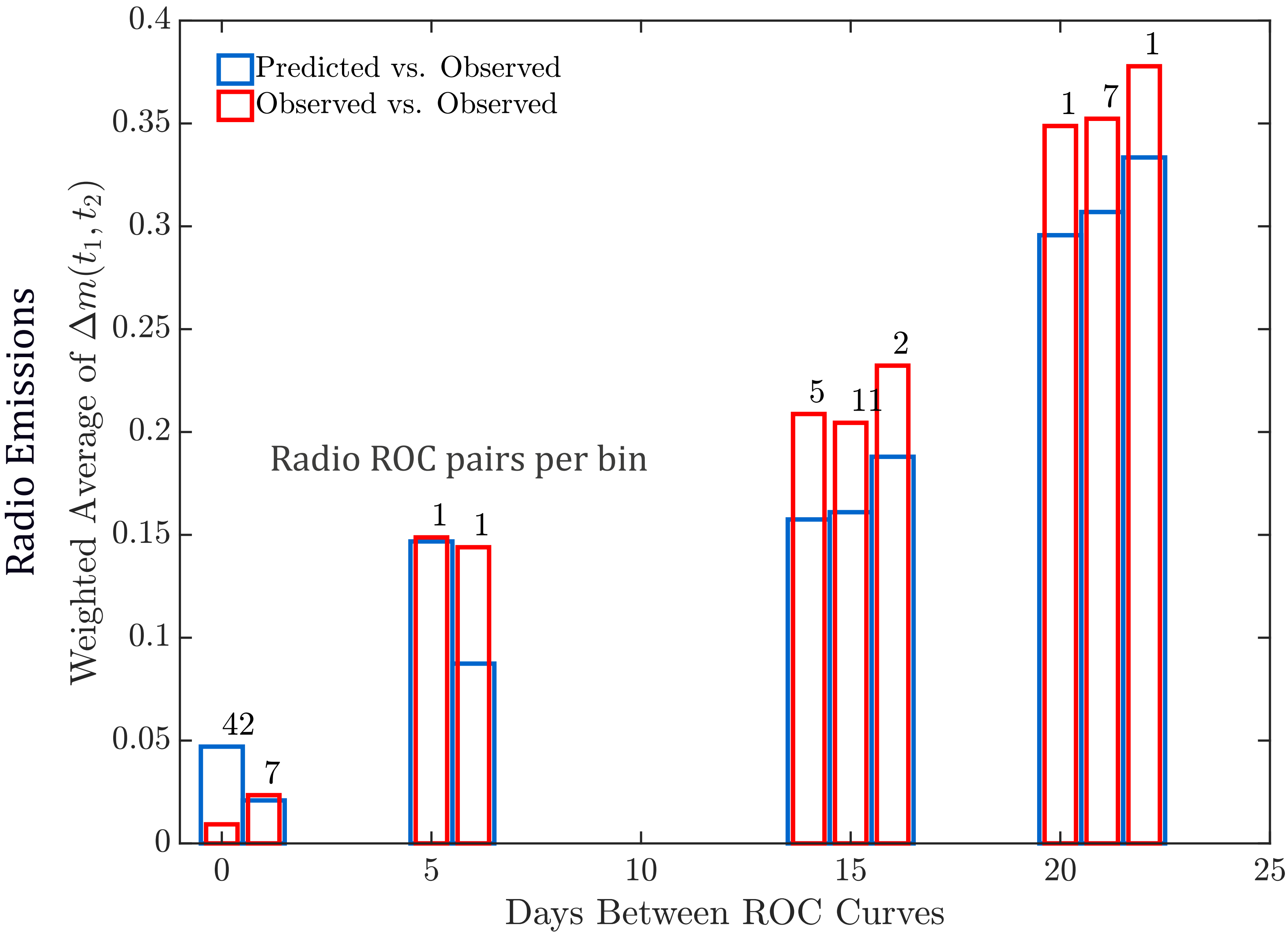
Radio Emissions



Magnitude Difference at Max Range Probability (4/5)



Magnitude Difference at Max Range Probability (5/5)



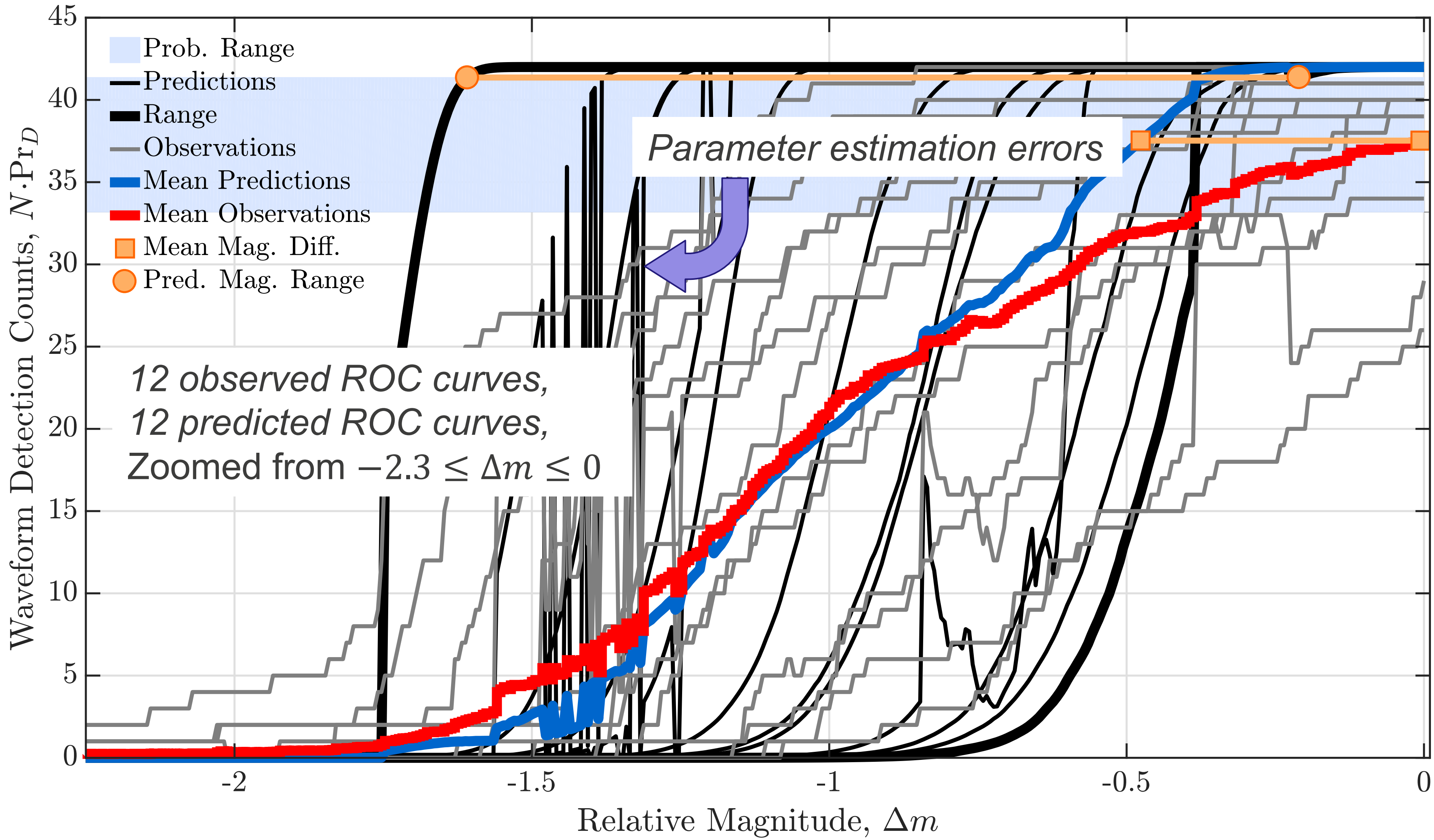
Quantifying the Predictive Capability of an Acoustic Emission, STA/LTA Detector

Estimate Magnitude Differences between Predicted and Observed ROC Curves

Process over 12 Days, $-2.3 \leq \Delta m \leq 0$

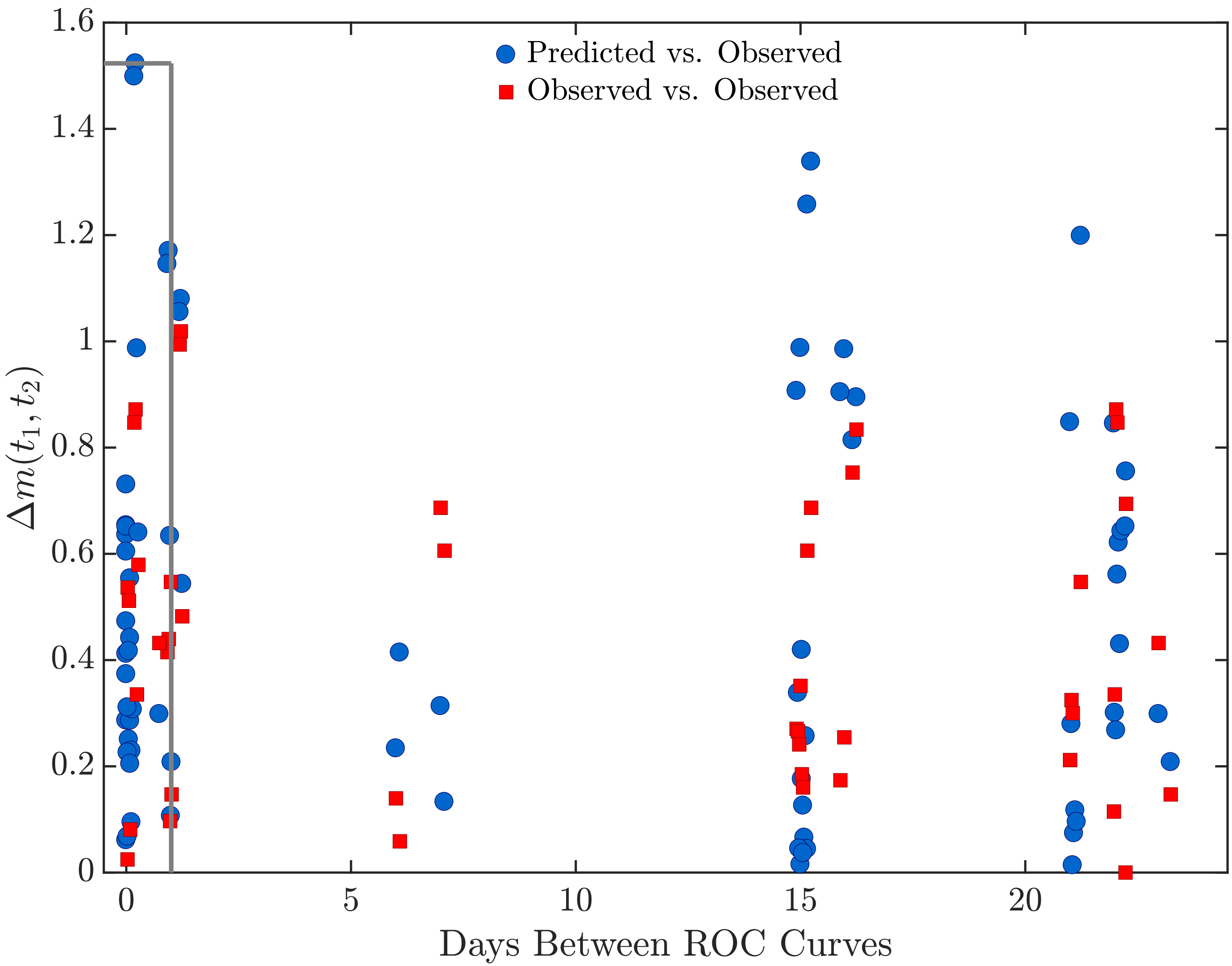
Acoustic Emissions from Explosions

Predicted versus Observed ROC Curves for an STA/LTA Detector

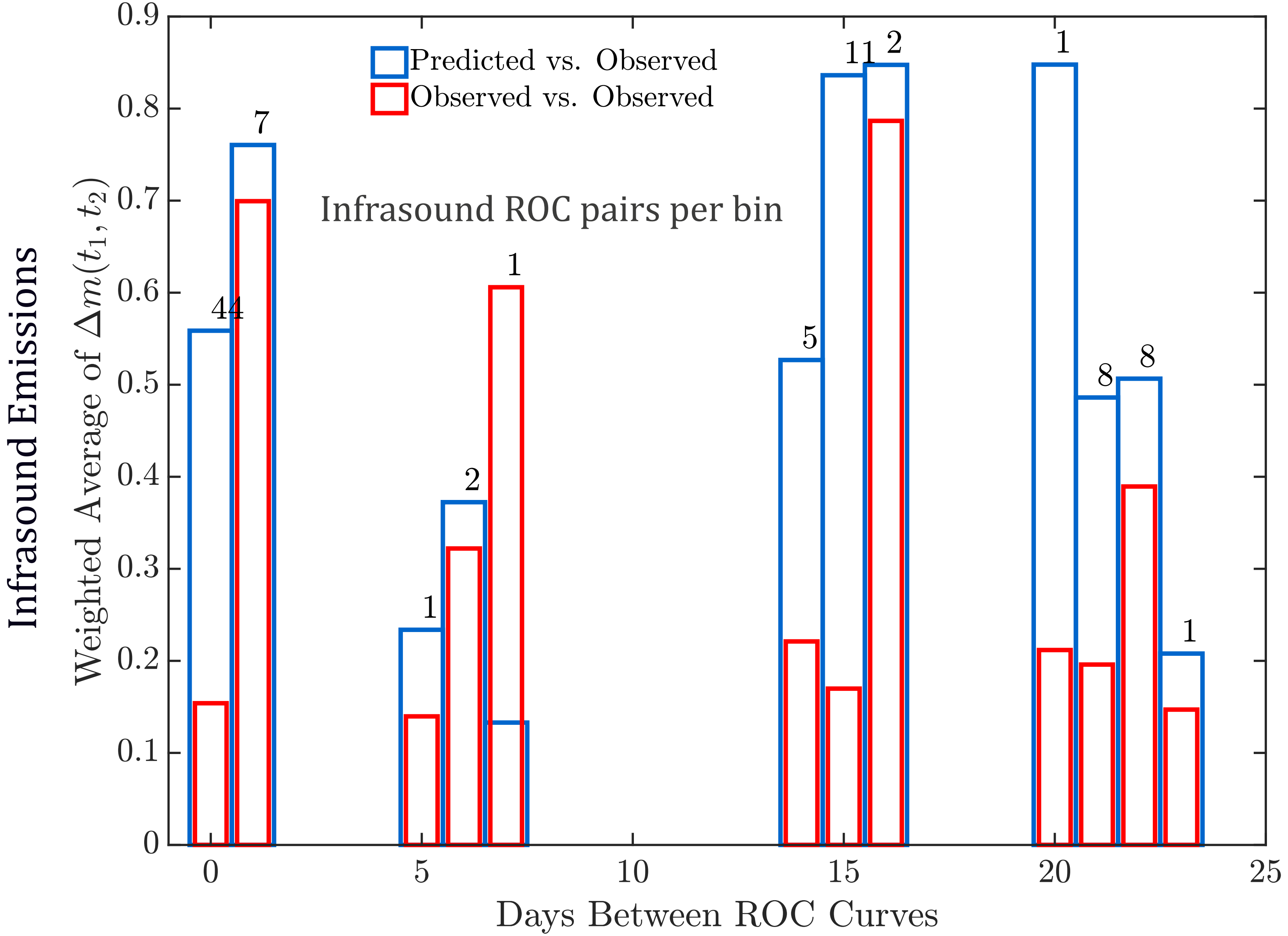


Magnitude Difference at Max Range Probability (1/2)

Acoustic Emissions



Magnitude Difference at Max Range Probability (2/2)



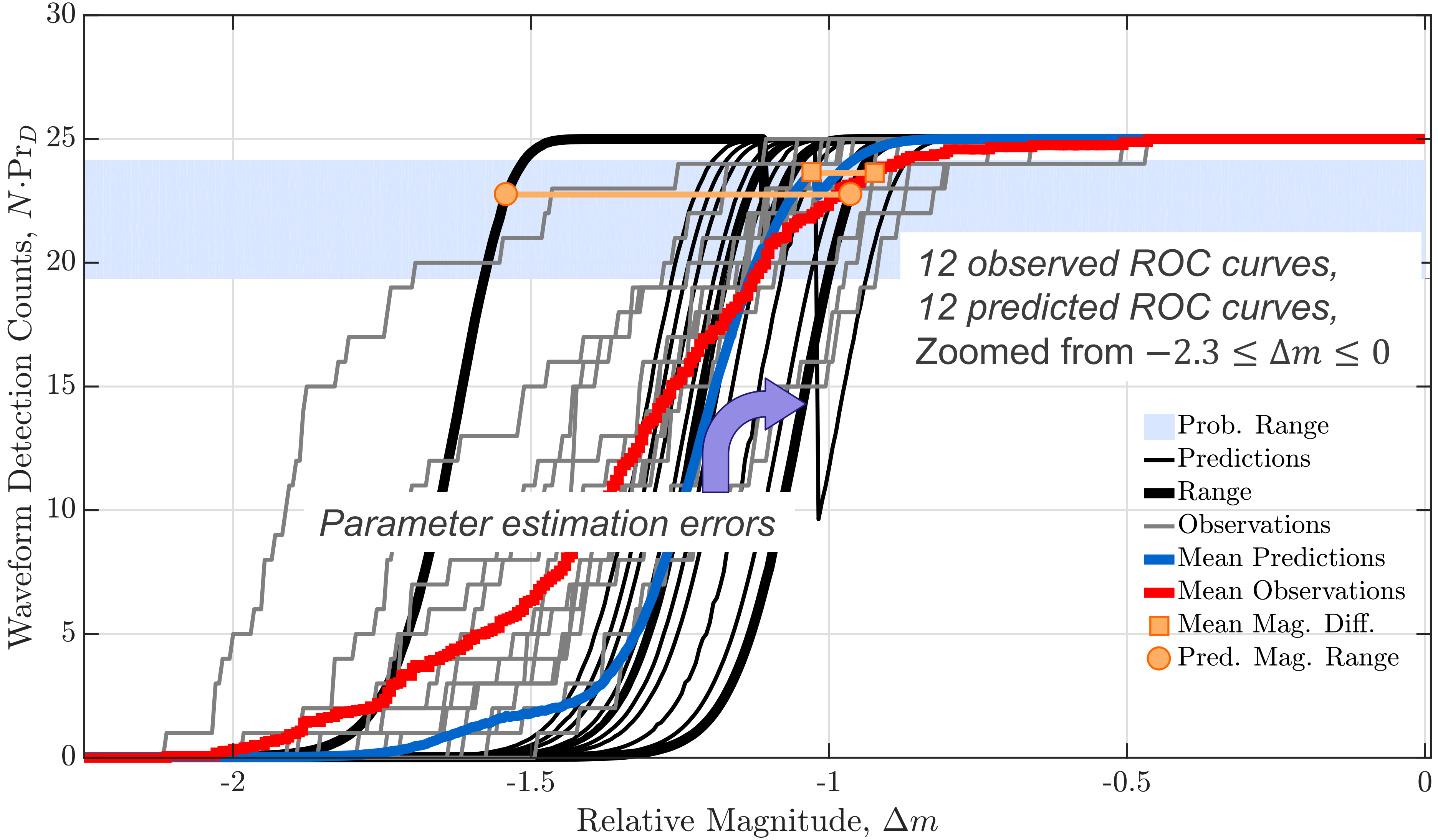
Quantifying the Predictive Capability of an Seismic Emission, Cross-Correlation Detector

Estimate Magnitude Differences between Predicted and Observed ROC Curves

Process over 12 Days, $-2.3 \leq \Delta m \leq 0$

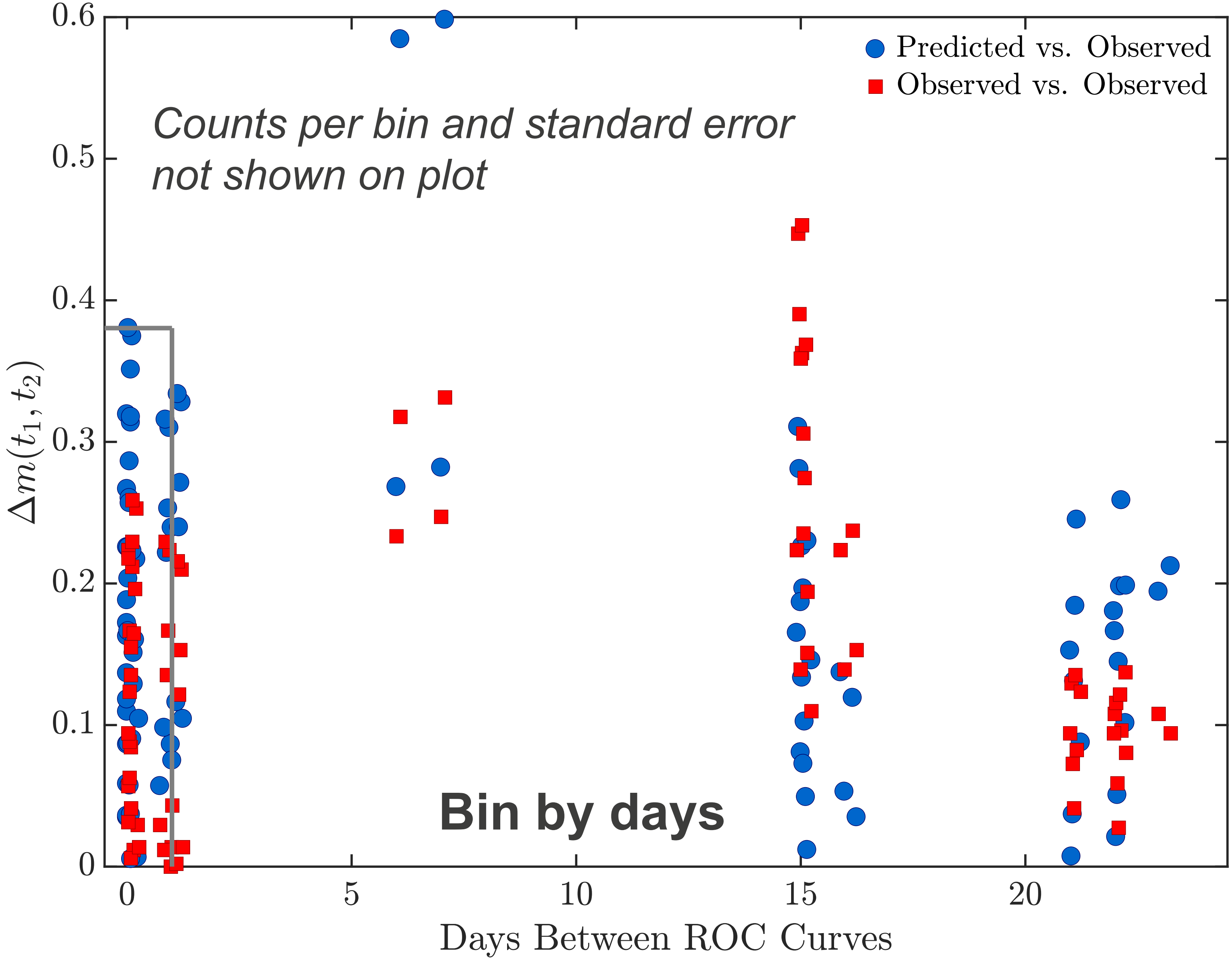
Acoustic Emissions from Explosions

Predicted versus Observed ROC Curves for a Correlation Detector

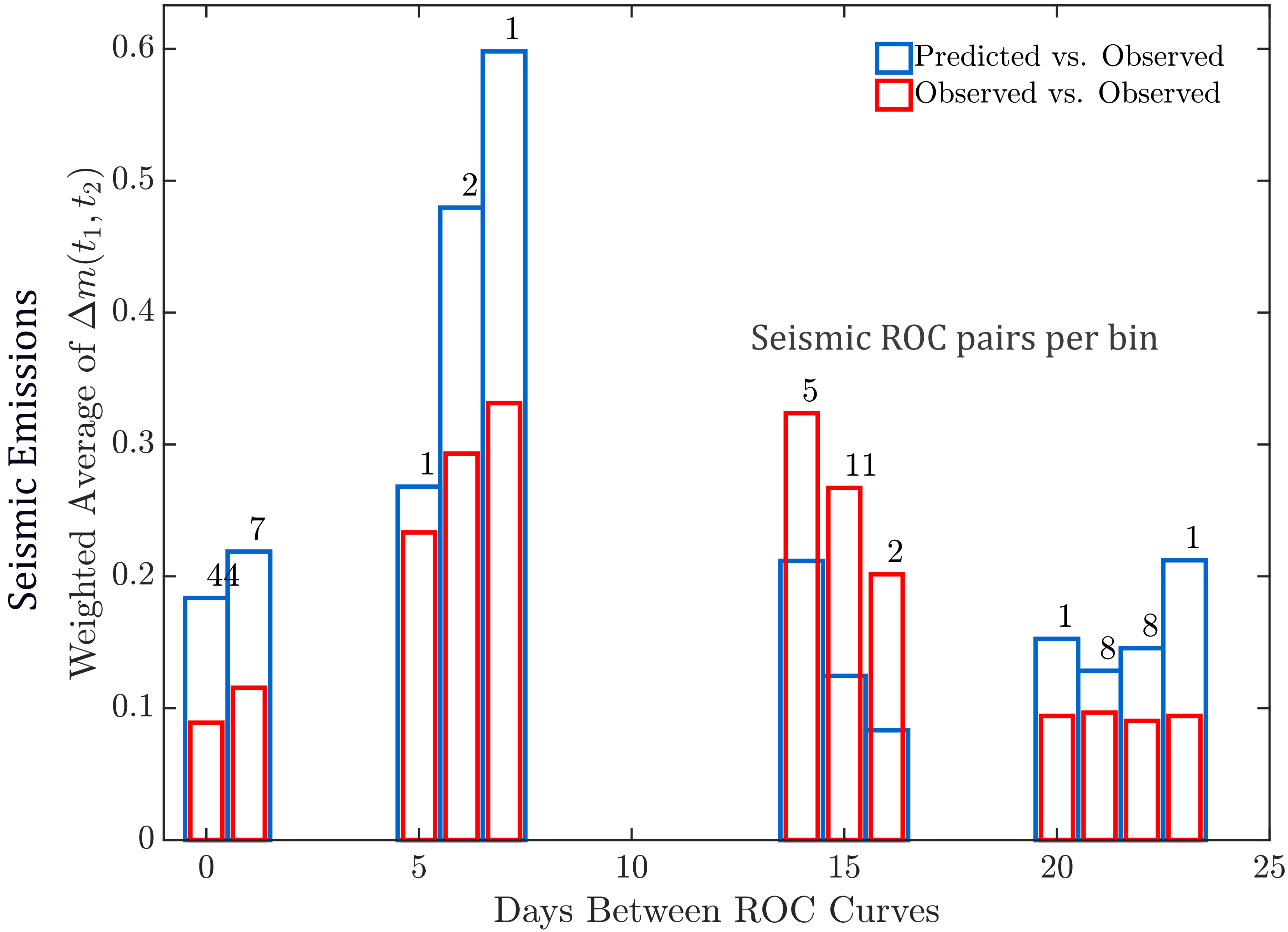


Magnitude Difference at Max Range Probability (1/2)

Seismic Emissions



Magnitude Difference at Max Range Probability (2/2)



Monitoring Challenges

1. Does **mean** predicted detector performance match **mean** observed performance?

2. Does observed versus predicted detector performance exceed day-to-day observed variability? That is, does predicted performance assembled on day $\boldsymbol{A}$ match observations from day $\boldsymbol{A}$ better than observations assembled on day $\boldsymbol{B}$?

3. What is the range in observed versus predicted magnitude discrepancies? That is, if a detector predictively identifies explosions of magnitude m with probability Pr_D, what is the observed, absolute range Δm the detector identifies explosions for probability Pr_D?

Some Solutions

1. SNR, radio detector is *effectively predictive*. STA/LTA acoustic detector is *qualitatively* predictive. Seismic correlation detector observations can *outperform predictions* (**explain!**)

2. Only SNR detector predictions consistently matched observations better than other observations.

3. Magnitude range **best**/**worst** cases, in probability range $0.8 \leq \mathrm{Pr}_D \leq 0.99$
   1. Radio: $\Delta m = 0.025/0.33$
   2. Acoustic: $\Delta m = 0.15/0.85$
   3. Seismic: $\Delta m = 0.10/0.60$

Summary

- ***Objective***: build a multi-signature predictive capability. "Predictive" means that if a hypothetical explosion of an anticipated size/yield occurs, we must quantify how well we can detect, associate, screen, locate, or characterize that source.

- ***Synthesis**:* ROC curves are predictive when averaged over time. However, empirical ROC curves calculated at different times are often as predictive as calculated ROC curves, over 1-12 day periods

Observed versus Theoretical Discrepancy Summary

Radio: $\Delta m = 0.025/0.33$
Acoustic: $\Delta m = 0.15/0.85$
Seismic: $\Delta m = 0.10/0.60$