Comparing RX and SSRX

Selected Topics in Image Processing

Course Project

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Overview

- Project Objectives
- Background
  - Hyper-Spectral Imagery (HSI)
  - Anomaly Detection Algorithms
  - Change Detection Algorithms
- Findings
- Innovation
- Conclusions

Project Objectives

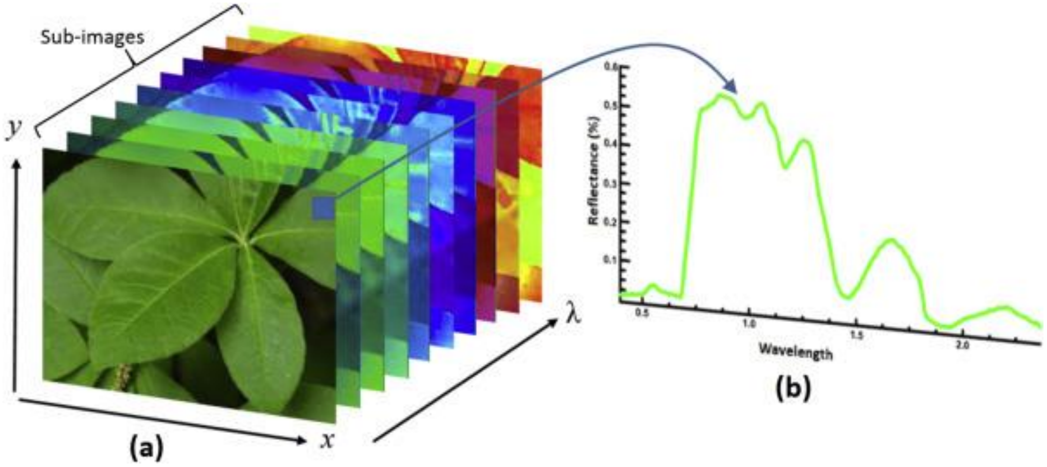
- Implement RX and SSRX algorithms using the RIT dataset.

- Compare the 2 algorithms using:
  - Spatial distributions
  - Scatter plots
  - Varying thresholds

Background

- Hyper-Spectral Imagery
- Anomaly Detection
- Change Detection

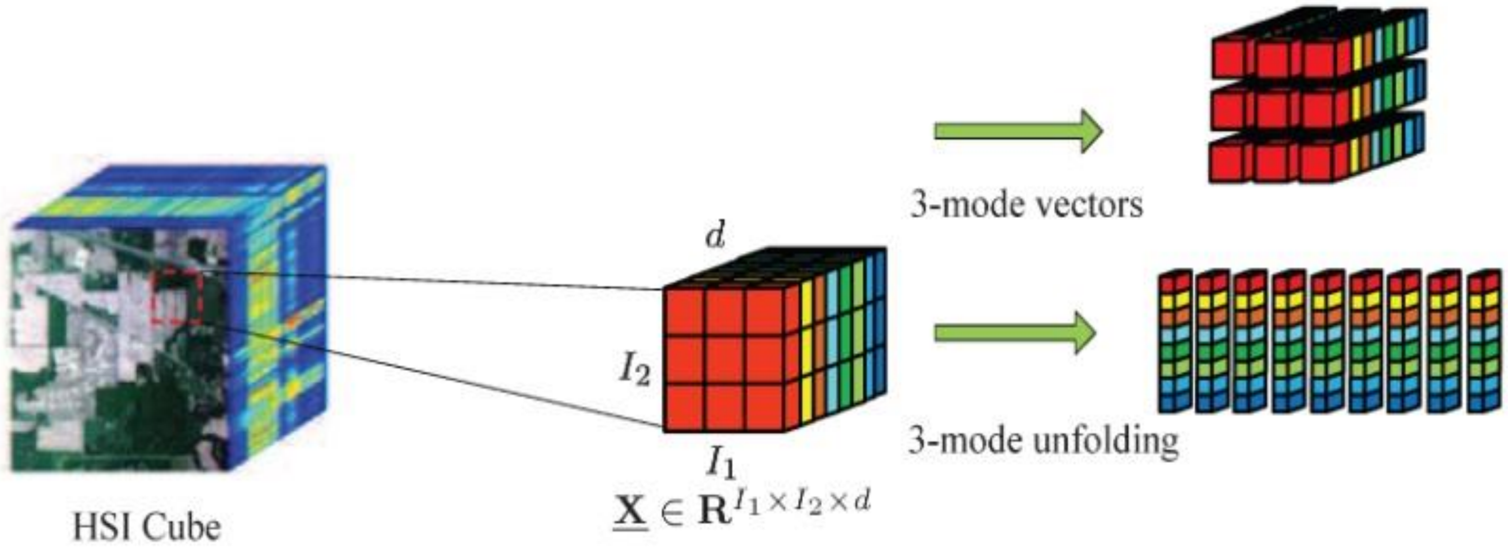
Background #1 – Hyper Spectral Images



- RGB channels -> 100+ channels
- Scalar pixel -> spectral signature

- Why HSI?
  - More data = more information (almost true)
  - Easy to identify different materials

Background #1 – Hyper Spectral Images



- 3D Representation
  - First 2 dimensions are spatial (geographic location)
  - Third dimension is spectral (wavelength)
- 2D Representation
  - Rows are random variables
  - Columns are observations
  - **Random Vector**

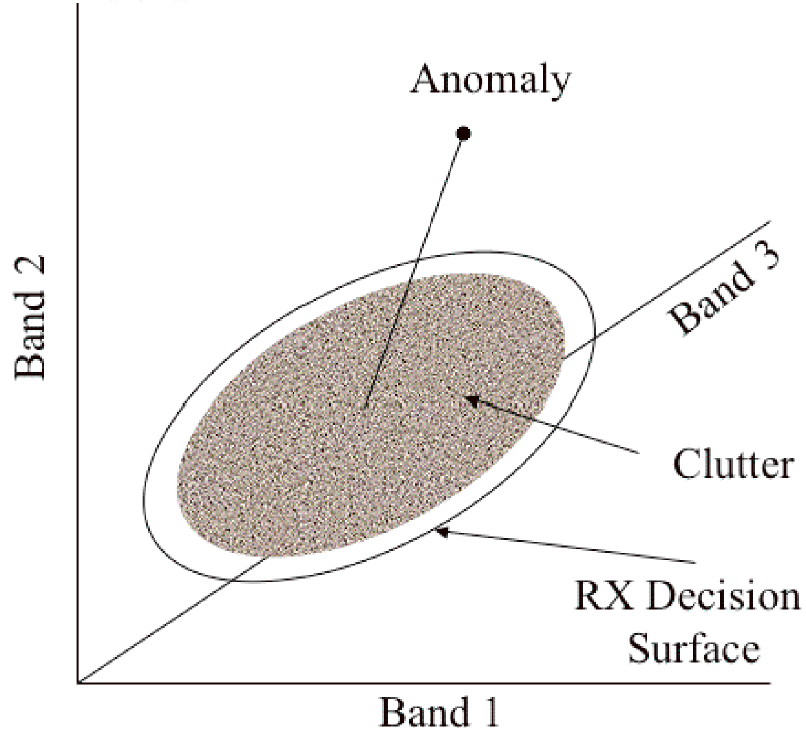
Background #2 – Anomaly Detection (RX)

- Problem Model:

$$H_0: \quad X = Bb + n$$
$$H_1: \quad X = Tt + n$$

- H_0 almost always true. How can we find H_1?
- No prior knowledge: span(T) can be entire spectral space.

Background #2 – Anomaly Detection (RX)



- Assumption: Anomalies are uniformly distributed
    - span(T) can be entire spectral space.
- Mahalanobis distance

$$RX: \ (x-m)^T \phi_X^{-1} (x-m) > \eta$$

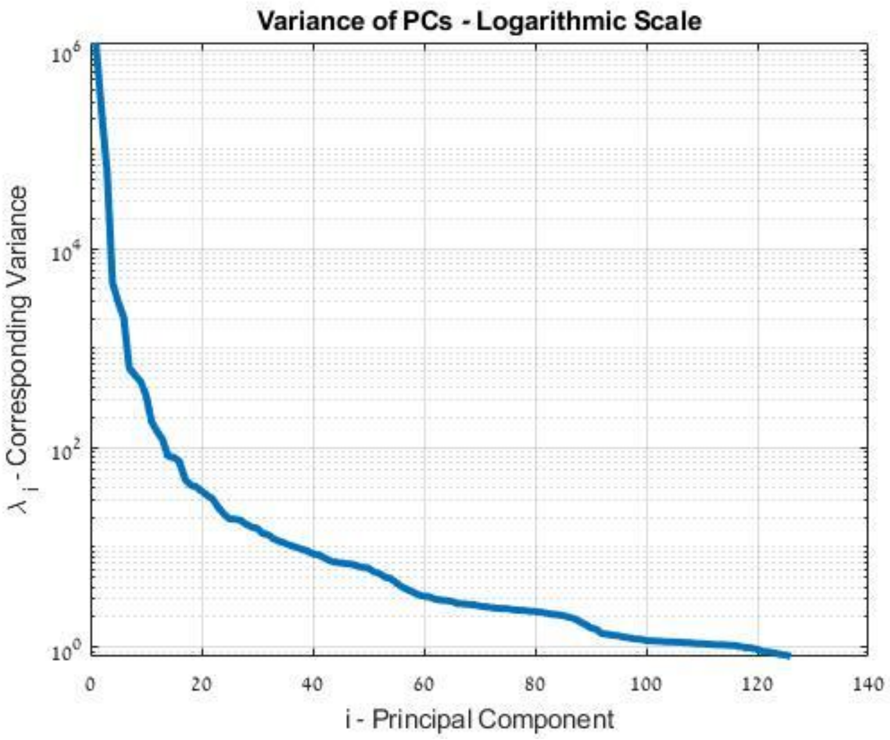
x – tested pixel

m – local estimation of x using neighbor pixels

ϕ_x – Covariance matrix (the best matrix in the world)

η – detection threshold (good starting guess: 3 sigma rule)

Background #2 – SSRX Motivation



- 6 orders of magnitude between biggest and smallest eigenvalue
- Where does most of the variance originate? Background

RX prioritizes the background!!

Background #2 – Anomaly Detection (SSRX)

- <u>Assumption</u>: Anomalies are no longer uniformly distributed!
- Principal Component Analysis (PCA)

$$\phi_x = V^T \Lambda V = [V_1 \cdots V_N]^T \begin{bmatrix} \lambda_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_N \end{bmatrix} [V_1 \cdots V_N], \qquad \lambda_1 > \lambda_2 > \cdots > \lambda_N$$

$$\widetilde{V_q} = \left[V_1 \cdots V_{N-q}\right]^T$$

$$Subspace\ Projection:\ \tilde{X} = \widetilde{V_q}^T \phi_X^{-1}(X - \mu_X)$$

Background #2 – Anomaly Detection (SSRX)

- Run RX on the projected data:

$$Subspace\ RX\ (SSRX):\ (\tilde{x}-m)^T \phi_{\tilde{x}}^{-1} (\tilde{x}-m) > \eta$$

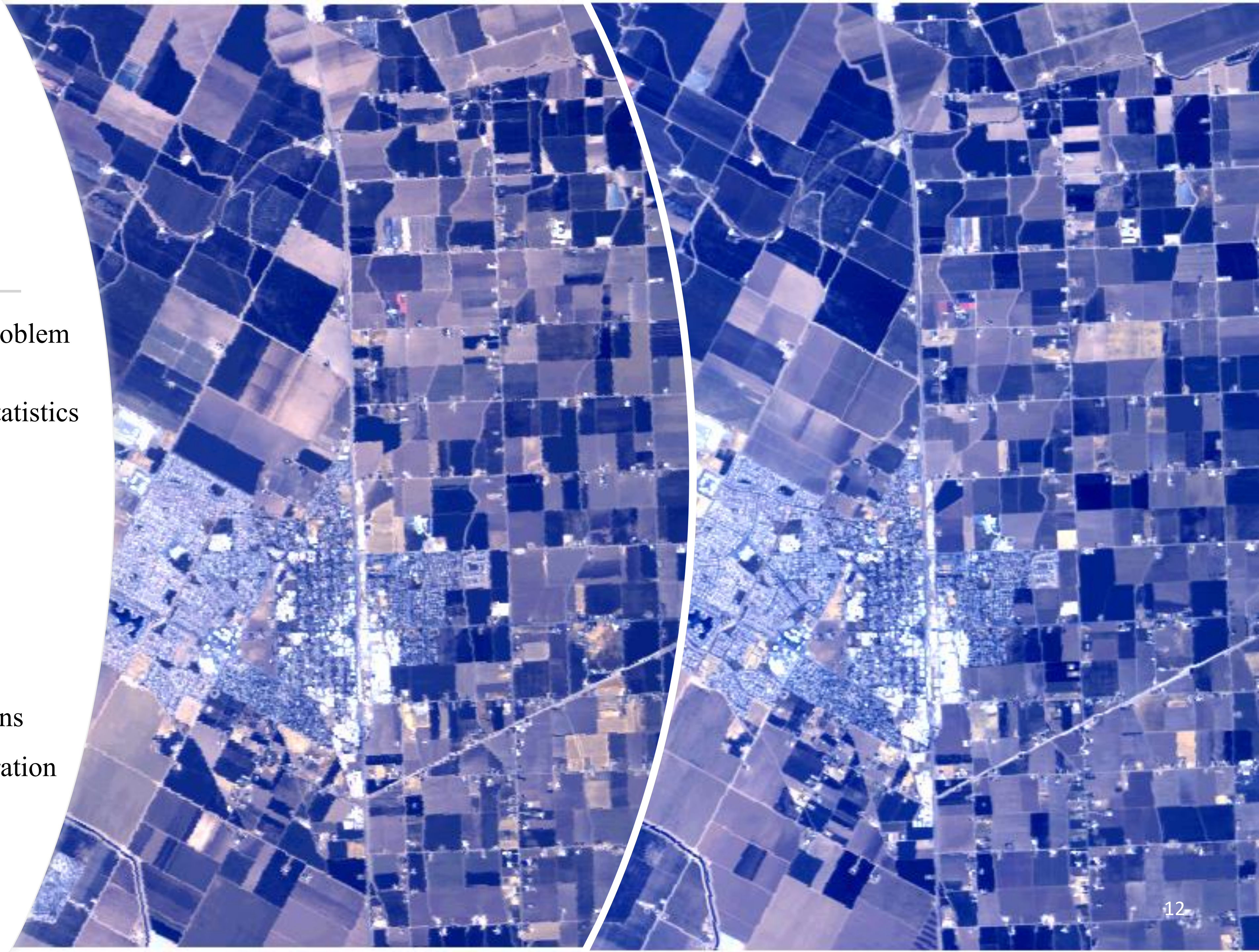
- Results of SSRX change according to the number of dropped PCs – q

Background #3 – Change Detection

- Unique anomaly detection problem

- Input: 2 images + 2nd order statistics
- Output: anomalous changes between the 2 imagtes

- Challenges:
  - Different time of day/month/year
  - Different light reflections
  - Imperfect image registration



Background #3 – Change Detection

- Estimate Y from X and the cross-covariance matrix ϕ_{XY}:

$$\tilde{Y} = \phi_{XY}\phi_X^{-1}X$$

- Calculate estimation error

$$\varepsilon = \tilde{Y} - Y$$

- Run the RX algorithm on the estimation error:

$$Chronochrome\ (CC): \quad (\varepsilon - m)^T \phi_\varepsilon^{-1}(\varepsilon - m) > \eta$$

$$Subspace\ Chronochrome\ (SSCC): (\varepsilon_{PCA} - m_{PCA})^T \phi_{\varepsilon_{PCA}}^{-1}(\varepsilon_{PCA} - m_{PCA}) > \eta$$

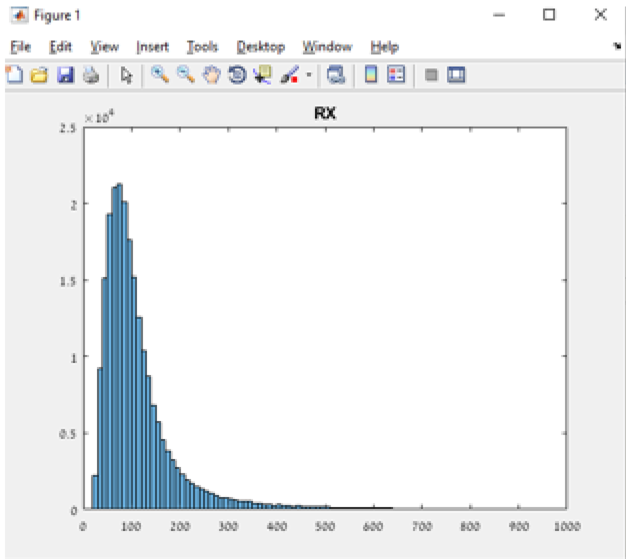
Methodology

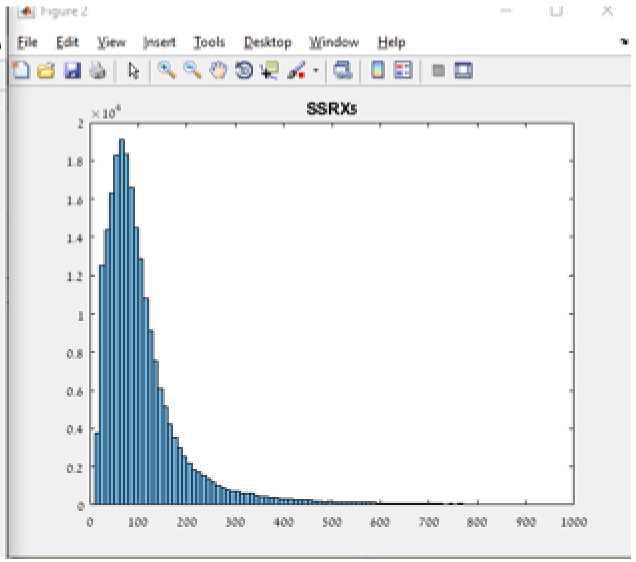
- Datasets
- Parameters

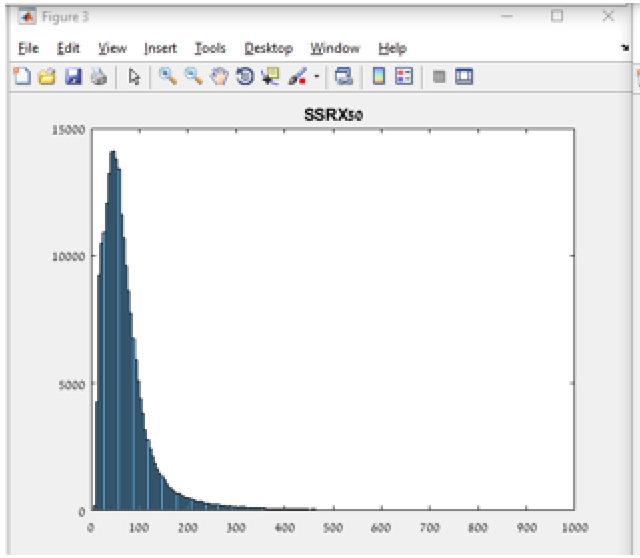
Methodology

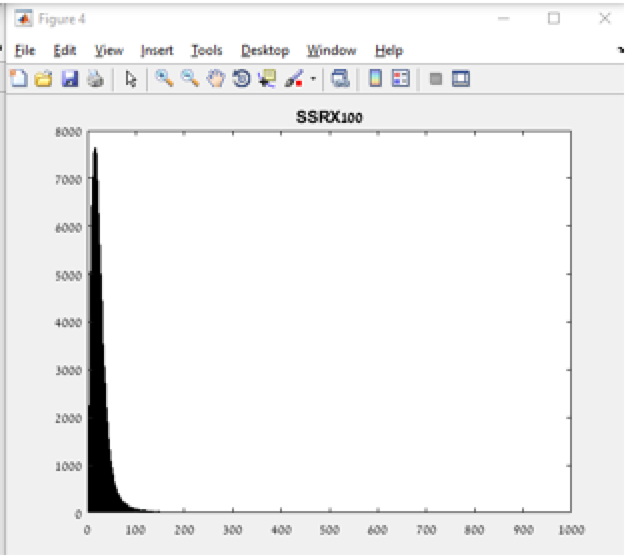
- Dataset: RIT Blind Test (800 x 200 x 126 cube, Cooke City Montana)
- MATLAB Implementation:
  - RX
  - SSRX with $q\epsilon\{2,5, 10, 20, 50, 75, 100, 120\}$
  - SSRX dropping low-variance PCs $q\epsilon\{5, 20,50,75, 100\}$
  - Thresholding using the 3-sigma rule and later custom values per algorithm

Nice Sanity Check
Mean Value is the Number of Channels





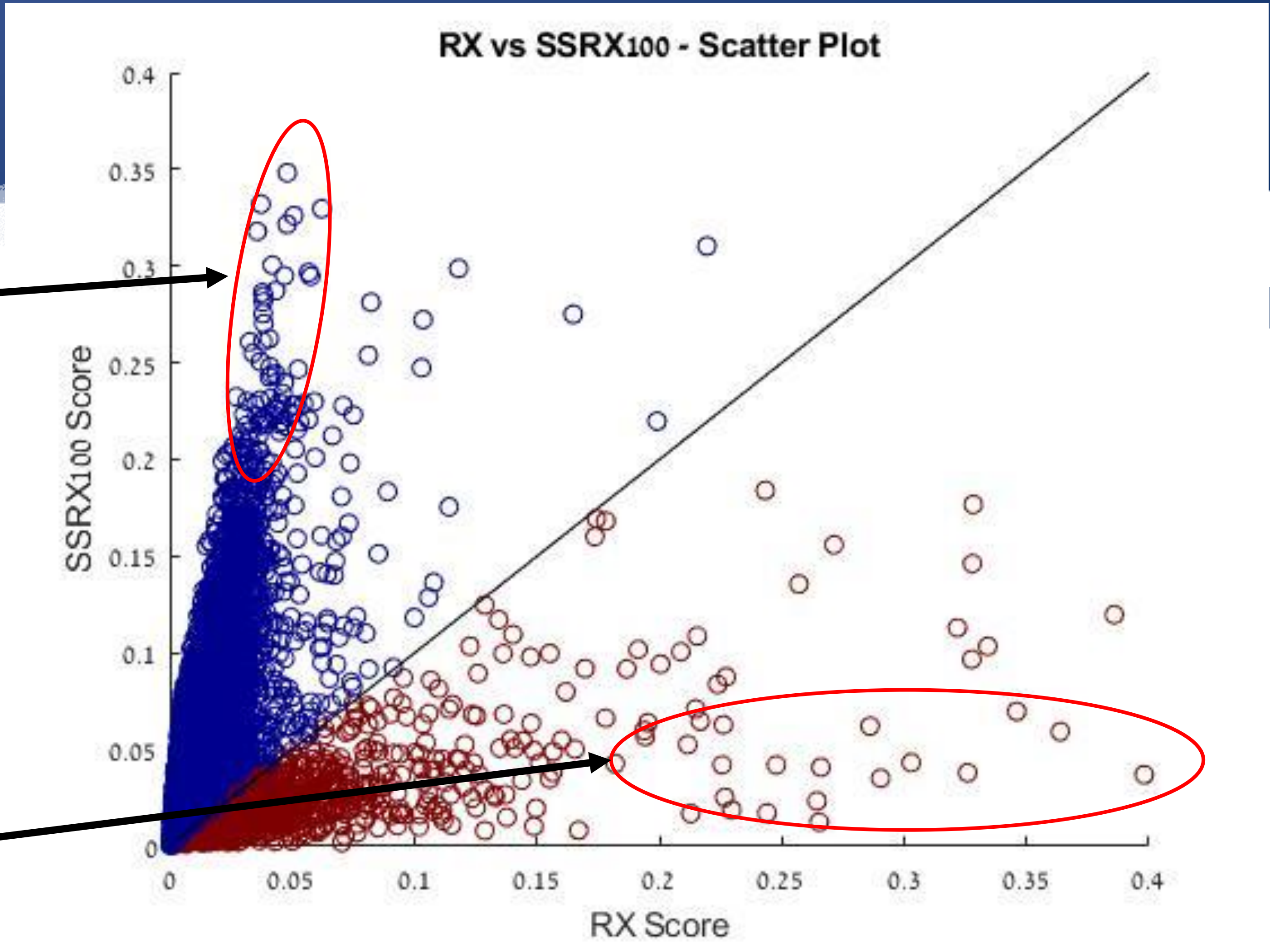




Scatter Plots 101

- Only SSRX detected

- Only RX detected

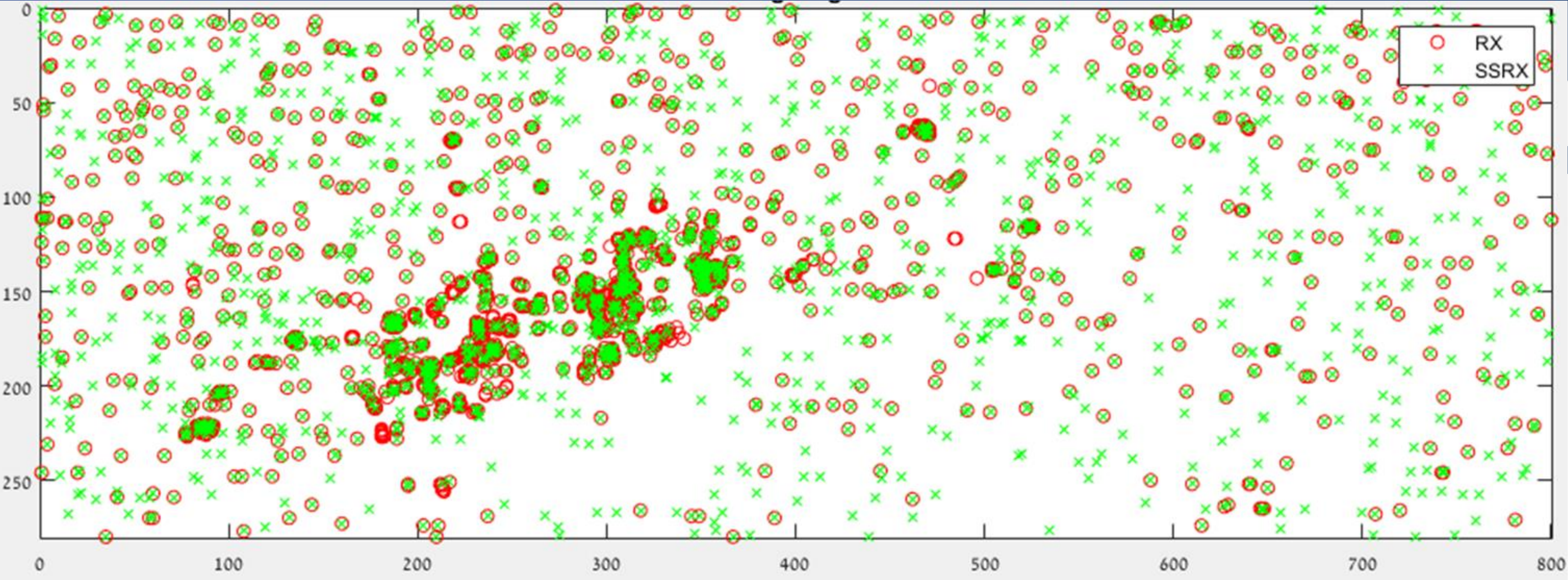


Findings

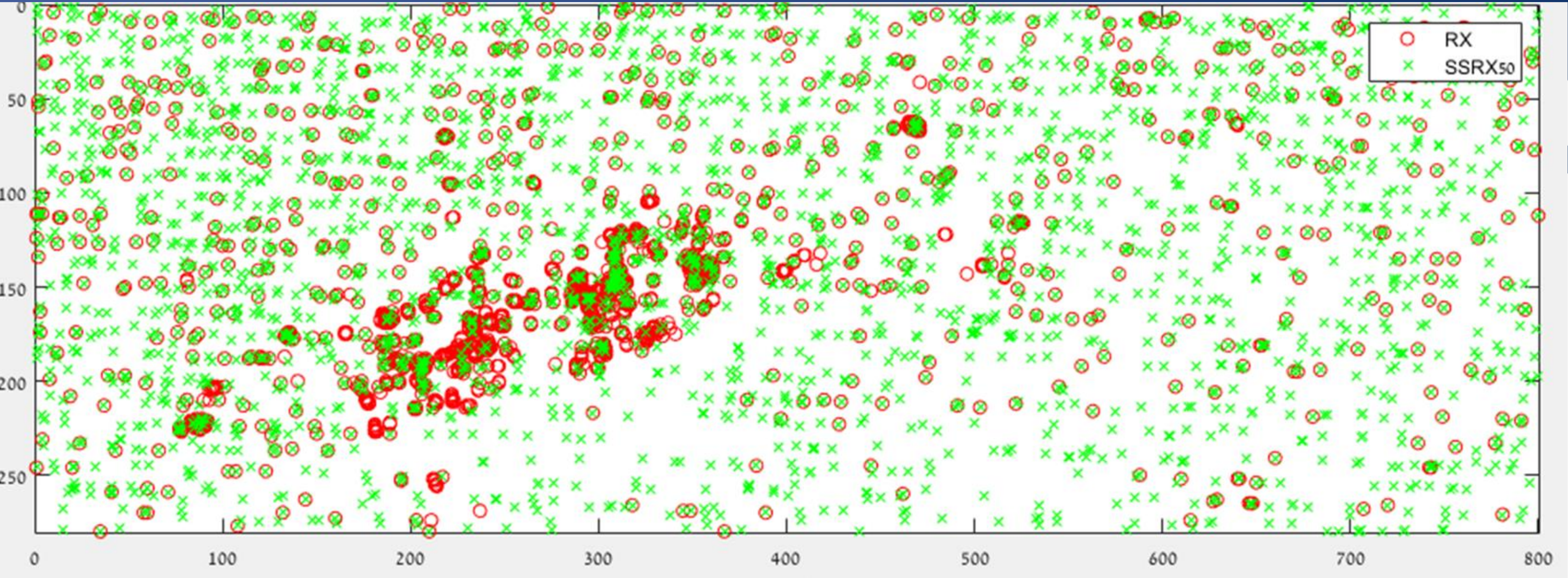
- Top Anomalies
- SSRX q Parameter
- Correlation
- Noisy Anomalies

Top Anomalies Persist In Both Algorithms

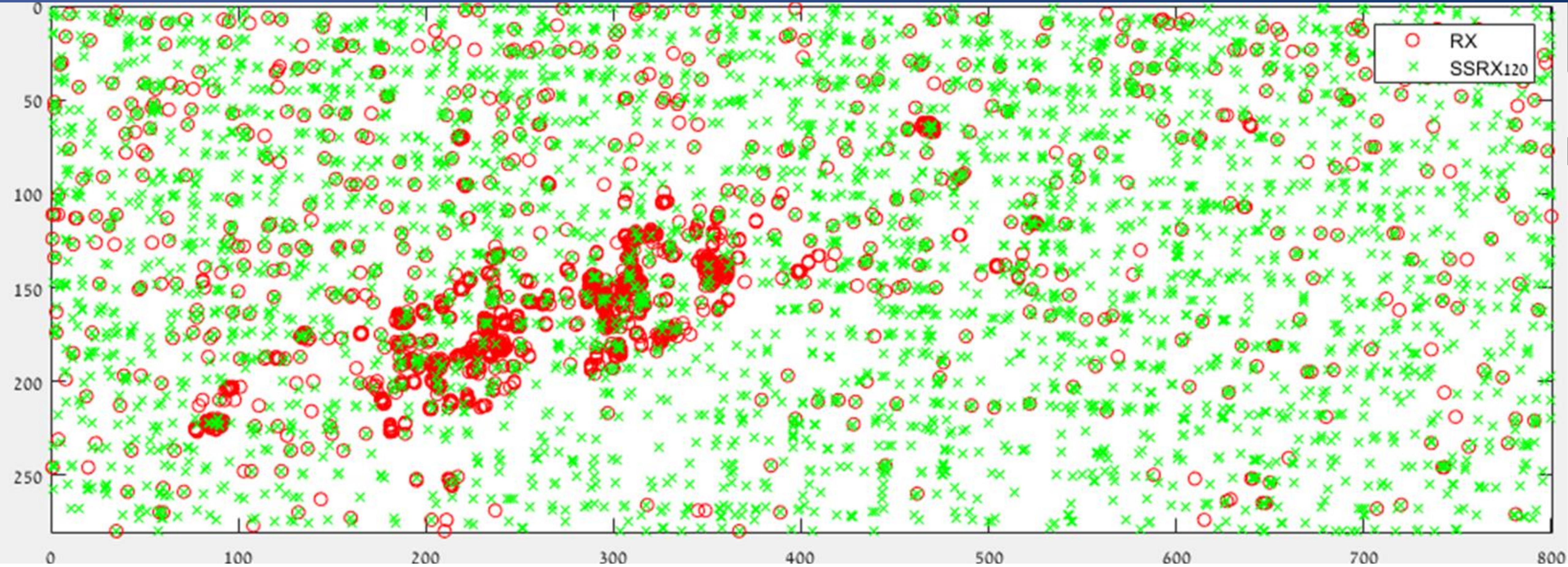
Increasing q -> Increased Noise (q=5)



Increasing q -> Increased Noise (q=50)

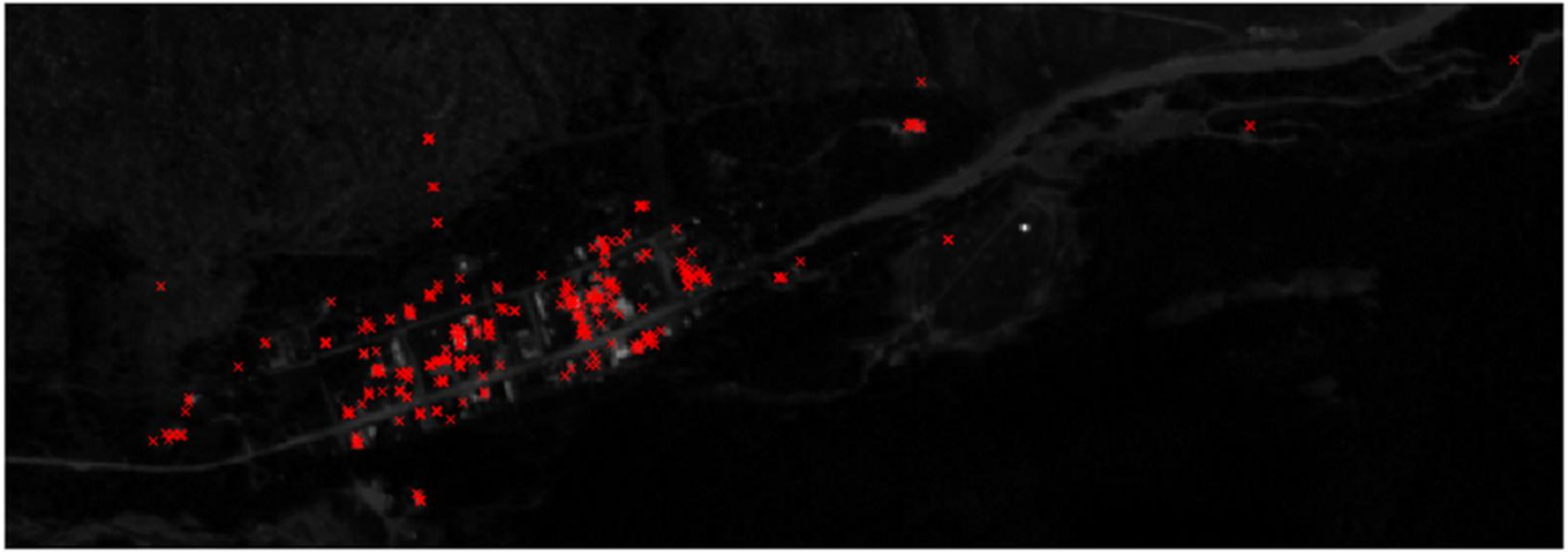


Increasing q -> Increased Noise (q=120)



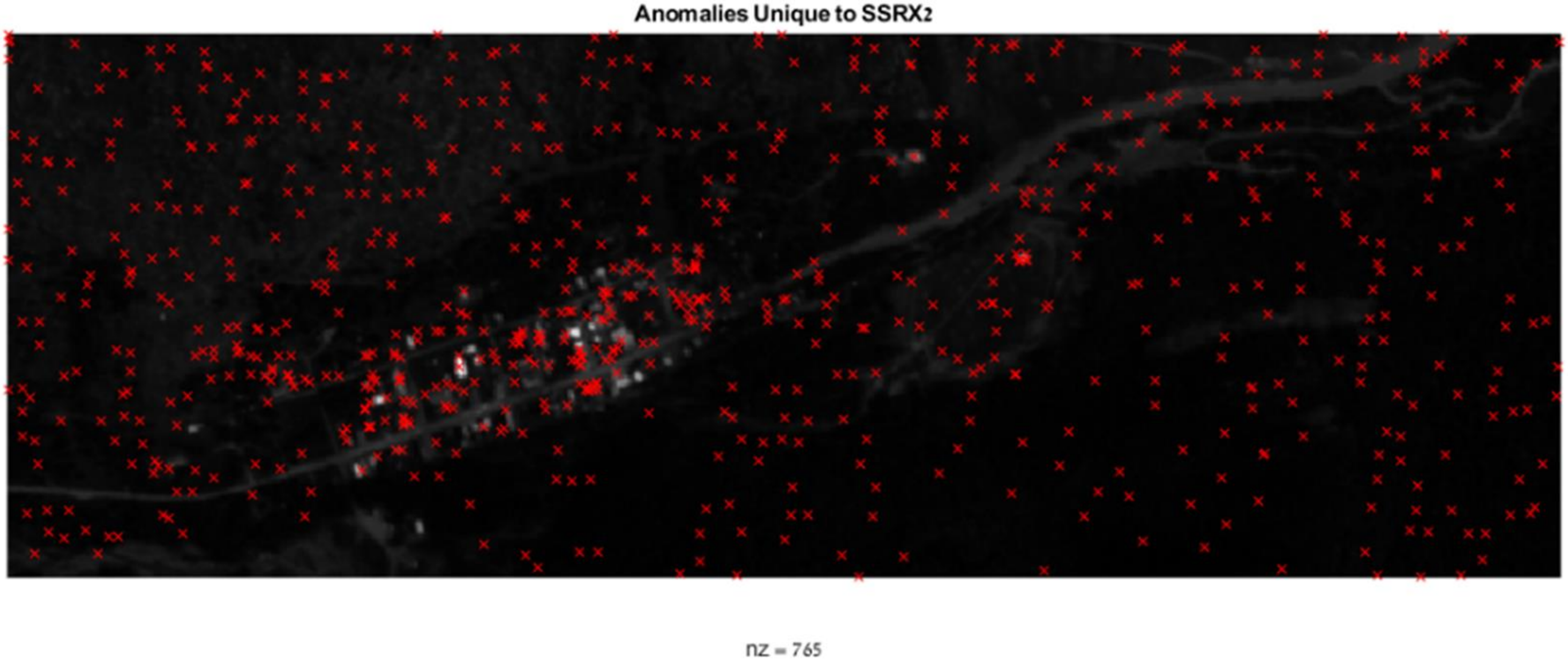
So What's The Difference? (Only RX)

Anomalies Missed by SSRX2

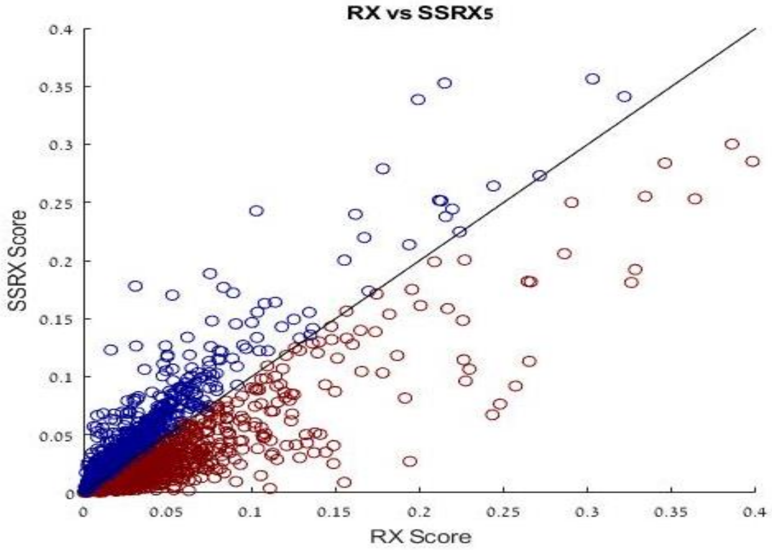


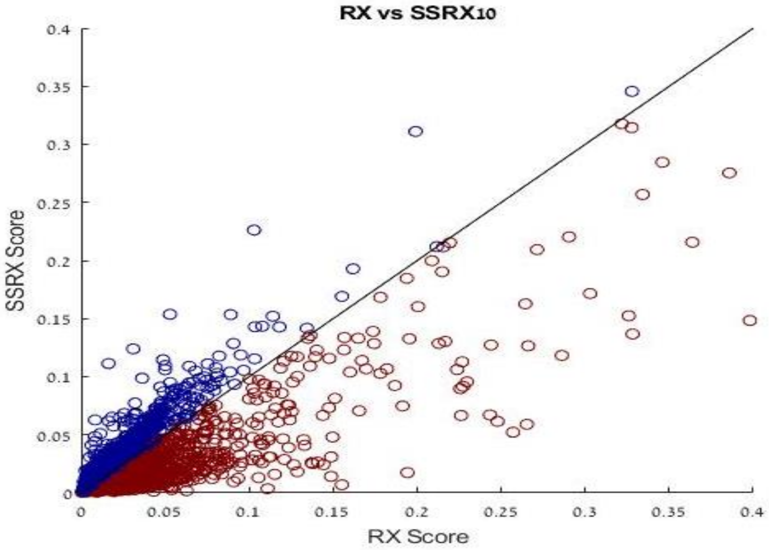
nz = 320

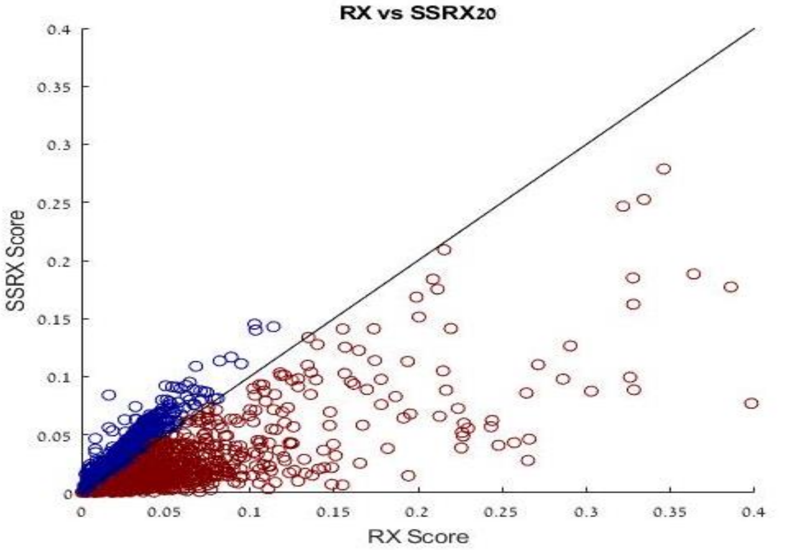
So What's The Difference?(Only SSRX)

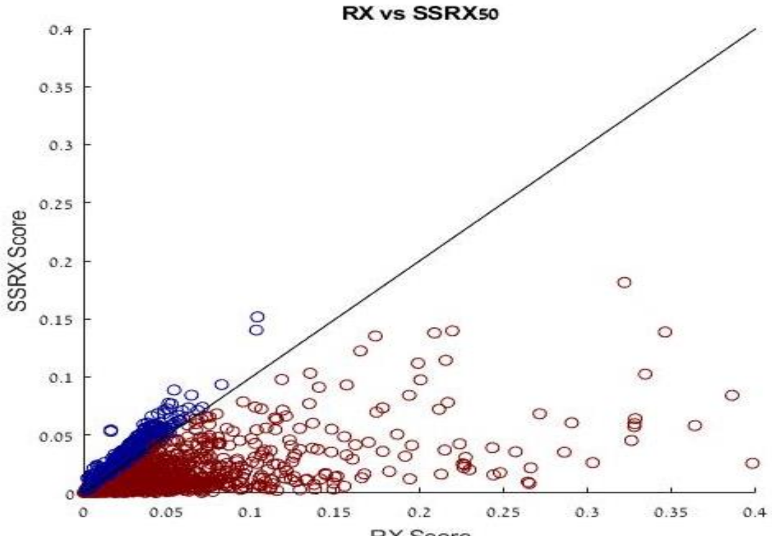


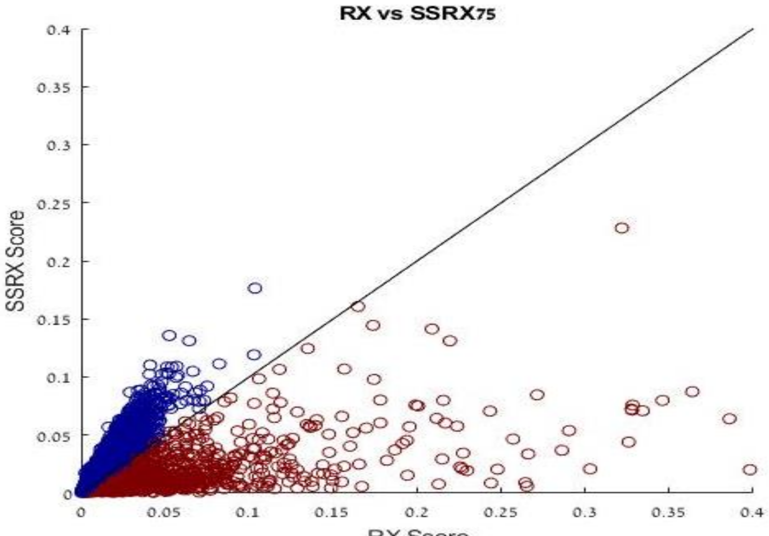
Scatter Plots – Correlation drops with PCs

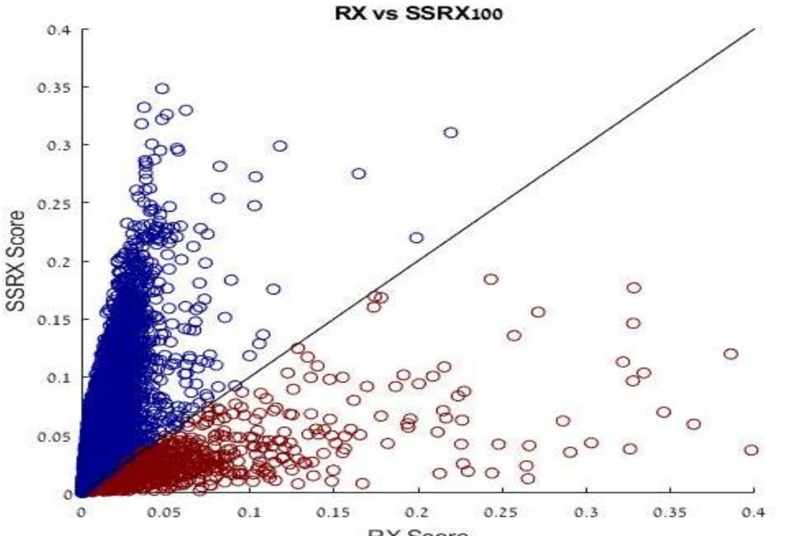




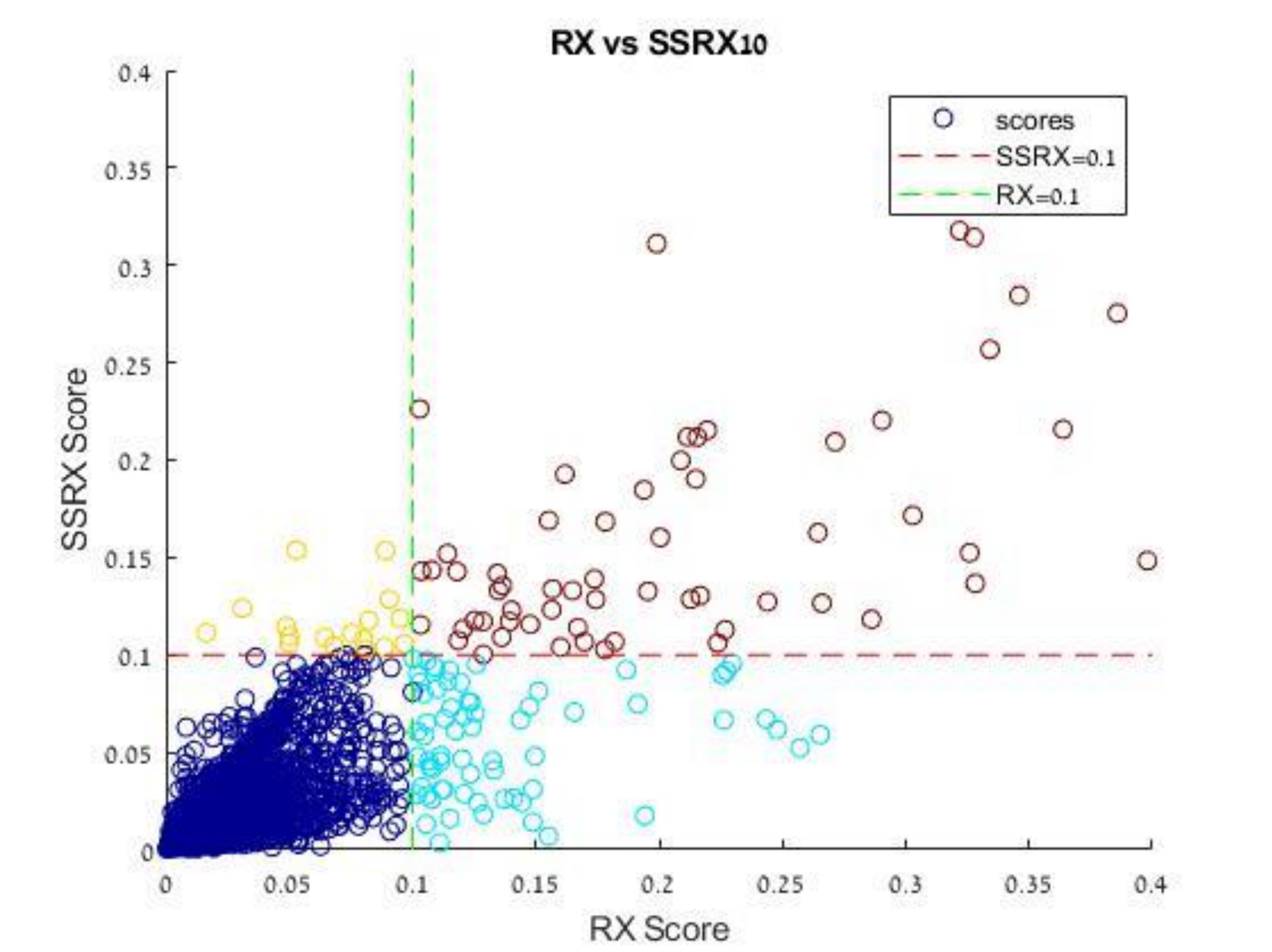








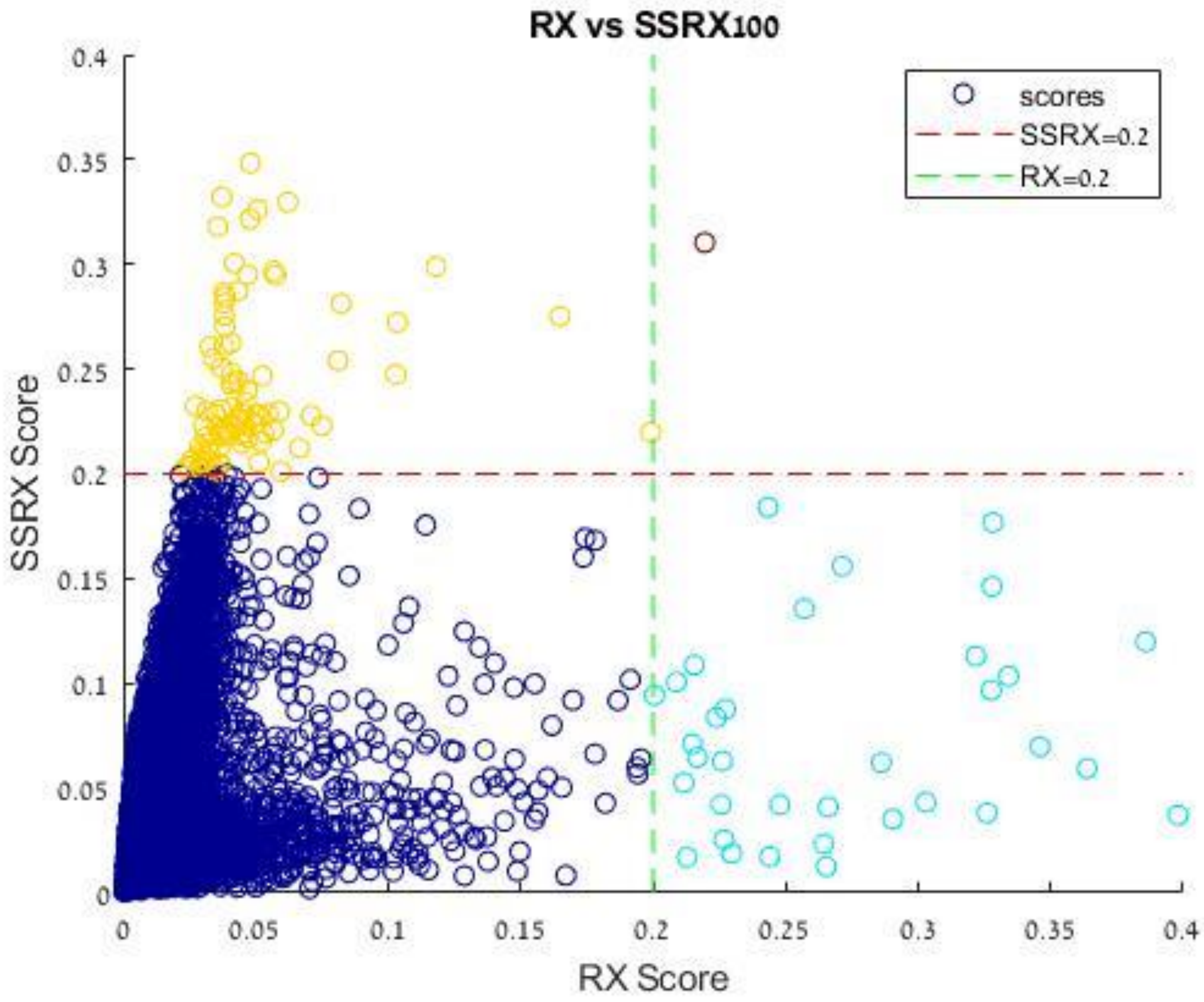
RX vs SSRX10 In-Depth

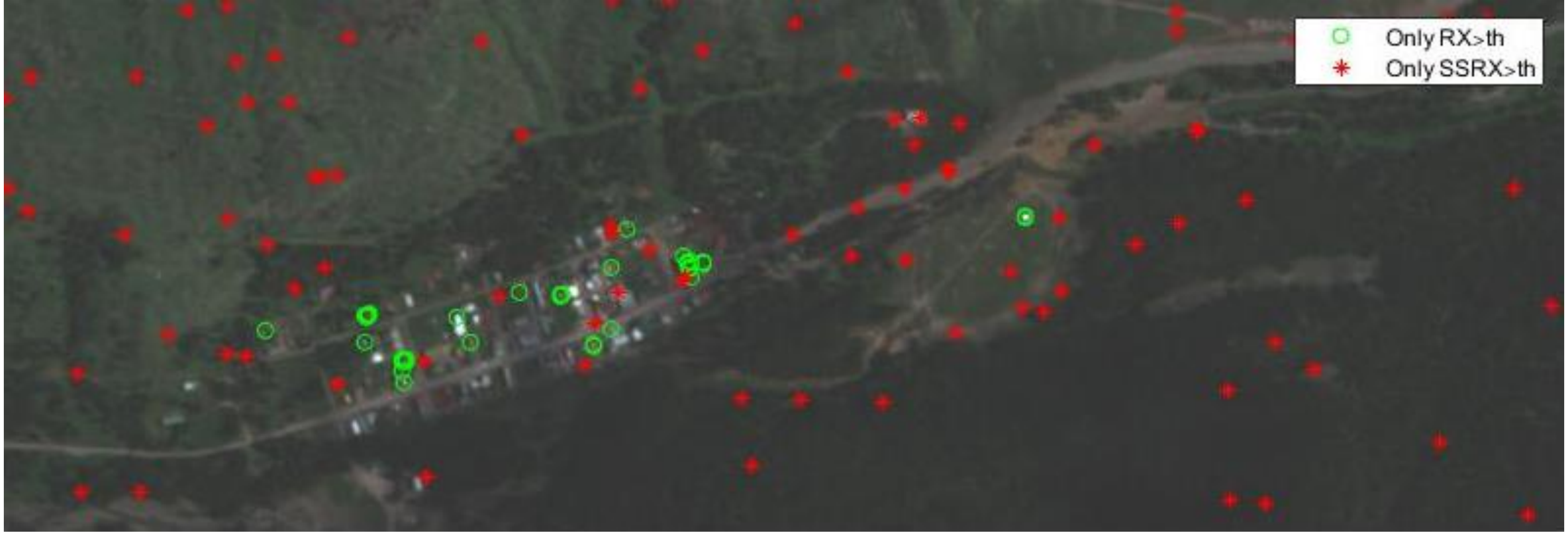



Only RX>th
Only SSRX>th

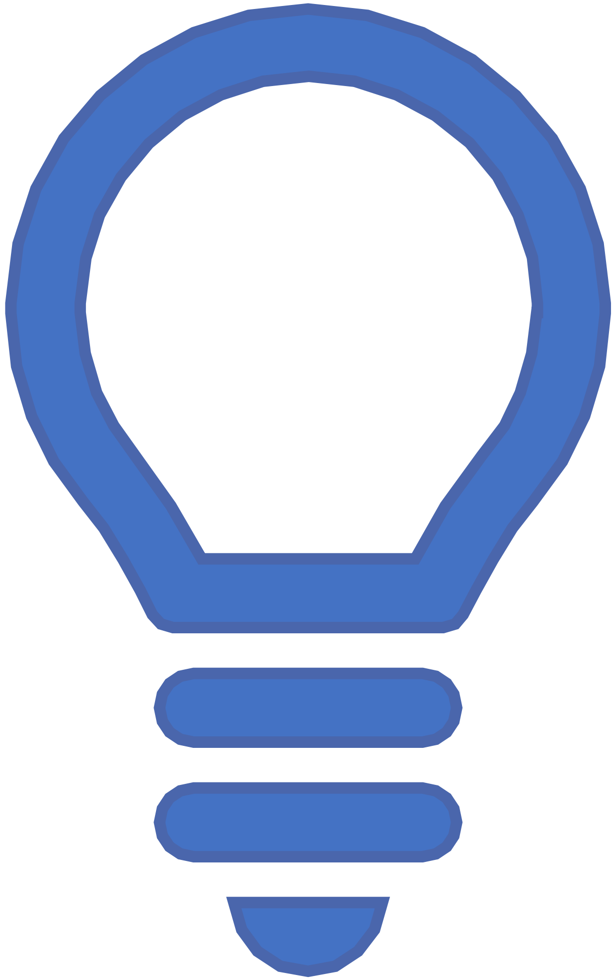

Both>th

RX vs SSRX100 In-Depth




Only RX>th
Only SSRX>th


Both>th



Innovation

Subspace Chronochrome Change Detection

Methodology

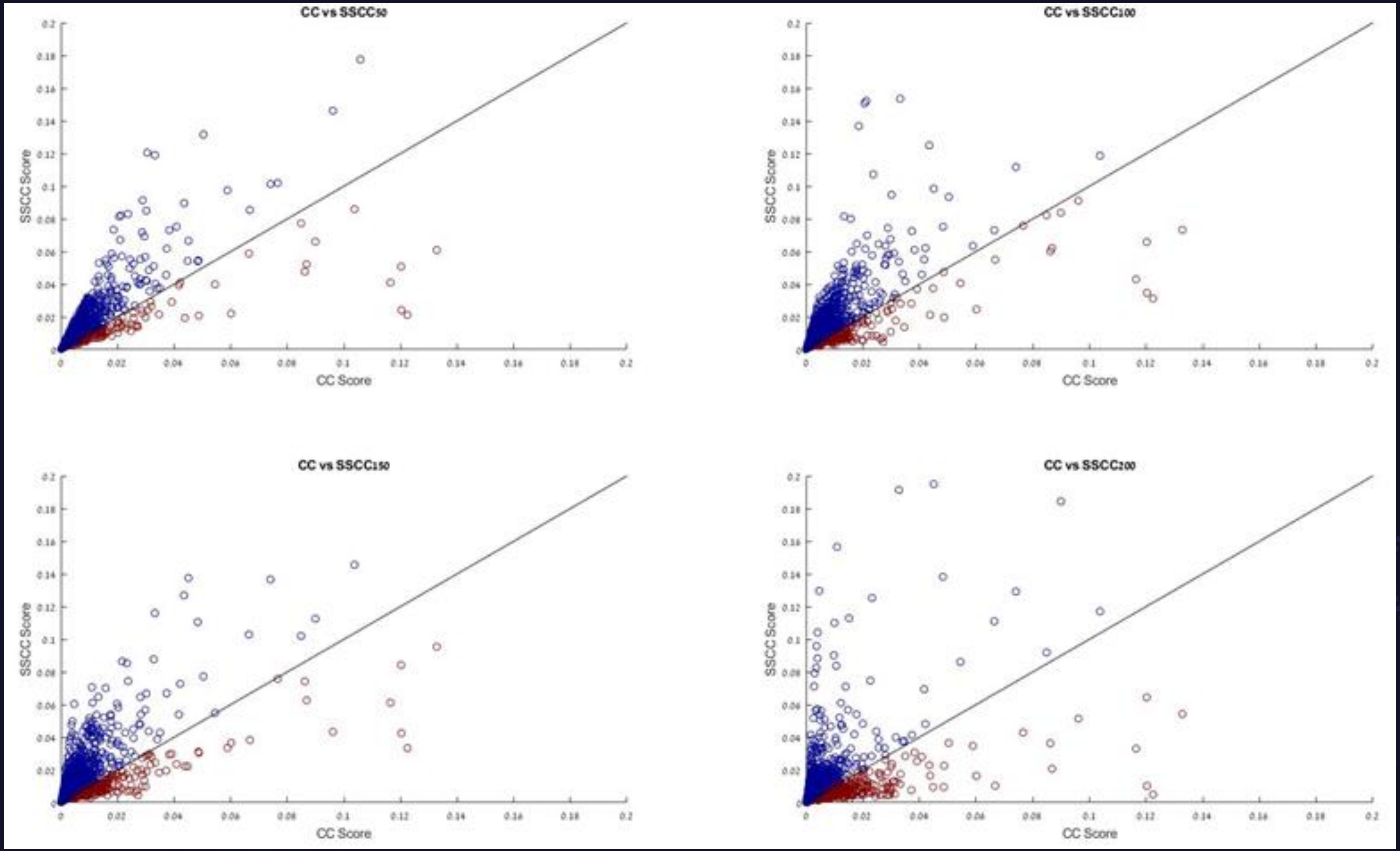
- Dataset: CITIUS Hyperspectral Change Detection
  - 600x500x224 cube, Patterson California

- MATLAB Implementation:
  - CC
  - SSCC with $q \epsilon \{50, 100, 150, 200\}$

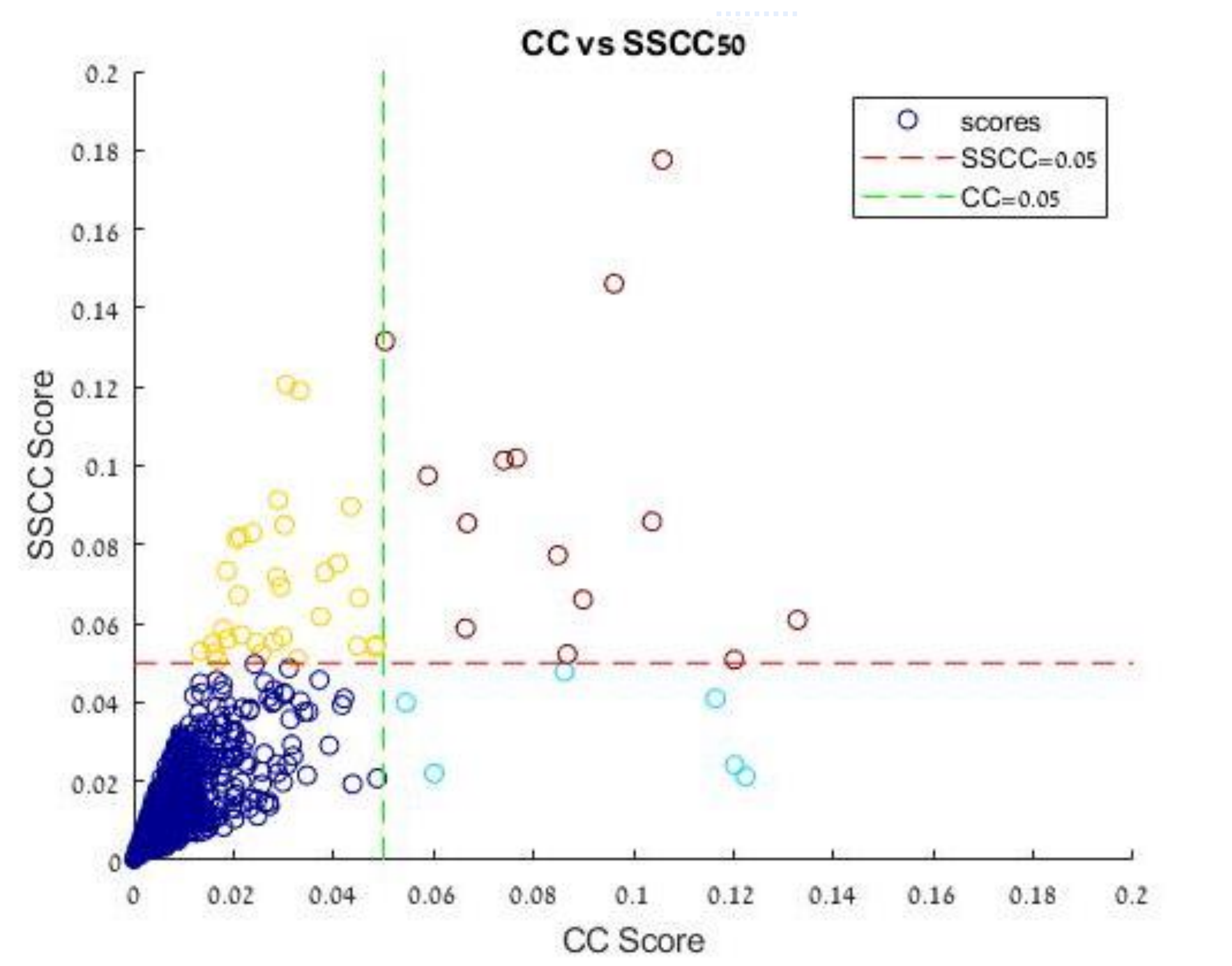
- Repeat the RX vs SSRX comparison using CC and SSCC

This is where subspace projection really shines!

Correlation drops with PCs

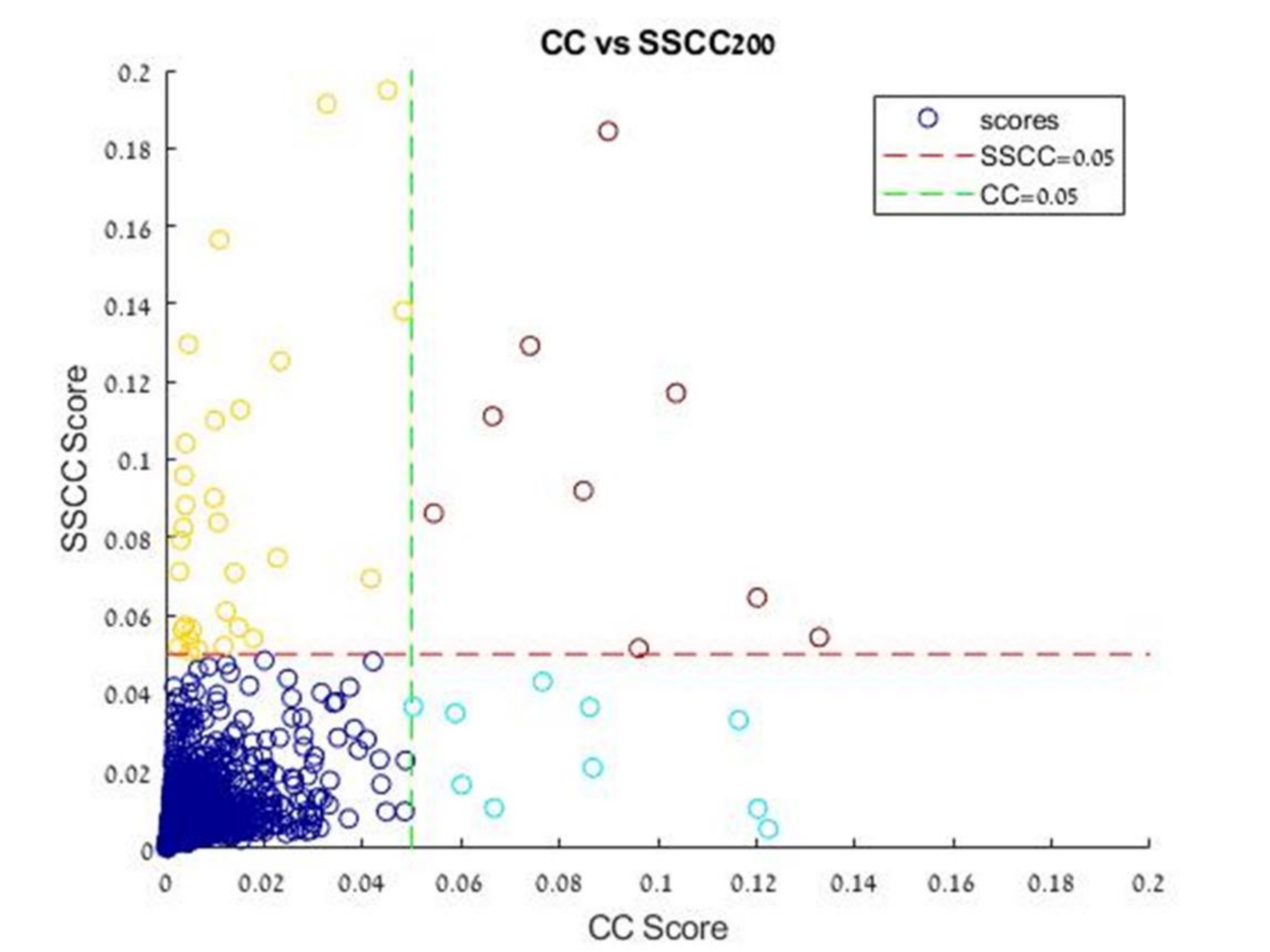


CC vs SSCC50 In-Depth

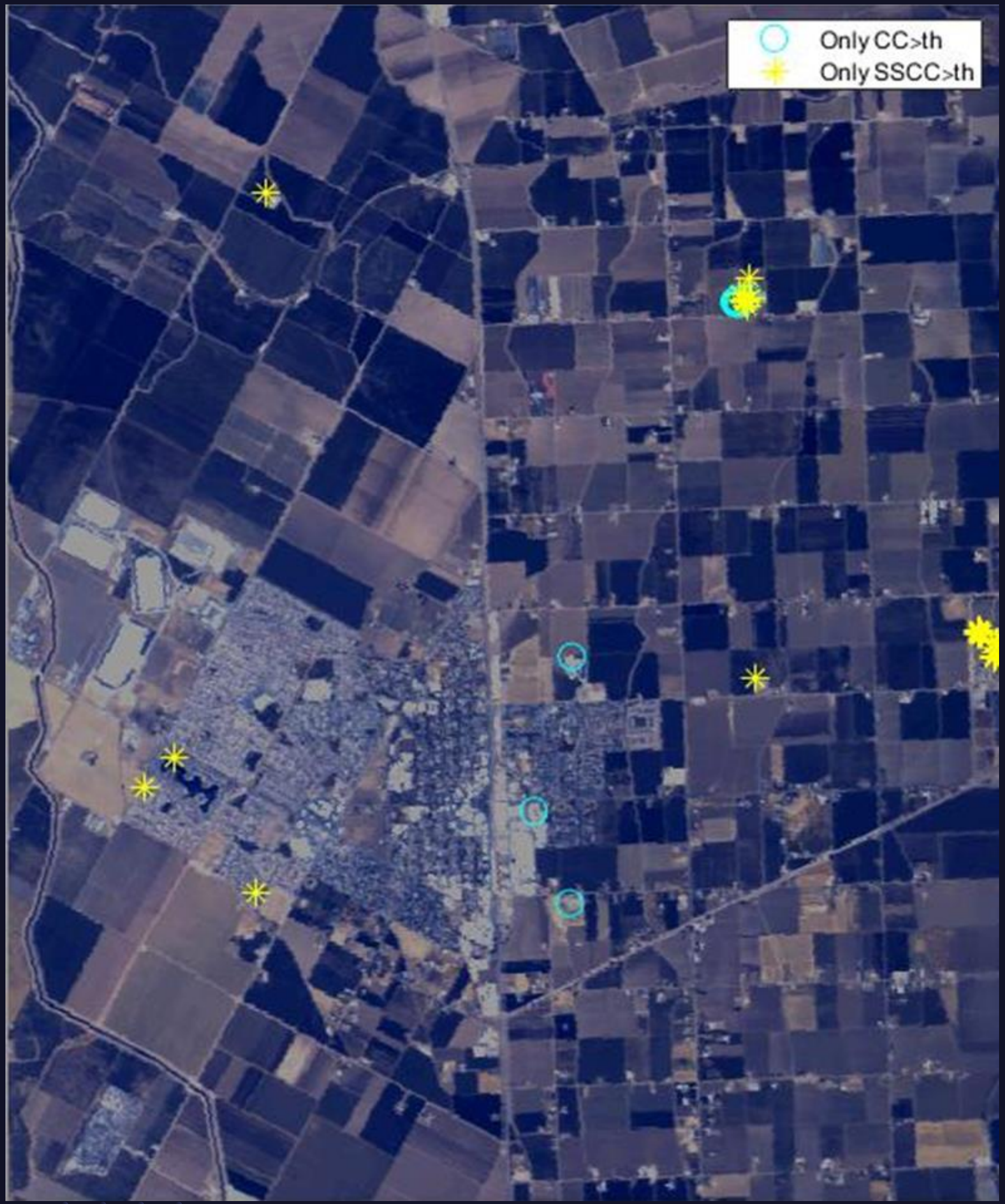


CC vs SSCC50 In-Depth

CC vs SSCC200 In-Depth



CC vs SSCC50 In-Depth



Conclusions

Which Algorithm Should We Use?

Conclusions

- RX provides a narrow set of anomalies that are far from the noise distribution.
- SSRX provides a wider set of anomalies, even within the noise distribution

Thank You For Listening! Any Questions?