Normalized Distance Measure for Optimal Histogram Matching Based Radiometric Normalization Performance measurement

Zhengwei Yang

USDA/NASS/ R&D Division

Tel: 703-877-8000x145

Zhengwei_yang@nass.usda.gov

OUTLINE

- Background
- Change Detection Methods
- Normalized Similarity Metrics
- Comparison Experiment Results
- Conclusions

Background

- Land cover change detection
  - Critical to production inventory monitoring and policy making;
- What is our focus among many land cover types:
  - Citrus grove
- What are challenges?
  - Data from different sensors (digital/film)
    - Radiometric, spatial resolution, spectral coverage differences (make the change detection very difficult)
- What is the method suitable for citrus grove change detection?

Change Detection Methods: Pre-classification

- Many methods:
  - Image differencing (normalized/non-normalized)
  - Change vector analysis;
  - Inner product analysis;
  - Image ratioing;
  - Vegetation Index differencing;
  - Spectral correlation analysis;
  - Principal Component Analysis (PCA);
- Straightforward – no classification (direct comparison);
- Many of them are sensitive to radiometric difference;
- Good sensor calibration and radiometric normalization may be needed;
- Difficult in handle images acquired with different sensors.

Change Detection Methods: Post-classification

- Two steps: 1) Classification; 2) Post classification analysis
- Post classification interpretation may introduce extra errors;
- Accuracy Depends on the Accuracy of the Classification
  - Best Accuracy: Bigger one of two classification errors;
  - Worst Accuracy: Sum of Two Classification errors;
- Complicated - require experienced & well trained analyst;
- Intra-class change is not defined
  - Difficult in detecting citrus growth
- Suitable for large scale land cover change detection (many cover types involved);
- Not best for single cover type change detection such Citrus

What Is An Ideal Method?

- Minimum human-machine interaction;
- User-friendly--require minimum experience and training for operation;
- Easy to understand and easy to implementation;
- Robust to various kinds of image data conditions;
- Robust to Radiometric difference;
- Invariant to image dynamic range.

Image Differencing – Manhattan & Euclidean

$$s_{rk} = \sum_{i=1}^{M}\sum_{j=1}^{N}\left|I_r(i,j,k) - I_{rh}(i,j,k)\right|, \forall k \in \{1,2,...,K\},\ r \in \{1,2,...,L\}$$

$$s_{rk} = \sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}\ [I_r(i,j,k) - I_{rh}(i,j,k)]^2}, \forall k \in \{1,2,...,K\},\ r \in \{1,2,...,L\}$$

- Direct comparison method - Image differencing
  - The most straightforward method, but not effective enough with radiometric differences!
  - Manhattan distance measure is biased to the histogram matching reference image with the histogram concentrating at the lower bits because most image pixels have lower gray values than that of images having more evenly distributed histograms across the whole dynamic range.
    - radiometric normalization using histogram matching;
  - Radiometric normalization using histogram matching is needed.
- Explore new distance metrics.

Histogram Matching for Normalization

- Why histogram matching normalization?
  - No need to subjectively select pseudo invariant areas for parameter estimation
  - Only small portions of the image change
  - The nonlinear transformation fits better for nonlinearity
- Histogram matching method

Let $p_u(x_i)$ and $p_v(y_i)$ be histograms of grey level $u=x_i$ and $v=y_i$. Their distributions are:

$$w_u(n) = \sum_{i=0}^{n} \mathrm{p_u}(\mathrm{x_i}) \;, \qquad w_v(k) = \sum_{i=0}^{k} \mathrm{p_v}(\mathrm{y_i}) \;, \qquad n, k = \{0, \ldots, L\text{-}1\}$$

Then, the histogram matching of the given $u=x_i$, is given by $v=y_k$, *where k is the* minimum value which satisfies $w_u(n) <= w_v(k)$.

Reference Optimization

- Both images can be reference image for histogram matching in change detection.
- Which image is better for reference?
  - Compare the histogram matched image with its reference to see how big the difference is w.r.t. different reference images;
- What is your difference metric?
  - Manhattan distance & Euclidean distance previously used. But they are isotropic and not good for comparing variables with different scale.

Reference Optimization

- Histogram matching performance measurement
  - To measure the effectiveness of histogram matching, we define an error measurement as:

$$E_{rk} = \sum_{i=1}^{M} \sum_{j=1}^{N} \left| I_r(i,j,k) - I_{rh}(i,j,k) \right|$$

- Reference optimization for each band
  - To find the optimal reference for each band, we propose the following optimization algorithm:

$$\underset{r,k}{MIN} \{ \sum_{i=1}^{M} \sum_{j=1}^{N} \left| I_r(i,j,k) - I_{rh}(i,j,k) \right| \}$$

Bray Curtis Distance

$$s_{rk} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left|I_r(i,j,k) - I_{rh}(i,j,k)\right|}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I_r(i,j,k) + I_{rh}(i,j,k)\right]}, \forall k \in \{1,2, \ldots, K\},\ \ r \in \{1,2, \ldots, L\}$$

- Bray Curtis distance is a normalized Manhattan distance measure
- Commonly used in botany, biology, ecology and environmental science and pharmaceutical research field. It is sometimes also called Sorensen distance, which views the space as grid similar to the city block distance.

Canberra Distance

$$s_{rk} = \sum_{i=1}^{M}\sum_{j=1}^{N}\frac{\left|I_r(i,j,k) - I_{rh}(i,j,k)\right|}{I_r(i,j,k) + I_{rh}(i,j,k)}, \forall k \in \{1,2, \ldots, K\}, \; r \in \{1,2, \ldots, L\}$$

- Canberra distance that is defined by the sum of series of a fraction differences between gray values of a pair of image bands. Each term of fraction difference is defined by the Manhattan distance of a pair of image pixels and normalized by the sum of the gray values of the pair of the pixels.
- Value is between 0 and 1. If one of coordinate is zero, the term becomes unity regardless other value, thus the distance will not be affected. Note that if both pixel values are zeros, we need to be defined as 0/0 = 0. This distance is very sensitive to a small change when both pixel values are near to zero.

Tanimoto Distance

$$T(x, y) = \frac{x \cdot y}{\|x\|^2 + \|y\|^2 - x \cdot y}$$

- A similarity metric for two vector attributes x and y;
- Originally, it's for discrete variables, widely used in biological, botanical analysis;
- Normalized metric [0, 1], with 1 for maximum similarity and 0 for minimum similarity

Experiments & Results

Data Processing & Experiments

- Data processing
  - Raw images (only rescaling & re-sampling);
  - Higher bits clipped (information compacted in lower bits);
  - Radiometric normalized with histogram transformation.
- Experimental scenarios
  - Different distance metrics

Raw Images without Clipping Nor Normalizing

2004 raw image

1999 raw image (Reference)

Clipped and Normalized 2004 Image

2004 clipped image

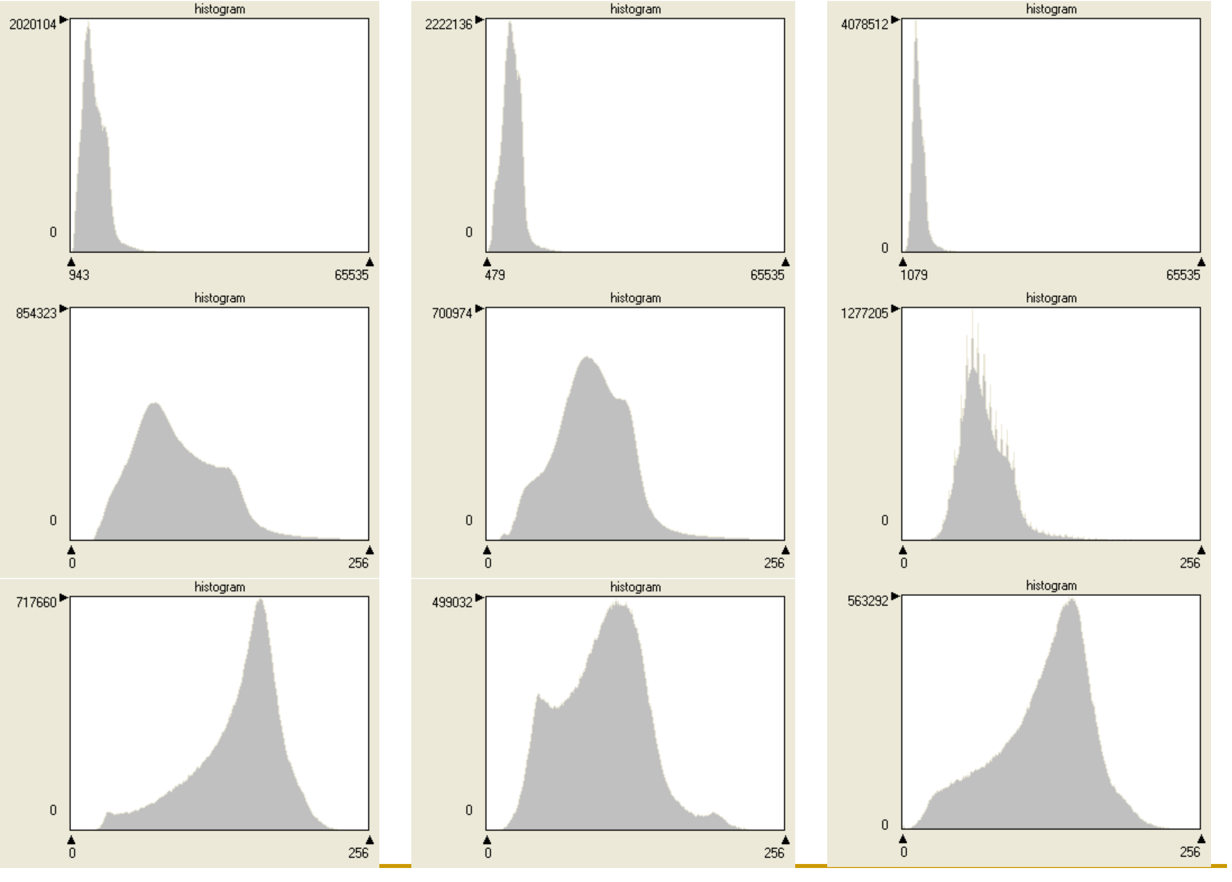
2004 image normalized to 1999

Reference Image Histograms

Original 2004 8-bit image histograms

Clipped 2004 8-bit image histograms

Original 1999 8-bit image histograms



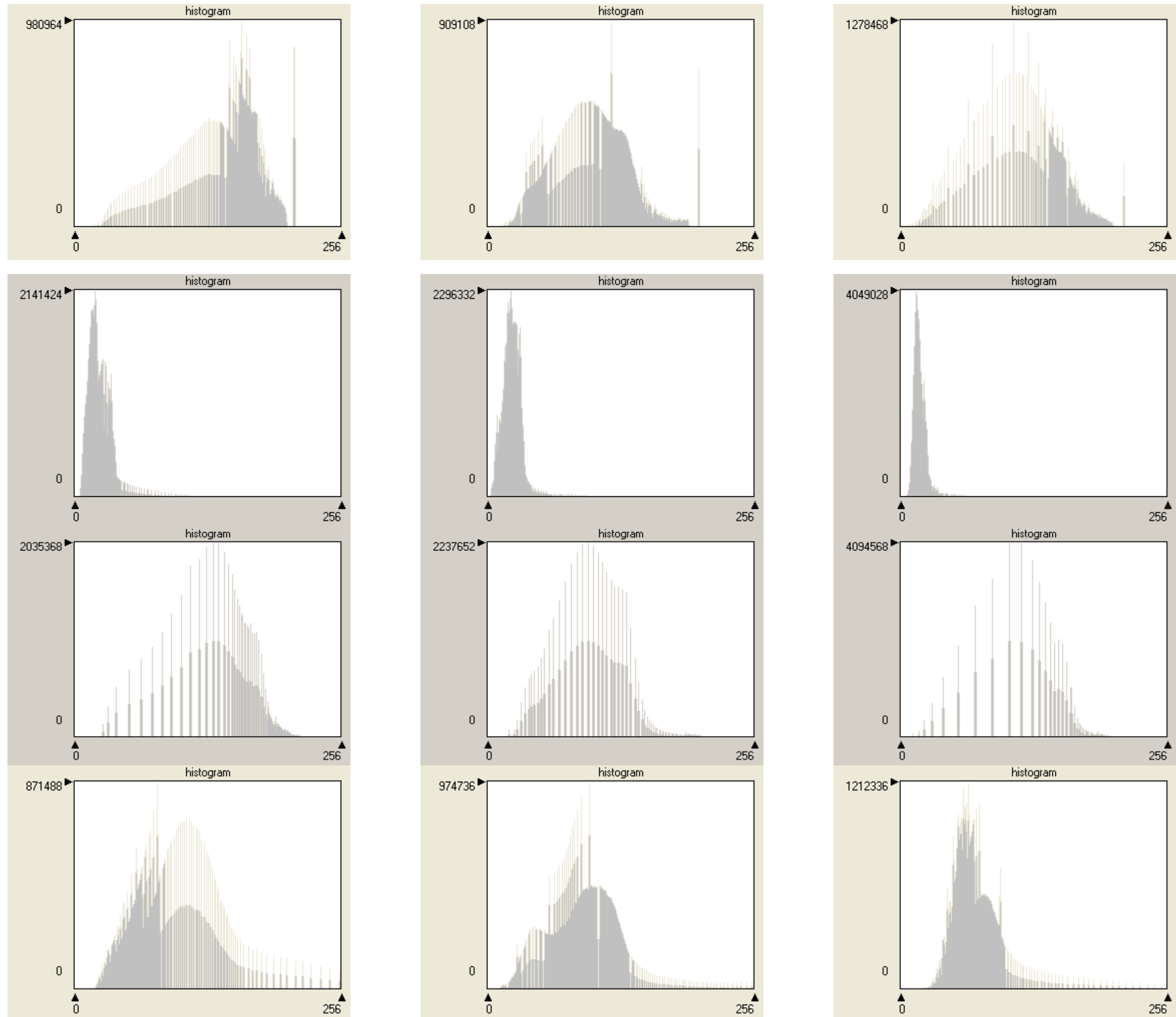
Histogram Matched Image Histograms

Histogram matched 2004 clipped image histograms with 1999 image as reference

Histogram matched 1999 image histograms with original 2004 image as reference

Histogram matched original 2004 image histograms with original 1999 image as reference

Histogram matched original 1999 image histograms with clipped 2004 image as reference



Comparison Results (I)

Image difference	Band 1	Band 2	Band 3
No Normalization	5,165,526,637	**3,334,340,163**	4,489,143,486
HMN, 1999 Image as Reference	1,333,636,088	**1,164,335,668**	1,238,088,703
HMN, 2004 Image as Reference	440,286,597	318,965,703	**223,107,908**

Bray-Curtis distance	Band 1	Band 2	Band 3
No Normalization	0.7109635	**0.6195418**	0.7365712
HMN, 1999 Image as Reference	***0.1072778***	0.1336297	0.1169591
HMN, 2004 Image as Reference	0.2094629	0.1553189	**0.1387766**

Comparison Results(II)

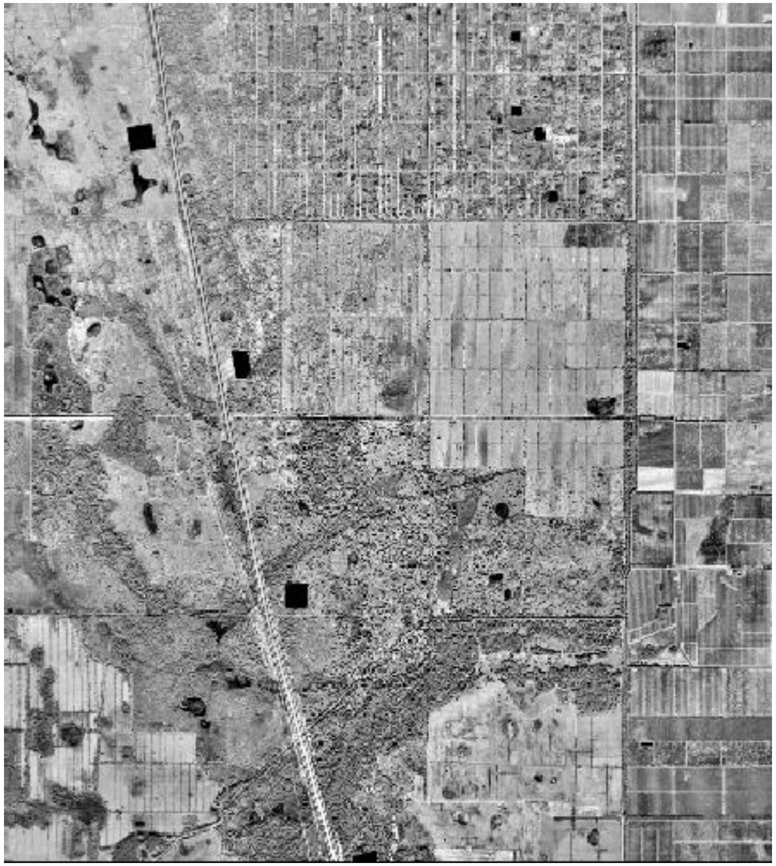
Canberra distance	Band 1	Band 2	Band 3
No Normalization	31,308,353	**26,930,712**	31,758,695
HMN, 1999 Image as Reference	***5,408,950***	6,500,654	6,164,361
HMN, 2004 Image as Reference	8,649,178	6,993,974	**5,259,038**

- Normalized distance and non-normalized distance yields different results. The best band and the best reference image for the different similarity measures are not the same.
- Normalized similarity metrics results are consistent.
- Normalized distance and non-normalized distance yields different results.

Change Detection Result

Images with Changes to be Detected

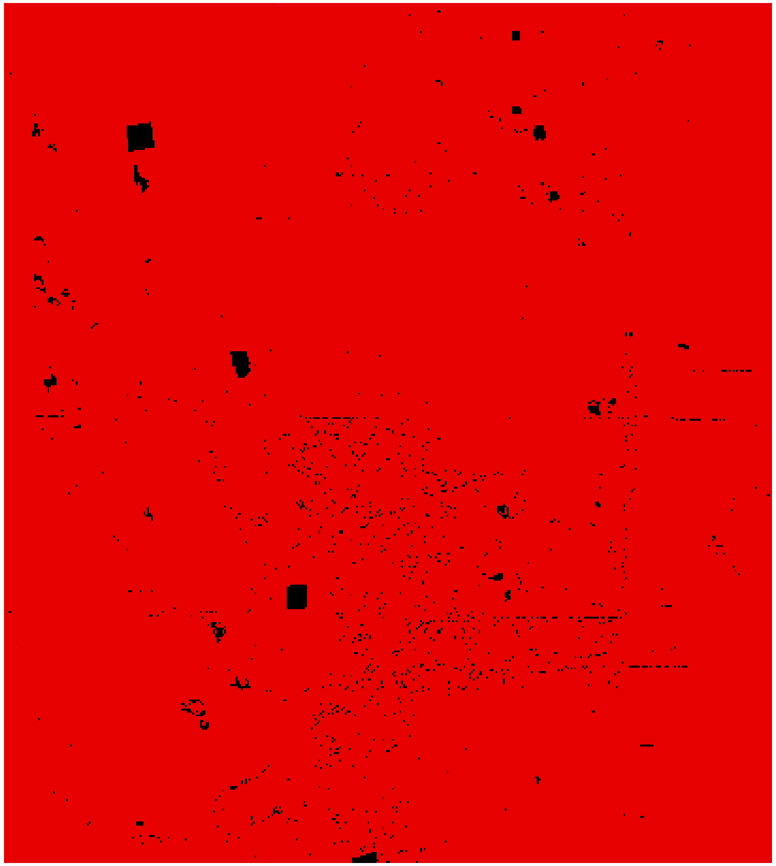
Distance Maps for Raw Image with no Clipping & Normalizing



Euclidean Dist Map

Tanimoto Dist Map

Change Maps for Raw Image with no Clipping & Normalizing (30%)

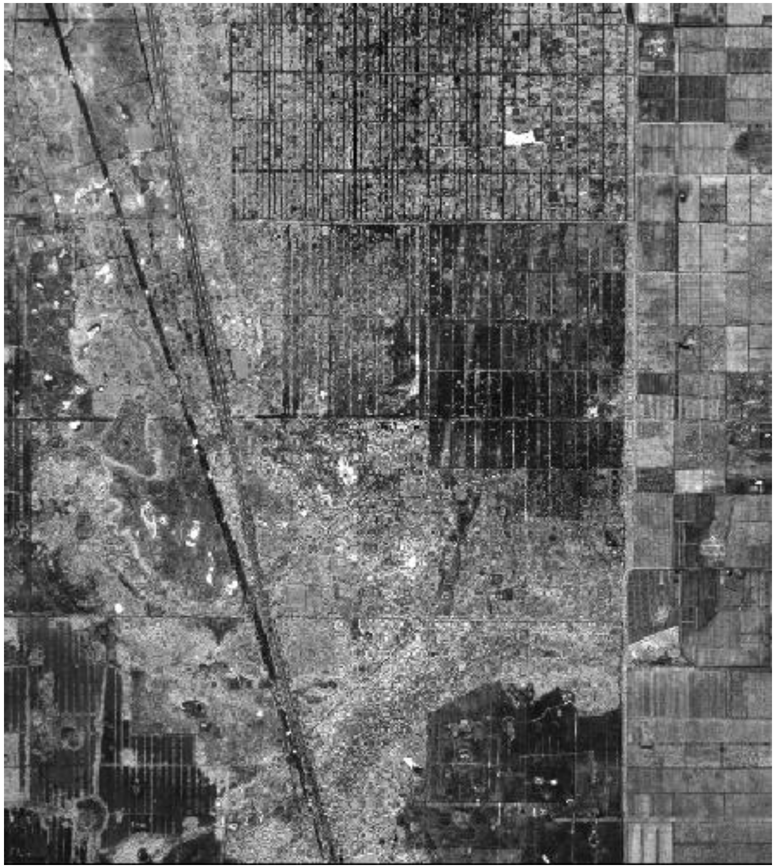


Euclidean

Tanimoto

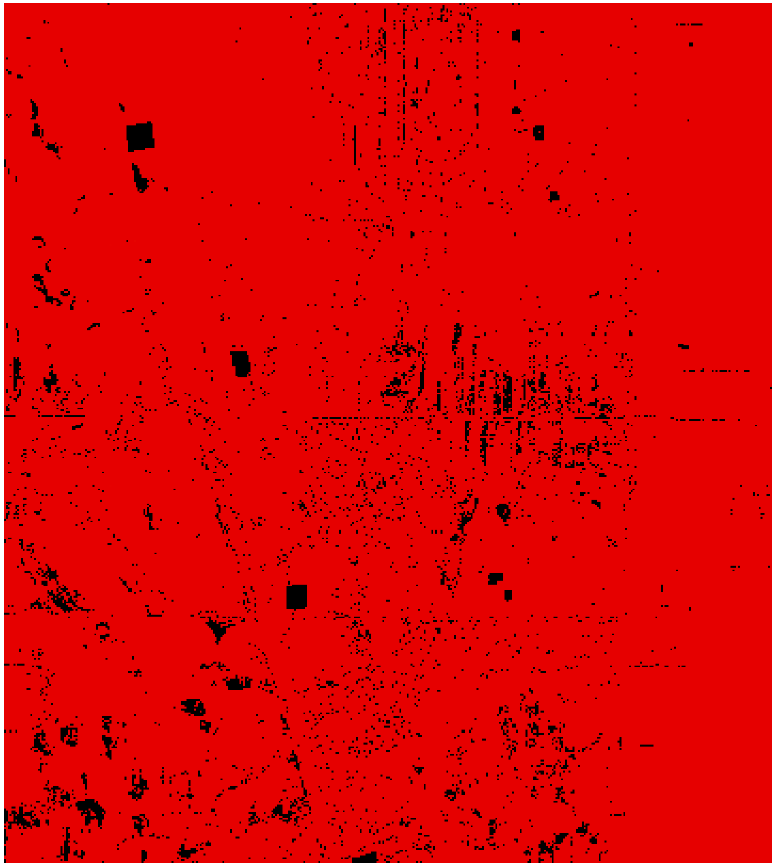
Distance Maps for Clipped Raw Images

Euclidean Dist Map

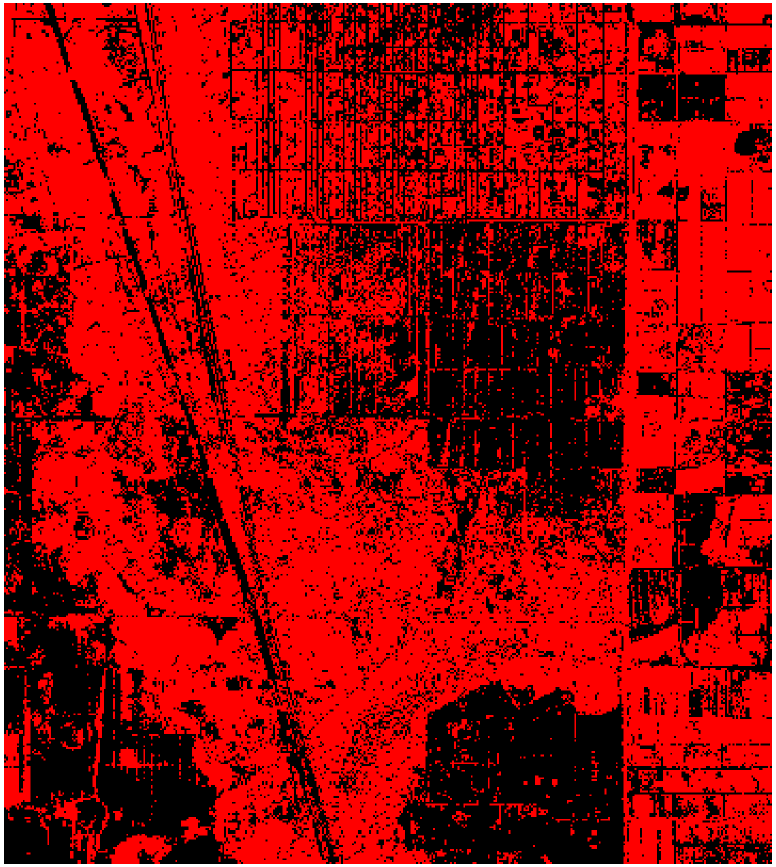


Tanimoto Dist Map

Change Maps for Clipped Raw image (20% Threshold)

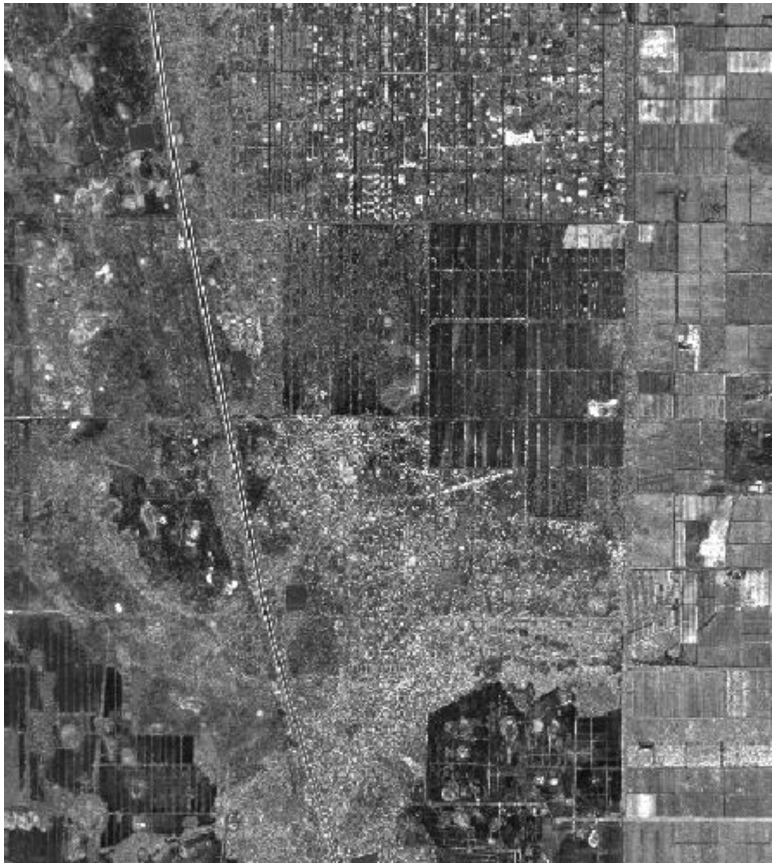


Euclidean Change Map

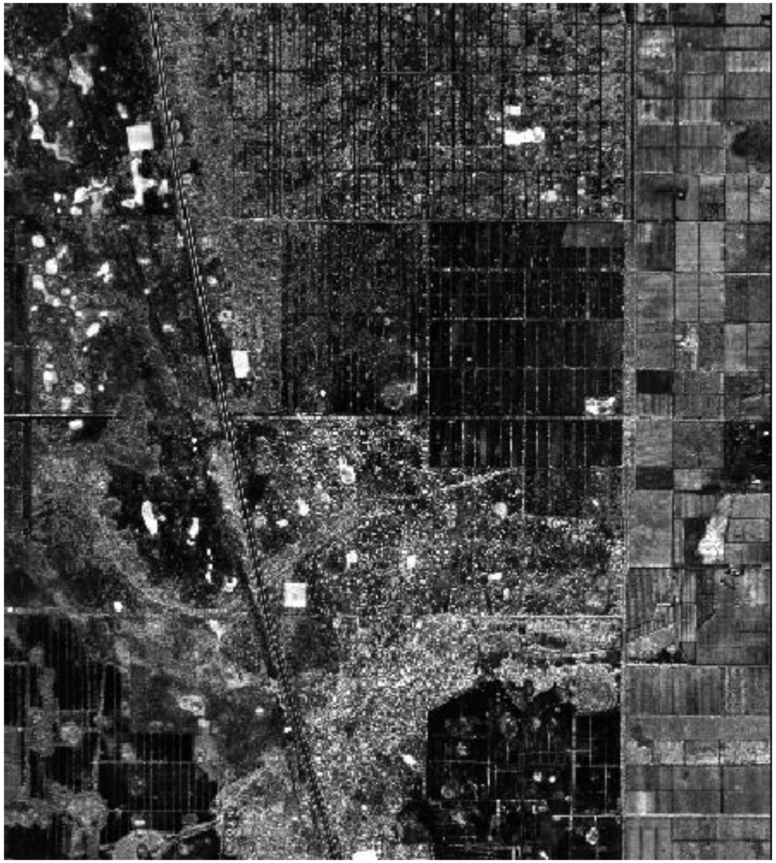


Tanimoto Change Map

Distance Maps for Normalized Images

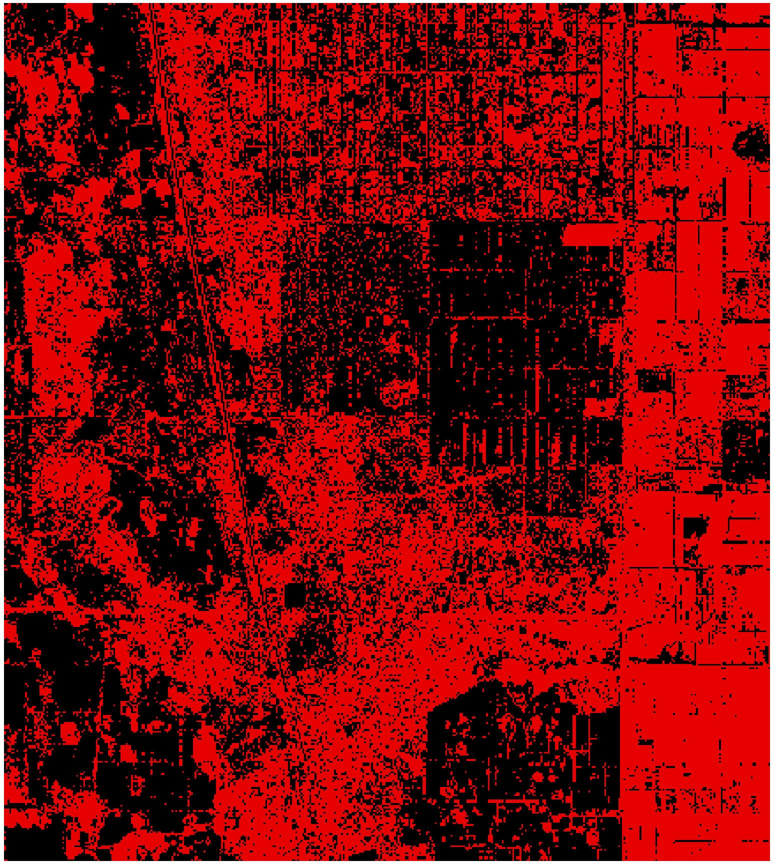


Euclidean Dist Map



Tanimoto Dist Map

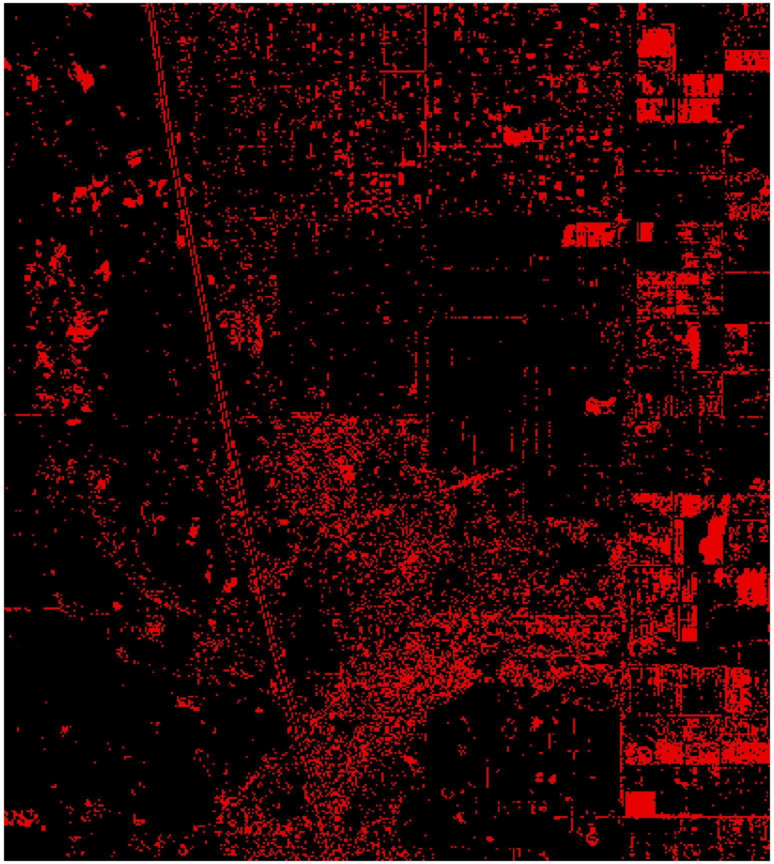
Change Maps for Normalized Images(20%)



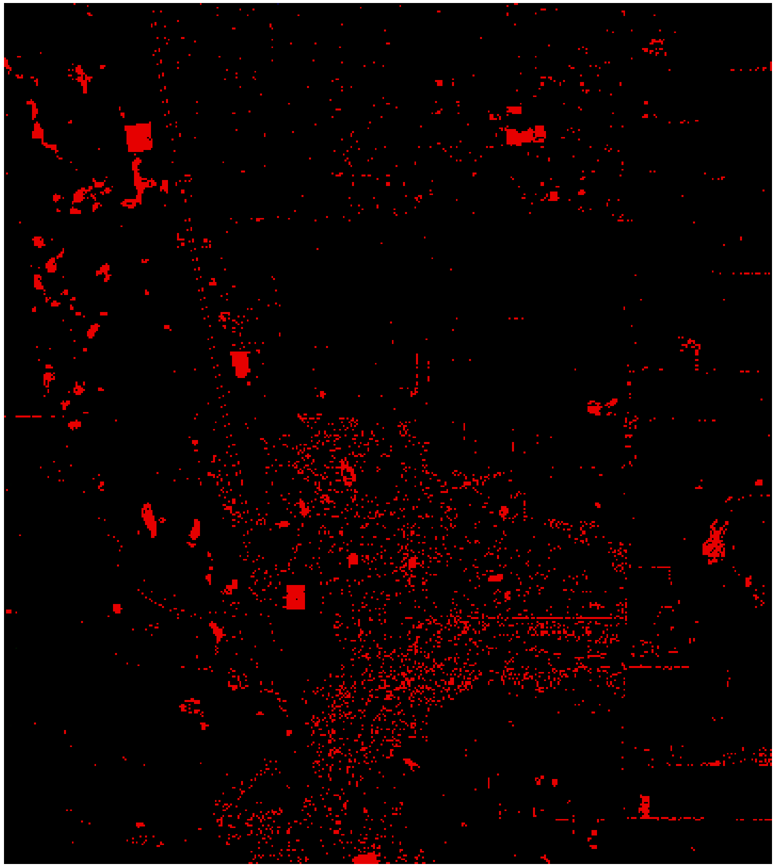
Euclidean Change Map

Tanimoto Change Map

Change Maps for Normalized Images (30%)



Euclidean Change Map



Tanimoto Change Map

Conclusions

- Normalized similarity metrics are significantly more sensitive to changes than Euclidean distance (This is evidenced by Tanimoto change maps with 20% threshold);
- Experimental results confirm that the normalized similarity metrics are more robust to radiometric difference than Euclidean distance;
- Radiometric normalization is still critical to effectiveness of using normalized similarity metrics for change detection;
- Change detection results indicate that the proposed nomalized similarity metric has comparable effectiveness to the Euclidean distance metric;
- The change detection threshold is critical to identify changes.

THANK YOU!

QUESTIONS & COMMENTS?