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Multitemporal Data Mining: From Biomass Monitoring to Nuclear Proliferation Detection

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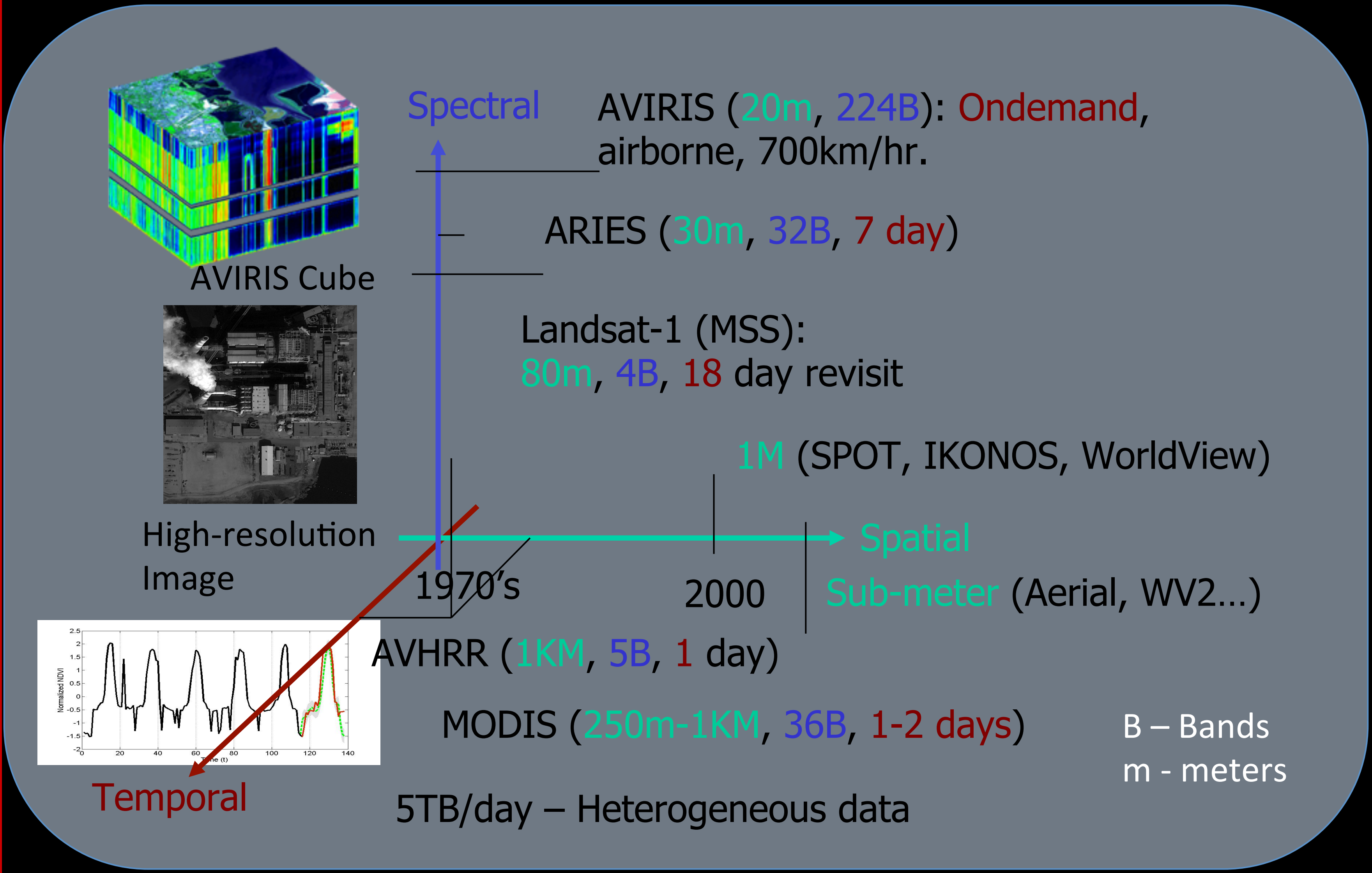
Outline

- Applications
  - Biomass Monitoring
  - Damage Assessments
  - Crop Mapping, Nuclear Proliferation, Settlements
- Algorithms
  - Gaussian Process (GP) Learning
  - Bi-temporal Hierarchical and Probabilistic
  - Multi-view, Semantic, and Multiple Instance Classification
- Outlook

Big Spatiotemporal (Remote Sensing) Data



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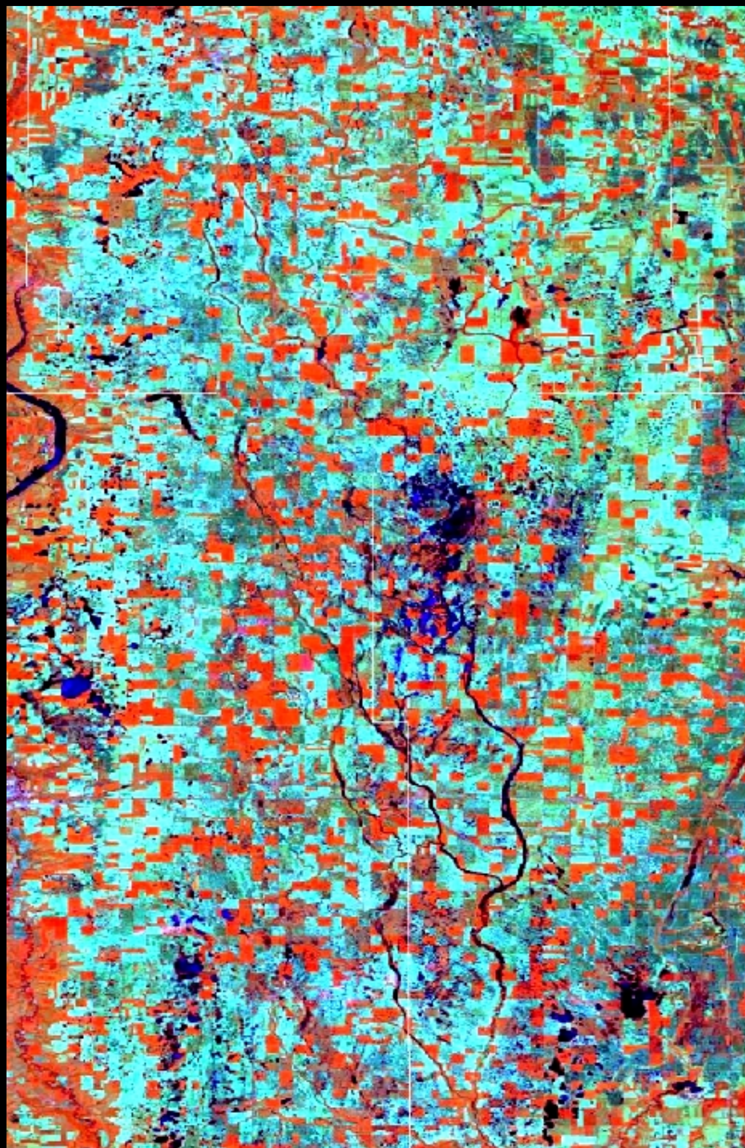
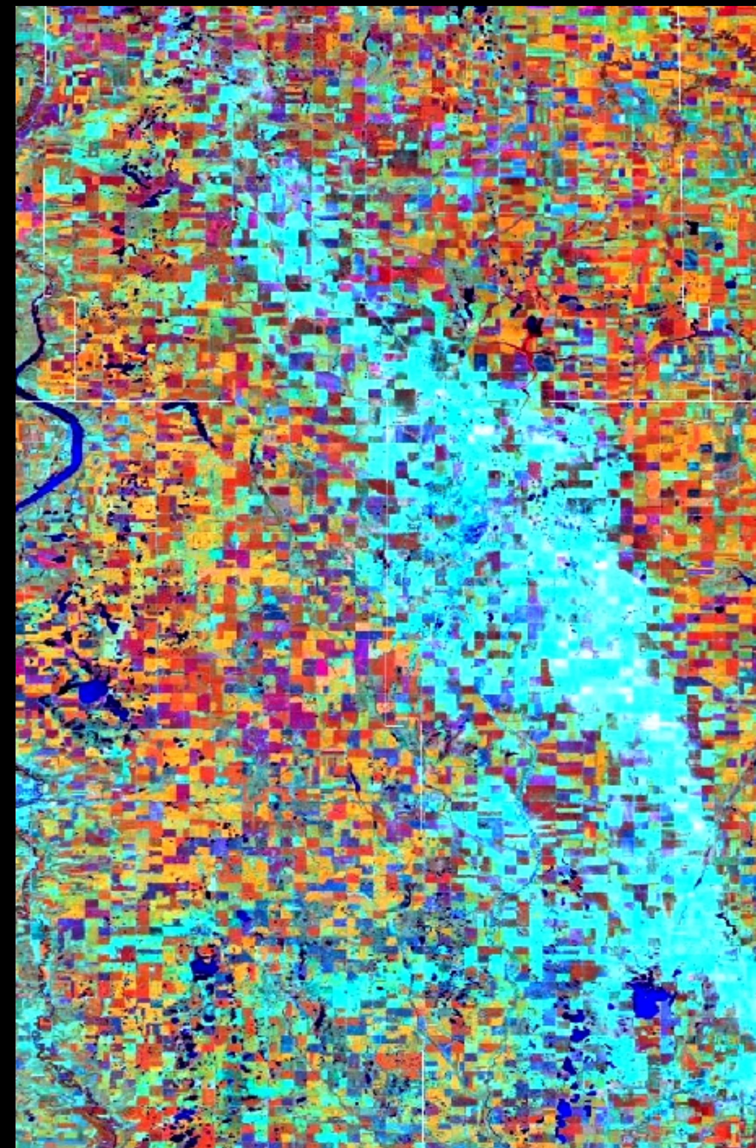
Applications

- Biomass Monitoring
- Damage Assessments
- Crop Mapping, Nuclear Proliferation, Settlements

Vegetation Damages





Seasonal Changes

AVHRR NDVI 1KM (1981-2000)

Biomass Monitoring

- Changes are dynamic and multifaceted
  - Population pressure (Present: ~7B; 2050: ~9B)
  - Bioenergy demands/policies
    - Strategic goals: Reduce gasoline use by 20% by 2017 and 30% by 2030.
    - 2007: 6.8 billion gallons
    - 2030: 60 billion gallons
  - Increasing emphasis on Feedstocks (DOE/OBP, "Biomass: Multi-Year Program Plan," March 2008).
  - Emphasis on growing energy crops (Cellulosic ethanol)
  - Diseases
  - Natural disasters
- This will lead to significant land use changes in US and other countries

Biomass Monitoring

- Supporting the national bioenergy infrastructure will demand moving to operational mode
  - Existing federal mapping efforts are slow, for example NLCD (Started: 1992, Released:2000; 2nd Ver. Started: 2001, Released: 2007) and Cropland Data Layer (CDL): Annual (not wall-to-wall)
  - Dynamic assessment of "State of Biomass"
- Timely and accurate biomass monitoring is extremely important for both economic and energy security
  - Crops are susceptible to diseases, natural disasters, droughts, early frost, etc.
    - 1970: Naturally occurring leaf blight disease destroyed crops ~ $ 1B
    - 2008: Iowa flood damages to croplands ~ $3B

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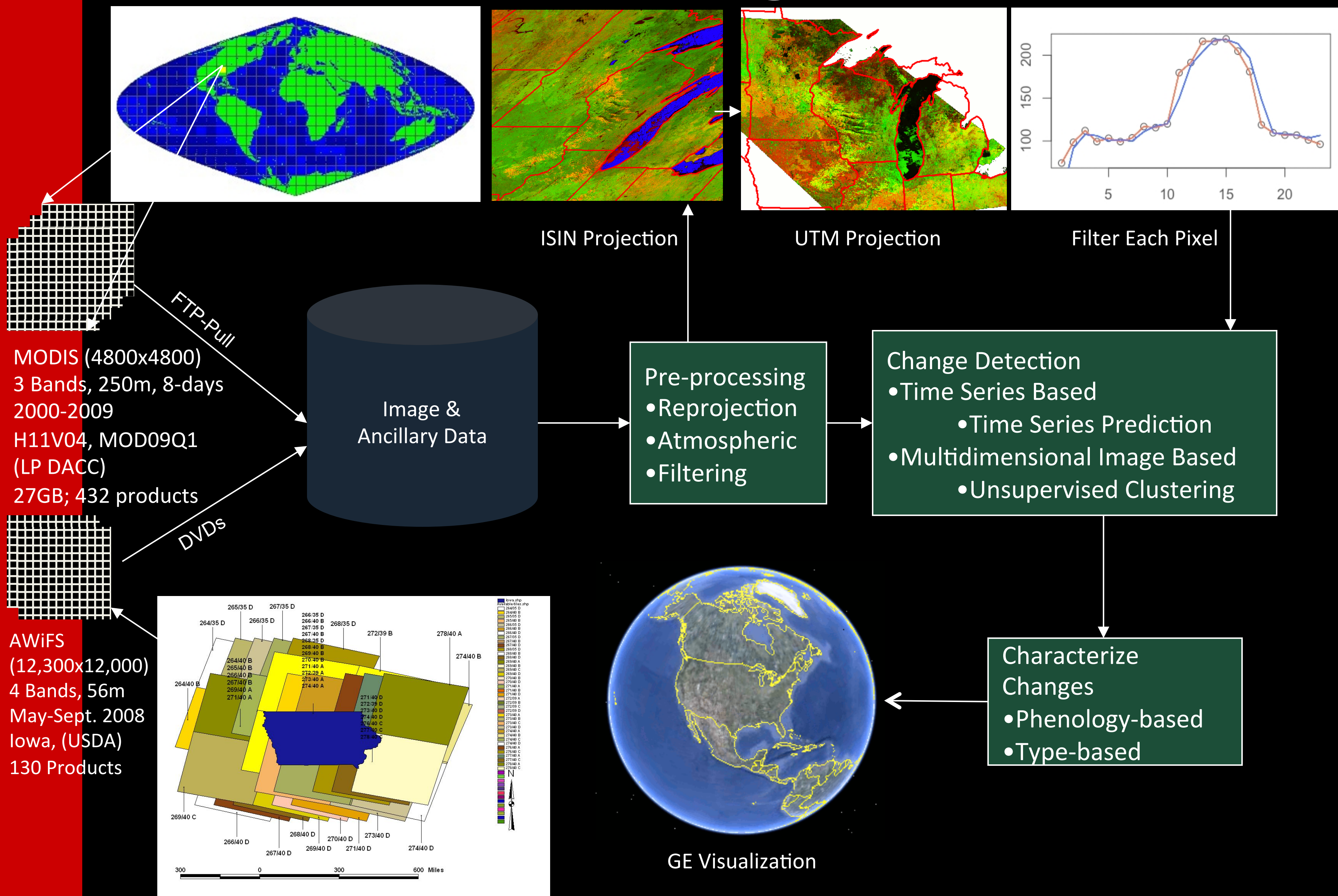
Biomass Monitoring Framework



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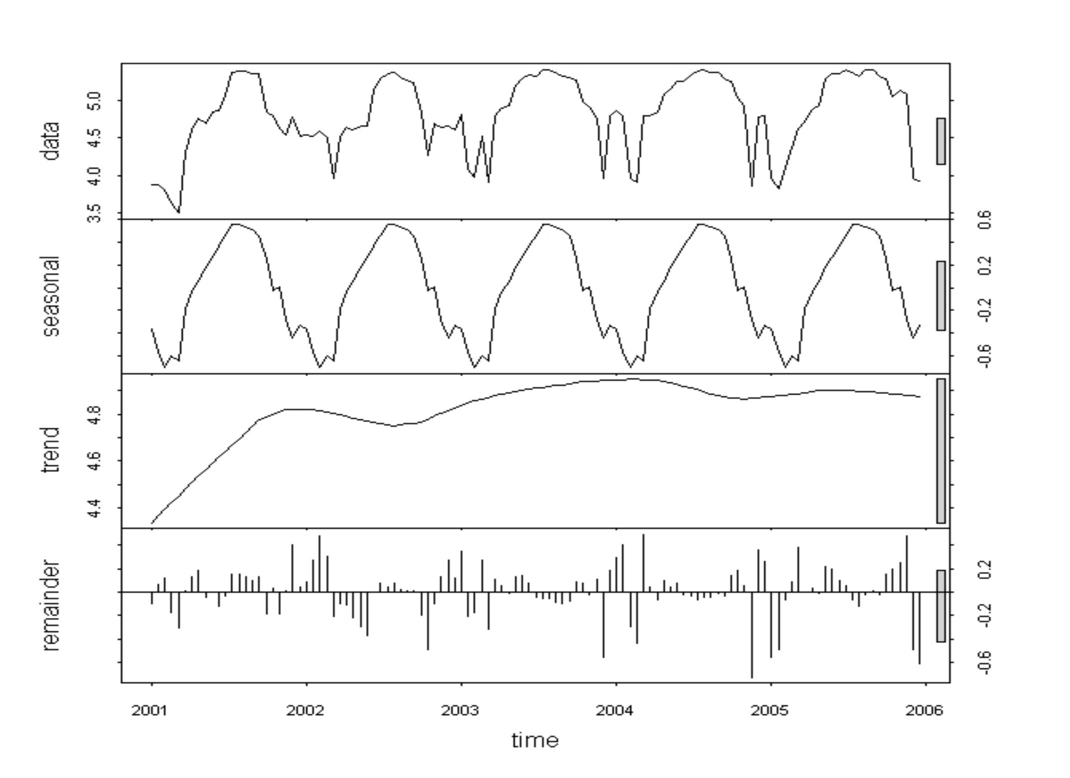
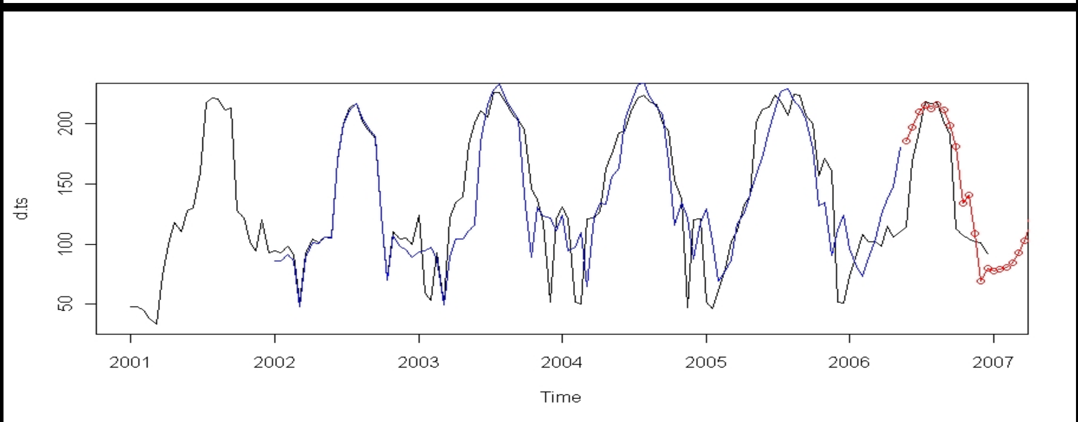
Time Series Based Change Detection

Basic algorithm
- Learn from past observations, that is, build a model that fits to all previous observations (NDVI time series)
- Using the model
  - Predict NDVI at next time step
- Determine if there is a change
  - Compare predicted value with observed (current NDVI image) value
  - If the difference is within a threshold, no change, else "possible change"
- Challenges
  - Which model
  - What is the appropriate threshold





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Gaussian Process (GP) Regression

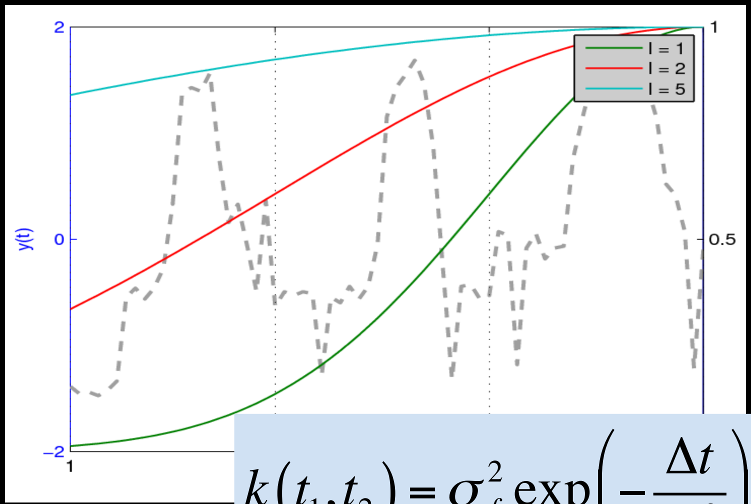
$$y_i = f(x_i) + \varepsilon$$

- GP Prior

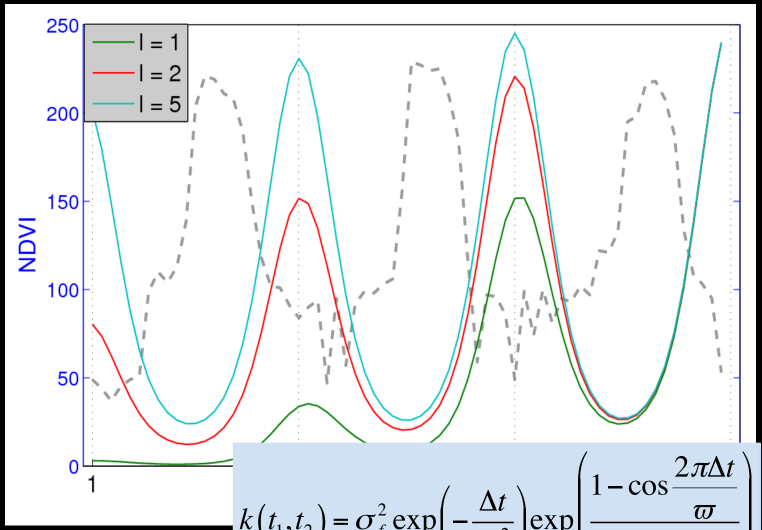
$$f(x_1), f(x_2), \ldots, f(x_n) \sim N(m(x), K)$$

$$K[k][j] = k(x_i, x_j)$$

- Covariance
  - Closer time instances should have similar values
  - Can capture seasonality via sinusoid covariance function



$$k(t_1, t_2) = \sigma_f^2 \exp\left(-\frac{\Delta t}{2l^2}\right)$$



$$k(t_1, t_2) = \sigma_f^2 \exp\left(-\frac{\Delta t}{2l^2}\right) \exp\left(\frac{1 - \cos\frac{2\pi\Delta t}{\varpi}}{a}\right)$$

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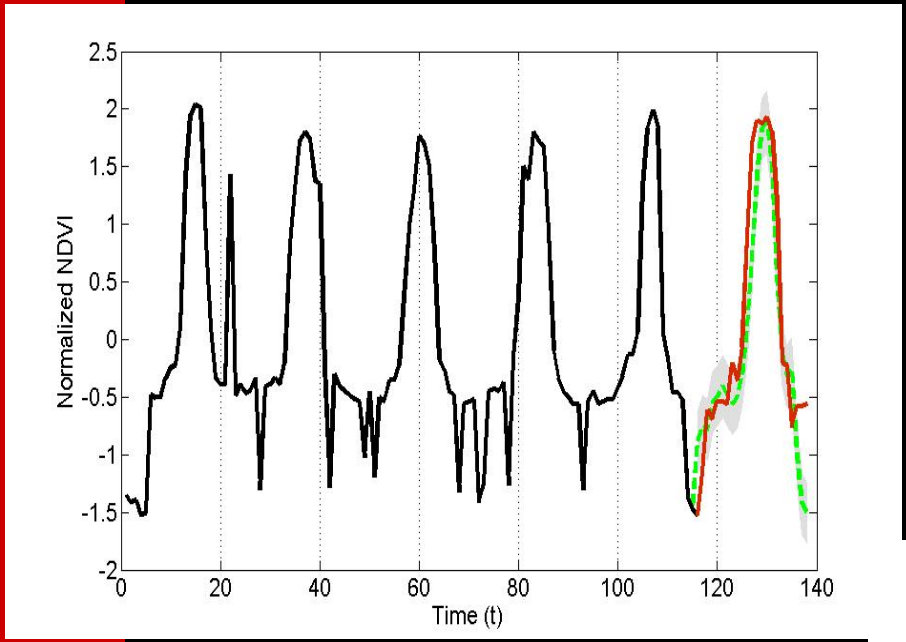
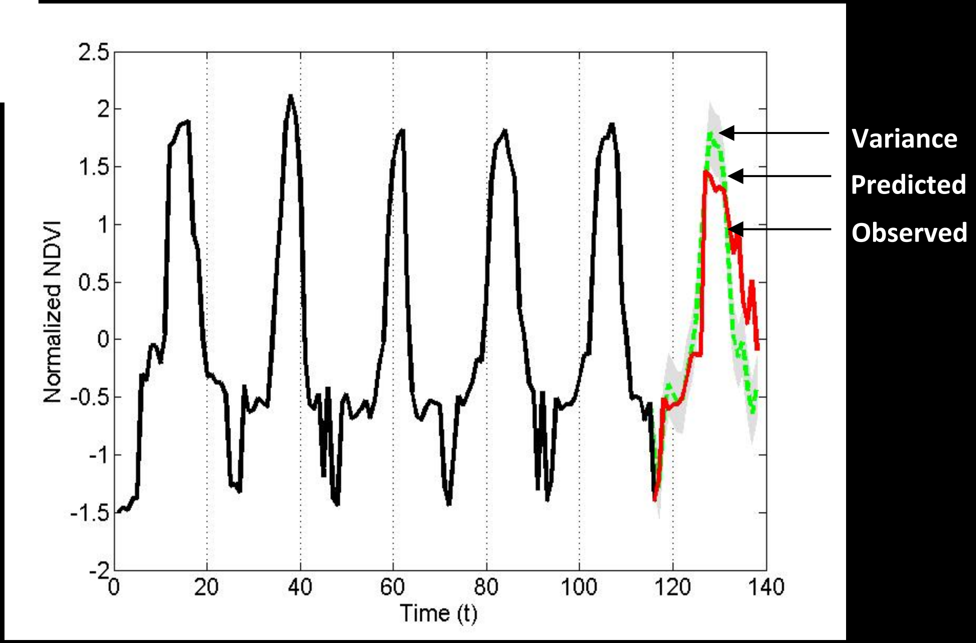
GP Based Change Detection



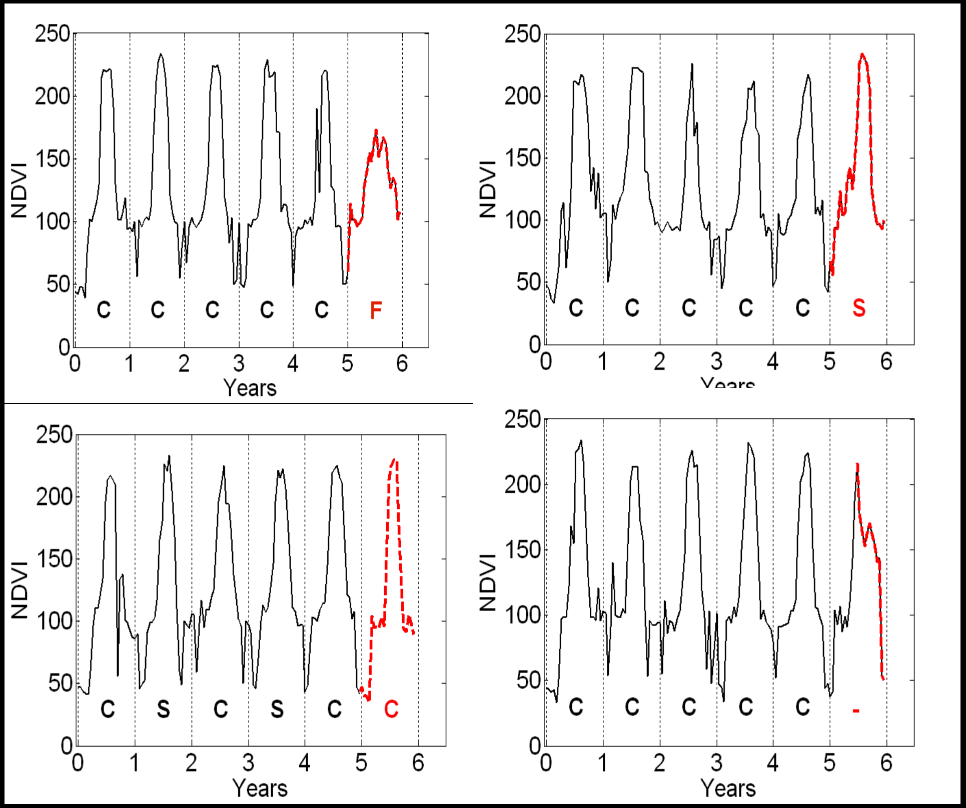
No Change

Change



Results

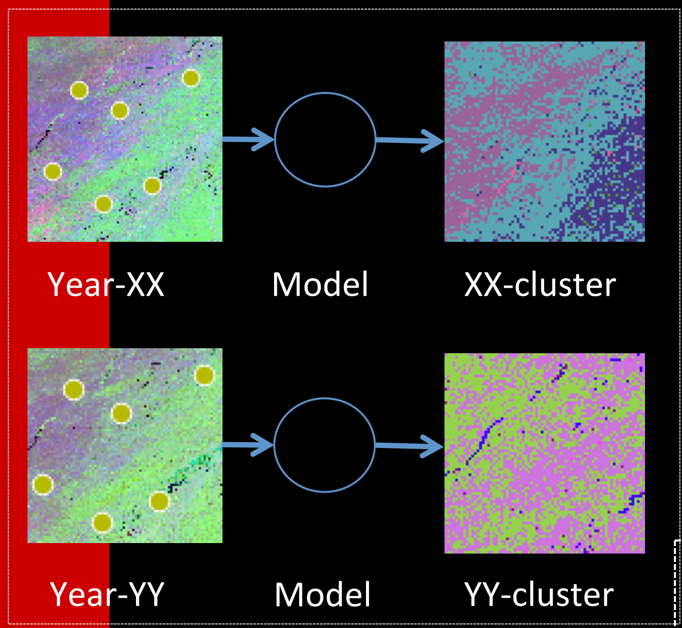
- MODIS Time Series From Iowa
  - 6 years (2001-2006)
  - 23 Observations/year
- Labeled data: 97
- Accuracy: 88%



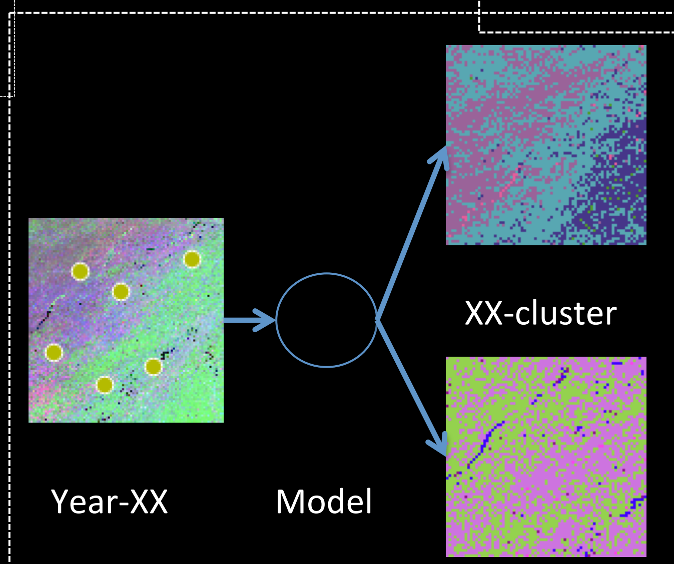
C-Corn; S-Soy; F-Fallow

Varun Chandola, Ranga Raju Vatsavai: A scalable gaussian process analysis algorithm for biomass monitoring. Statistical Analysis and Data Mining 4(4): 430-445 (2011)

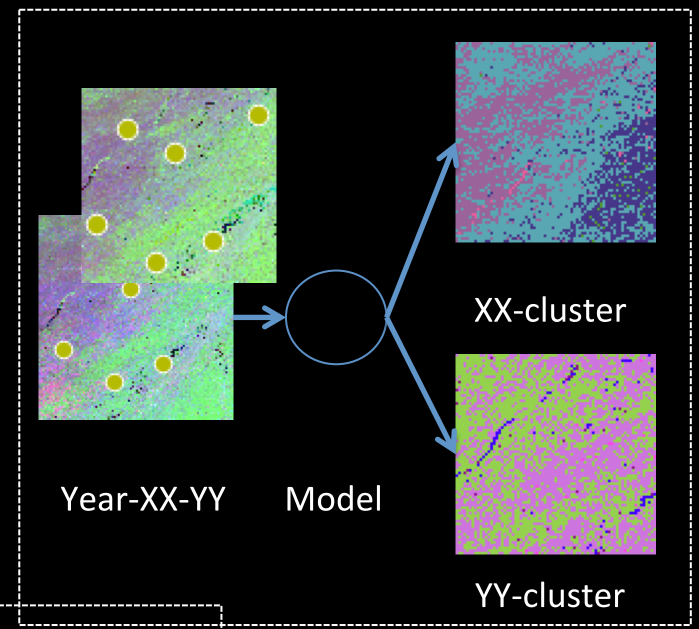
Biannual Changes



(a) Year-wise independent cluster model



(b) Single year model



(c) Combined year model

Unsupervised Methods

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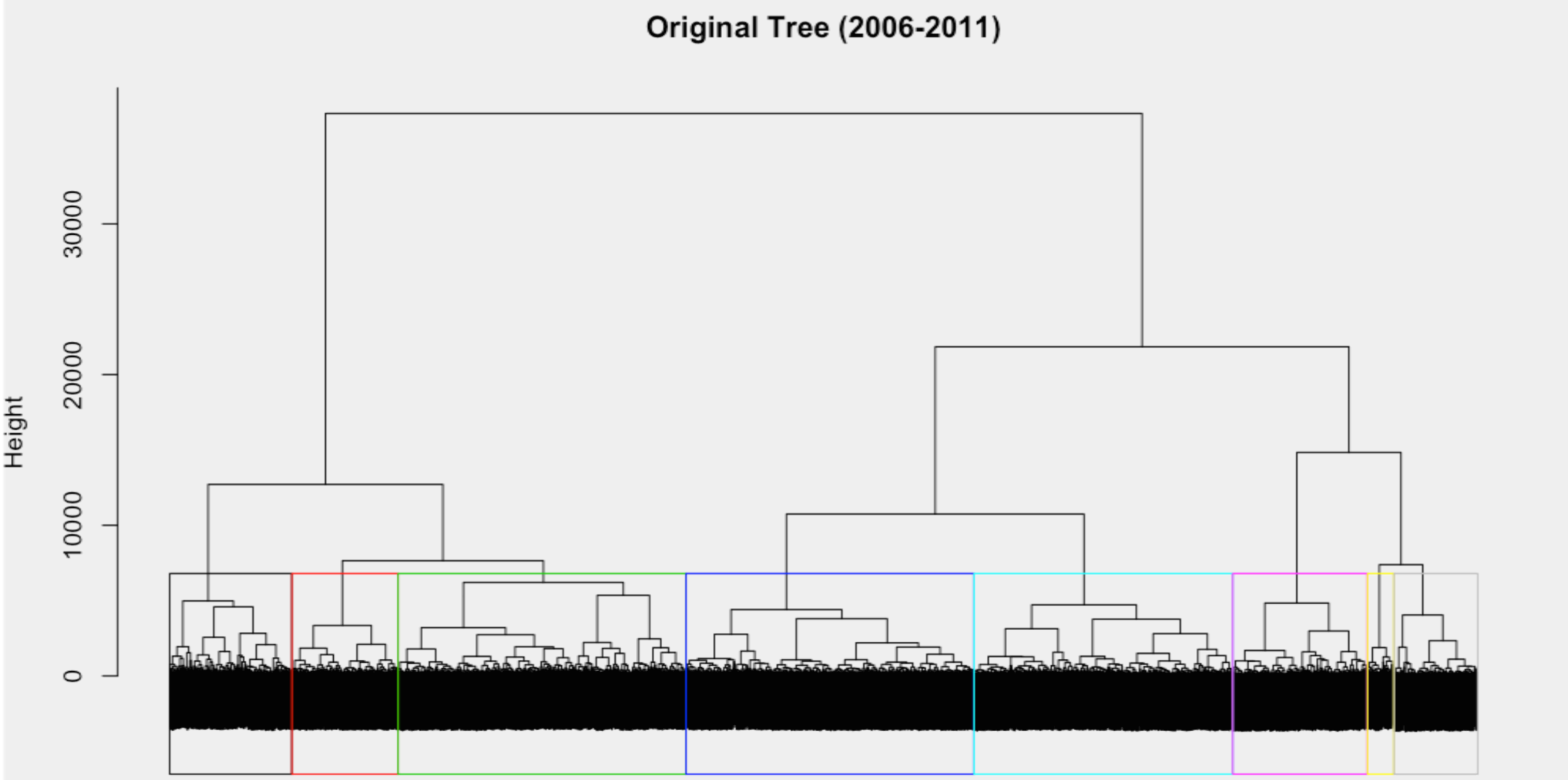
Hierarchical Change Detection

- Hierarchical clustering
  - Grouping NDVI time-series by similarity
- Extract change relationships
- Generate change image

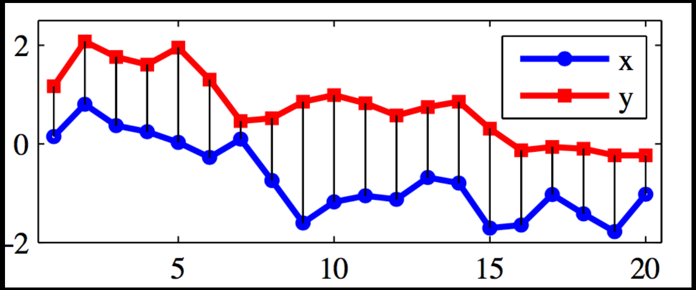
Hierarchical Model

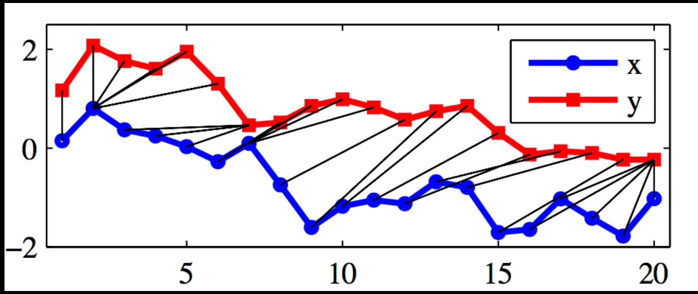


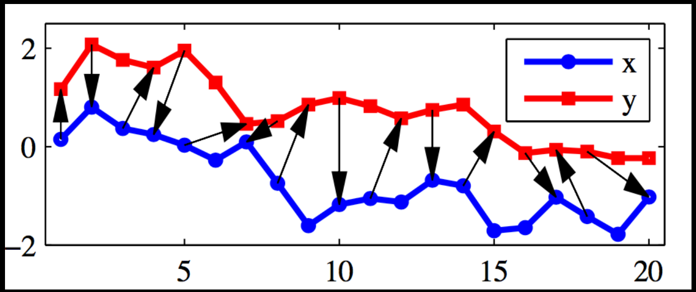
1	2	3	4	5	6	7	8
759	221	759	322	682	355	280	70

Similarity Measures

- Dynamic Time Warping (DTW; Berndt and Clifford, 1994)
- Edit Distance on Real Sequences (EDR; Chen et al., 2005)
- Minimum jump costs (MJC; Serra and Arcos, 2012)







Source: Joan Serra, Josep Ll. Arcos. An Empirical Evaluation of Similarity Measures for Time Series Classification

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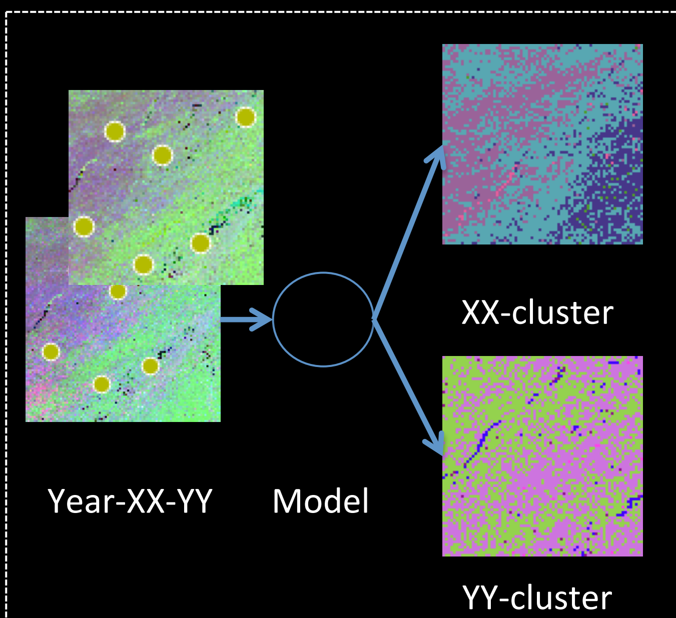
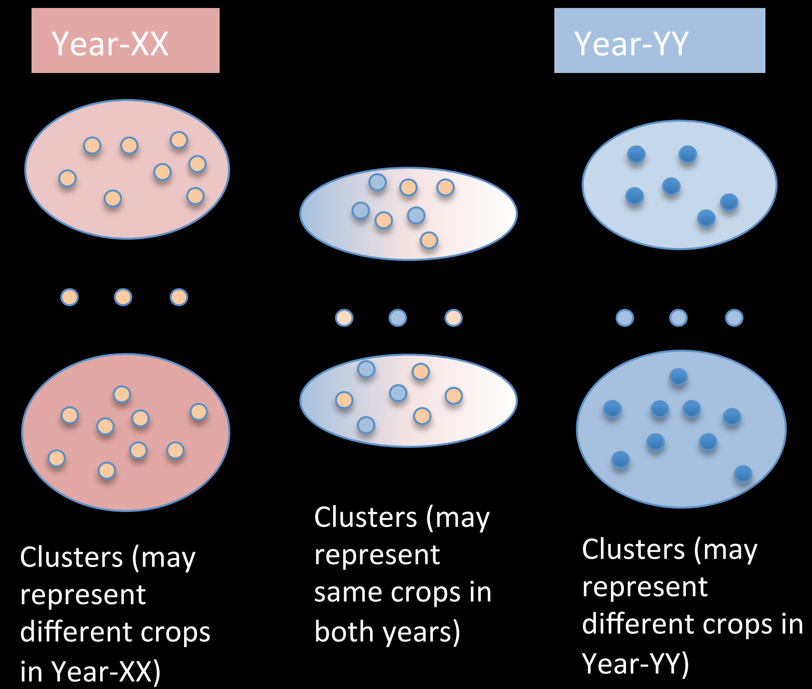
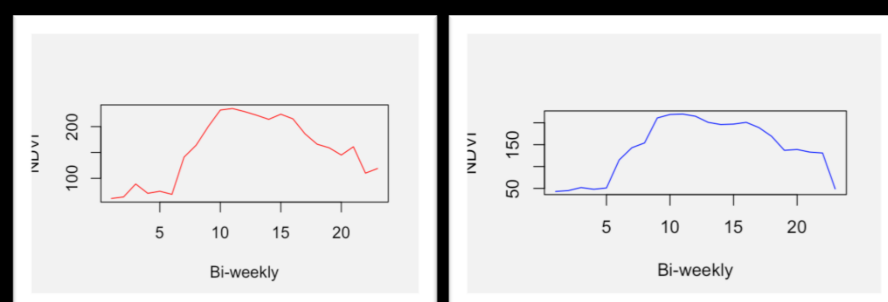
Combined Model

- Build model on samples from Y1 and Y2 (Y12.HM)
- Use Y12.HM to predict labels for Y1 and Y2







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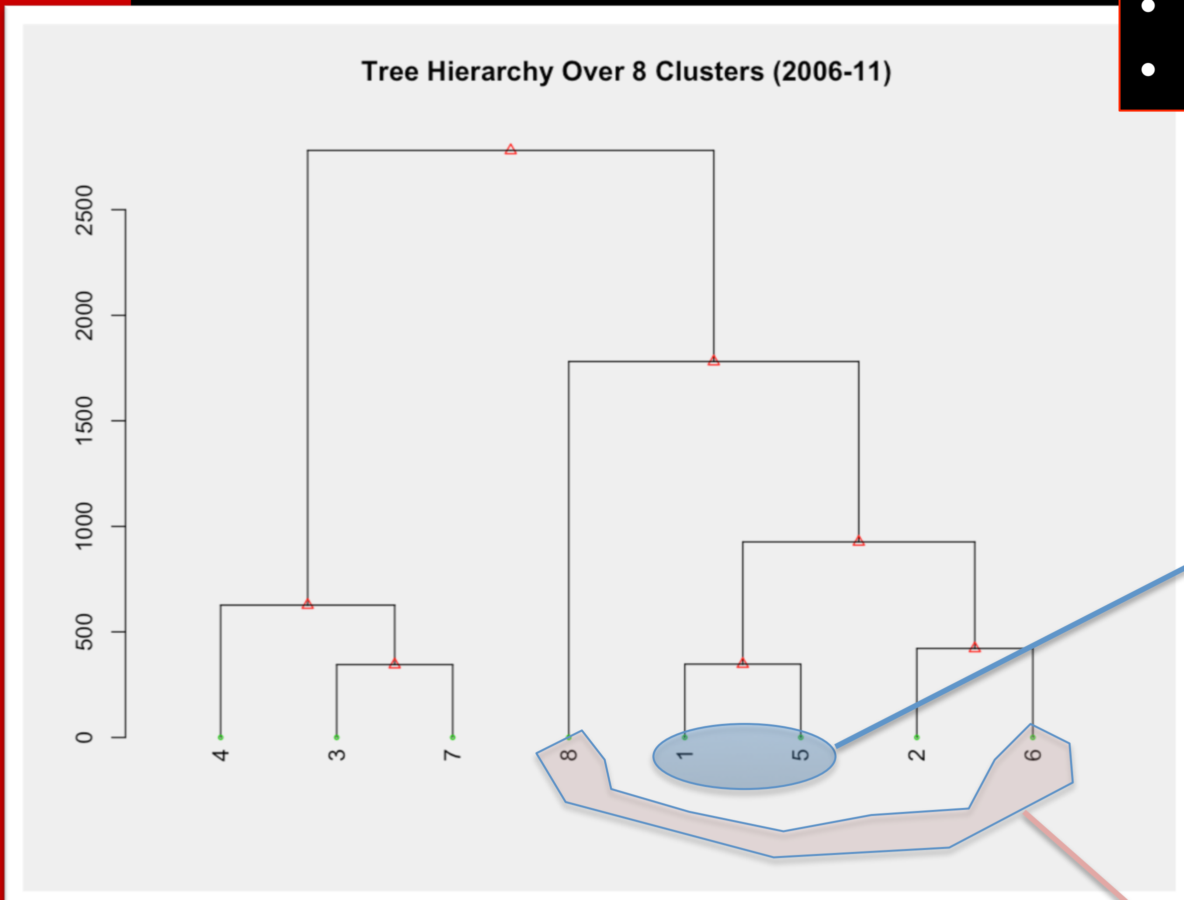
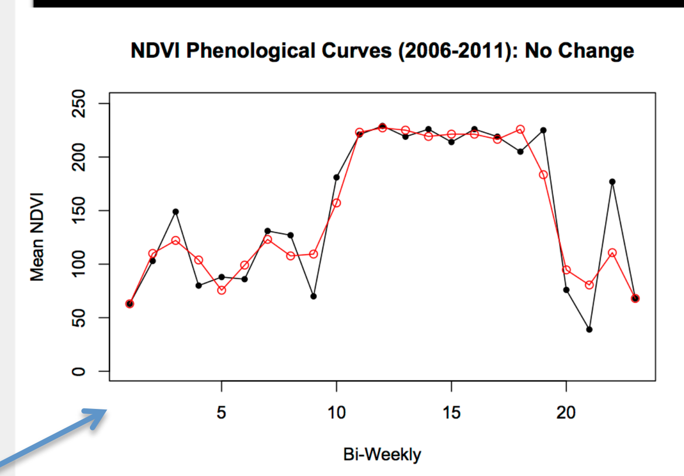
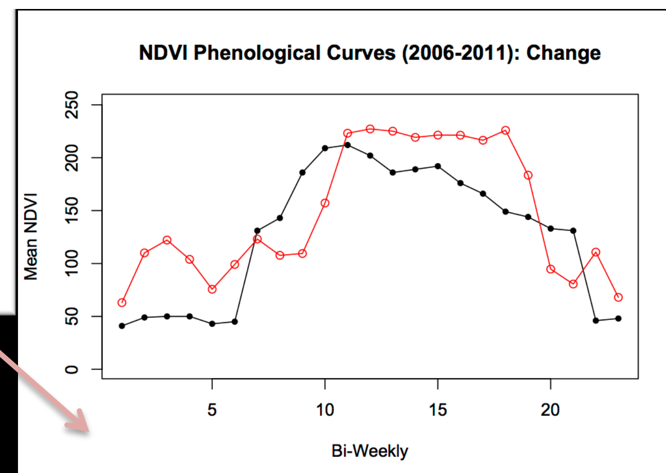
Extract Hierarchical Changes

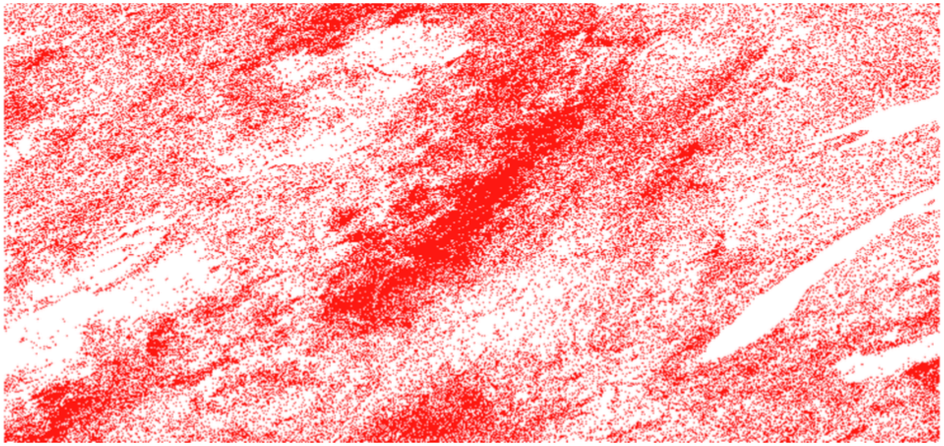
- If (Y1=1 && Y2 = 6) CH=2
- If (Y1=8 && Y2 = 2) CH=3
- …



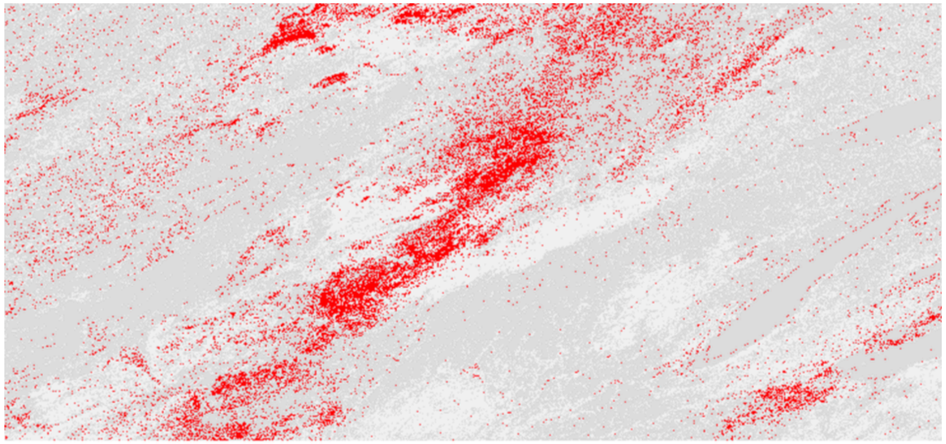




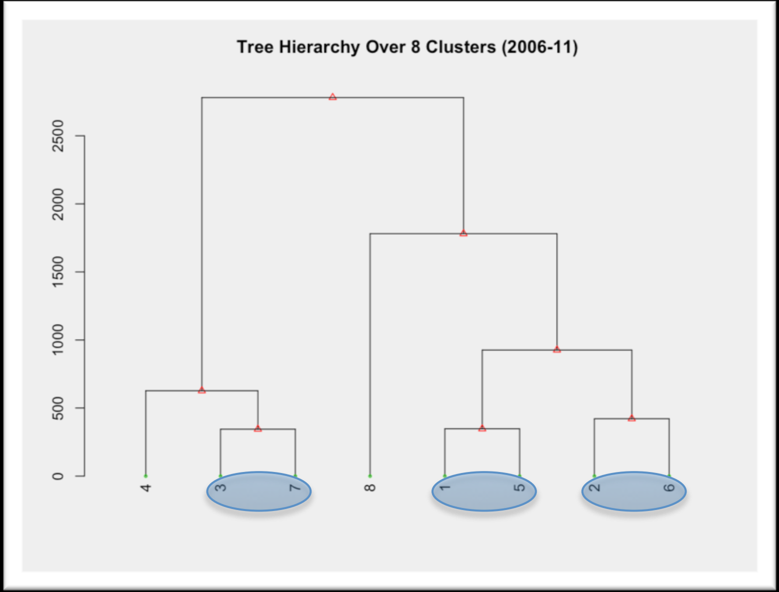
Results



K-Means



Hierarchical



K-Means over predicts changes (3-7;1-5;2-6)

Year	K-Means	HC
2001-02	33	08
2001-03	29	08
2001-04	30	06
2001-05	31	06
2001-06	34	08
2001-07	31	06
2001-08	33	06
2001-09	30	06
2001-10	36	08
2001-11	35	09

Ranga Raju Vatsavai. Hierarchical Change Detection. (Under Review)

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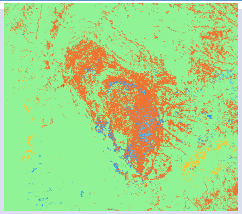
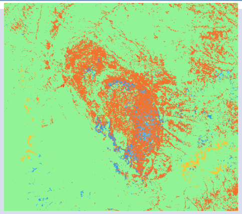
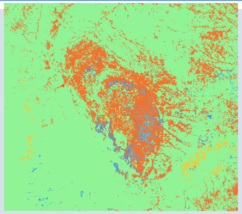
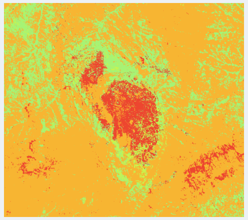
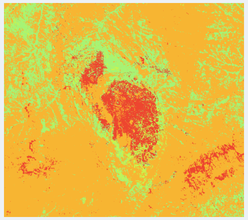
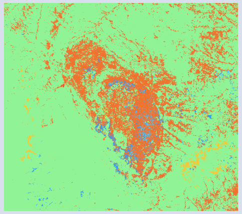
Other Applications

	Y1	Y2	Y3	Y4
Y1				
Y2				
Y3				

Online Change Browser

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Applications

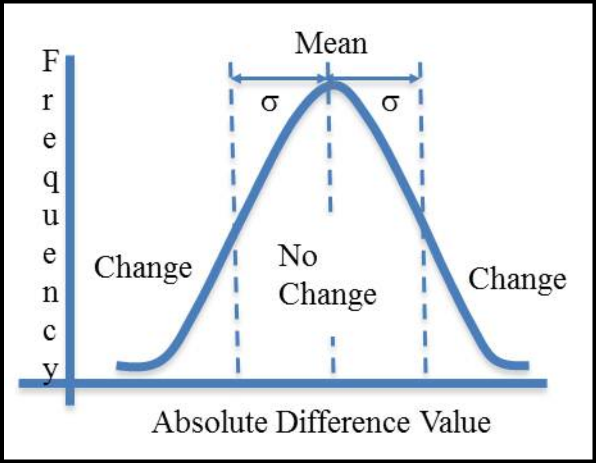
- Biomass Monitoring
- Damage Assessments
- Global Crop Mapping

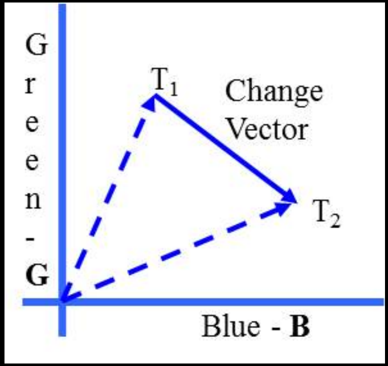
Damage Assessments

- Settlement Dynamics
  - Damages to existing structures
  - New construction
- Biomass
  - Forest fires
  - Floods and Hail Storms
  - Disease

Bi-temporal Change Detection

- Image Differencing
  - $I_{Diff}(i,j) = I_2(i,j) - I_1(i,j)$
  - Thresholding, Sensitive to noise
- Ratio of Means
  - $I_{Ratio}(i,j) = I_2(i,j) / I_1(i,j)$
  - Robust to multiplicative noise
- Inner Product and Spectral Correlation
- Multivariate Alteration Detection (MAD)
- L. Bruzzone, F. Bovolo, 2013





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Limitations

- Point based – at individual pixel (or small neighborhood)
- Mostly Univariate
- Multivariate (e.g., MAD) techniques produce multi-band change maps
- Mostly the output is continuous (requires thresholding)

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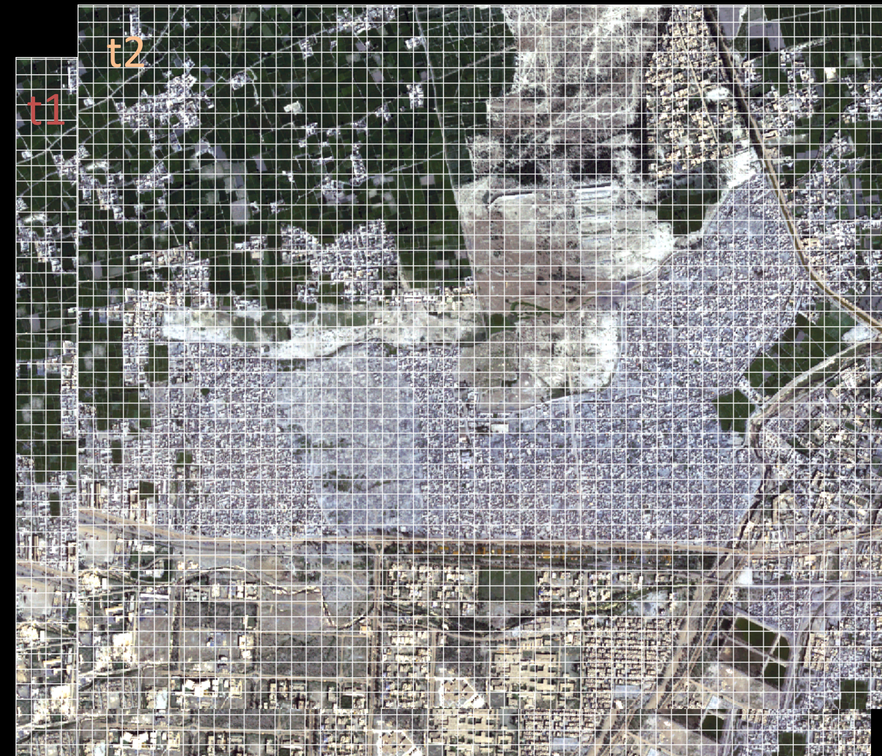
Probabilistic Approach

- Divide image into fixed grids
- Model that data in a grid is generated by probability distribution
- Estimate the overlap between two grids (distributions)
  - No change: distributions should be highly overlapping
  - Change: less overlap between distributions



Highly overlapping to No overlap

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Probabilistic Approach

- Distribution over grid-pair distances
- Gaussian Mixture Model (GMM)

$$P(x_i \mid \Theta) = \sum_{j=1}^{K} \alpha_j P_j\left(x_i \mid \theta_j\right)$$

- Compute Model Parameters Using Expectation Maximization (EM)

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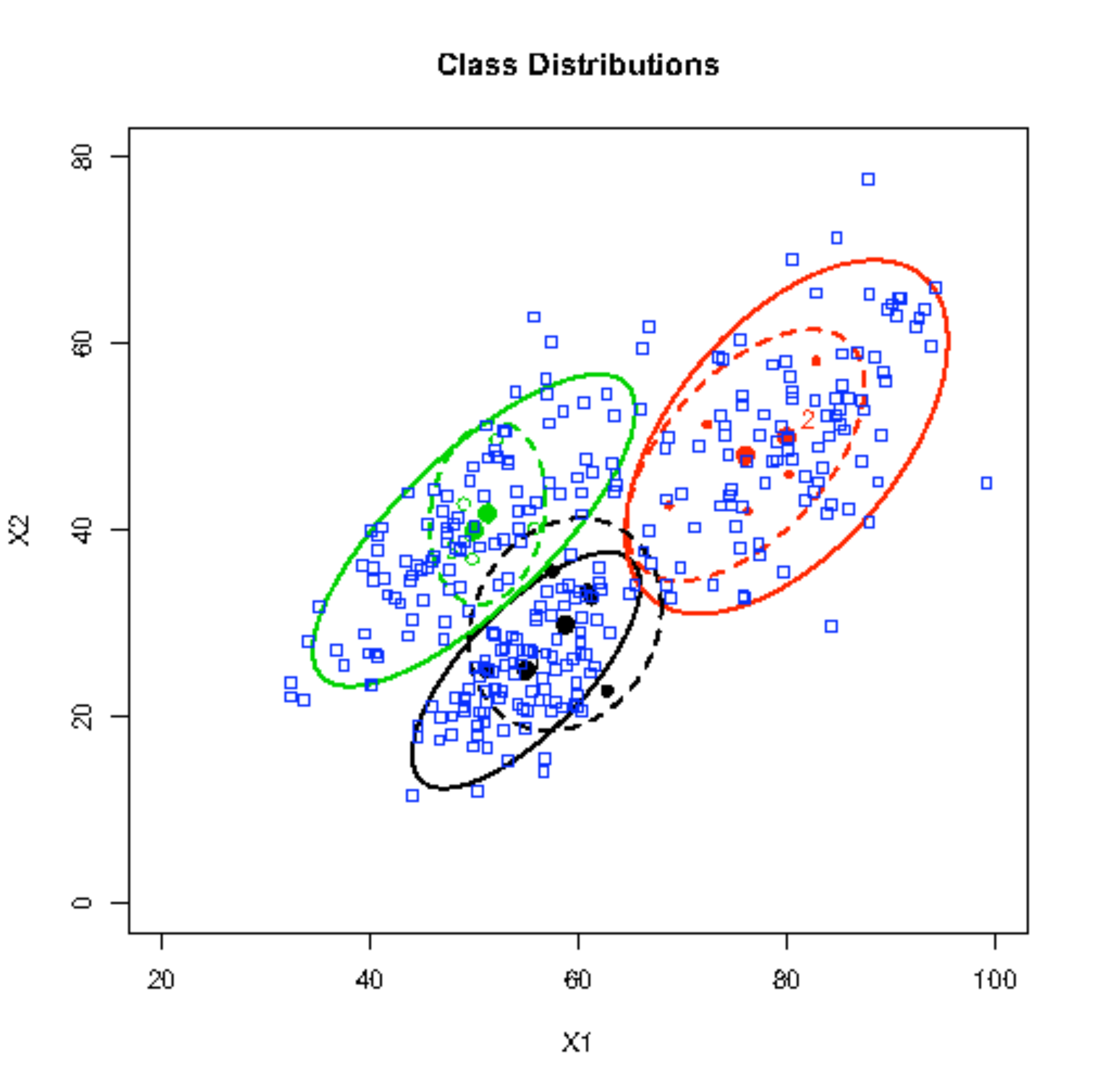
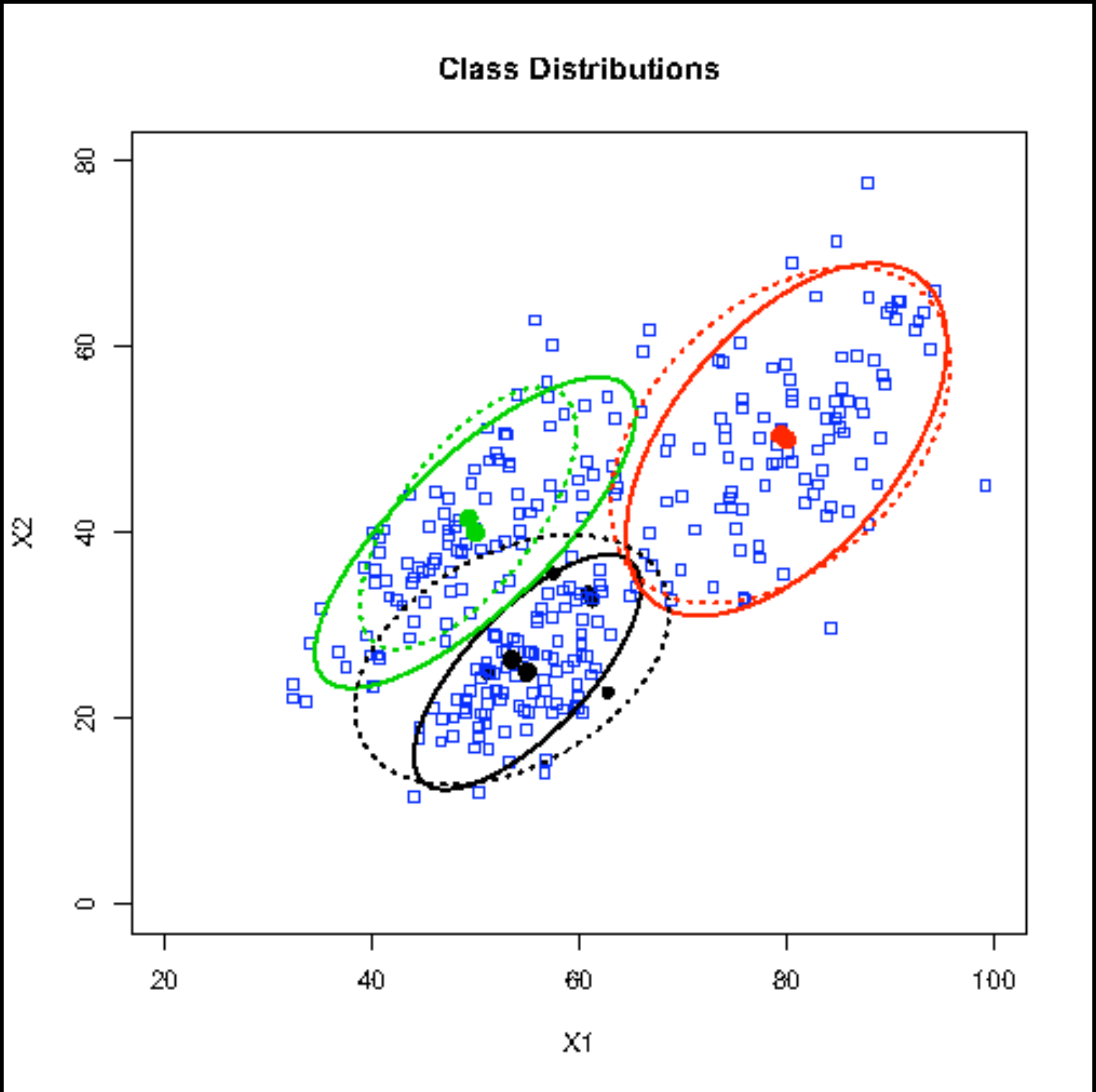
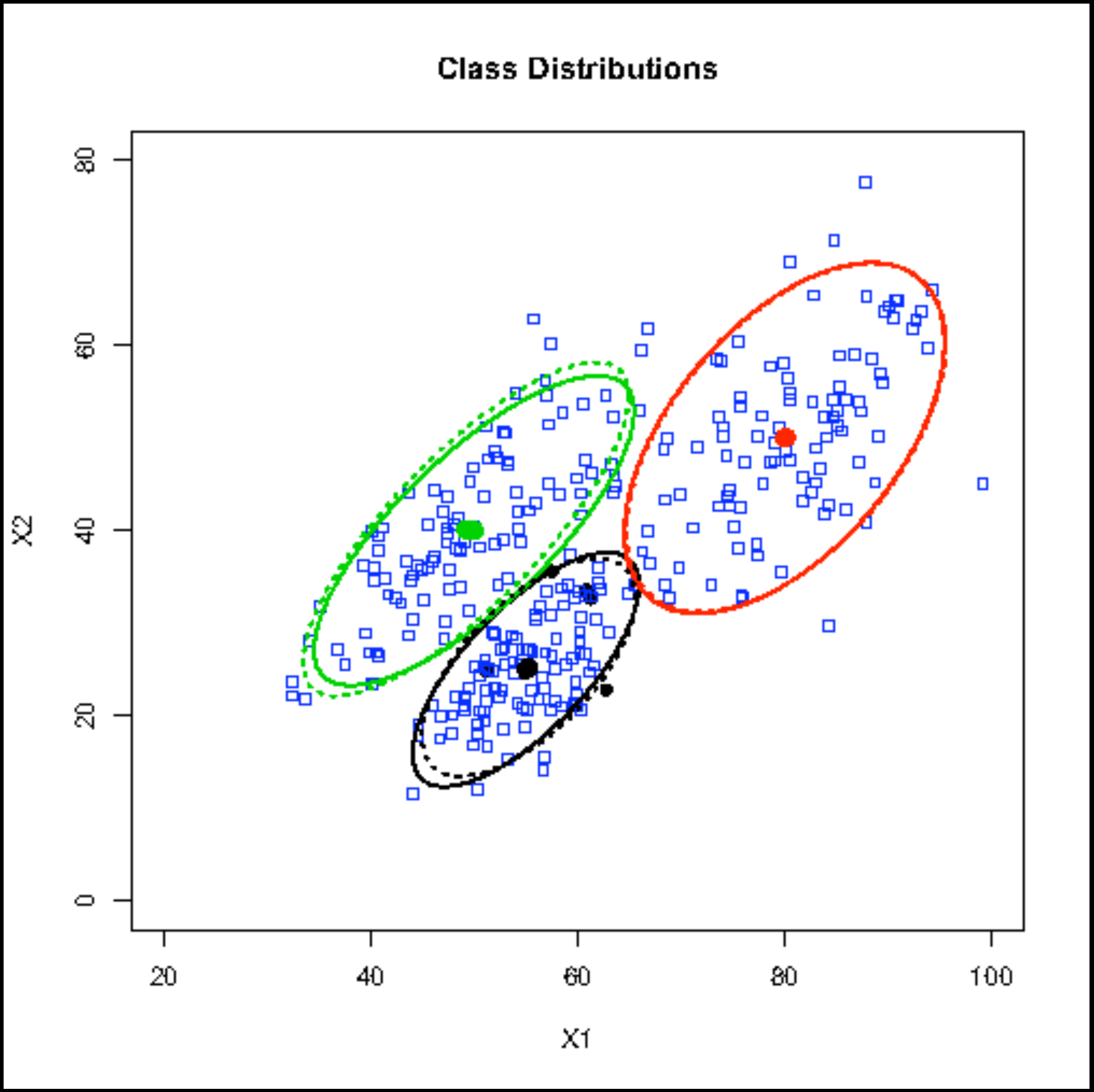
GMM Execution Trace



GMM Execution Trace



GMM Execution Trace



GMM Execution Trace

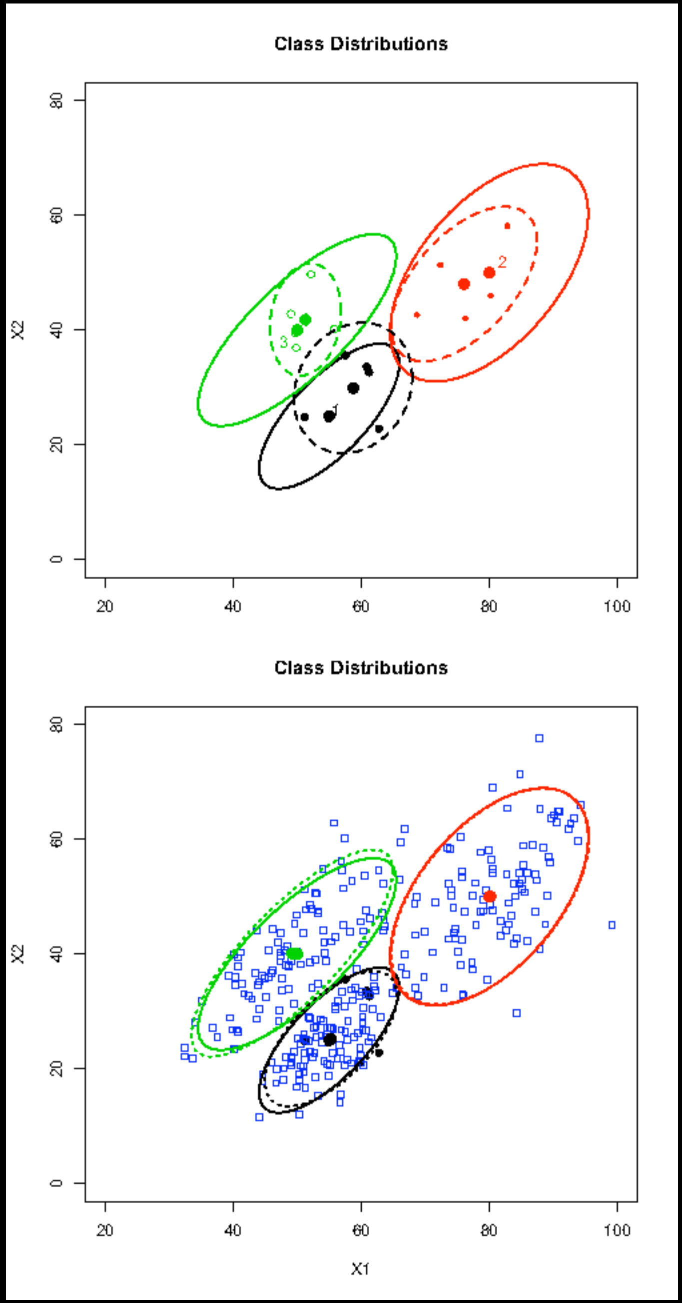
- Expectation Maximization (EM)
- E-Step

$$e_{ij} = \frac{\left|\hat{\Sigma}_j^k\right|^{-1/2} \exp\left\{-\frac{1}{2}\left(x_i - \hat{\mu}_j^k\right)^T \hat{\Sigma}_j^{-1,k}\left(x_i - \hat{\mu}_j^k\right)\right\}}{\sum_{l=1}^{M}\left|\hat{\Sigma}_l^k\right|^{-1/2} \exp\left\{-\frac{1}{2}\left(x_i - \hat{\mu}_l^k\right)^T \hat{\Sigma}_l^{-1,k}\left(x_i - \hat{\mu}_l^k\right)\right\}}$$

- M-Step

$$\alpha_j = \frac{\sum_{i=1}^{N} e_{ij}}{N}, \qquad \hat{\mu}_j^{k+1} = \frac{\sum_{i=1}^{N} e_{ij} x_i}{\sum_{i=1}^{N} e_{ij}},$$

$$\text{and} \quad \hat{\Sigma}_j^{k+1} = \frac{\sum_{i=1}^{N} e_{ij}\left(x_i - \hat{\mu}_j^{k+1}\right)\left(x_i - \hat{\mu}_j^{k+1}\right)^T}{\sum_{i=1}^{N} e_{ij}}$$



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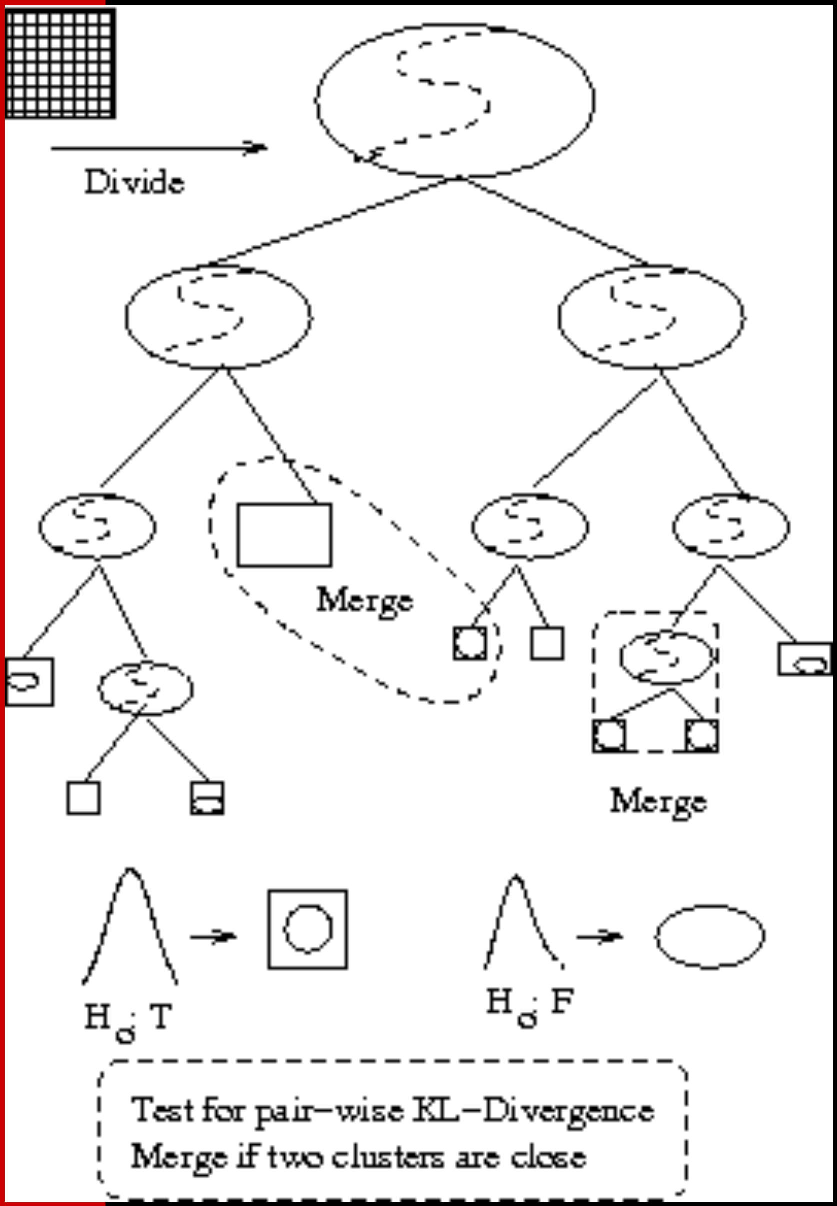
Challenge: How Many Clusters?



Inputs: D, sample dataset; significance (default p-value = 0.05), initial K (default = 2), nClusters = K

Loop 1: WHILE (TRUE):

Loop 2: FOR 1:nClusters

Statistical test: Shapiro-Wilk test.

Check: **IF** a cluster fails statistical test,

THEN split that cluster into two

clusters using GMM-Clustering;
increment nClusters and K;

ELSE accept cluster,

decrement nClusters

Clustering: GMM-Clustering(failed-cluster data-samples, new K)

Merge: Compute KL-Divergence,

IF two-clusters are closer than threshold,

THEN decrement K

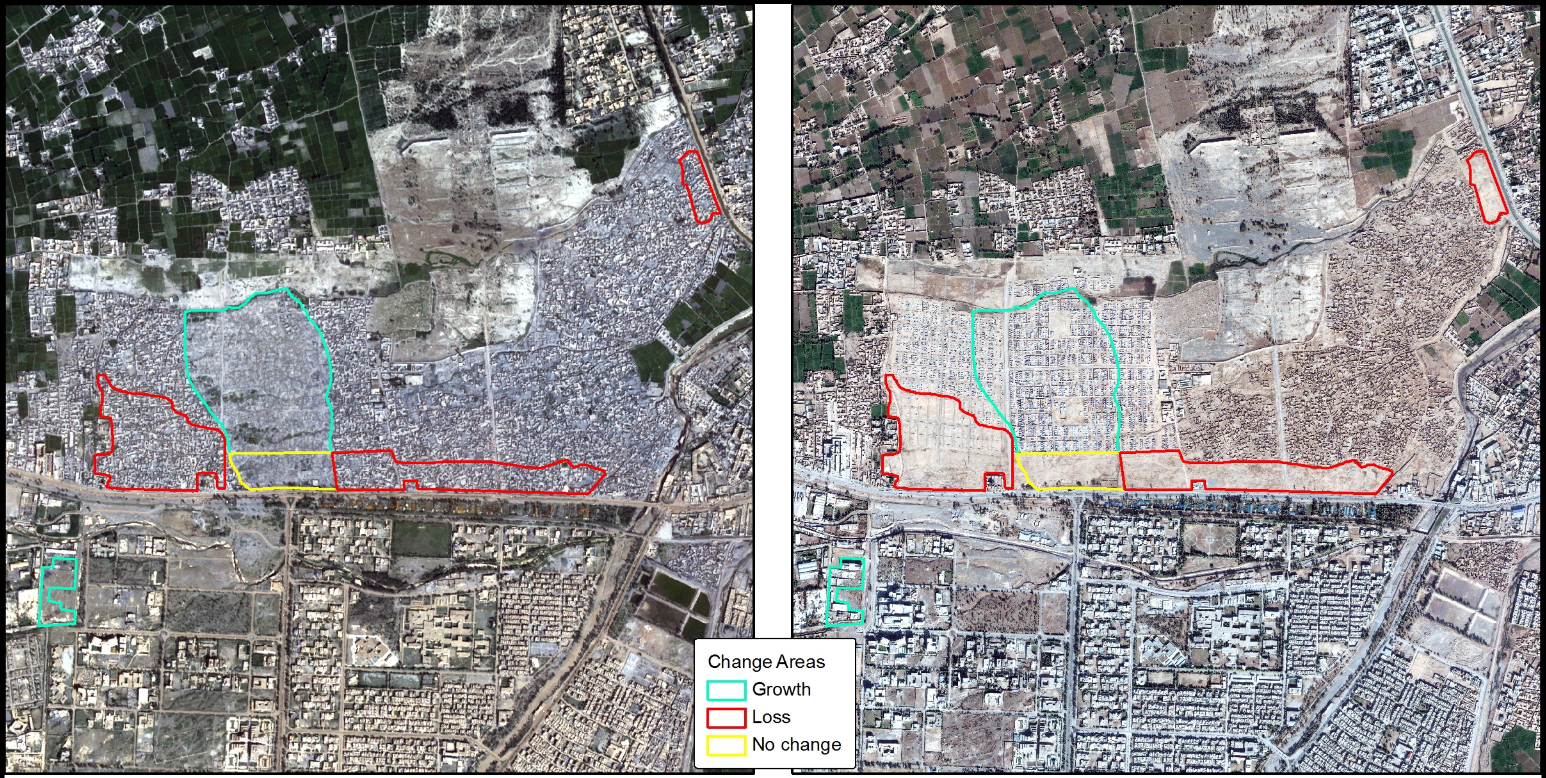
continue (Loop 2)

Check: **IF** nClusters = 0 (break, Loop 1)

Output: Parameter vector Θ.

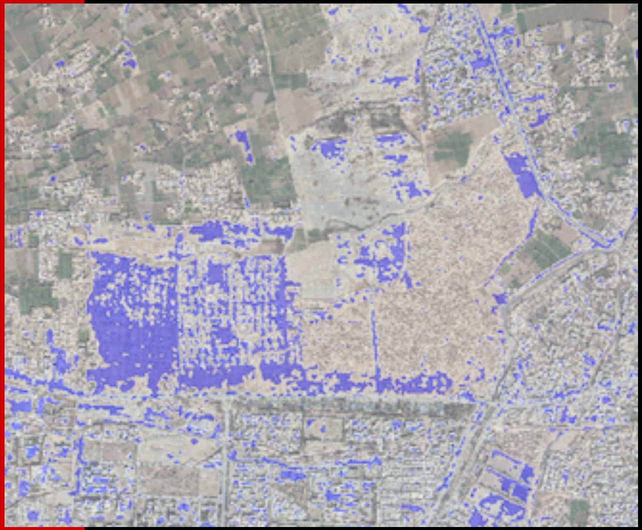
Results

- Kacha Garhi Camp, Pakistan
- Established 1980 for Afghan Refugees
- QuickBird (2004 and 2009, 4B, 2.4m)

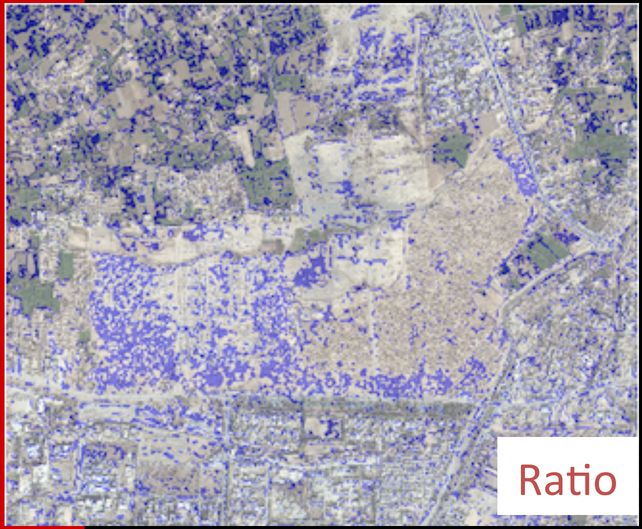


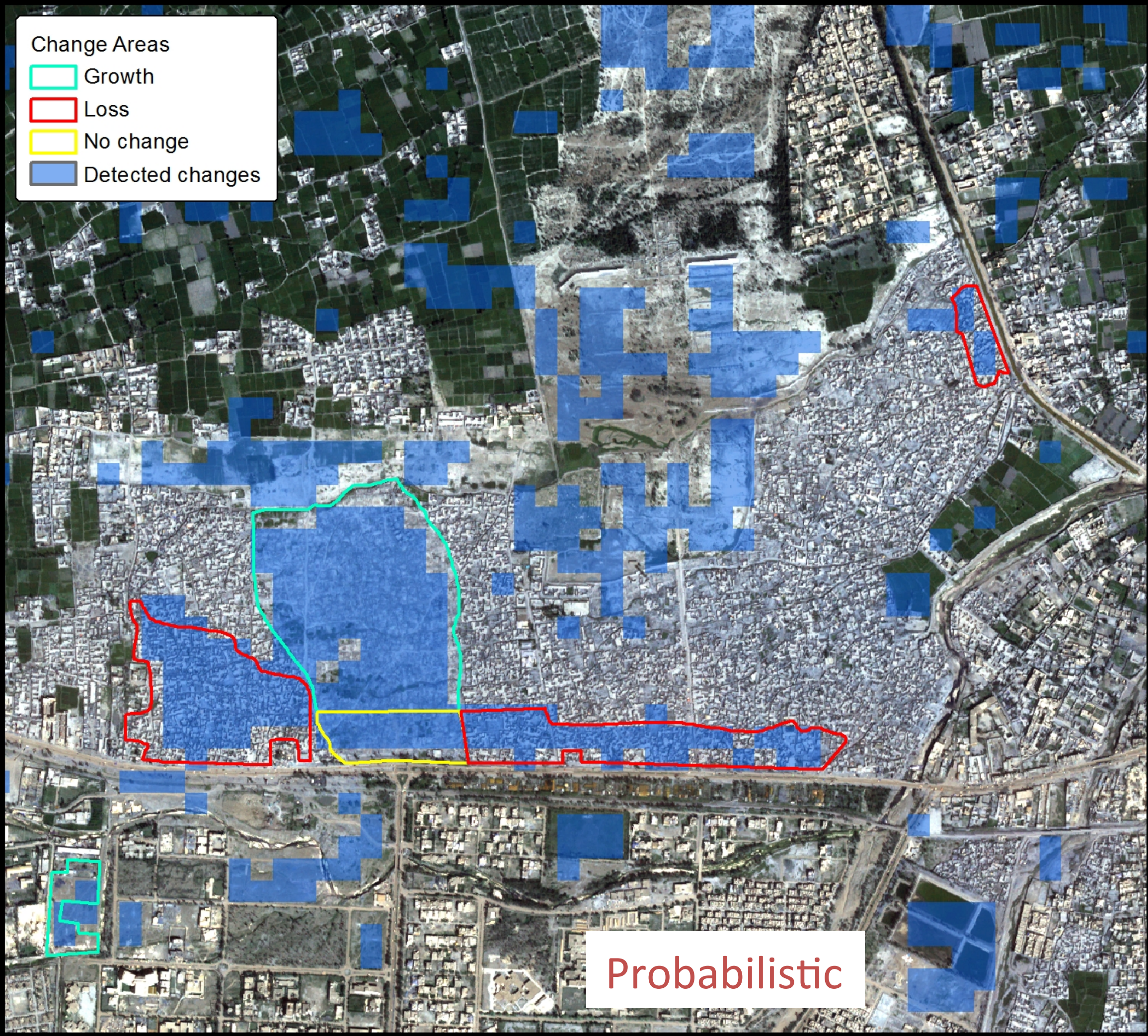
(a) 2004 (a) 2009

Results



Difference

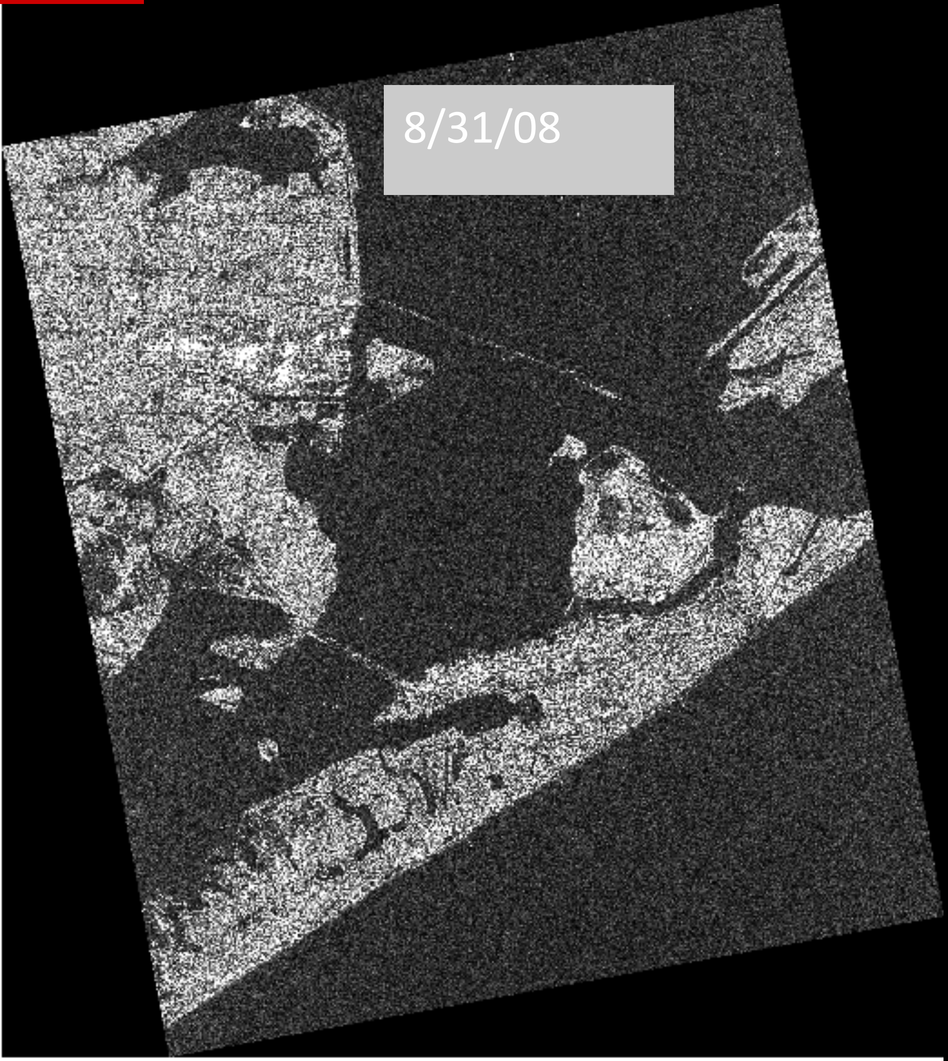


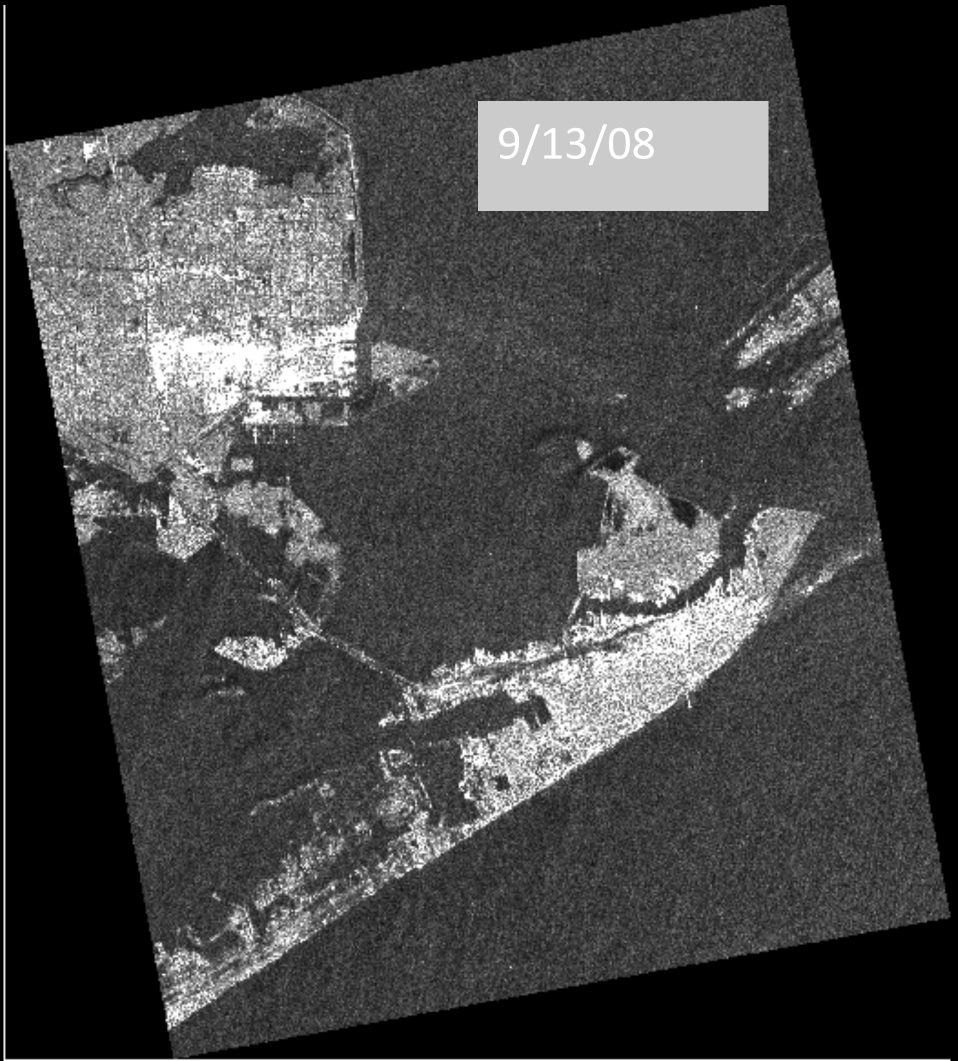


Ranga Raju Vatsavai, Jordan Graesser: Probabilistic Change Detection Framework for Analyzing Settlement Dynamics Using Very High-resolution Satellite Imagery. ICCS 2012: 907-916

Results

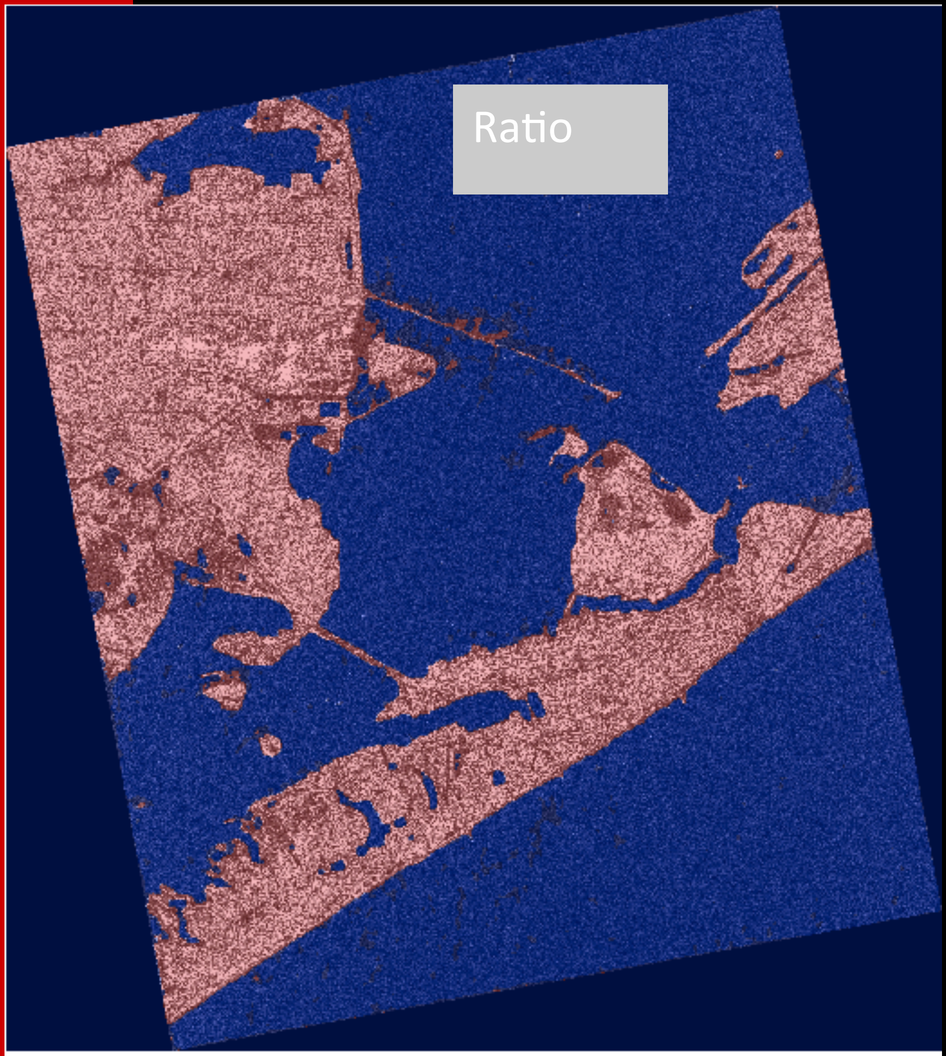
- SAR Imagery during Ike – noise, spatial resolution (1.56m vs. 12.5m)

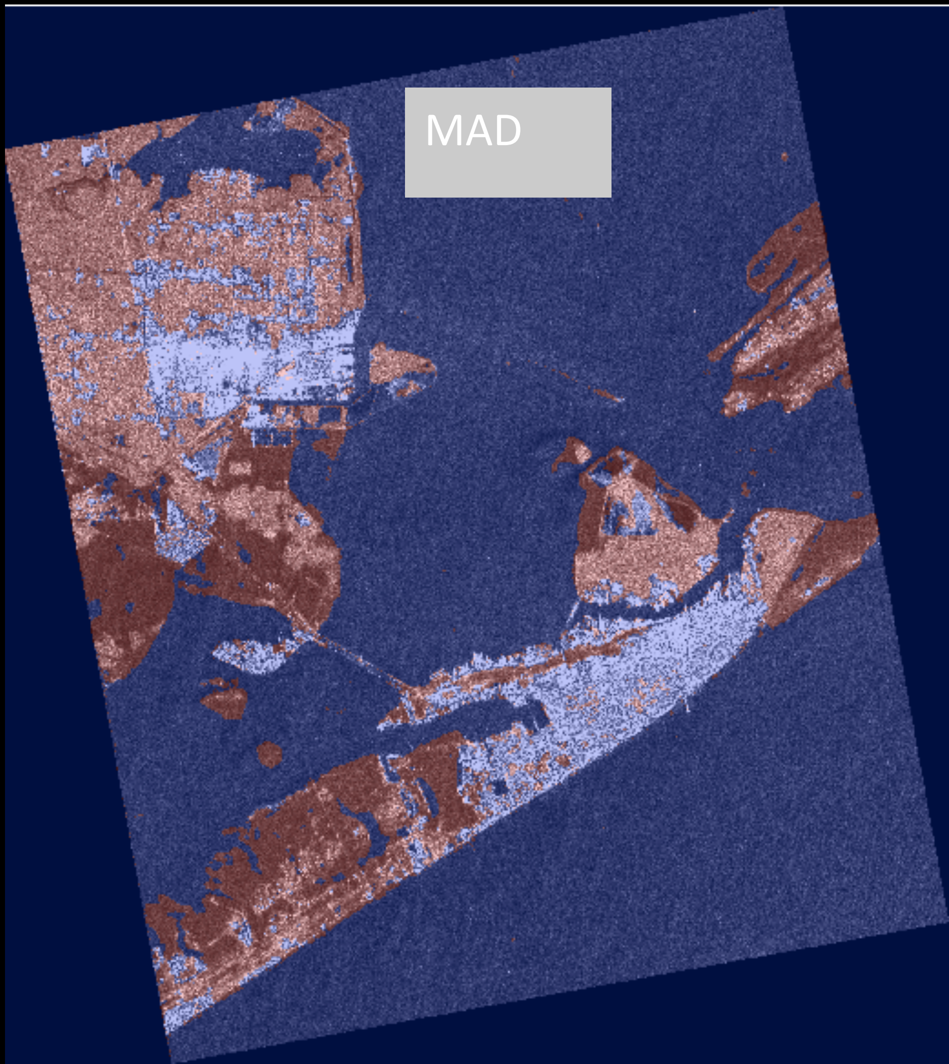




Results

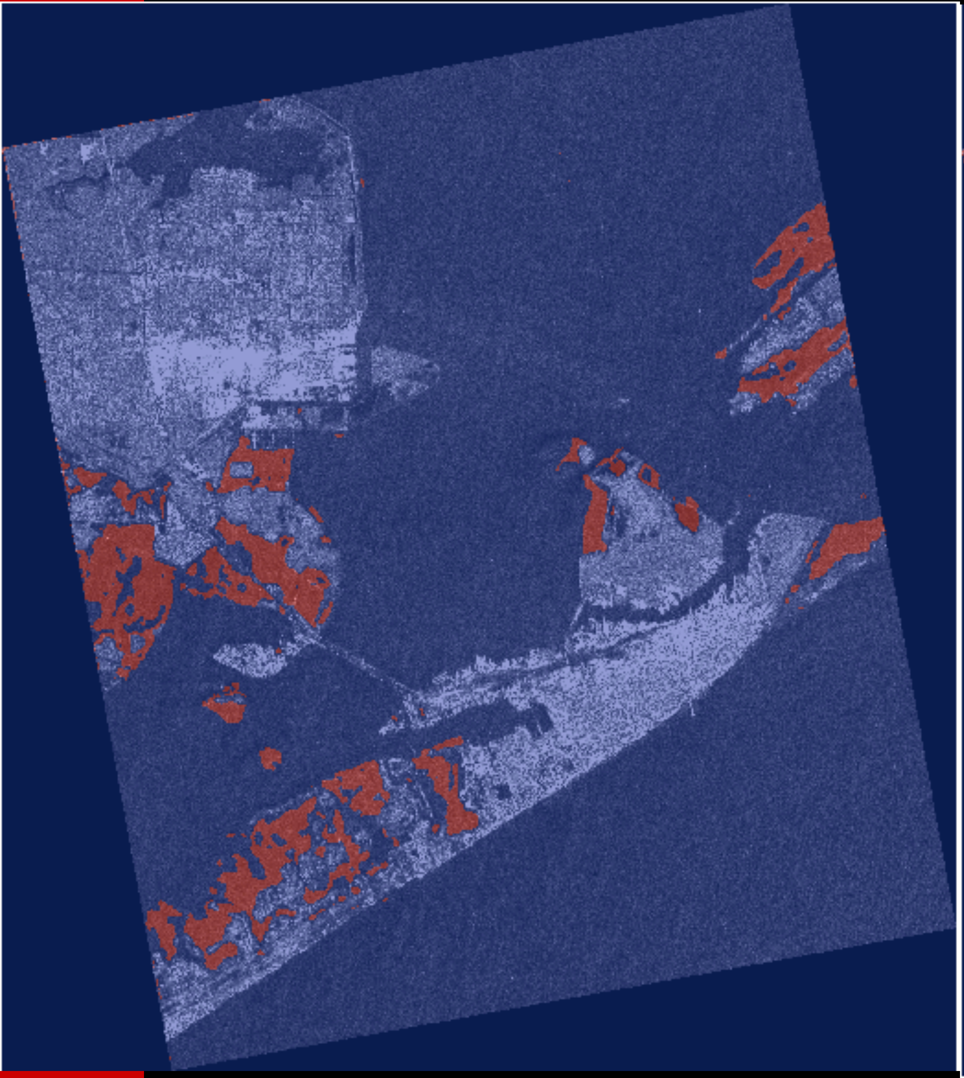
- Off-the-shelf techniques predict almost every pixel as change

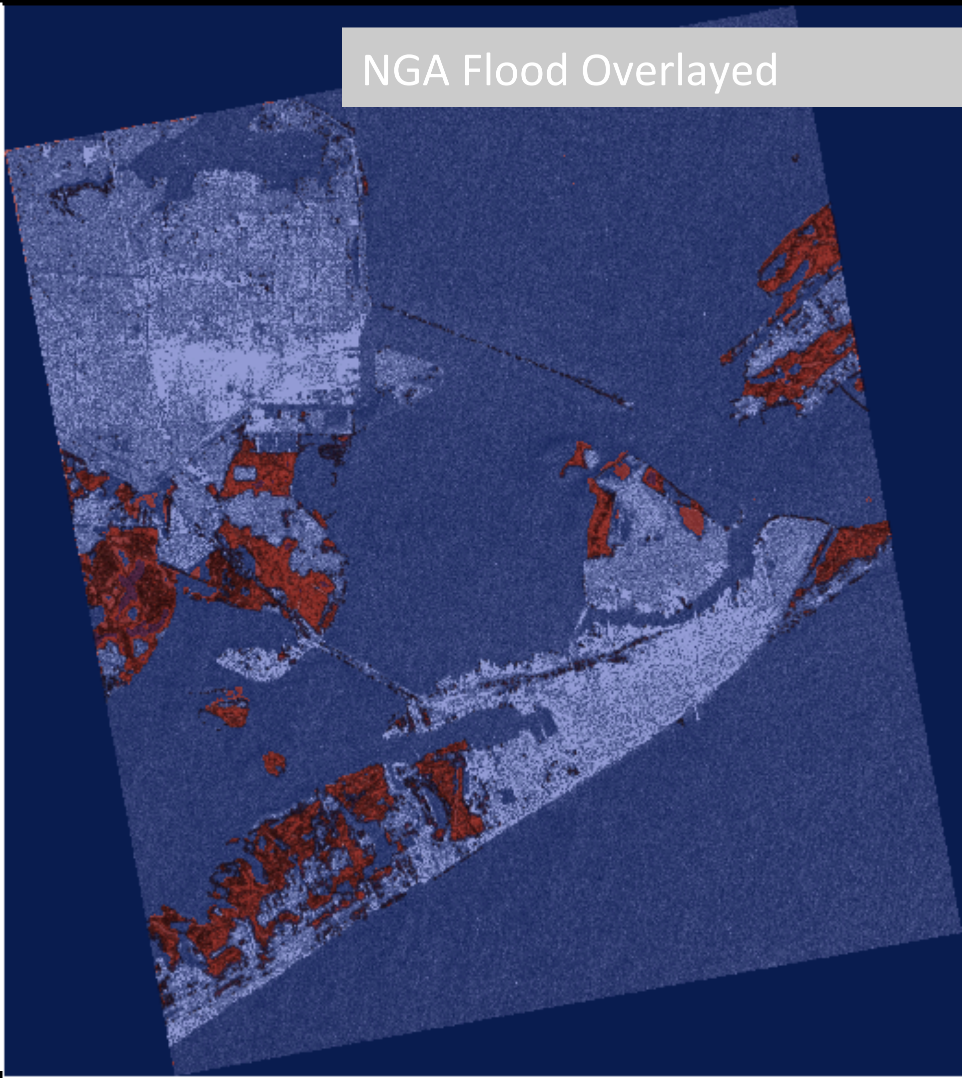




Results

- Probabilistic Approach





Applications

- Biomass Monitoring
- Damage Assessments
- Crop Mapping, Semantic Classification, Settlement (slum) mapping

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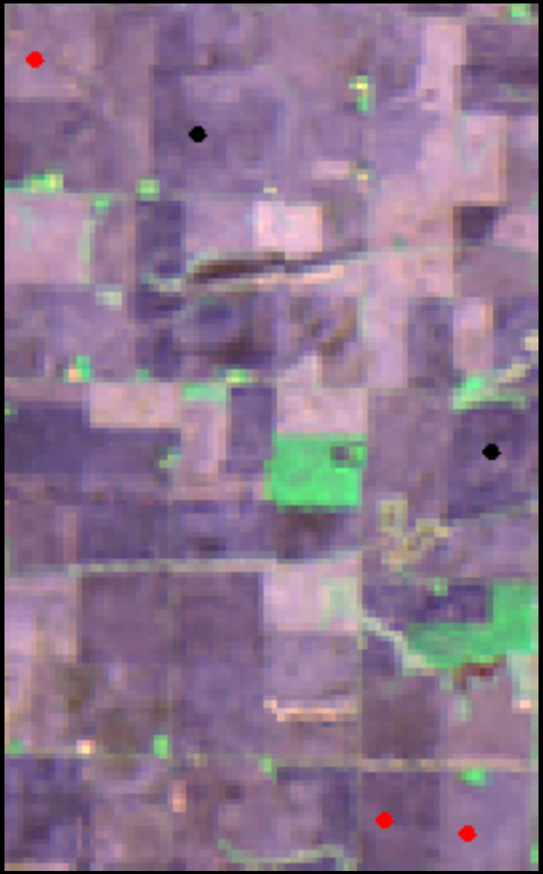
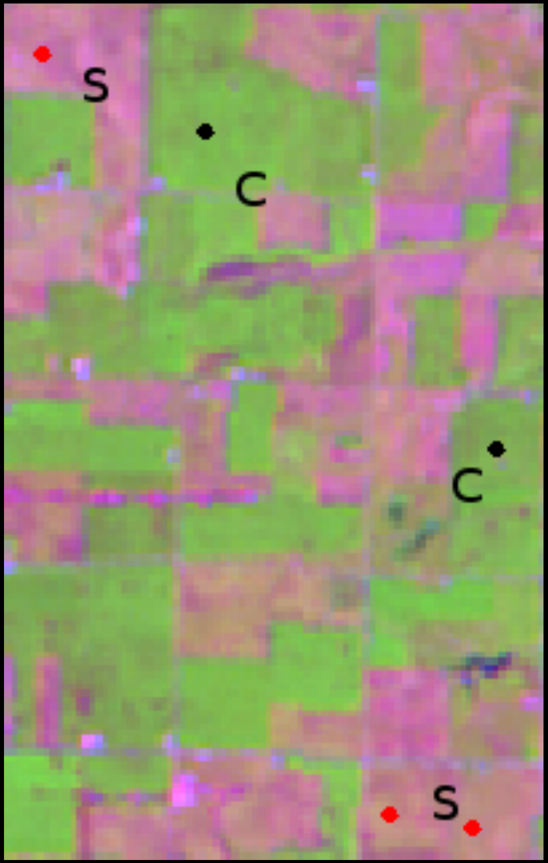
Multi-temporal Classification



AWiFS (May 3, 2008; FCC (4,3,2))



AWiFS (July 14, 2008; FCC (4,3,2))

Thematic Classes: C-Corn, S-Soy

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Multi-temporal Classification

	corn	soy	alfa	grass	water	dvlpd	forest	wetlnd
corn	0.00	957.98	2000.00	1999.98	2000	1999.45	1859.75	2000
soy	957.98	0.00	2000.00	2000.00	2000	2000.00	1999.11	2000
alfa	2000.00	2000.00	0.00	2000.00	2000	1998.70	1999.89	2000
grass	1999.98	2000.00	2000.00	0.00	2000	1790.64	1973.95	2000
water	2000.00	2000.00	2000.00	2000.00	0.00	2000.00	2000.00	2000
dvlpd	1999.45	2000.00	1998.70	1790.64	2000	0.00	1817.02	2000
forest	1859.75	1999.11	1999.89	1973.95	2000	1817.02	0.00	2000
wetlnd	2000.00	2000.00	2000.00	2000.00	2000	2000.00	2000.00	0.00

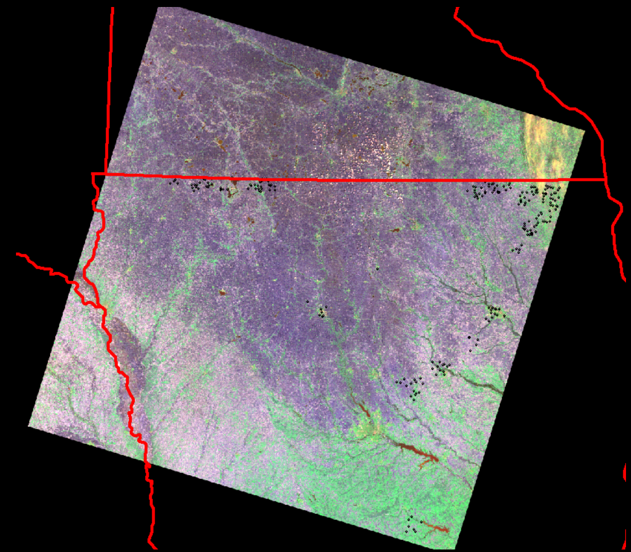
TABLE 6. Transformed Divergence Between Classes from May Image

	corn	soy	alfa	grass	water	dvlpd	forest	wetlnd
corn	0.00	1610.59	2000	927.95	2000	2000.00	1993.94	1999.65
soy	1610.59	0.00	2000	1252.87	2000	1997.30	2000.00	2000.00
alfa	2000.00	2000.00	0.00	2000.00	2000	2000.00	2000.00	2000.00
grass	927.95	1252.87	2000	0.00	2000	1992.04	1999.50	1999.76
water	2000.00	2000.00	2000	2000.00	0.00	2000.00	2000.00	2000.00
dvlpd	2000.00	1997.30	2000	1992.04	2000	0.00	2000.00	1999.31
forest	1993.94	2000.00	2000	1999.50	2000	2000.00	0.00	1734.34
wetlnd	1999.65	2000.00	2000	1999.76	2000	1999.31	1734.34	0.00

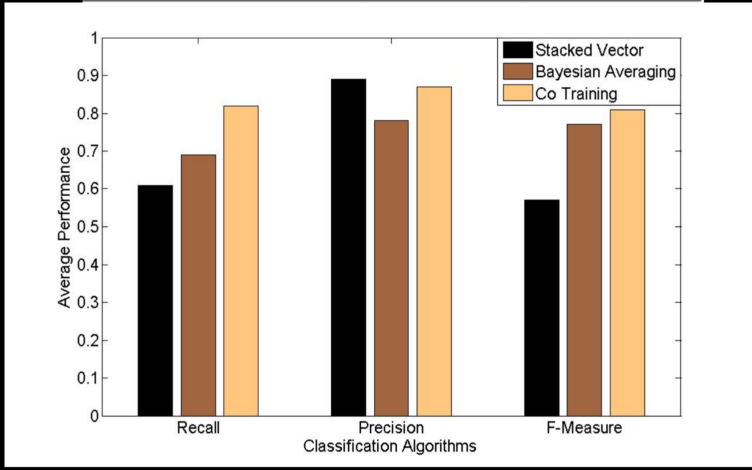
TABLE 7. Transformed Divergence Between Classes from July Image

Multi-view Approach

- Multi-temporal images are different views of same phenomena
  - Learn single classifier on different views, chose the best one through empirical evaluation
  - Combine different views into a single view, train classifier on single combined view – stacked vector approach
  - Learn classifier on single view and combine predictions of individual classifiers – multiple classifier systems
    - Bayesian Model Averaging
  - Co-training
    - Learn a classifier independently on each view
    - Use predictions of each classifier on unlabeled data instances to augment training dataset for other classifier



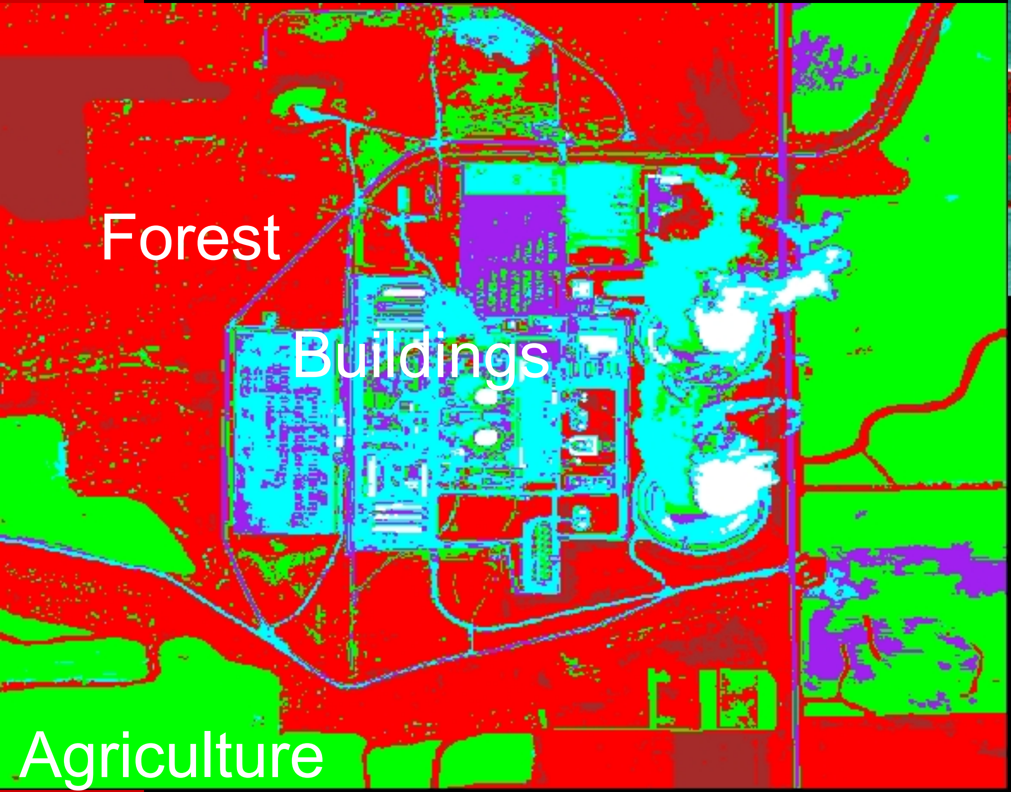
Class	Training	Validation
Corn	261	261
Soybean	225	225
Alfa alfa	27	27
Grass	189	180
Water	18	18
Developed	90	99
Deciduous Forest	117	117
Wetlands Forest	18	36
Total:	945	963



Varun Chandola, Ranga Raju Vatsavai: Multi-temporal remote sensing image classification - A multi-view approach. CIDU 2010: 258-270

Image Classification

- **How about high-resolution images and semantic labels?**



- **Does this kind of thematic classification make sense for identifying nuclear power plant? Can these thematic classes imply above image as nuclear plant?**

What is missing?

Containment Building

Turbine Generator

Cooling Towers

Semantics:
Set objects like:
Switch yard,
Containment Building,
Turbine Generator,
Cooling Towers
AND
Their spatial arrangement may imply a semantic label like "nuclear power plant"

Semantic Classification

- **Covert image into regions of interest (roi)**
  - **Could be a regular window of fixed size (e.g., gridding)**
  - **Arbitrary shaped region (e.g., by segmentation)**
- **Compute local descriptors over roi's**
  - **Extract features (e.g., texture, edges, …)**
- **Quantize descriptors into words**
  - **Forms the visual vocabulary**
  - **Each word is single label (all words with-in same cluster) or visual word**
- **Build the bag-of-visual-words, by finding the frequency of occurrence of each word in the image (document)**
- **Fit LDA model and use it to predict topics**

Pixels to features

Features to words

Words to topics

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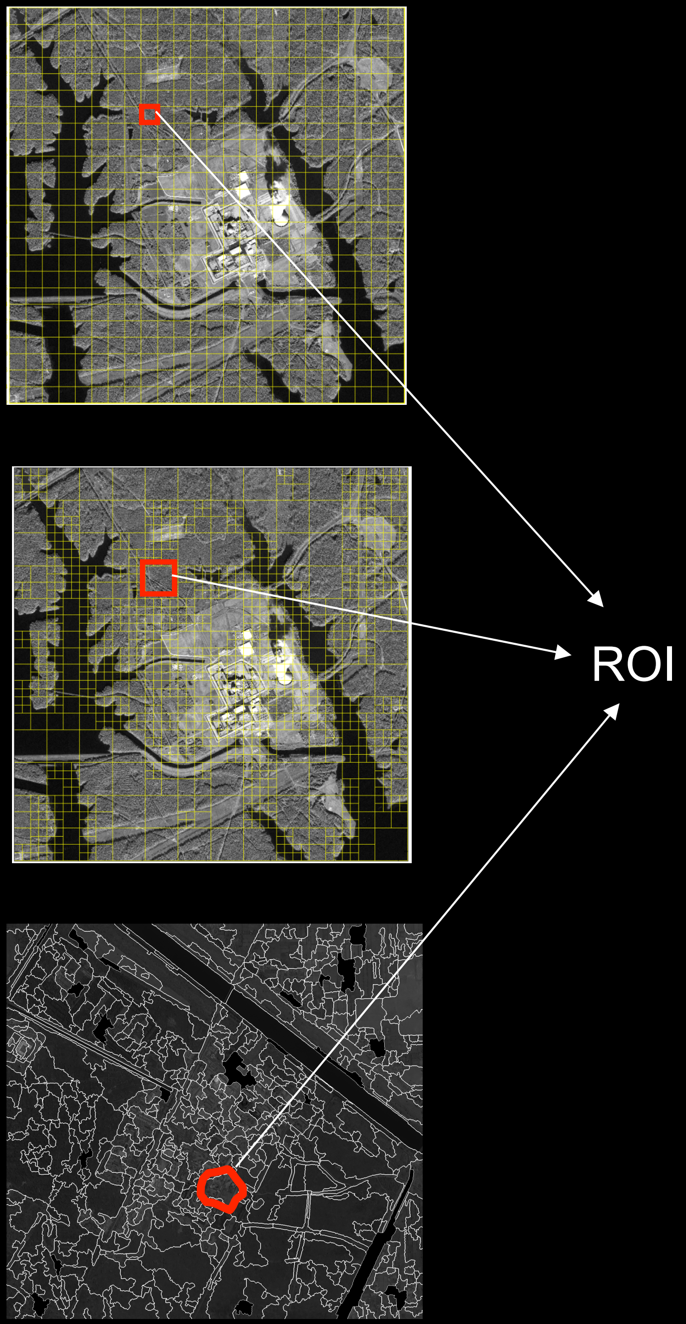
Pixels to Features

- Low-level Features
  - Spectral/Intensity feature
  - Local Edge Pattern
  - Local Binary Pattern
  - Edge Orientation
  - Line Support Regions
- ROI's can be fixed size tile, variable size tile or irregular polygon.



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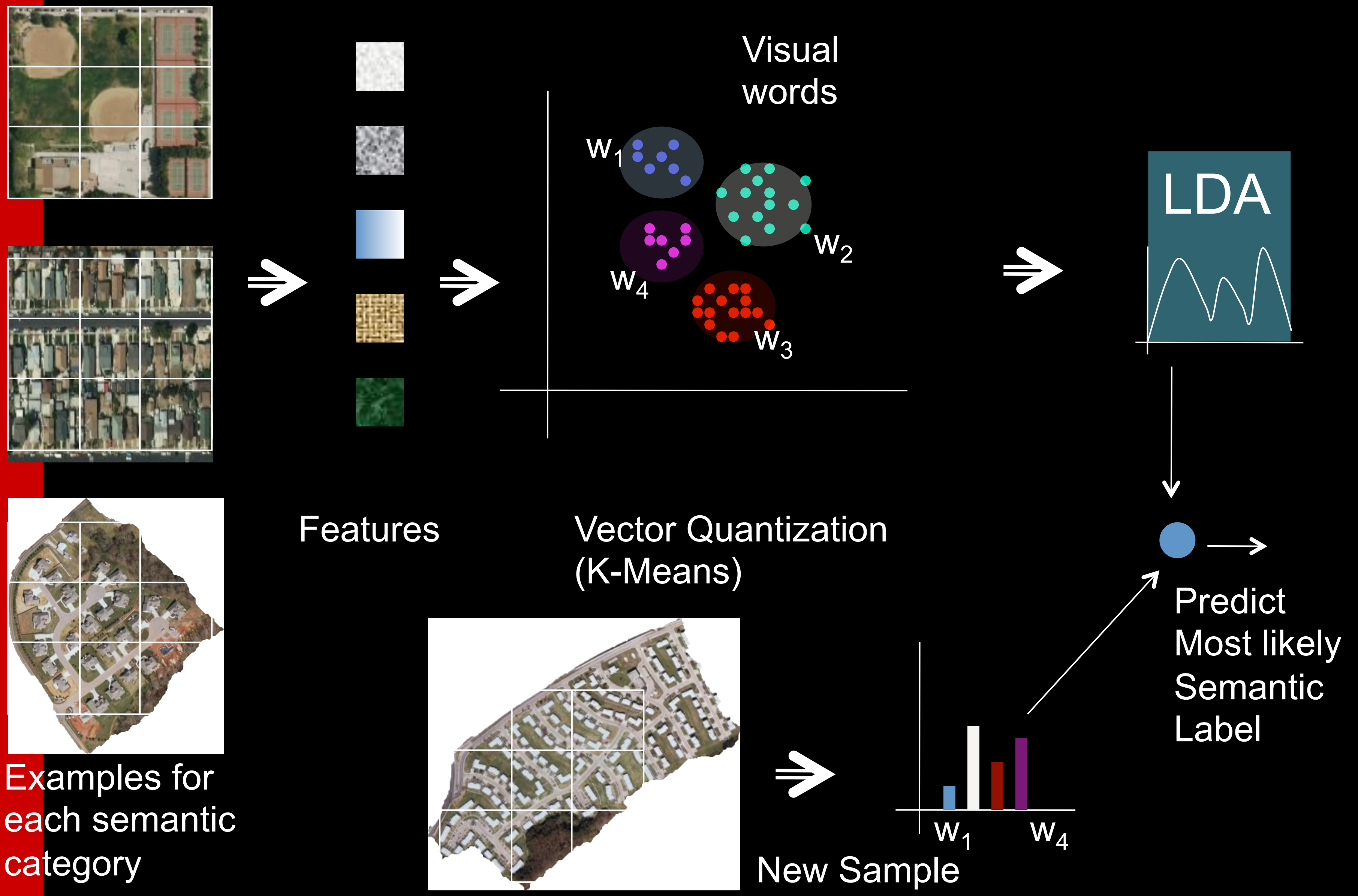
Semantic Classification Framework



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Results

Category	Training	Test	Total
Airport	8	10	18
Coal	13	17	30
Nuclear	20	55	75
Total	41	82	123

Ground Truth	Airport	Coal	Nuclear	Producers Accuracy (%)
Airport	6	3	1	60.0
Coal	1	10	6	58.8
Nuclear	0	9	46	85.2
Users Accuracy (%)	85.7	45.5	86.8	75.6

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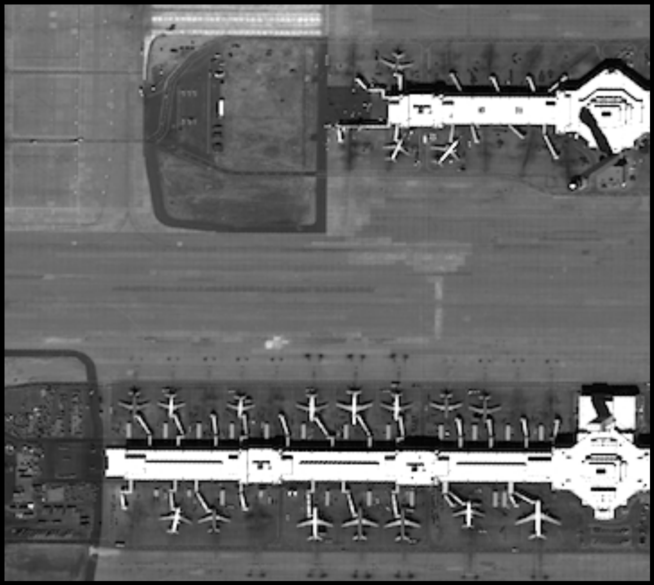
Results



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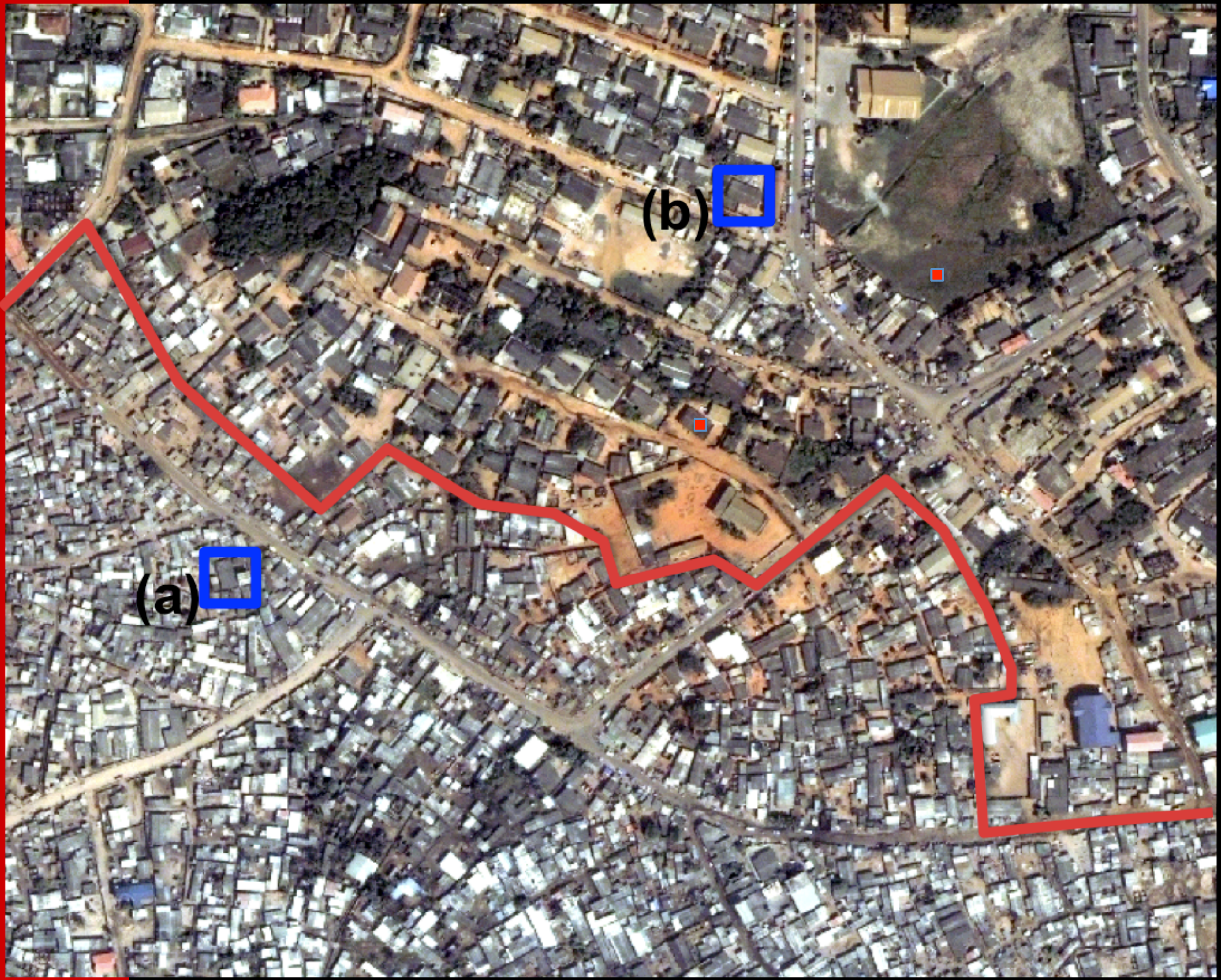
Settlement Mapping

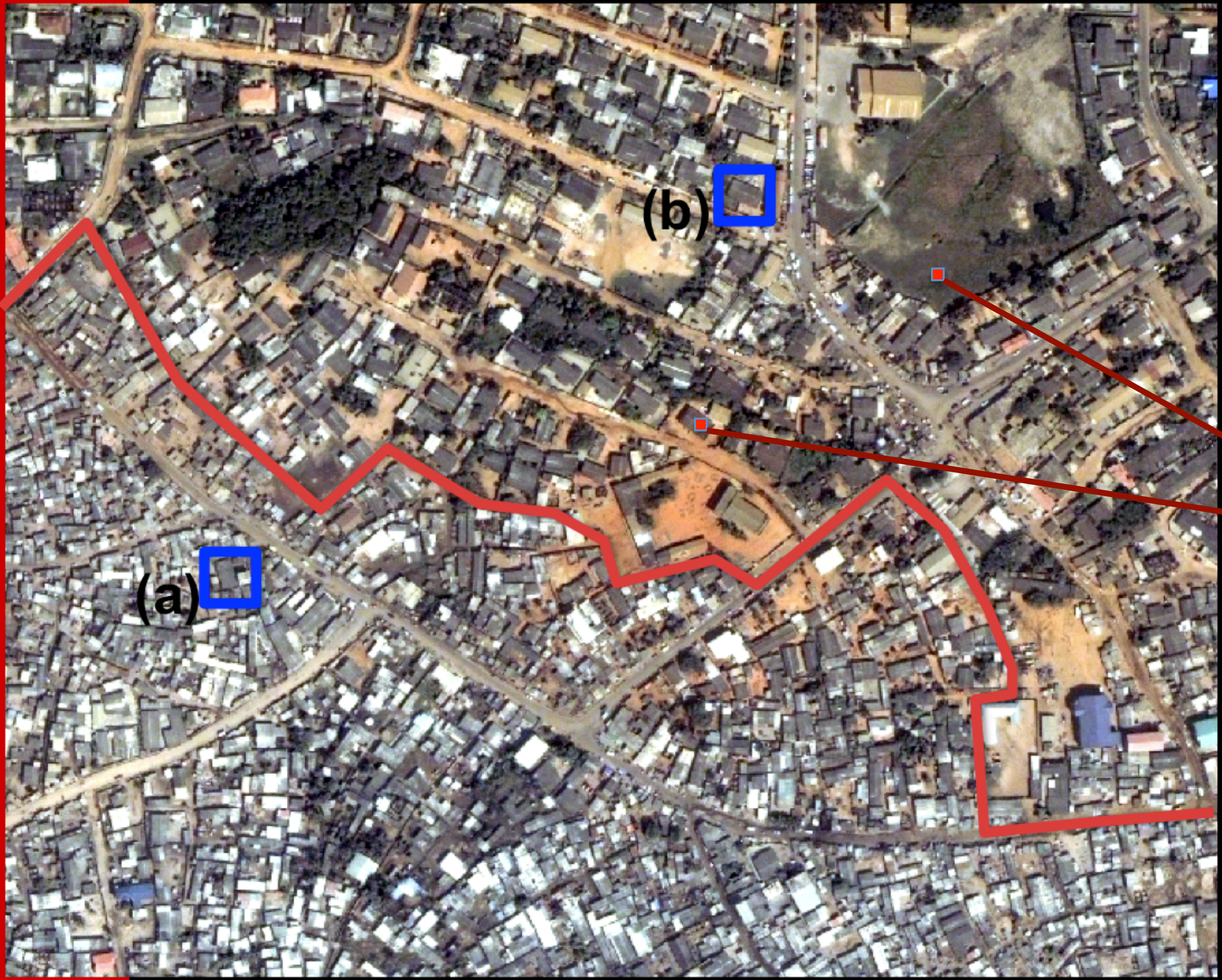
- Challenge: classifying different neighborhoods
  - Urban social scientists have treated ‘neighborhood’ in much the same way as courts of law have treated pornography: a term that is hard to define precisely, but everyone knows it when they see it. -- Galster (2001)

VHR Imagery



Can we recognize different urban neighborhoods in VHR imagery?

Classification Challenges



- Pixel-based or single-instance classification

Pixels from different objects

Difficult to distinguish

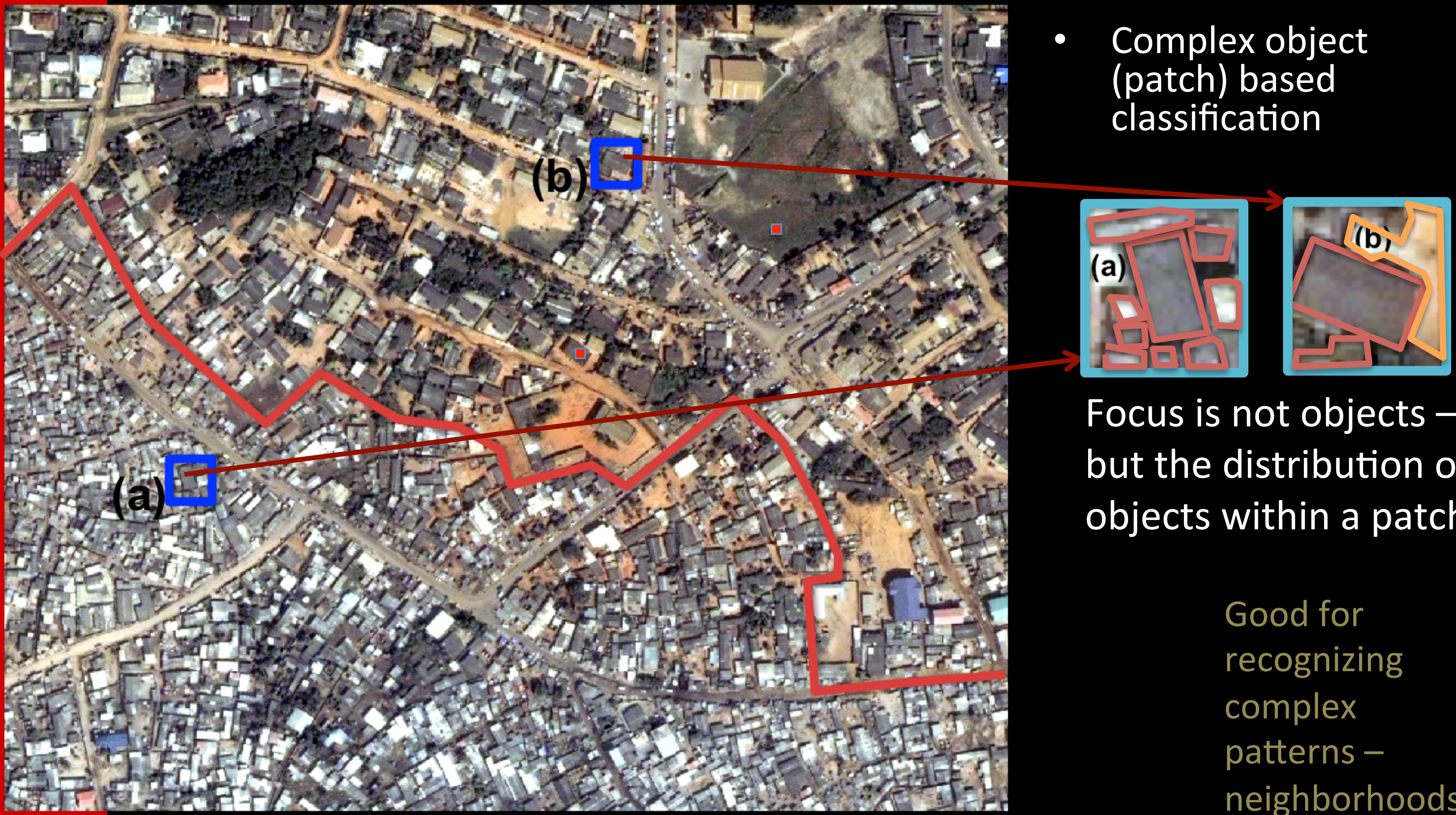
Classification Challenges

- Object based classification

Objects (buildings) from different neighborhoods

Good for recognizing objects, but difficult to distinguish neighborhoods

Classification Challenges



- Complex object (patch) based classification

Focus is not objects – but the distribution of objects within a patch

Good for recognizing complex patterns – neighborhoods

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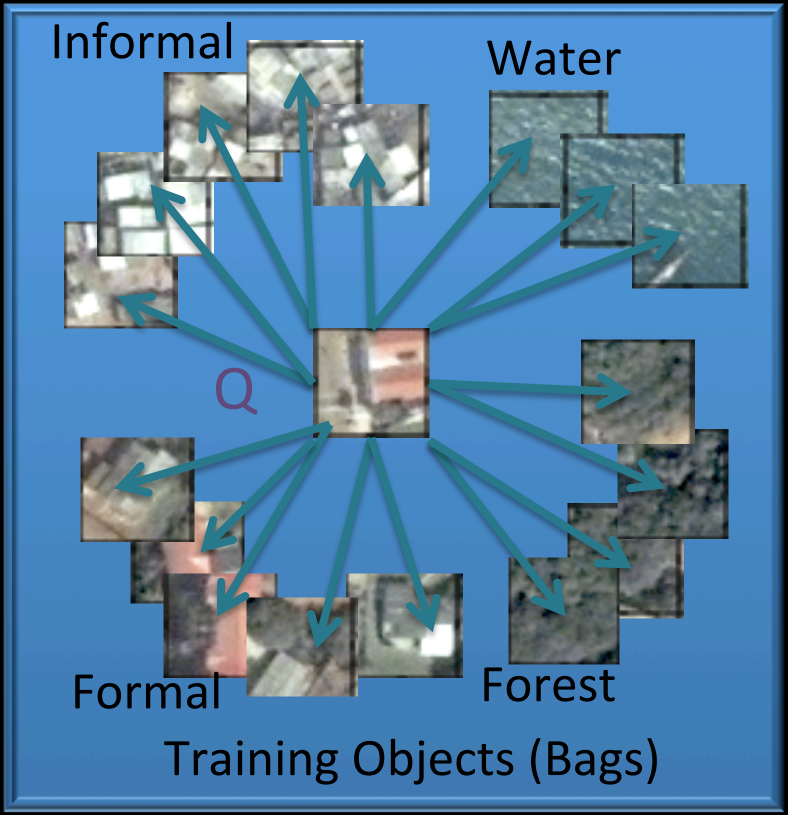
Complex Object Based Image Analysis

- Objective is same as pixel-based, however instead of pixels we are dealing with patches
  - Given a model (set of image patches)
  - Predict class label for a new sample (patch)

Challenges:

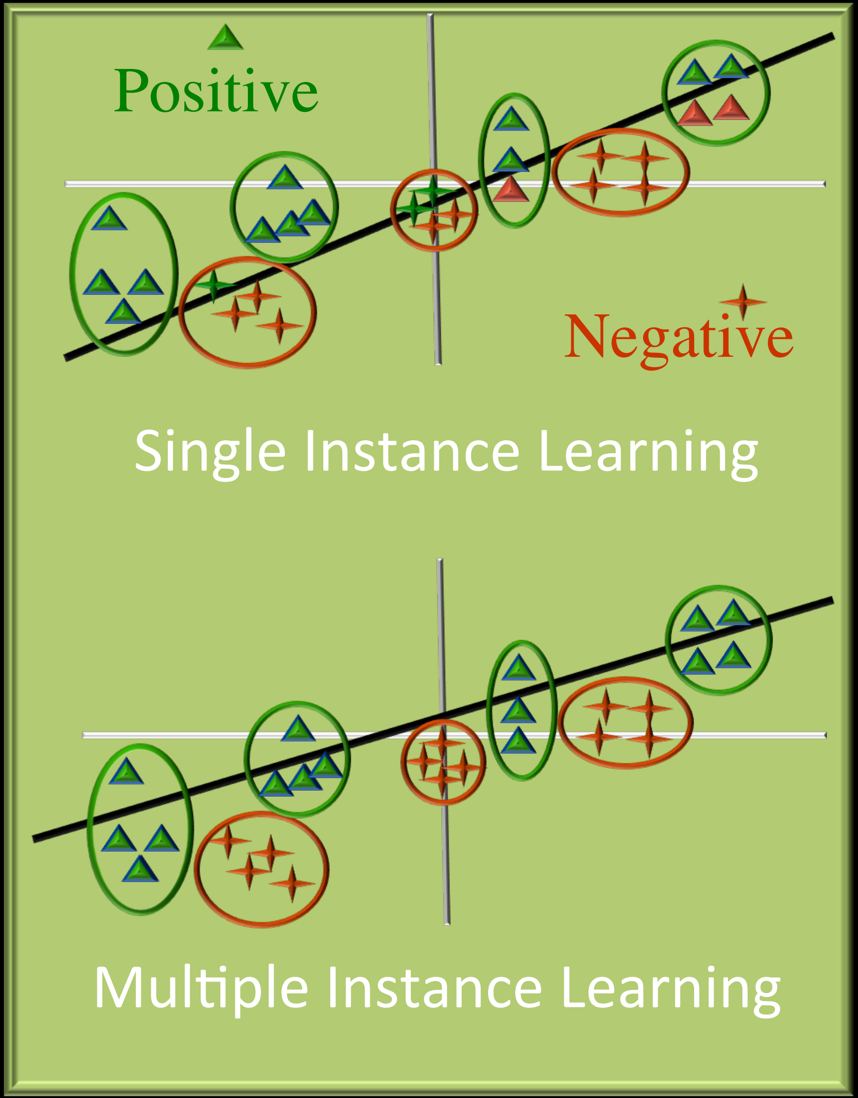
- How to compute similarity between patches?

Moving from single instance learning to multiple instance learning



Single Instance Vs. Multiple Instance Learning

- Each window (segment/ object) is modeled as bag of points
- Each bag is labeled as +1/-1
- A new bag is positive if at least one instance in the bag is on the positive side of the decision surface
- A new bag is is negative if all points in the bag are on the negative side of the decision surface



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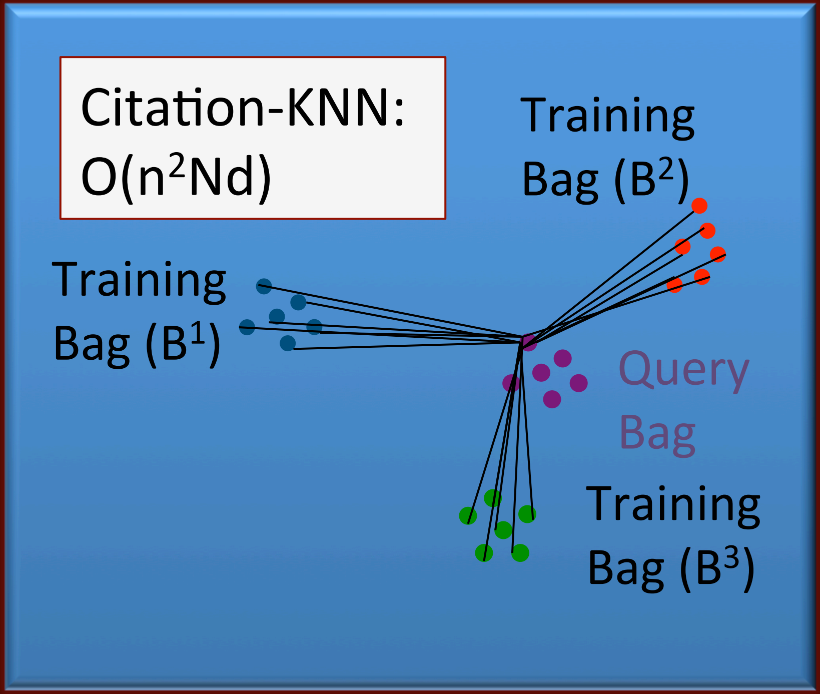
Nearest Neighbor Solution

- How to compute similarity between patches?
  - Citation-KNN
    - Hausdorff distance

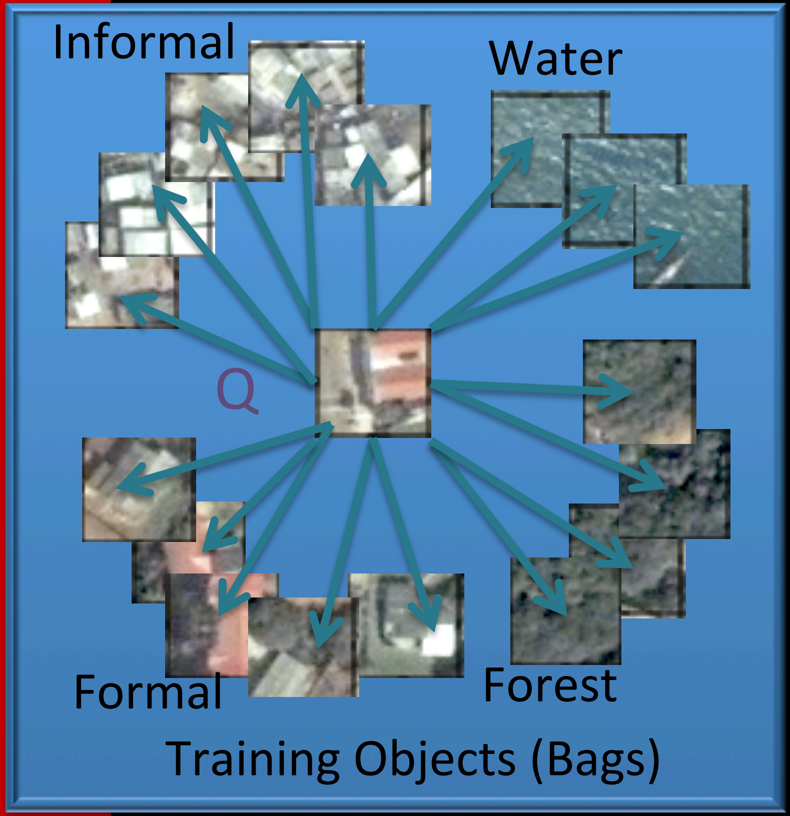


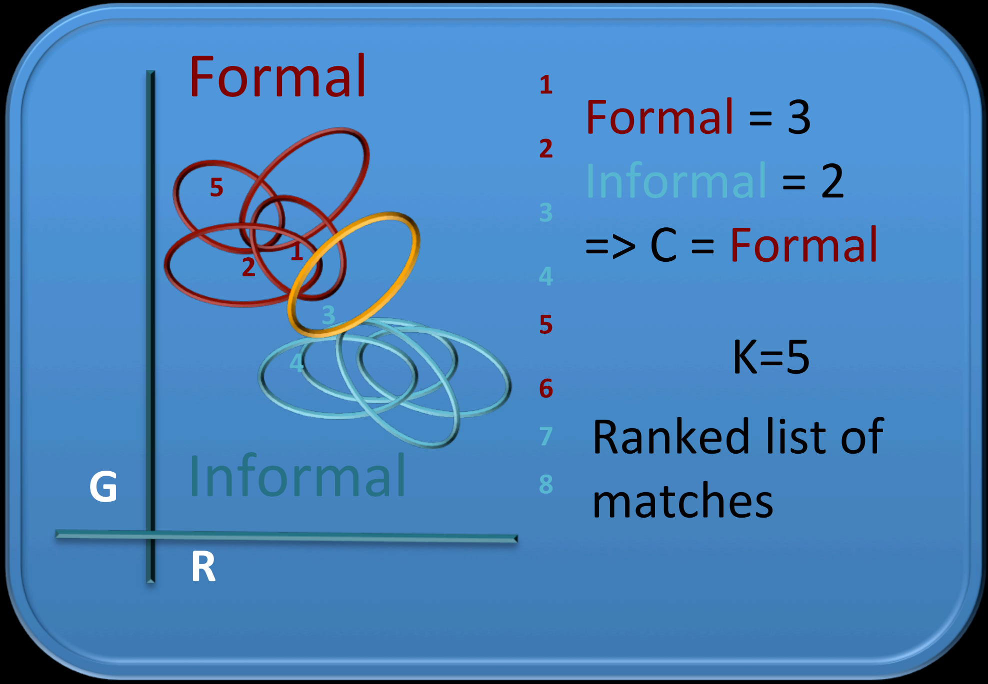
n = number of elements in a patch/bag
N = number of training bags
d = dimensionality

$$Dist(A,B) = \underset{\substack{1\le i\le n\\ 1\le j\le n}}{Min}\left(Dist(a_i,b_j)\right) = \underset{a\in A}{Min}\,\underset{b\in B}{Min}\|a-b\|$$

Gaussian MIL

- Instead of Hausdorff distance, compute KL Divergence





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Experimental Results

City	Citaiton-KNN	Regression	RF	MLP	NB	GMIL Model
Accra	76.25	71.25	72.08	69.58	75.66	95.66
Caracas	82.96	78.15	81.85	81.81	74.07	85.00
La Paz	80.97	77.17	78.26	80.23	76.08	83.25
Kandahar	79.78	64.89	69.14	73.93	60.1	81.20

Vatsavai, KDD-2013

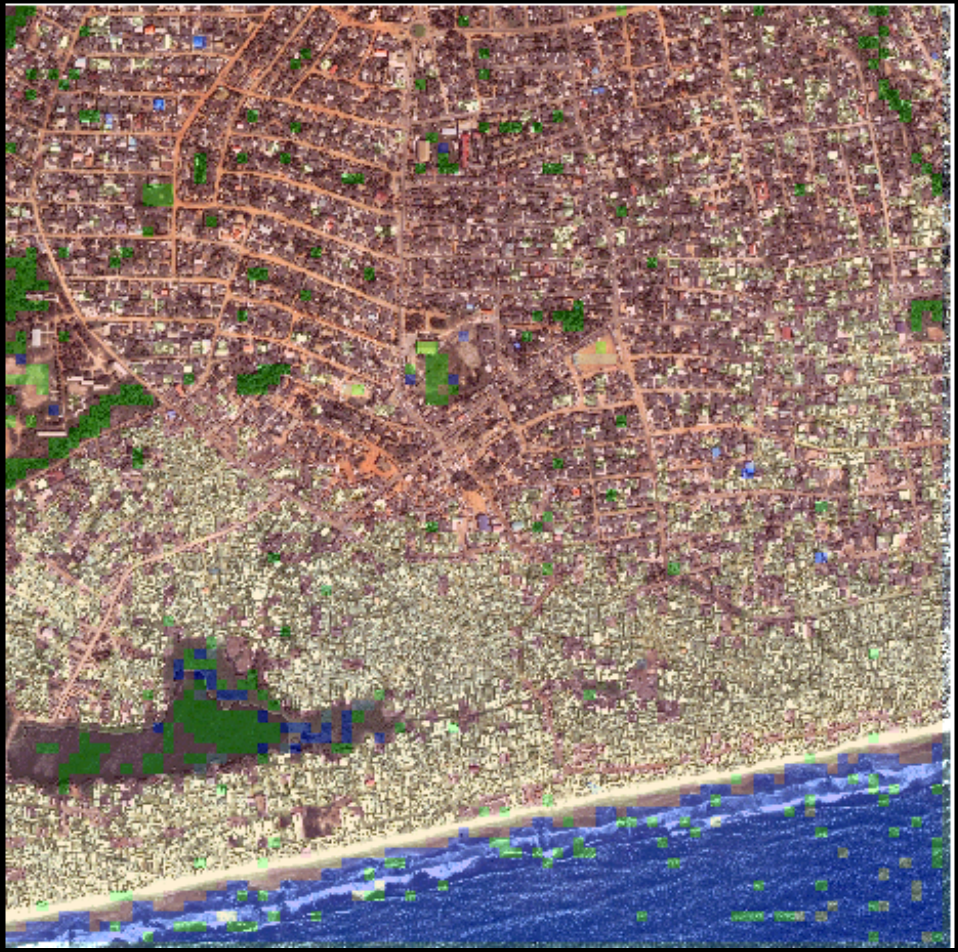
DigitalGlobe CitySphere Imagery
- Spatial Resolution
  - 0.6 meters
- Spectral Resolution
  - 3 Bands (RGB)

Milwaukee, Wisconsin, USA
- RGB, 1 meter
- Downtown (82/89)
- Residential (49/42)
- Grass (13/8)
- Trees (7/11)
- Feature (NDVI, ED)
- GMIL (82.8%)
- GMIL-IF (79.7%, 81.6%)

GMIL-IF

Classification Output

FCC (RGB)



FCC (RGB) + Classification Overlay

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Conclusions and Outlook

- Continuous Monitoring
  - Full automation is still a challenge
  - Multi*: sensor, resolution, temporal
- Mining for Interesting Patterns
  - Automated Event Generation
- Modeling Spatial and Temporal Relationships
- Computational Challenges
  - $O(N^3)$
  - Approximate solutions
  - Exploitation of true heterogeneity of modern compute node

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- MultiTemp-15 Organizers

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