Remote Sensing Laboratory
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# CHANGE DETECTION IN MULTITEMPORAL REMOTE SENSING IMAGES

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# Outline


1. Current trends and background on multitemporal images
2. Change detection in medium/high resolution multispectral images
3. Change detection in medium/high resolution SAR images
4. Change detection in VHR multispectral images
5. Change detection in VHR SAR images
6. Change detection in hyperspectral images
7. Change detection in multisensor/multisource images
8. Conclusion

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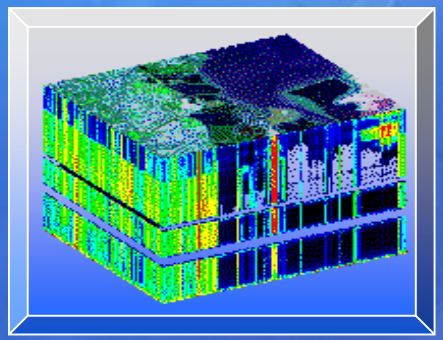
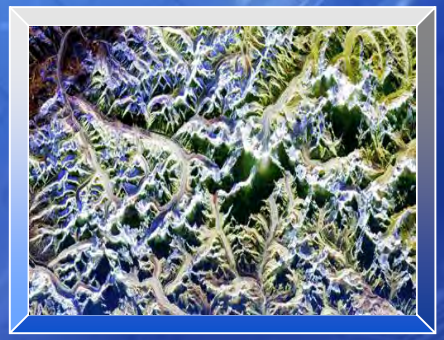
# 1. Current Trends and Background on Multitemporal Images

# Introduction: Remote Sensing

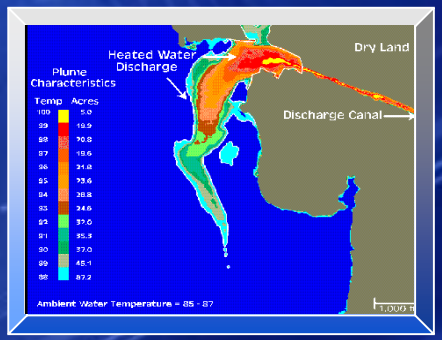
Multispectral



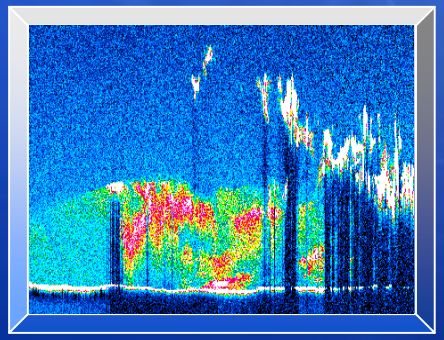
Hyperspectral



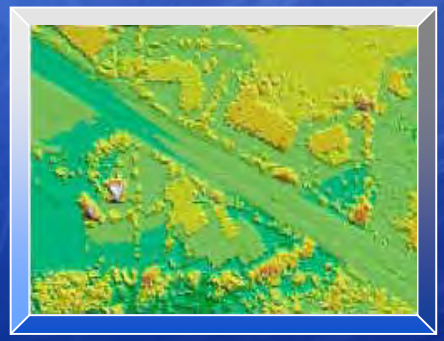
RADAR / SAR



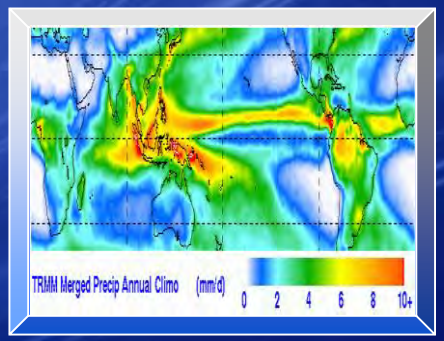

Thermal



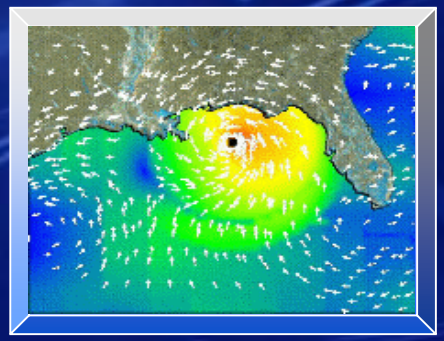
LIDAR - Atmosphere



LIDAR - Altimeter




Passive Microwave



Scatterometer

# Multitemporal Images

In the last 10 years we had a significant increase in the interest on topics related to the time series and the analysis of multitemporal data:

- ✓ Sharp increase in the number of papers published on the major remote sensing journals (e.g., IEEE Transactions on Geoscience and Remote Sensing, IEEE Geoscience and Remote Sensing Letters, IEEE Journal on Selected Topics in Applied Earth Observation and Remote Sensing, Remote Sensing of Environment, International Journal of Remote Sensing).
- ✓ Increased number of related sessions in international conferences.
- ✓ Increased number of projects related to multitemporal images and data.

# Multitemporal Images

The increased interest in multitemporal data analysis is due to many issues:

- ✓ Increased number of satellites with increased revisitat time that allow the acquisition of either long time series or frequent bitemporal images.
- ✓ New policy for data distribution of archive data that makes it possible a retrospective analysis on large scale (e.g. the Landsat Thematic Mapper archive).
- ✓ New policies for the distribution of new satellites data (e.g. ESA Sentinel, Landsat 8).

# Multitemporal Images: Change Detection

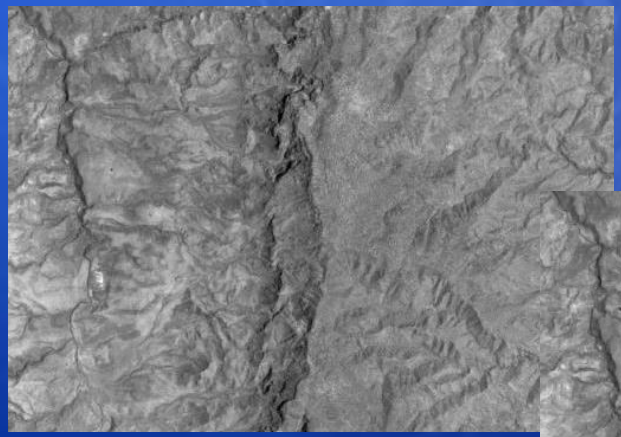
- ✓ Change detection (CD): process that analyzes multitemporal remote sensing images acquired on the same geographical area for identifying changes occurred between the considered acquisition dates.

- ✓ We can define different change detection problems:
  - Binary change detection.
  - Multiclass change detection.
  - Change detection in long time series of images.

# Taxonomy of CD Problems

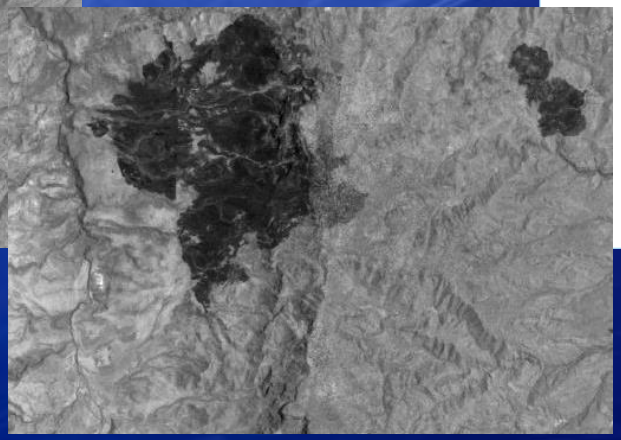
1. Binary change detection

- ✓ Goal: production of binary maps in which changed and unchanged areas are separated;
- ✓ Number of images: 2 (or pairs of images extracted from a series);
- ✓ Application domain: detection of abrupt (step) changes.



Mexico, April 2000

Mexico, May 2002



Map of burned areas

# Taxonomy of CD Problems

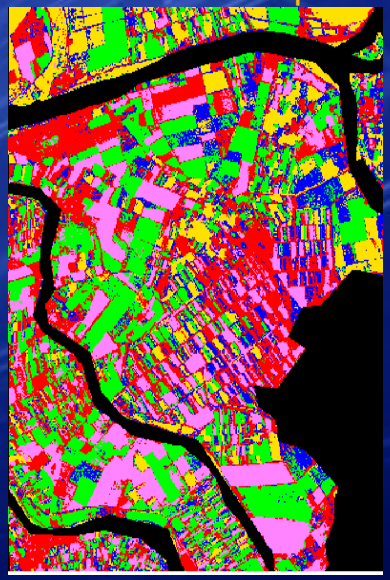
## 2. Multiclass change detection

- ✓ Goal: generation of a change-detection map in which land-cover transitions are explicitly identified;
- ✓ Number of images: 2 (or pairs of images extracted from a series);
- ✓ Application domain: updating thematic maps, detection of multiple changes.

May 1995 (Landsat)

July 1995 (Landsat)

Thematic Map

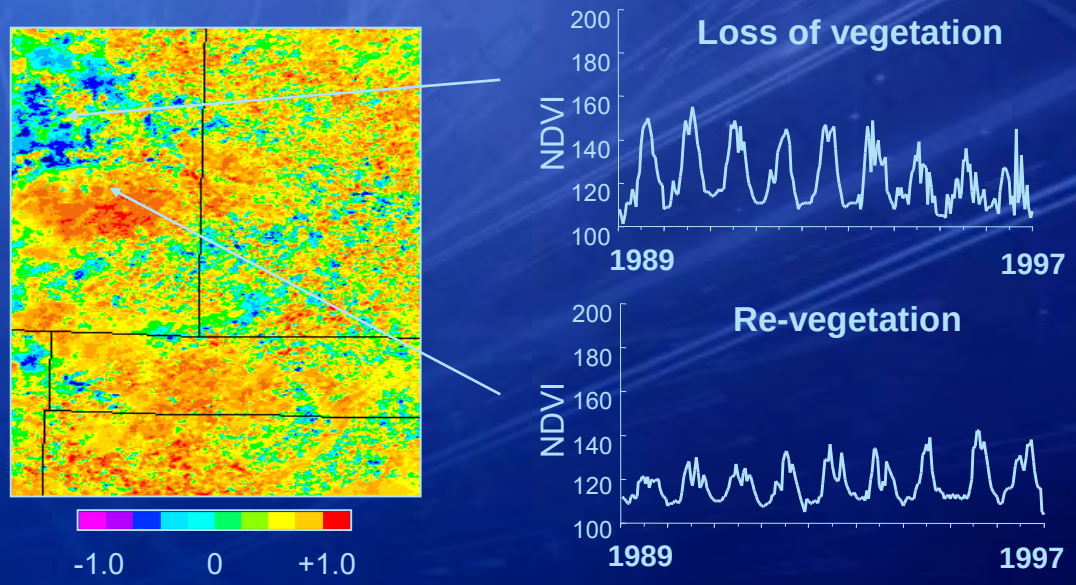


- URBAN URBAN
- BARE SOIL SUGAR BEET
- WHEAT BARE SOIL
- BARE SOIL CORN
- BARE SOIL SOYBEAN

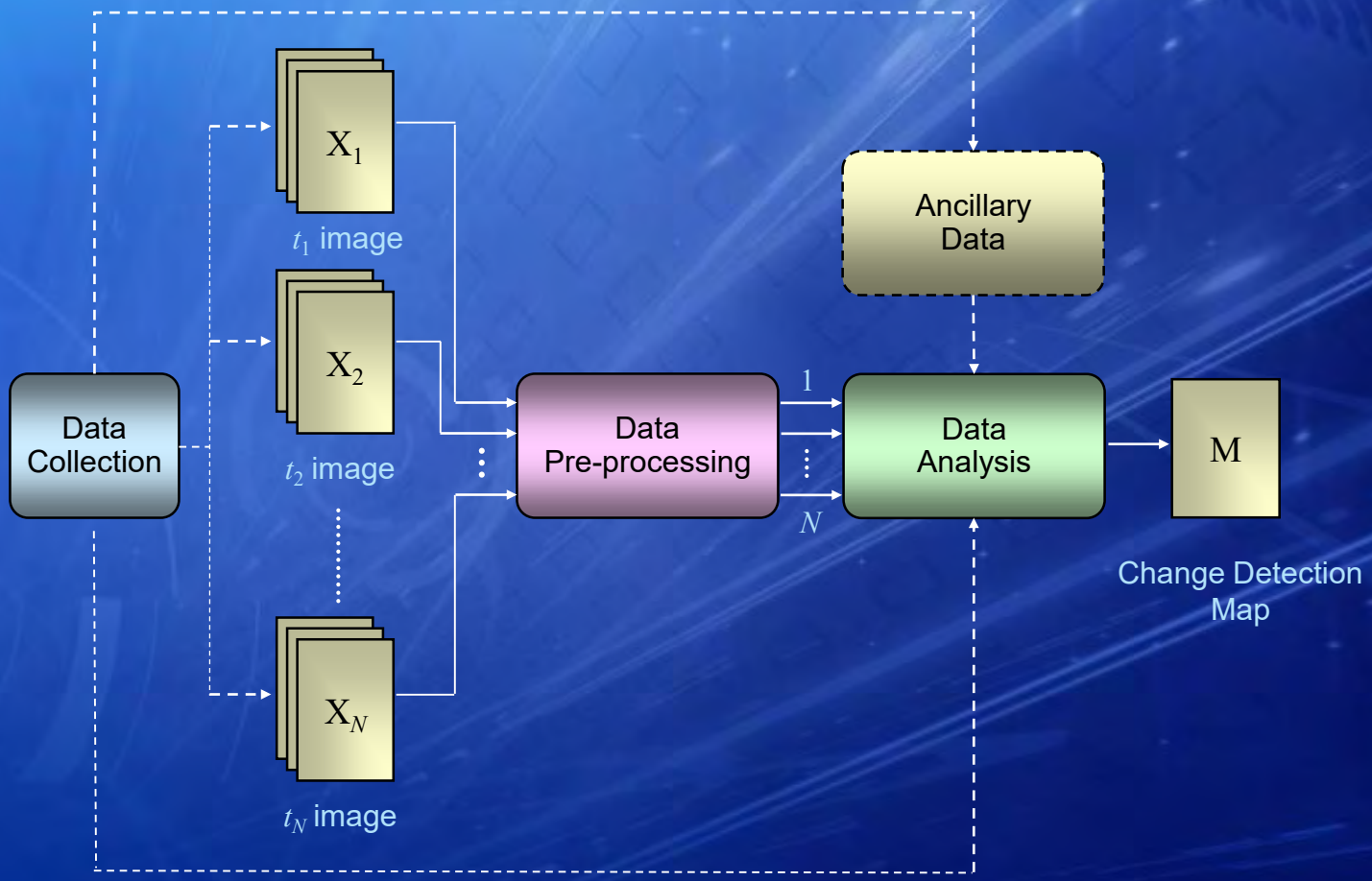
# Taxonomy of CD Problems

3. Change detection in long time series of images

- ✓ Goal: detection of changes associated with modifications of the behavior of the temporal signature of a land cover between two time series (detection of long term changes);
- ✓ Number of images: 2 time series made up on n images (n>>2);
- ✓ Application domain: monitoring seasonal/annual changes.



# Change Detection Architecture




F. Bovolo, L. Bruzzone, "The Time Variable in Data Fusion: a Change Detection Perspective," *IEEE Geoscience and Remote Sensing Magazine*, Vol. 3, No 3, pp. 8-26, 2015.

# Change Detection: Sensors and Satellites

- ✓ Geometrical resolution: the geometrical detail required from the application is of major importance for the choice of the sensor and of both the pre-processing and data analysis algorithms.

- ✓ Spectral resolution: the complexity of the addressed problem and the end-user's requirements involve constraints on the choice of the kind of sensor (active or passive) and on the necessary spectral resolution.

- ✓ Acquisition frequency: high acquisition frequency may result in a high probability to include in the analysis data taken from different sensors (e.g. different satellites, in-situ sensor networks, etc.) with important consequences in the data analysis phase.

- ✓ Meteorological conditions: the constraints on the robustness of the system to clouds or atmospheric conditions (e.g. related to the latitude of the investigated area) result in constraints for the choice of both the sensor and the satellite.

# Change Detection: Application Requirements

- ✓ Ground reference data ("ground truth"): it is important to understand if it is possible to collect ground reference data for the training of the processing algorithms or if the system should be completely unsupervised.

- ✓ Prior information: it is important to collect all the prior information available on the application in order to translate it in possible useful constraints in the phase of design of algorithms.

- ✓ Ancillary data: it is important to identify possible ancillary data that can be used in the development of the system according to a multisource processing architecture.

# Change Detection: User Needs

- ✓ User expectation: given an application, it is important to properly understand the final goal of the users. Different specific goals result in the choice of different processing strategies and algorithms.

- ✓ Cost: the economical cost of the development of the architecture and of the operational use of the system should be properly understood.

- ✓ Processing time: it is important to identify the requirements (if any) related to the expected processing time for the developed service.

# Change Detection: Requirements

Most common assumptions of the automatic techniques used for change detection:

✓ Radiometric issues

- Sensor: should be possibly the same for all the images of the series;
- Acquisition season:
  - Should be possibly the same for applications associated to the detection of abrupt changes;
  - Should be properly sampled over the year for applications associated to the monitoring of the seasonal evolutions of phenomena.
- Atmospheric conditions:
  - Different conditions in different portions of multitemporal images should be compensated (non-stationary effects of the atmosphere);
  - Clouds should be properly detected and removed;
  - Light conditions should be as similar as possible.

# Change Detection: Requirements

- ✓ Geometrical issues
  - Sensor: should be possibly the same for all the items of the temporal series to guarantee a similar acquisition geometry.
  - Satellite orbit: should be the same (ascending or descending), especially when SAR sensors are used.
  - View angle: should be possibly the same, but it may change in multisensor sequences, or in series acquired by sensors with variable incidence angle.
  - Topography: a complex topography makes ortho-rectification and geometrical corrections more difficult and strongly dependent on the quality of available digital elevation model (critical with different view angles).

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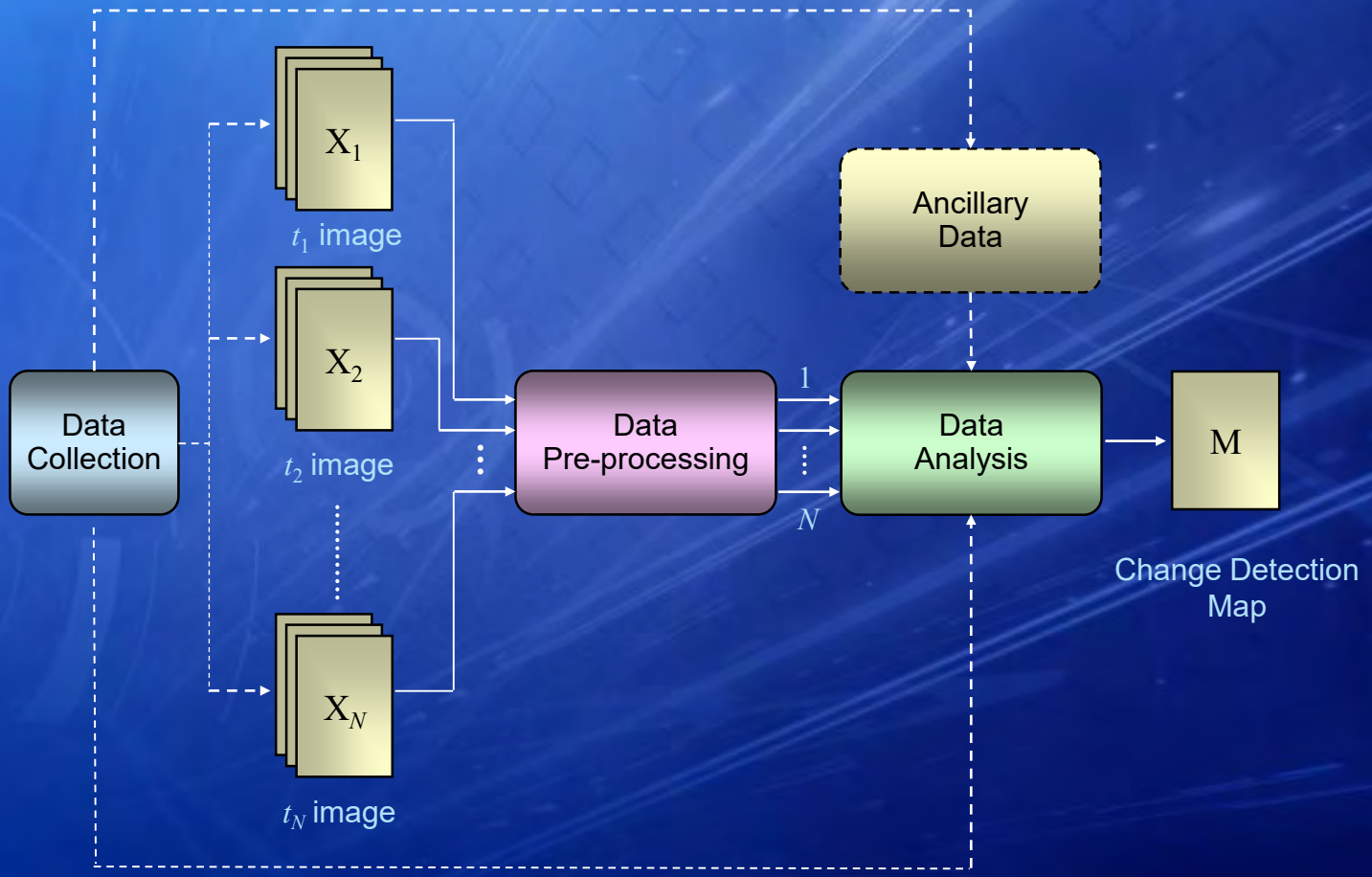
# 2. Change Detection in Medium/High Resolution Multispectral Images

# Change Detection Architecture



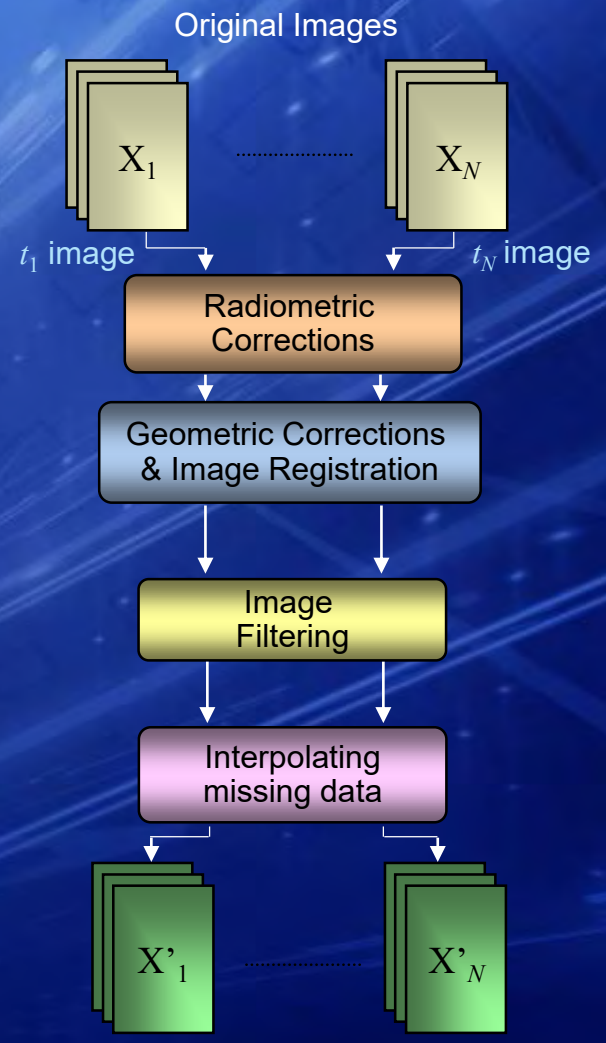
# Data Pre-processing: Multispectral Images

Very important with optical images

Mandatory in all change-detection techniques

Depends on the specific sensor considered and on the quality of the considered images

Depends on the requested acquisition frequency and data availability (careful application, see information theory!)



# Data Pre-processing: Radiometric Corrections

Differences in light and atmospheric conditions between the two acquisition times can be mitigated by applying radiometric calibration to the images. Two different approaches can be applied:

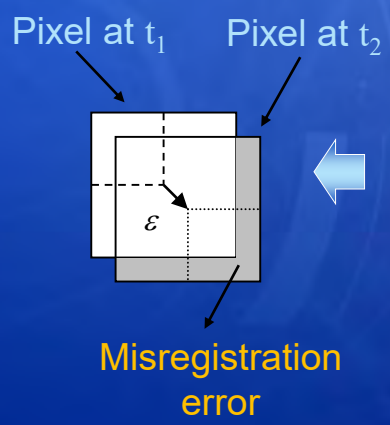
- ✓ Absolute calibration: digital numbers are transformed into the corresponding ground reflectance values (radiometric transfer models, regression algorithms applied to ground-reflectance measurements collected during the data acquisition phase).
- ✓ Relative calibration: modification of the histograms, so that the same gray-levels values in the two images can represent the same reflectance values, whatever the reflectance values on the ground may be (histogram matching).

The choice of one of the two approaches depends on the particular application considered and on the specific information available.

# Data Pre-processing: Image Registration

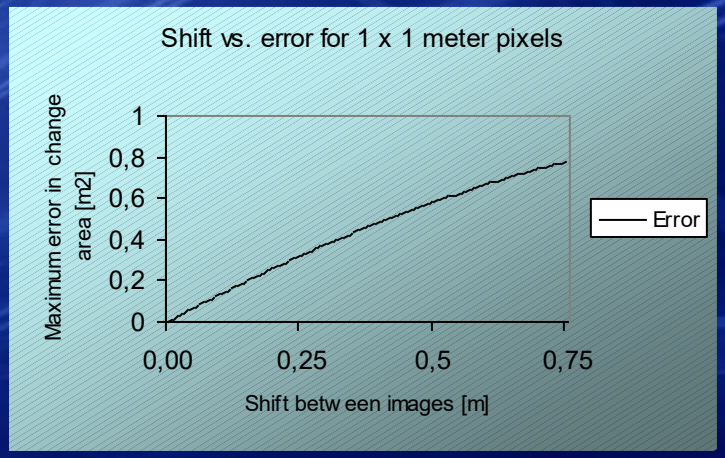
Generally it is not possible to obtain a perfect alignment between multitemporal images. This is mainly due to local defects in the geometries of the images.

Residual misregistration results in a very critical source of noise, which is called "registration noise"




Generic effect of misregistration

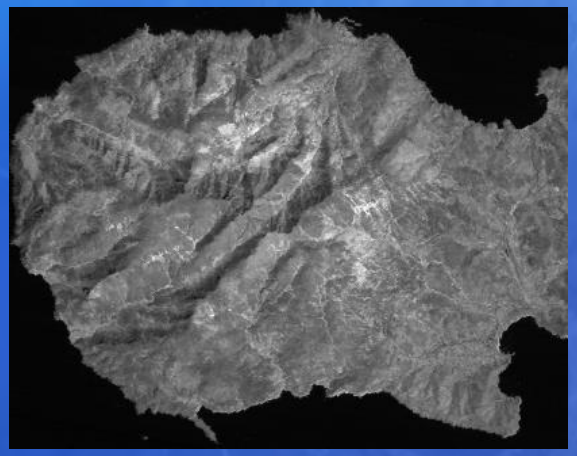
Error in area as a function of the displacement in high resolution sensors



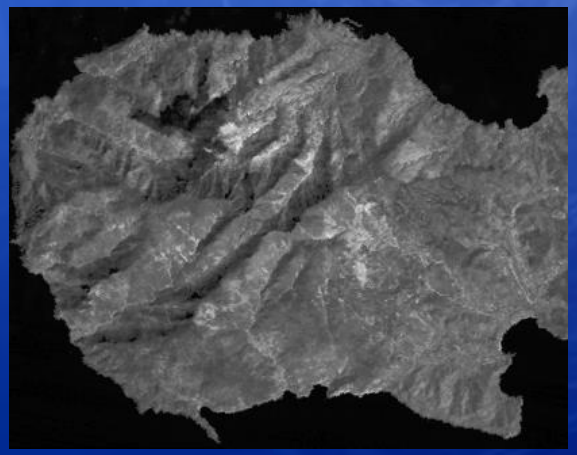
# Data Pre-processing: Registration Noise Effects

Elba Island, Landsat-TM4

August 1992



September 1994

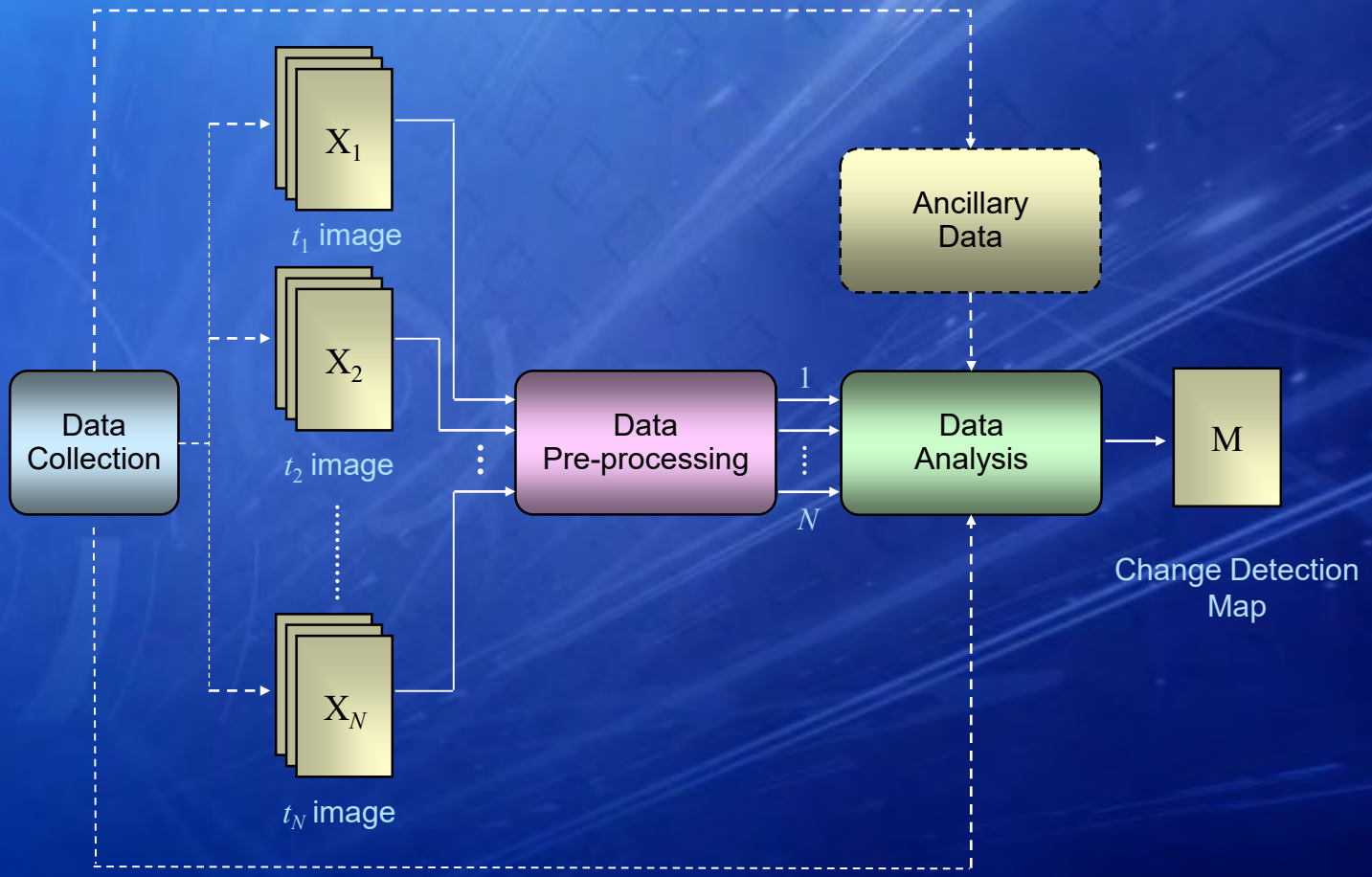


$t_1$ image

$t_2$ image

Change-detection map

# Change Detection Architecture



# Binary Change Detection: Examples

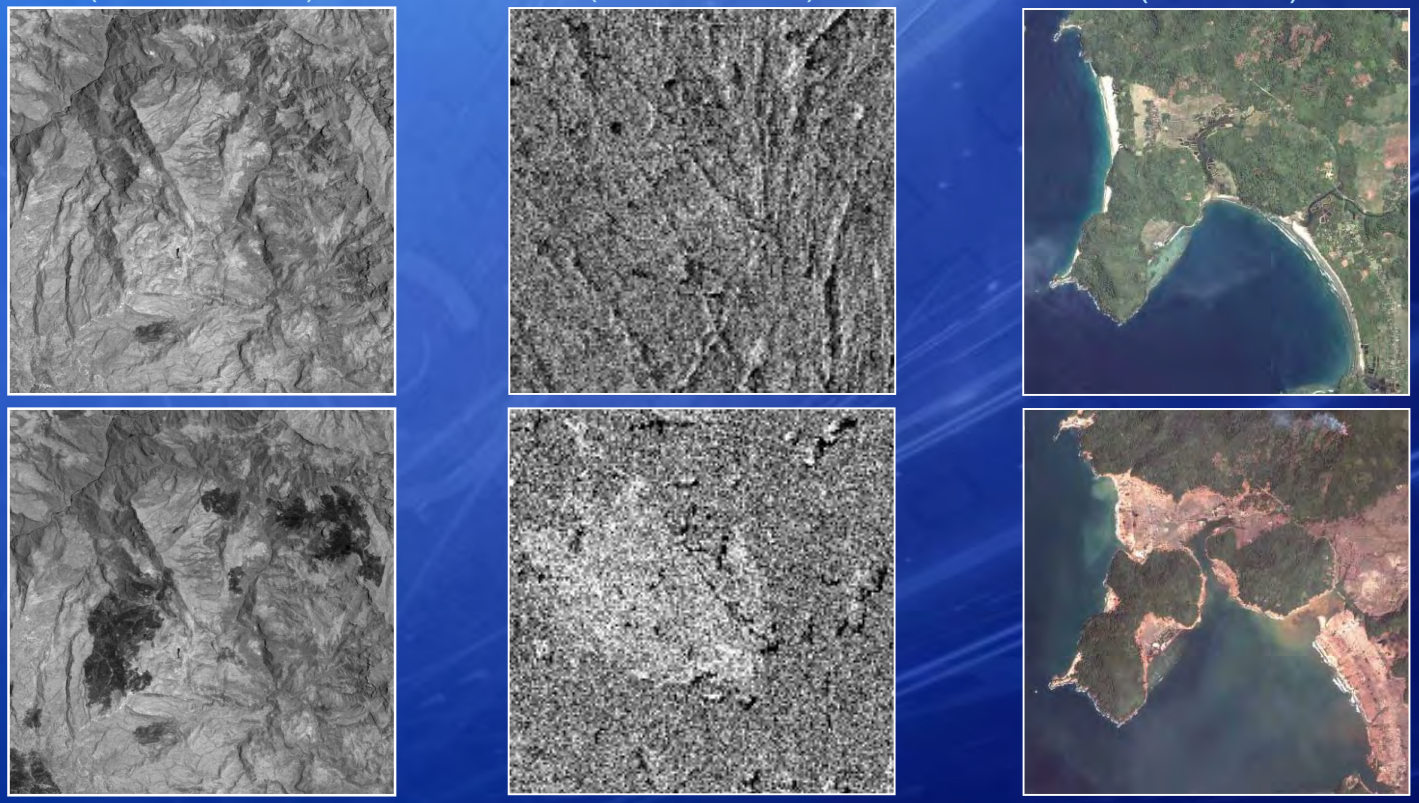
Landsat TM
(Burned Area)

ERS-1
(Burned Area)

Quickbird
(Tsunami)

Before Change

After Change

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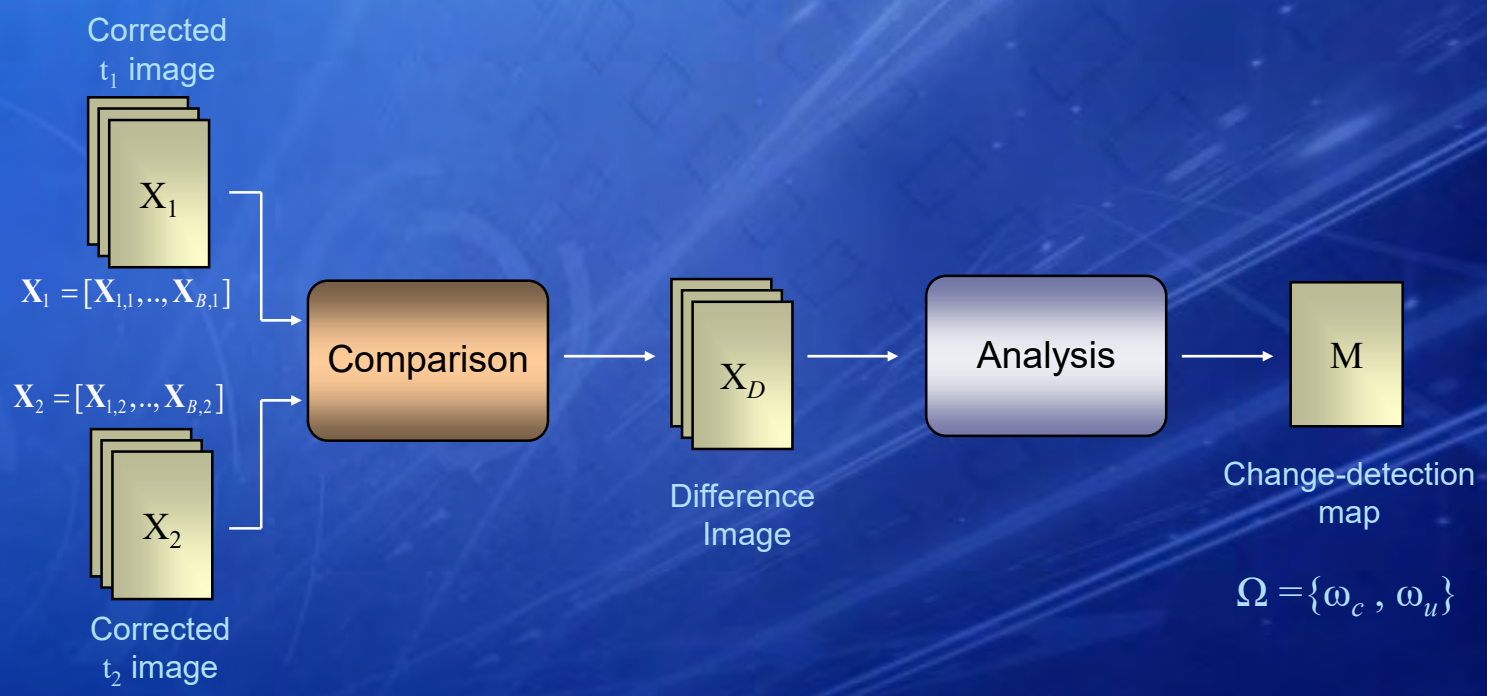
# Binary Change Detection in Remote Sensing

Binary change detection in remote-sensing images is characterized by several peculiar factors that render ineffective some of the multitemporal image analysis techniques typically used in other application domains. Some of these factors are:

- ✓ Differences in light conditions, sensor calibration, and ground moisture at the two acquisition dates considered;
- ✓ Absence of a reference background;
- ✓ Lack of a priori information about the shapes of changed areas;
- ✓ Non-perfect alignment (registration noise) between the two considered images;
- ✓ Different acquisition conditions of multitemporal images (view angle, shadows, etc.).

# Binary CD in Multispectral Images: Typical Architecture



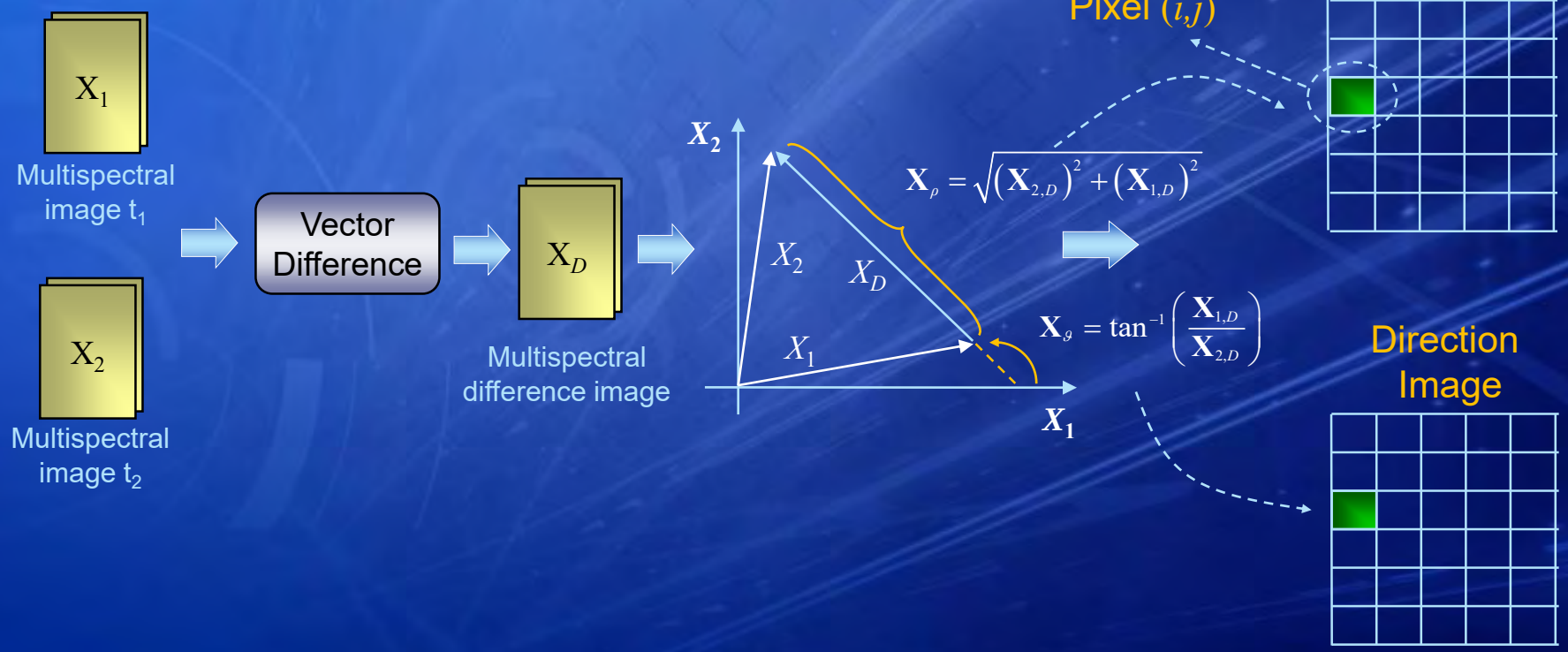
# CD in Multispectral Images: Comparison Operators

| Technique | Feature vector $f_k$ at the time $t_k$ | Computation of $X_D$ |
|---|---|---|
| Univariate image differencing | $\mathbf{f}_k = X_k^b$ | $X_D = \mathbf{f}_1 - \mathbf{f}_2 + C$ |
| Vegetation index differencing | $\mathbf{f}_k = V_k$ | $X_D = \mathbf{f}_1 - \mathbf{f}_2 + C$ |
| Change vector analysis | $\mathbf{f}_k = [X_k^1, .., X_k^m]$ | $X_D = \lVert \mathbf{f}_1 - \mathbf{f}_2 \rVert$ |
| Regression | $\mathbf{f}_1 = X_1^b$ and $\mathbf{f}_2 = \hat{X}_2^b$ | $X_D = \mathbf{f}_1 - \mathbf{f}_2 + C$ |
| Principal component Analysis | $\mathbf{f}_k = [P_k^1, .., P_k^m]$ | $X_D = \lVert \mathbf{f}_1 - \mathbf{f}_2 \rVert$ |

$b$: variable associated with the spectral channel
$k$: variable associated with the acquisition date

# Change Vector Analysis (CVA)

Assumption: only 2 spectral channels are considered for each date.



# Polar Change Vector Analysis

*Polar Domain*

$$D = \{\rho, \vartheta : 0 \le \rho < \rho_{max} \text{ and } 0 \le \vartheta < 2\pi\}$$

$\rho$ -> Random variable associate to magnitude image $X_\rho$

$\vartheta$ -> Random variable associate to direction image $X_\vartheta$

*Circle of unchanged pixels*

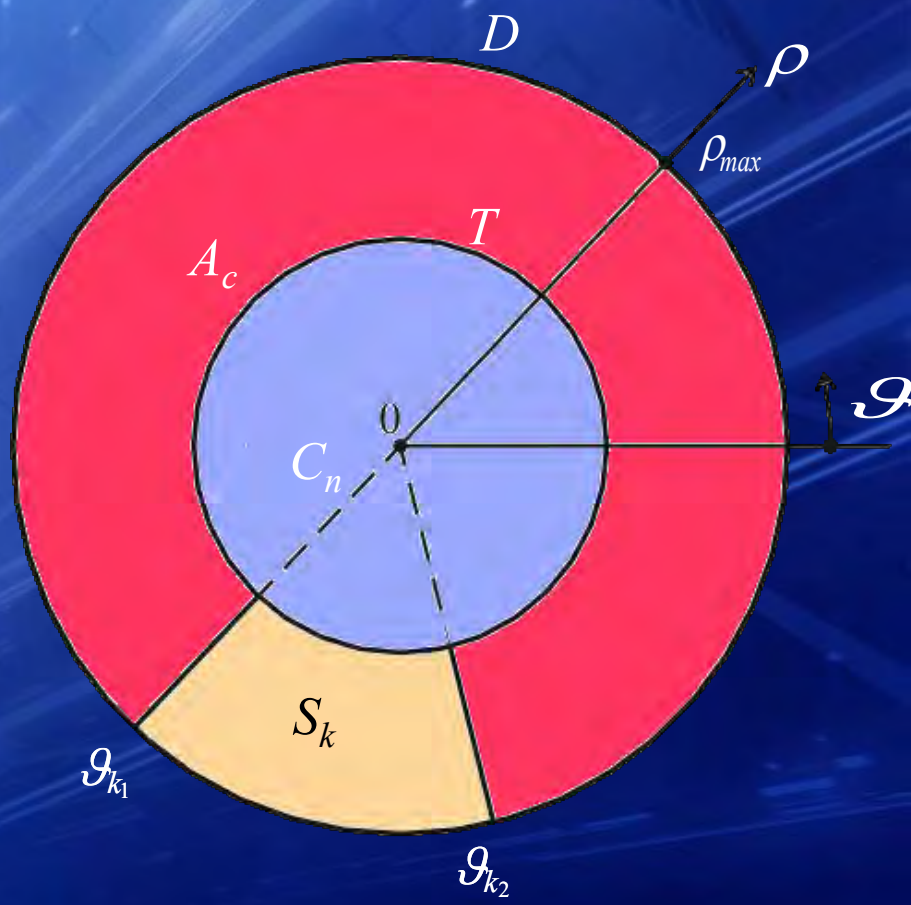
$$C_n = \{\rho, \vartheta : 0 \le \rho < T \text{ and } 0 \le \vartheta < 2\pi\}$$

*Annulus of changed pixels*

$$A_c = \{\rho, \vartheta : T \le \rho \le \rho_{max} \text{ and } 0 \le \vartheta < 2\pi\}$$

*Sector of changed pixels*

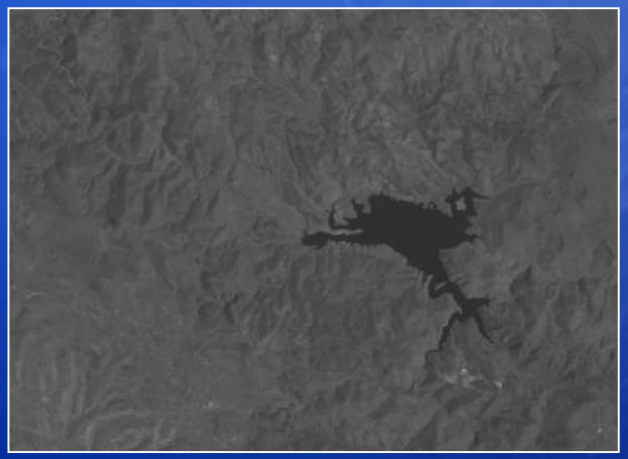
$$S_k = \{\rho, \vartheta : \rho \ge T \text{ and } \vartheta_{k_1} \le \vartheta < \vartheta_{k_2},\ 0 \le \vartheta_{k_1} < \vartheta_{k_2} < 2\pi\}$$



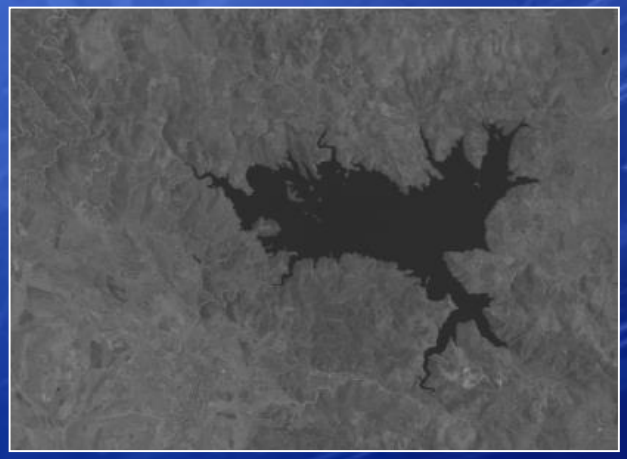
# Polar Change Vector Analysis: Example

Study area: Lake Mulargia, Sardinia Island (Italy).

Multitemporal data set: a portion of 412×300 pixels of two images acquired by the TM sensor of Landsat-5 satellite in September 1995 and July 1996.



Before Change

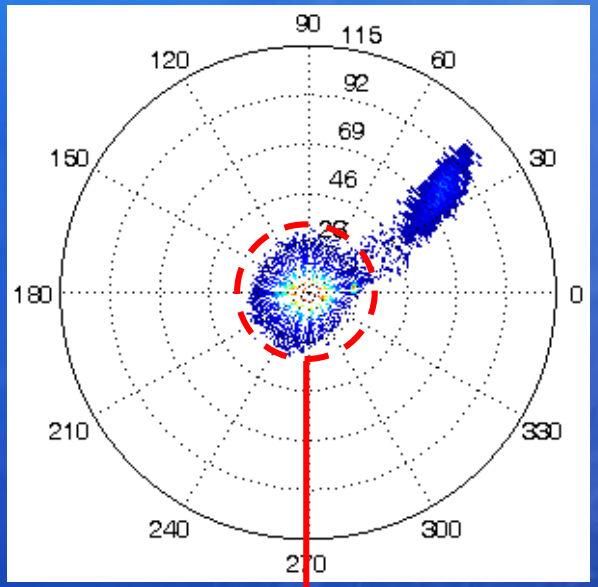


After Change

Reference Map

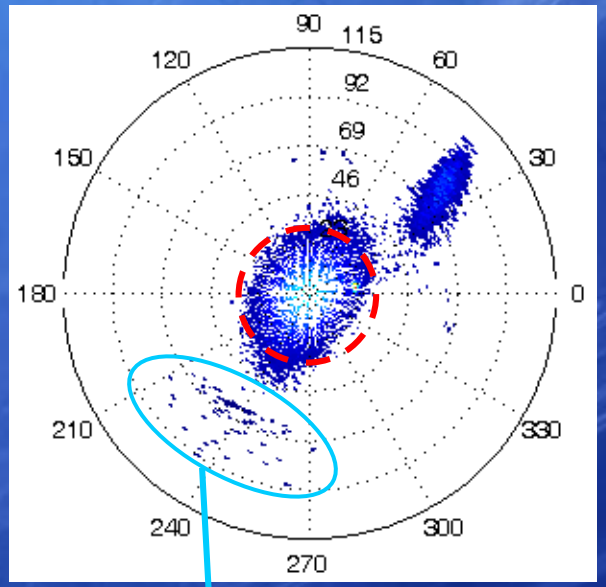
# Polar Change Vector Analysis: Example

Corrected Images (Ideal case)



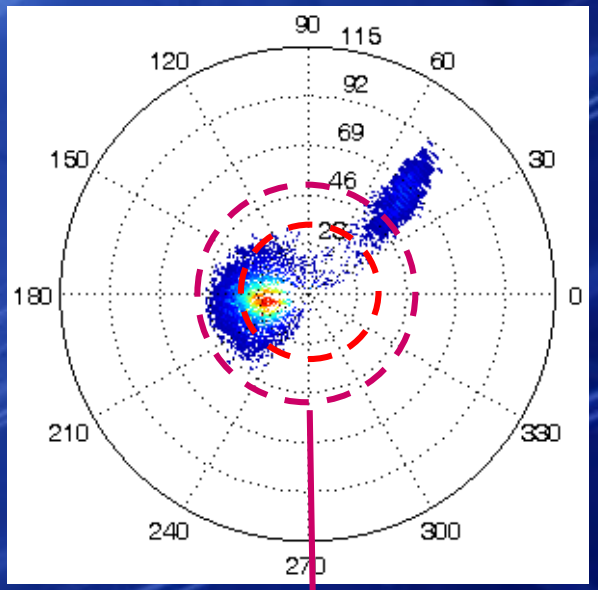

Optimal threshold value on the magnitude variable: ideal case

Registration noise effects

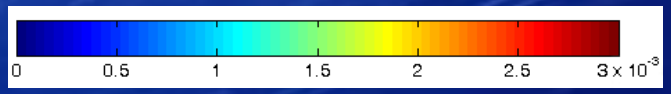



Registration noise effects

Radiometric difference effects




Threshold value on the magnitude variable: radiometric distortion case



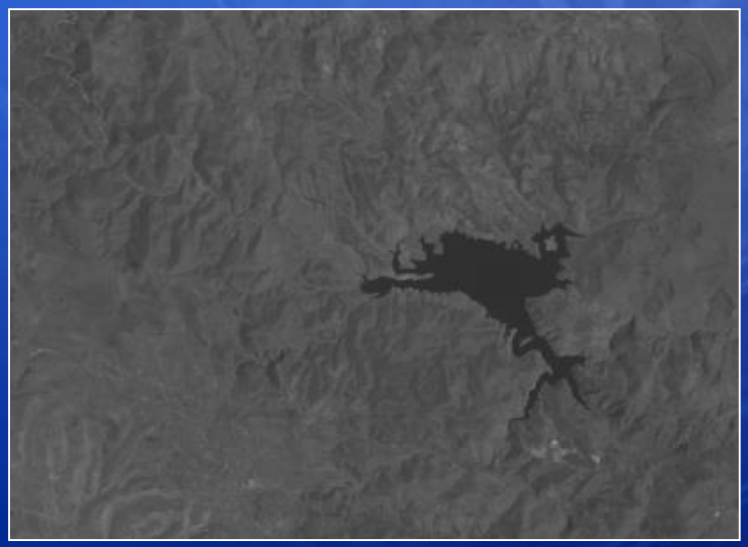

F. Bovolo, L. Bruzzone, A Theoretical Framework for Unsupervised Change Detection Based on Change Vector Analysis in Polar Domain, *IEEE Transactions on Geoscience and Remote* Sensing, Vol. 45, No.1, 2007, pp.218-236.

# Polar Change Vector Analysis: Example

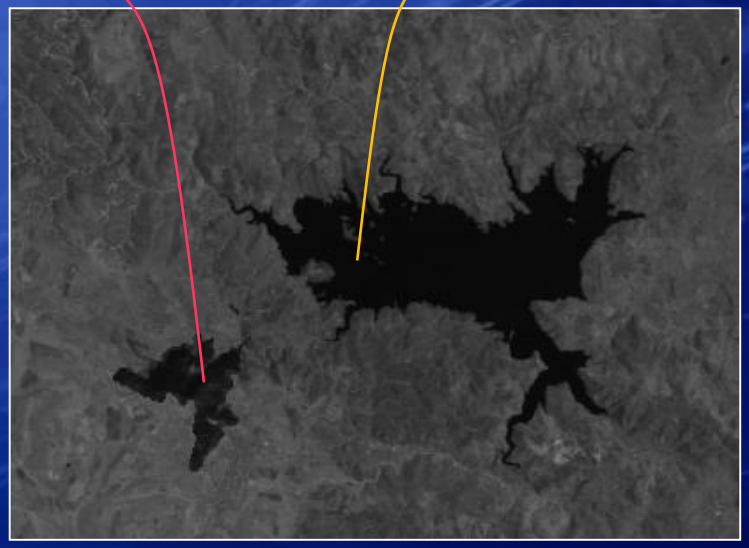
Study area: Lake Mulargia, Sardinia Island (Italy).

Multitemporal data set: a portion of 412×300 pixels of two images acquired by the TM sensor of Landsat-5 satellite in September 1995 and July 1996.

Changes: 1 natural change, 1 simulated change.

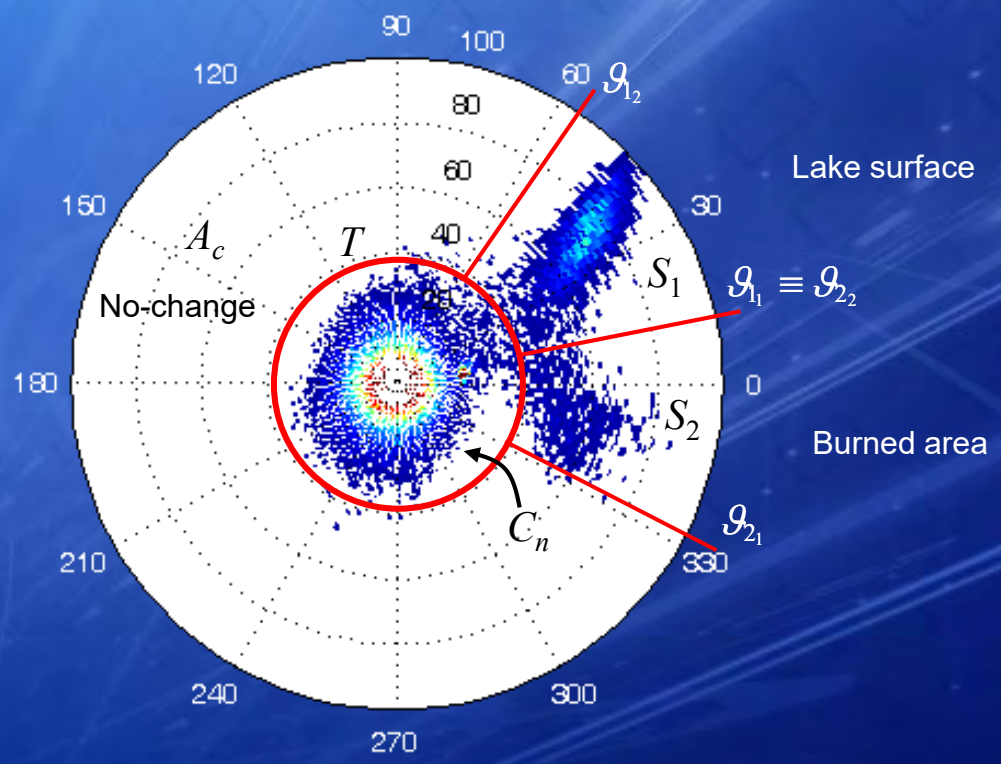


September 1995




July 1996

# Polar Change Vector Analysis: Example




F. Bovolo, S. Marchesi, L. Bruzzone, “A Framework for automatic and unsupervised detection of multiple changes in multitemporal images,” IEEE Transactions on Geoscience and Remote Sensing, Vol. 50, No. 6, pp. 2196–2212, 2012.

# Compressed Change Vector Analysis ($C^2VA$)

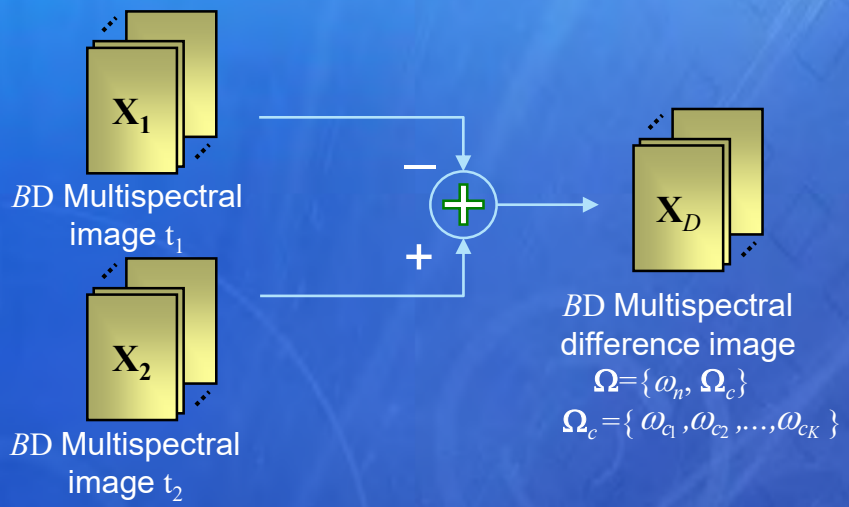
- ✓ CVA in 2 dimensions permits to easily visualize the change information in polar coordinates, but may results in the loss of information due to spectral channel selection.

- ✓ CVA may be applied on $B > 2$ spectral channels in hyperspherical coordinates. However, when $B$ is greater than 3 it is impossible to visualize the data in the polar domain.

- ✓ Compressed CVA ($C^2VA$) can overcome the abovementioned limit of polar CVA.

F. Bovolo, S. Marchesi, L. Bruzzone, "A Framework for Automatic and Unsupervised Detection of Multiple Changes in Multitemporal Images," IEEE Transactions on Geoscience and Remote Sensing, Vol. 50, No. 6, pp. 2196-2212, 2012.

# Compressed Change Vector Analysis ($C^2VA$)

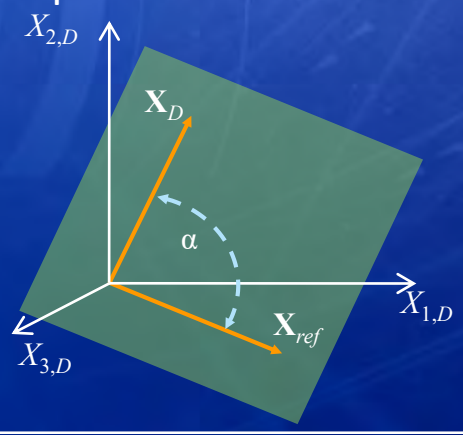



Magnitude: the length of the multispectral difference vector ($\mathbf{X}_D$).

$$\mathbf{X}_\rho = \sqrt{\sum_{b=1}^{B} \mathbf{X}_{b,D}^2} = \sqrt{\sum_{b=1}^{B} \left(\mathbf{X}_{b,2} - \mathbf{X}_{b,1}\right)^2}$$

$b$th spectral band of $X_1$

Direction: the angle between the multispectral difference vector ($\mathbf{X}_D$) and a reference vector ($\mathbf{X}_{ref}$) in a $B$D space.




$$\mathbf{X}_\alpha = \arccos\left( \sum_{b=1}^{B} \left(\mathbf{X}_{b,D}\mathbf{X}_{b,ref}\right) \Big/ \sqrt{\sum_{b=1}^{B} \mathbf{X}_{b,D}^2 \sum_{b=1}^{B} \mathbf{X}_{b,ref}^2} \right)$$

$$\alpha \in [0, \pi]$$

$B$D unit vector

$$\mathbf{X}_{ref} = \left[\frac{\sqrt{B}}{B}, \ldots, \frac{\sqrt{B}}{B}\right]$$

# Compressed Change Vector Analysis ($C^2VA$)

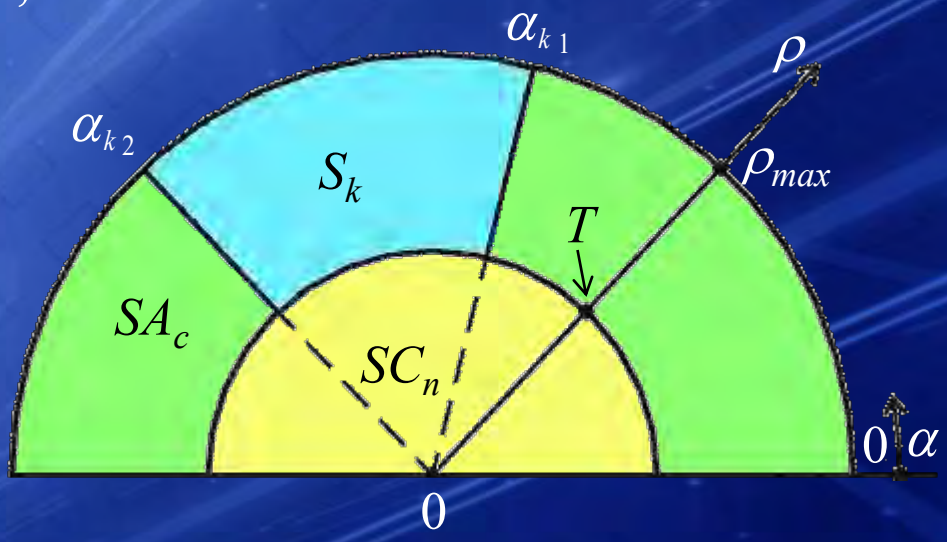
## Definitions

1. *Compressed CVA ($C^2VA$) Domain*

$$C^2VA = \{\rho, \alpha : 0 \le \rho < \rho_{max} \text{ and } 0 \le \alpha < \pi\}$$

$$\rho_{max} = max\left\{\sqrt{\sum_{b=1}^{B} X_{b,D}^2}\right\}$$

$\alpha$ -> Random variable associate to direction image $\mathbf{X}_\alpha$




2. *Semi-Circle of unchanged pixels*

$$SC_n = \{\rho, \alpha : 0 \le \rho < T \text{ and } 0 \le \alpha < \pi\}$$

3. *Semi-Annulus of changed pixels*

$$SA_c = \{\rho, \alpha : T \le \rho \le \rho_{max} \text{ and } 0 \le \alpha < \pi\}$$

4. *Annular sector of the k-th kind of change*

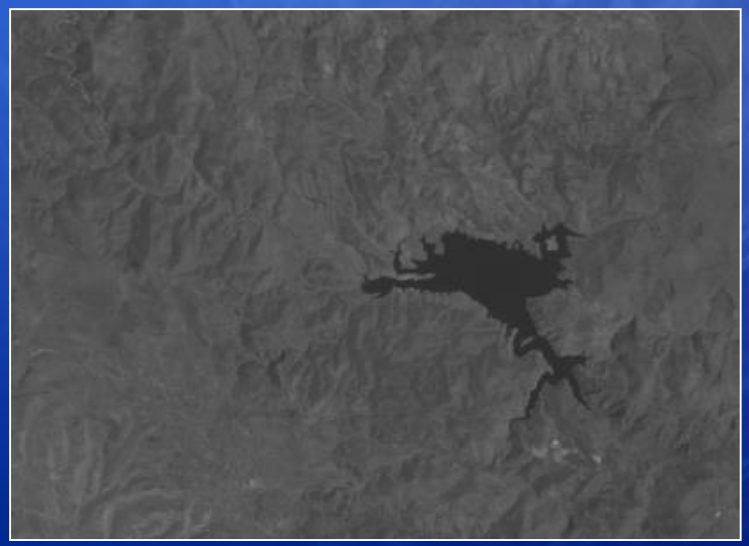
$$S_k = \{\rho, \alpha : \rho \ge T \text{ and } \alpha_{k1} \le \alpha < \alpha_{k2}, 0 \le \alpha_{k1} < \alpha_{k2} < \pi\}$$

# C²VA: Example

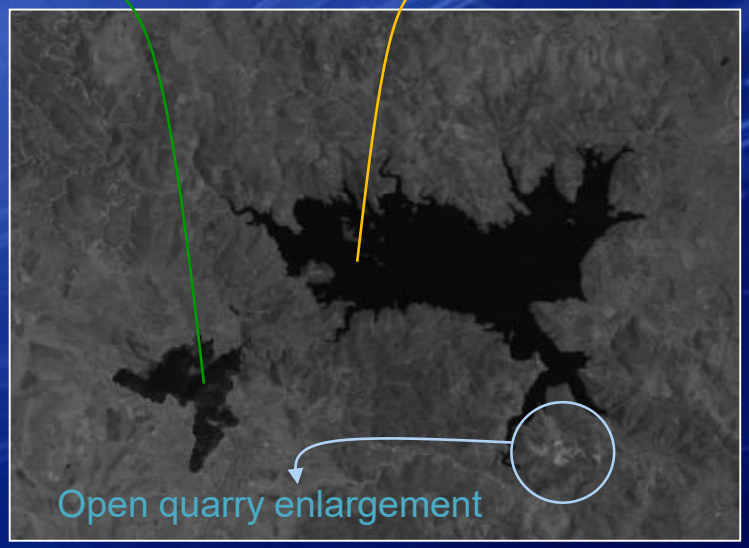
Study area: Lake Mulargia, Sardinia Island (Italy).

Multitemporal data set: a portion of 412×300 pixels of two images acquired by the TM sensor of Landsat-5 satellite in September 1995 and July 1996.

Changes: 2 natural changes, 1 simulated change

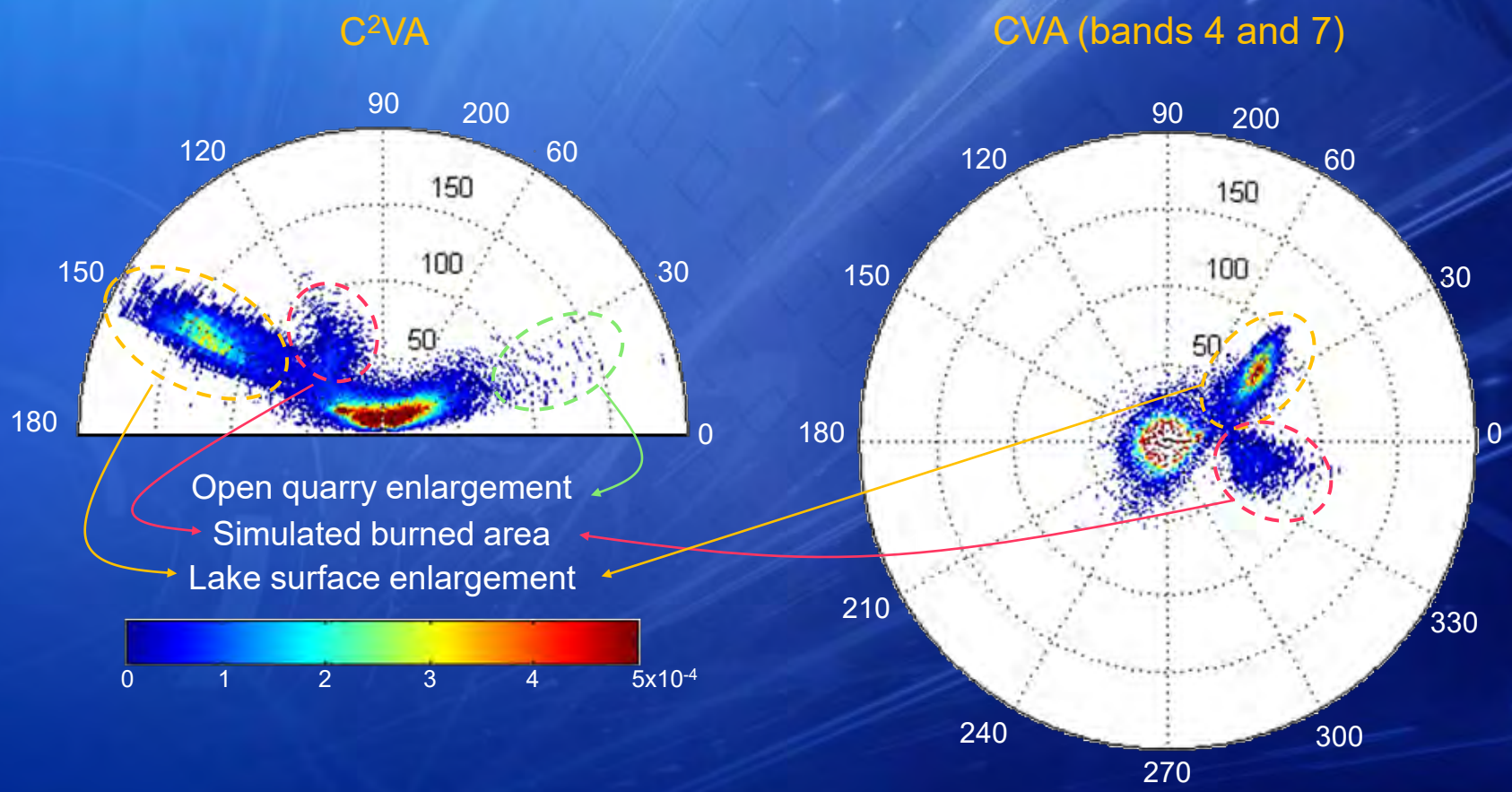


September 1995

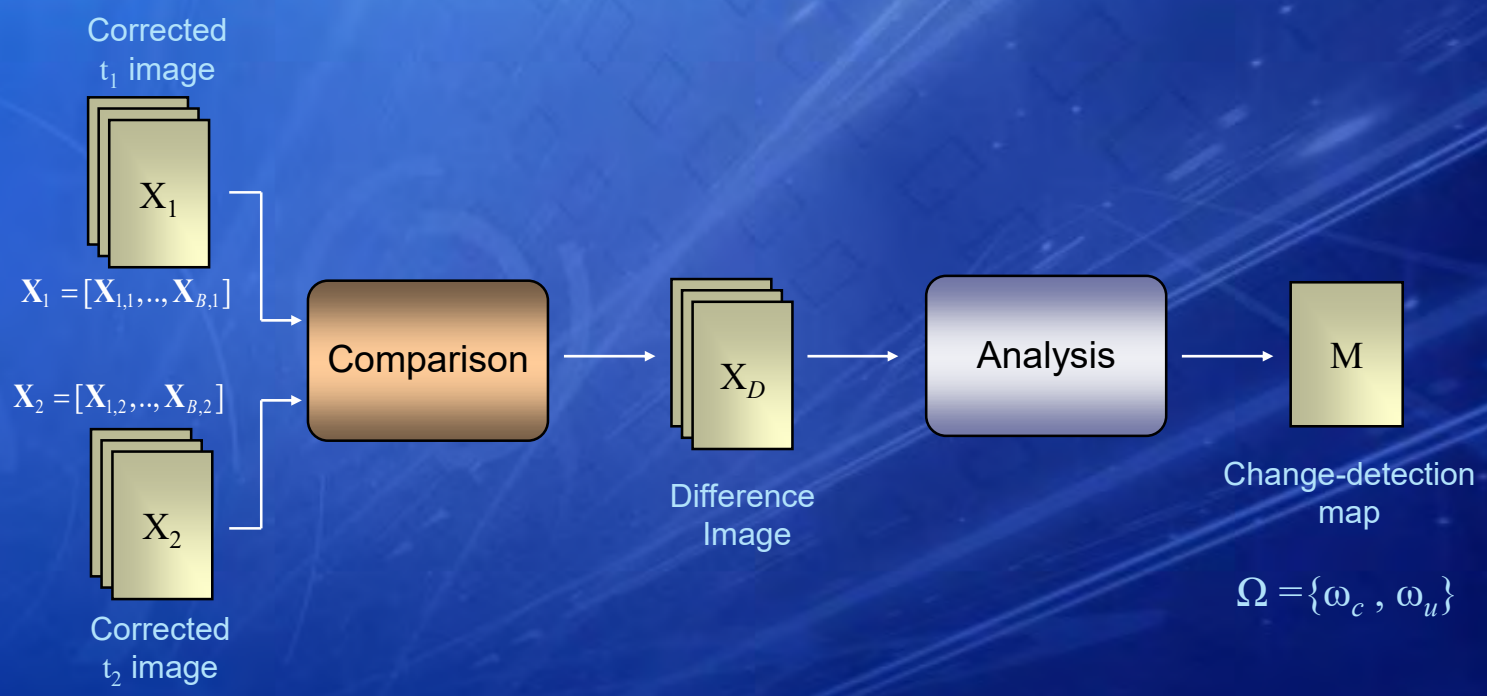



July 1996

# C²VA: Example

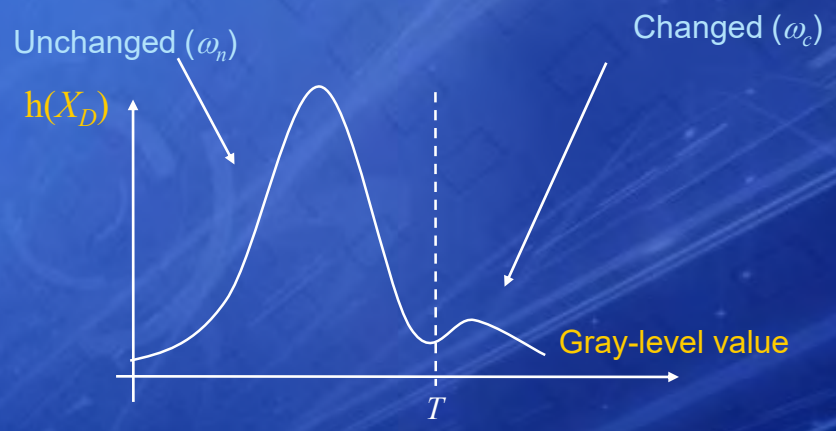


# Binary CD in Multispectral Images: Typical Architecture



# CVA and C²VA Thresholding: Bayesian Framework

The discrimination between changed and unchanged classes (in the histogram of the magnitude image) can be carried according to algorithms inspired to the Bayes classification criterion:




$$p\left(X_D\right) = P(\omega_c)\,p(X_D|\omega_c) + P(\omega_n)\,p(X_D|\omega_n)$$

Problem: the estimation problem should be solved in an unsupervised way.

# CVA and C²VA Thresholding: Bayesian Framework

**Pixel based**

- Direct detection of the decision threshold with implicit estimation of the statistical terms of classes
- Explicit estimation of the statistical terms of classes with the Expectation-Maximization (EM) algorithm
  - Bayes rule Minimum error
  - Bayes rule Minimum cost

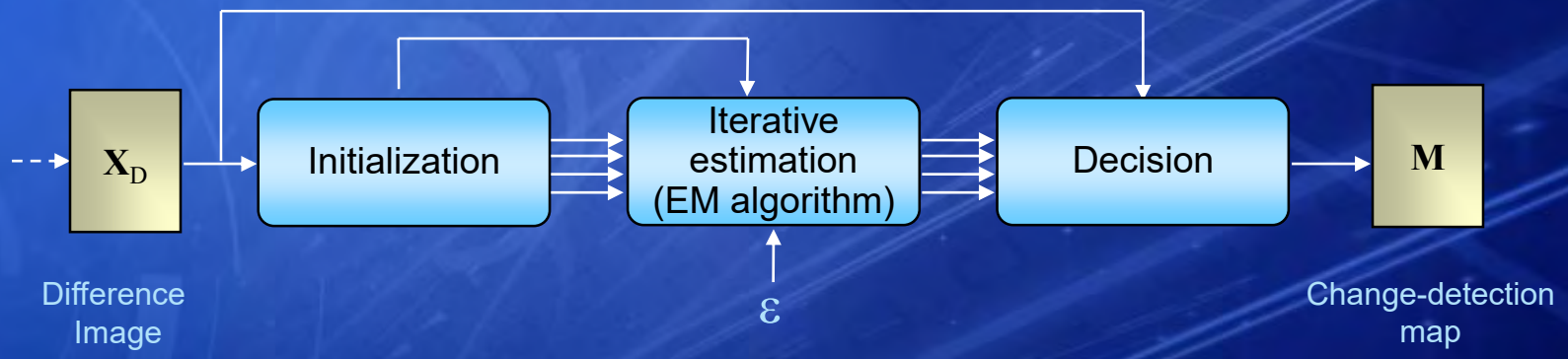
**Context based**

- Markov Random Fields (MRF) based regularization strategy

# Bayesian Framework: EM-Based Technique

The problem can be solved with a 3-step procedure:

- ✓ Model definition and Initialization;
- ✓ Iterative estimation of the statistical terms of the difference image;
- ✓ Decision.





M. Zanetti, F. Bovolo, L. Bruzzone, "Rayleigh-Rice Mixture Parameter Estimation via EM Algorithm for Change Detection in Multispectral Images" *IEEE Transactions on Image Processing*, Vol. 24, No. 12, pp. 5004-5016, 2015.

L. Bruzzone, D. Fernández Prieto, "An adaptive semi-parametric and context-based approach to unsupervised change detection in multitemporal remote sensing images", *IEEE Transactions on Image Processing*, Vol. 11, No. 4, April 2002, pp. 452-466.

L. Bruzzone, D. Fernández Prieto, "Automatic analysis of the difference image for unsupervised change detection", *IEEE Trans. Geosci. Rem. Sens.*, Vol. 38, No.3, May 2000, pp. 1171-1182.

# Bayesian Framework: Statistical Models

- ✓ Gaussian model: $$p(X_D \mid \omega_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(X_D - \mu_i)^2}{2\sigma_i^2}\right)$$

  Mean value

  Variance

- ✓ Rayleigh model: $$p(X_D \mid \omega_i) = \frac{X_D}{\sigma_i^2} \exp\left(-\frac{X_D^2}{2\sigma_i^2}\right)$$

- ✓ Rice model: $$p(X_D \mid \omega_i) = \frac{X_D}{\sigma_i^2} \exp\left(-\frac{X_D^2 + M_i^2}{2\sigma_i^2}\right) I_0\left(\frac{X_D M_i}{\sigma_i^2}\right)$$

  Non centrality parameter

- ✓ Semi-parametric mixture model: $$p(X_D \mid \omega_i) = \frac{1}{R_i} \sum_{r=1}^{R_i} \frac{1}{h} k\left(-\frac{(X_D - Y_r)^2}{k}\right)$$

  Kernel function

# Bayesian Framework: EM-Based Technique

Initialization of the parameters of the selected statistical model:

- ✓ A priori knowledge available: define two sets on the basis of the expected structure of the histogram such that pixels in them have a high probability to belong to $\omega_n$ and $\omega_c$, respectively, and compute initial parameter values.
- ✓ A priori knowledge unavailable: initialize parameters by applying a technique based on genetic algorithms.

# Bayesian Framework: EM-Based Technique

- At each iteration of the EM algorithm the value of the likelihood function $L(\theta)$ between the difference image distribution and the estimated mixture distribution increases.
- A local maximum of the log-likelihood function is reached at convergence.
- It is possible to show that the EM iterative equations for the Gaussian model are as follows:

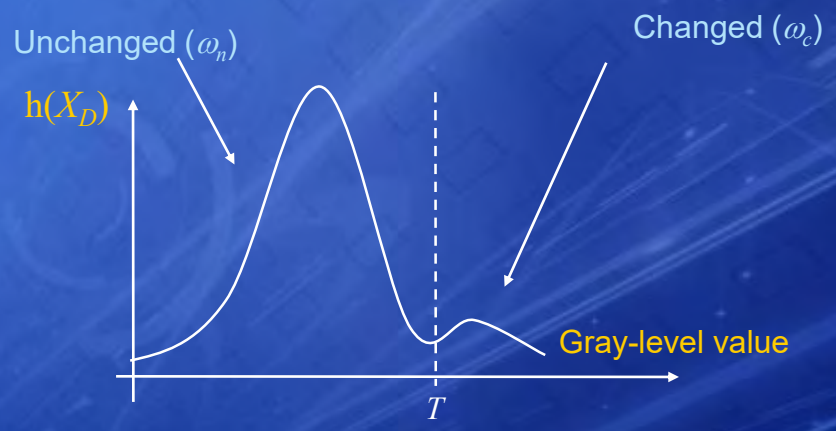
$$P^{t+1}(\omega_n) = \frac{\sum_{X(i,j)\in \mathbf{X_D}} \frac{P^t(\omega_n)\, p^t\left(X(i,j)/\omega_n\right)}{p^t\left(X(i,j)\right)}}{IJ}$$

$$\mu_n^{t+1} = \frac{\sum_{X(i,j)\in \mathbf{X_D}} \frac{P^t(\omega_n)\, p^t\left(X(i,j)/\omega_n\right)}{p^t\left(X(i,j)\right)} X(i,j)}{\sum_{X(i,j)\in \mathbf{X_D}} \frac{P^t(\omega_n)\, p^t\left(X(i,j)/\omega_n\right)}{p^t\left(X(i,j)\right)}}$$

$$(\sigma_n^2)^{t+1} = \frac{\sum_{X(i,j)\in \mathbf{X_D}} \frac{P^t(\omega_n)\, p^t\left(X(i,j)/\omega_n\right)}{p^t\left(X(i,j)\right)} \left[X(i,j)-\mu_n^t\right]^2}{\sum_{X(i,j)\in \mathbf{X_D}} \frac{P^t(\omega_n)\, p^t\left(X(i,j)/\omega_n\right)}{p^t\left(X(i,j)\right)}}$$

# CVA and C²VA Thresholding: Bayesian Framework

The discrimination between changed and unchanged classes (in the histogram of the magnitude image) can be carried according to algorithms inspired to the Bayes classification criterion:




$$p\left(X_D\right) = P(\omega_c)\,p(X_D|\omega_c) + P(\omega_n)\,p(X_D|\omega_n)$$

Problem: the estimation problem should be solved in an unsupervised way.

# Bayesian Framework: EM-Based Technique

At the convergence of the iterative algorithm, the parameters estimated can be used according to three different strategies:

- ✓ Bayes rule for the minimum error (BRME) (pixel based):

$$\frac{P(\omega_c)}{P(\omega_n)} = \frac{p(X_D / \omega_n)}{p(X_D / \omega_c)}$$

- ✓ Bayes rule for the minimum cost (BRMC) (pixel based):

$$\frac{P(\omega_c)}{kP(\omega_n)} = \frac{p(X_D / \omega_n)}{p(X_D / \omega_c)}$$

Ratio between the costs of missed and false alarms

# Bayesian Framework: Markov Random Fields

Bayes rule for the minimum error with Markov Random Fields (MRF) for modeling the prior terms of classes (context based). Minimization of the following energy function:

$$U(\mathrm{X}_D, \mathrm{C}_l) = \sum_{1\le i\le I} \sum_{1\le j\le J} \left[ U_{data}\left(X_D(i,j)/C_l(i,j)\right) + U_{context}\left(C_l(i,j)/\left\{C_l(g,h),\ \ (g,h)\in \mathrm{N}(i,j)\right\}\right)\right]$$

Grey levels statistics energy term

Interpixel class dependence energy term

Neighborhood system

| | | |
|---|---|---|
| | (i-1,j) | |
| (i,j-1) | (i,j) | (i,j+1) |
| | (i+1,j) | |

First Order Neighborhood system

Second Order Neighborhood system

| | | |
|---|---|---|
| (i-1,j-1) | (i-1,j) | (i-1,j+1) |
| (i,j-1) | (i,j) | (i,j+1) |
| (i+1,j-1) | (i+1,j) | (i+1,j+1) |

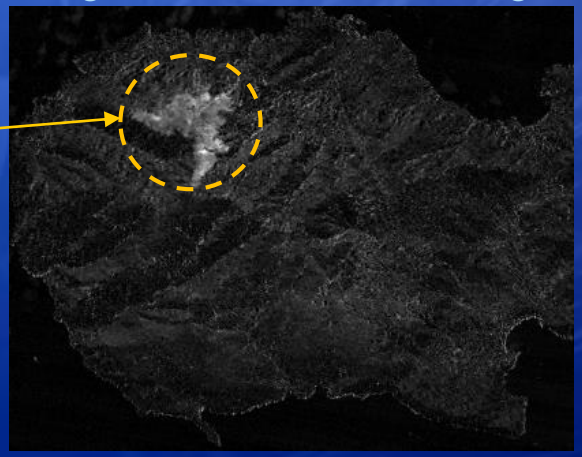
# Example: Manual Thresholding

Landsat TM, Pre-event

Landsat TM, Post-event

Magnitude Difference Image

Burned area

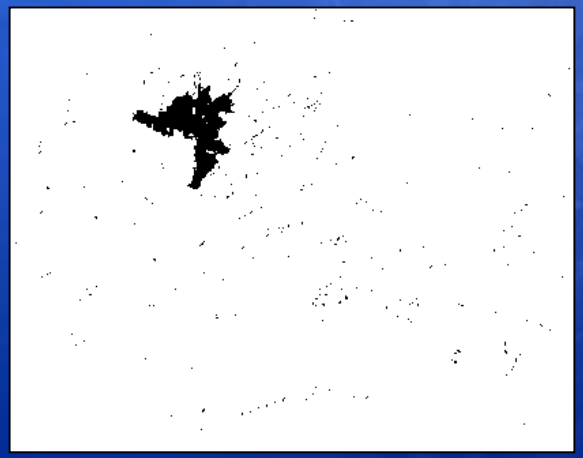


Pixel-Based Change Detection Map

# Example: Bayesian Framework

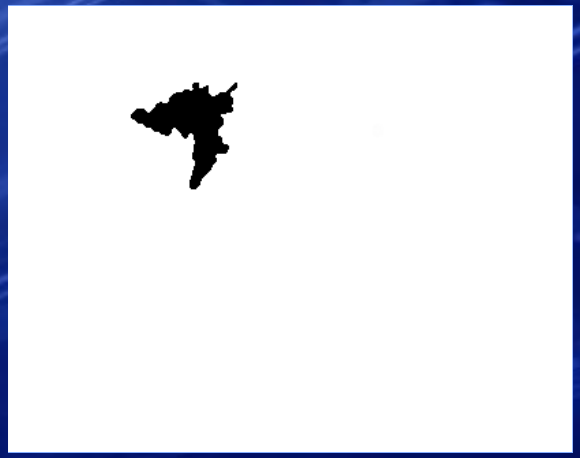
August 1994

September 1994



Bayesian BRME

Bayesian MRF



Reference map

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University of Trento
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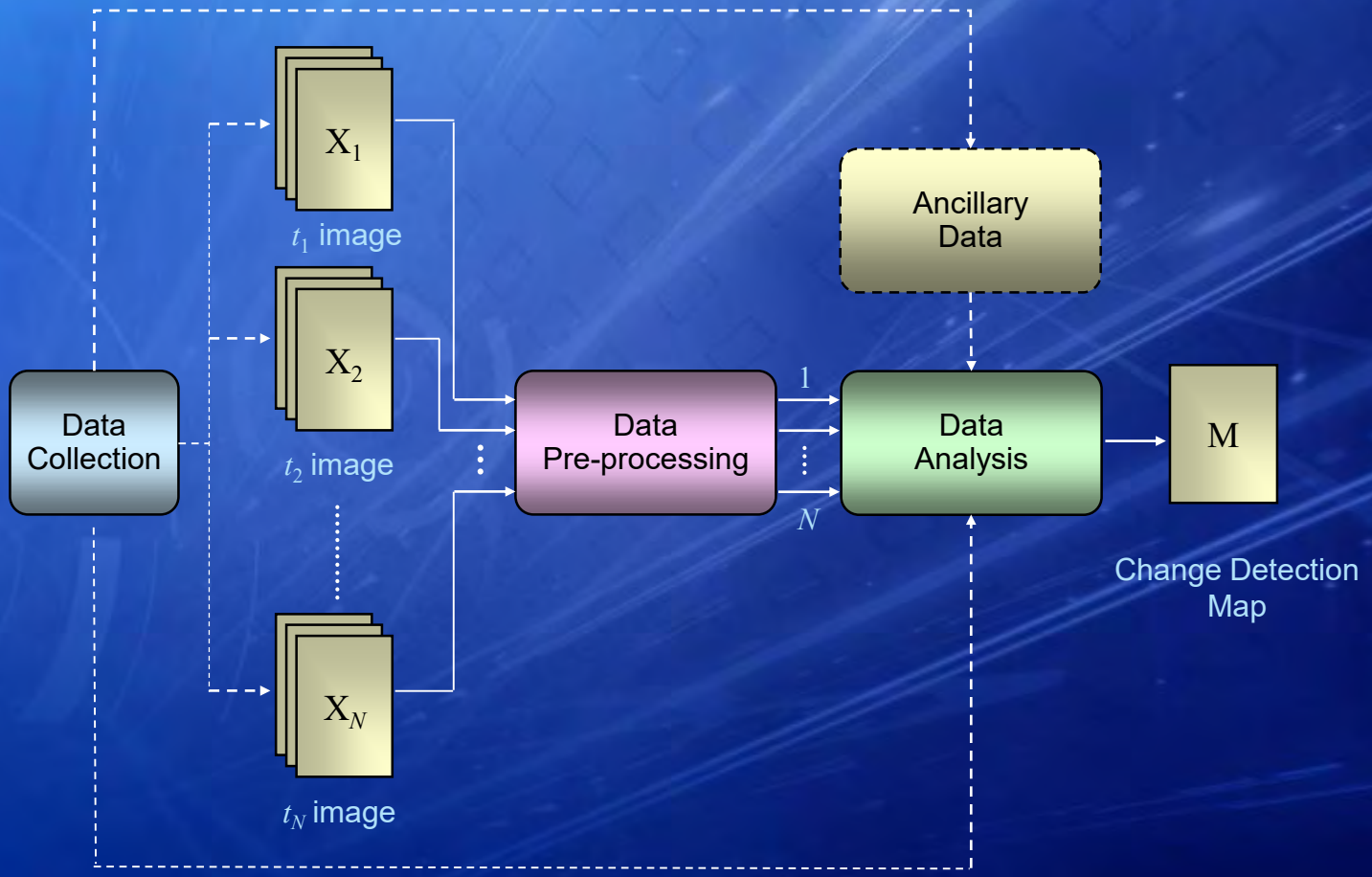
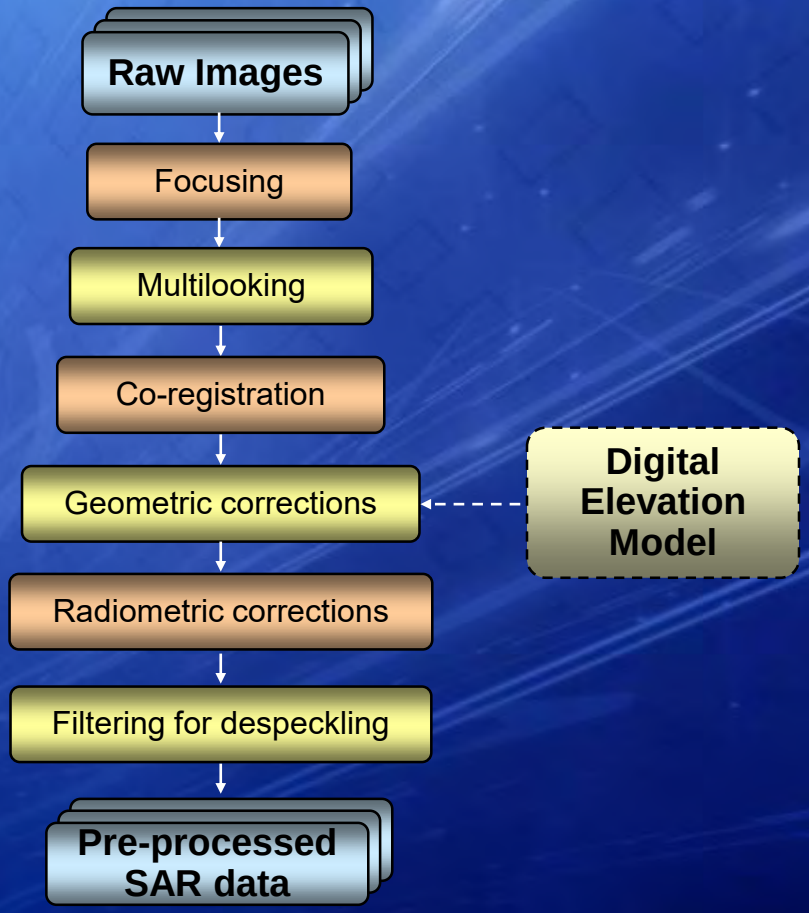
# 3. Change Detection in Medium/High Resolution SAR Images

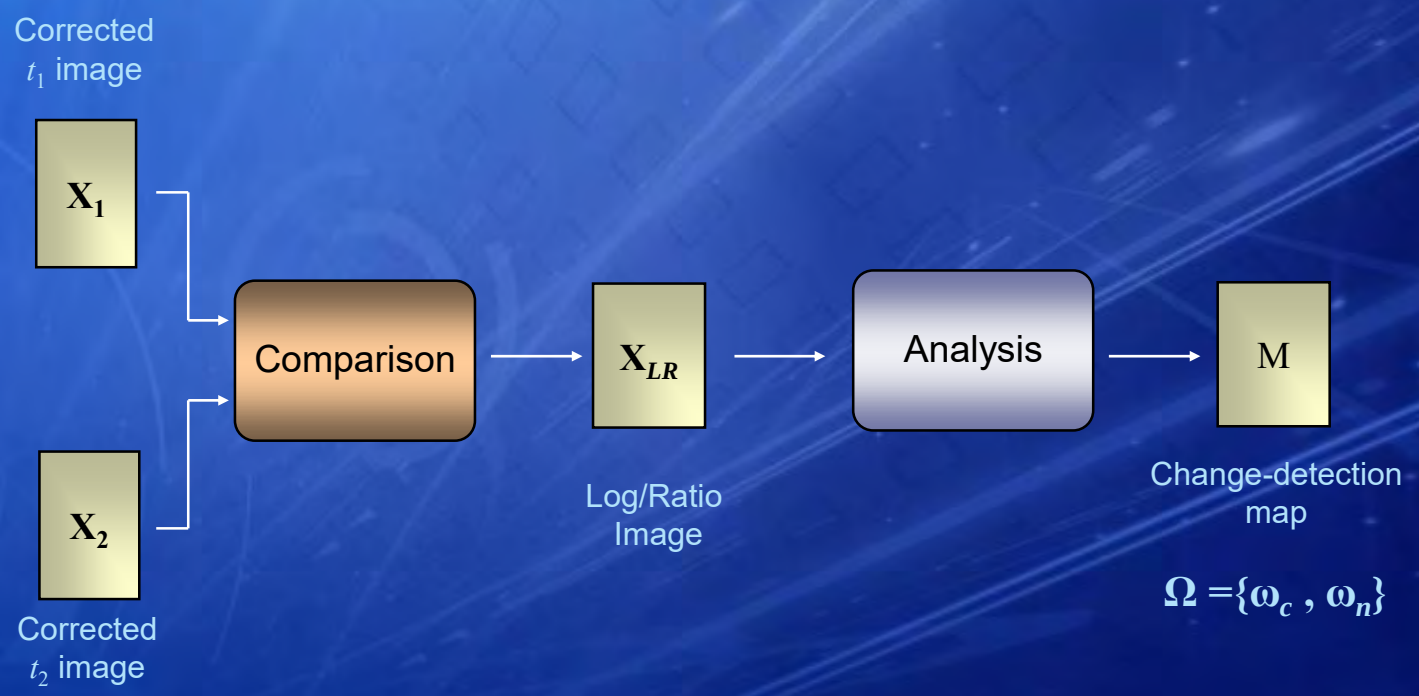
# Change Detection Architecture



# Data Pre-processing: SAR Images



# Binary CD in SAR: Typical Architecture



# Binary CD in SAR: Comparison Operators

| Technique | Feature vector $f_k$ at the time $t_k$ | Computation of $X_D$ |
|---|---|---|
| Image rationing | $f_k = X_k^b$ | $X_D = f_2 / f_1$ |
| Kullback-Leibler distance (Similarity measures) | $f_k = [p(X_k)]$ | $KL(X_2 \| X_1) = \int \log(f_1/f_2) f_1$ |
| Difference of scattering matrix element products | $f_k = [S_{HH} S_{VV}^*]$ | $X_D = f_1 - f_2$ |
| Difference of scattering matrix amplitude correlation coefficients | $f_k = \left[ \frac{S_{HH} S_{VV}^*}{\sqrt{\lvert S_{HH} \rvert^2 \lvert S_{VV} \rvert^2}} \right]$ | $X_D = f_1 - f_2$ |

$k$: variable associated with the acquisition date

# Binary CD in SAR: Comparison Operators

Difference operator

Mean intensities of $X_1$ and $X_2$ in an homogeneous area

Equivalent number of looks

$$P(X_D \mid \bar{I}_1, \bar{I}_2) = \frac{L^L}{(L-1)!} \frac{1}{(\bar{I}_1 + \bar{I}_2)^L} \exp\left(-\frac{L X_D}{\bar{I}_2}\right) \sum_{j=0}^{L-1} \frac{(L-1+j)!}{j!\,(L-1-j)!} X_D^{L-1-j} \left[\frac{\bar{I}_1 \bar{I}_2}{L(\bar{I}_1 + \bar{I}_2)}\right]^j$$

The statistical distribution of the difference image depends on both:

- ✓ the relative change between the intensity values in the two images;
- ✓ a reference intensity value.

This leads to a higher change-detection error for changes occurred in high intensity regions of the image than in low intensity regions (i.e., changes are detected in a different way in dark and bright regions).

# Binary CD in SAR: Comparison Operators

## Ratio operator

- ✓ Reduces the multiplicative distortions common to the two considered images due to speckle noise;
- ✓ Makes the distribution of the ratio image depending only on the relative changes between images.

Equivalent number of looks

Mean intensities

$$P(X_R \mid \bar{I}_1, \bar{I}_2) = \left(\frac{\bar{I}_2}{\bar{I}_1}\right)^L \frac{(2L-1)!}{(L-1)!^2} \frac{X_R^{\,L-1}}{\left[\bar{I}_2/\bar{I}_1 + X_R\right]^{2L}}$$

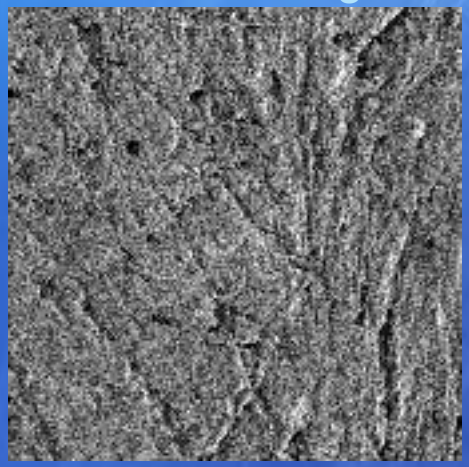
## Log-ratio operator ($\mathbf{X}_{LR}$)

- ✓ Produces more symmetrical statistical distribution of the classes of changed and unchanged pixels;
- ✓ Transforms the residual multiplicative noise model into an additive noise model:

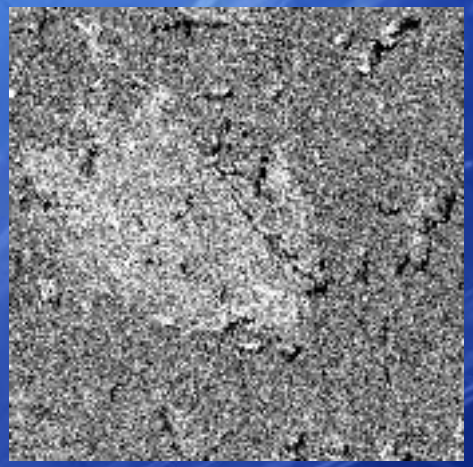
$$\log(X_D) = \log(\boldsymbol{f}_2 \,/\, \boldsymbol{f}_2) = \log(\boldsymbol{f}_2) - \log(\boldsymbol{f}_1)$$

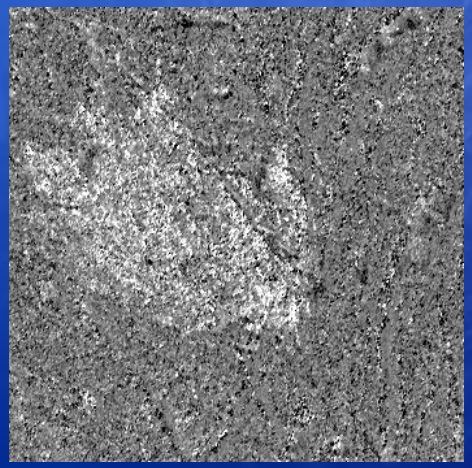
# Binary CD in SAR: Comparison Operators

Before change

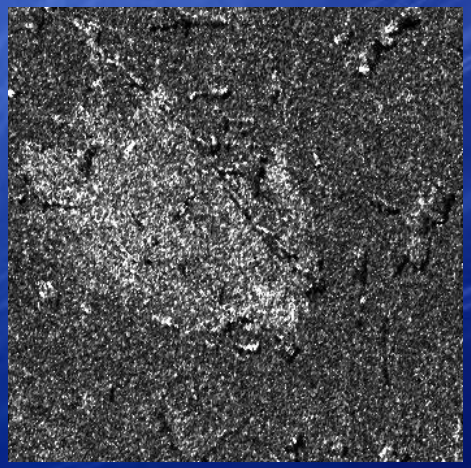


After change

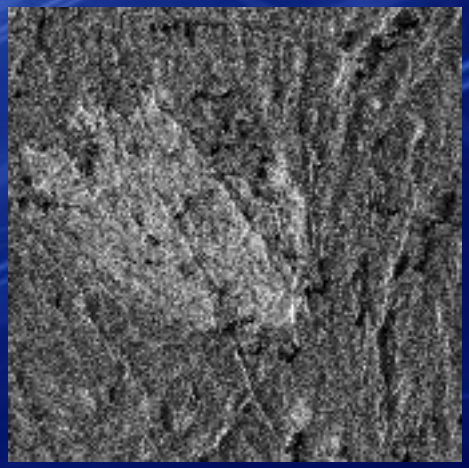




Difference operator



Ratio image



Log-ratio image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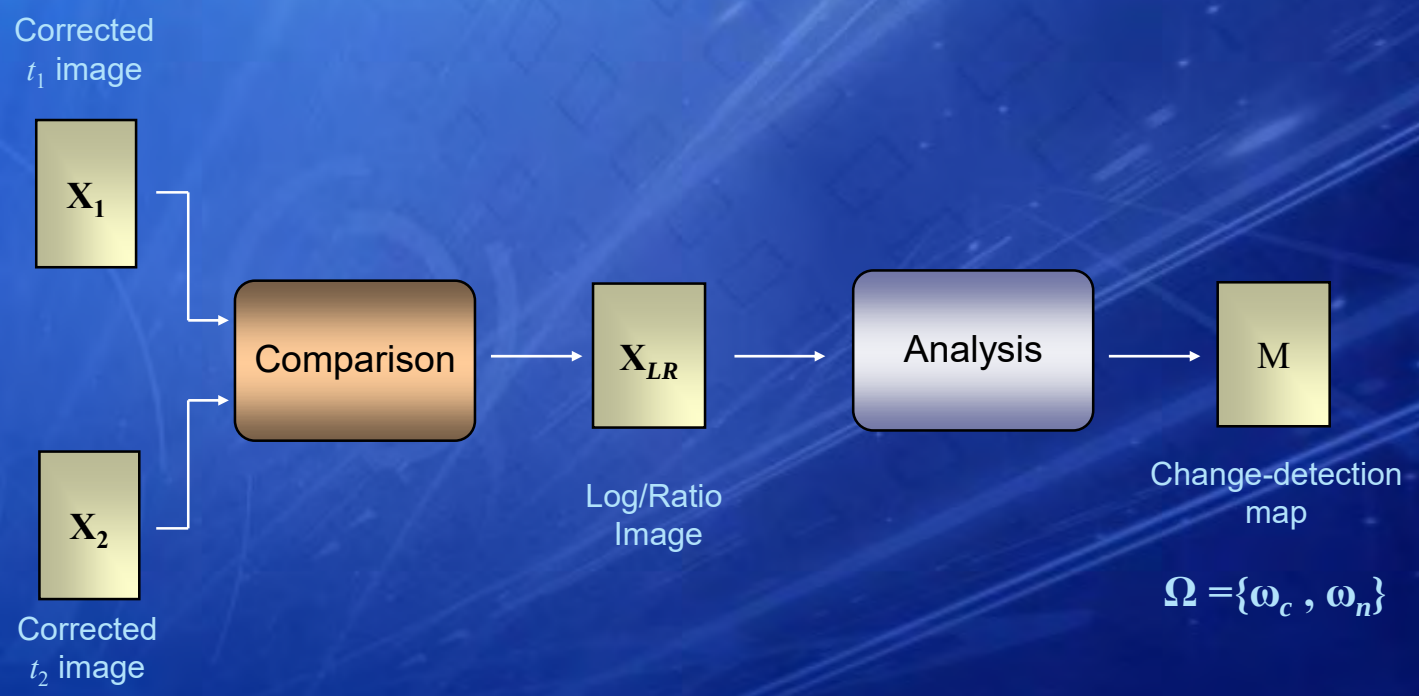
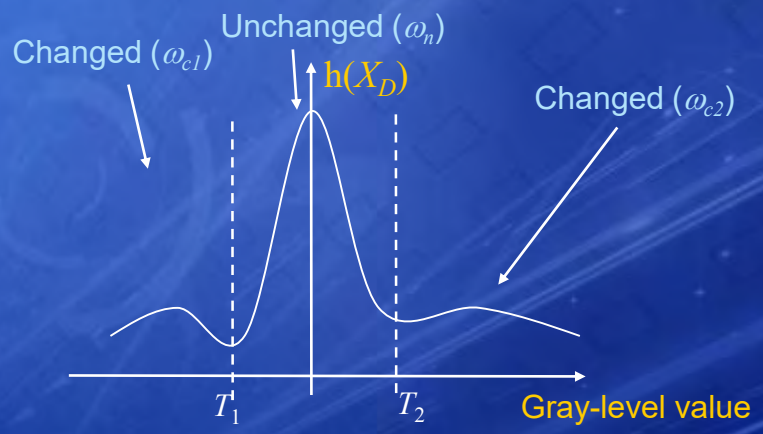
# Binary CD in SAR: Typical Architecture



# Log-ratio Image Analysis: Bayesian Framework

The discrimination between changed and unchanged classes (in the histogram of the log-ratio image) can be carried out according to algorithms inspired to the Bayes classification criterion.




$$p(X_D) = P(\omega_n)p(X_D/\omega_n) + \sum_{i=0}^{N} P(\omega_{c_i})p(X_D/\omega_{c_i}) \quad N = 0,1,2$$

Problem: the estimation problem should be solved in an unsupervised way.

# Log-ratio Image Analysis: Bayesian Framework

**Pixel based**

- Direct detection of the decision threshold with implicit estimation of the statistical terms of classes
- Explicit estimation of the statistical terms of classes with the Expectation-Maximization (EM) algorithm
  - Bayes rule Minimum error
  - Bayes rule Minimum cost

**Context based**

- Markov Random Fields (MRF) based regularization strategy

# Log-Ratio Image Analysis: Statistical Models

- Gaussian model: $$P(X_D \mid \omega_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left( -\frac{(X_D - \mu_i)^2}{2\sigma_i^2} \right)$$

- Generalized Gaussian model:

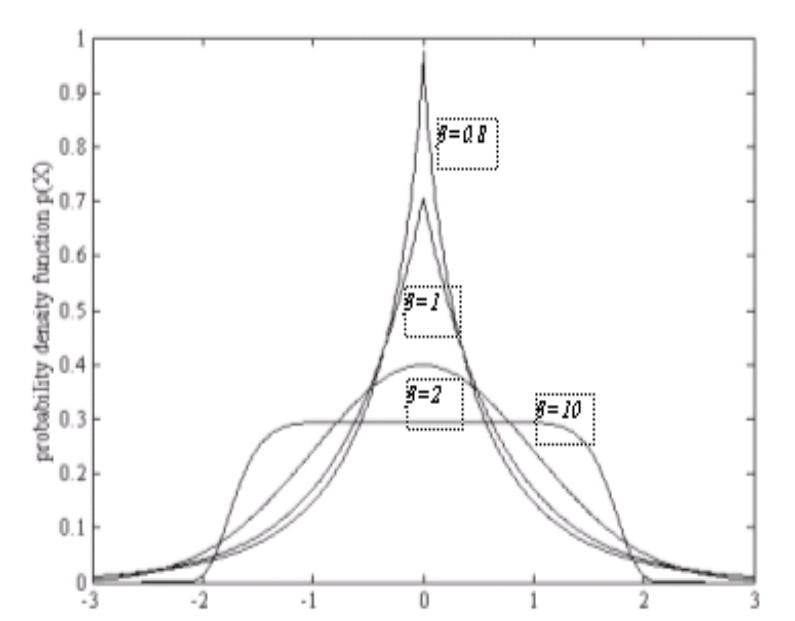
Gamma function

$$P(X_D \mid \omega_i) = \frac{b_i \beta_i}{2\Gamma(1/\beta_i)} \exp\left( -\frac{1}{\sigma_i} \sqrt{\frac{\Gamma(3/\beta_i)}{\Gamma(1/\beta_i)}} \left| X_L - m_i \right| \right)^{\beta_i}$$

Mean value

$$b_i = \frac{1}{\sigma_i} \sqrt{\frac{\Gamma(3/\beta_i)}{\Gamma(1/\beta_i)}}$$

Shape parameter




- Generalized Gamma model

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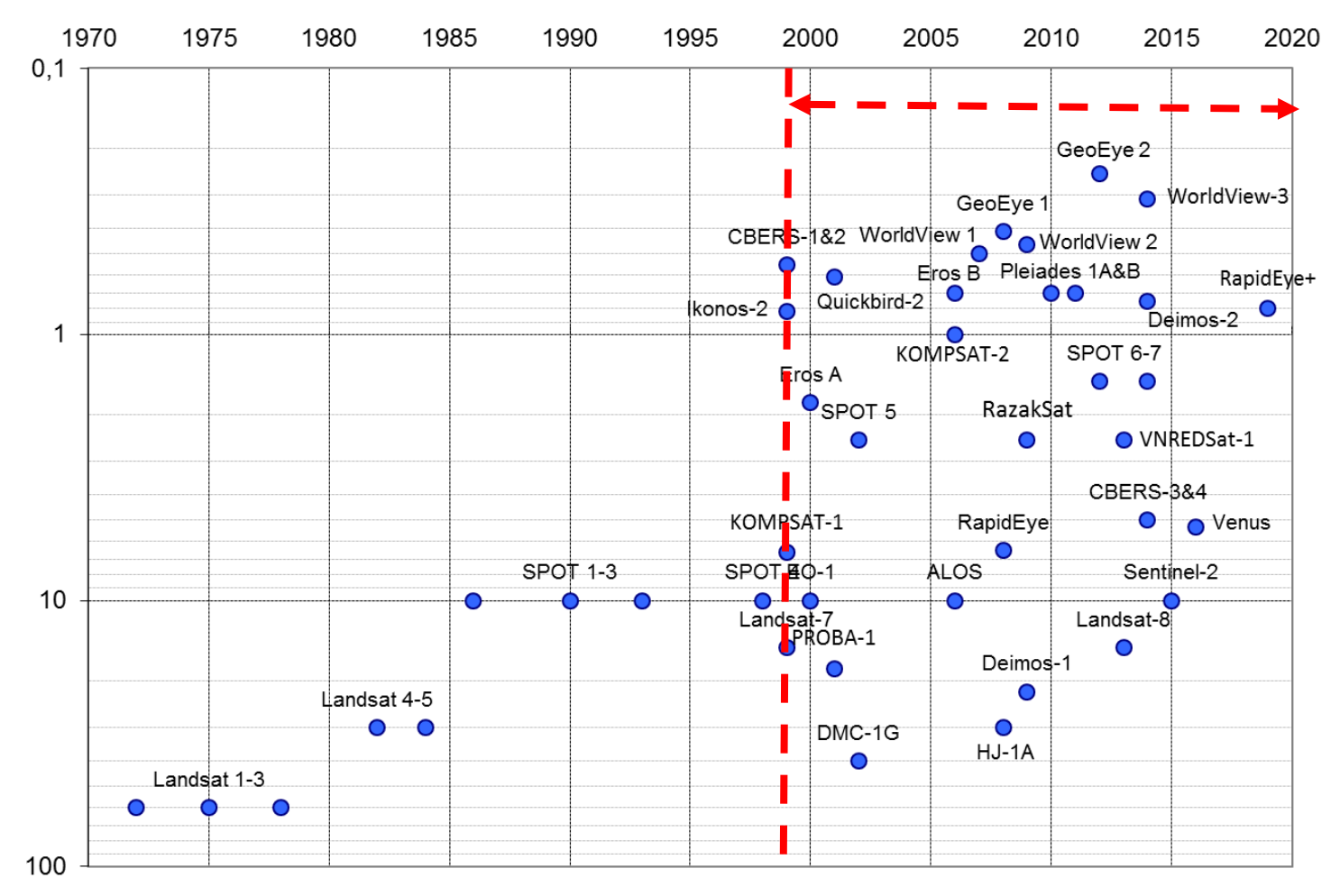
# 4. Change Detection in Very High Resolution Multispectral Images

# New Satellites with VHR Multispectral (MS) Sensors





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# CD in Multitemporal VHR MS images

July 2006

October 2005

Quickbird images of the city of Trento (Italy)

# CD in Multitemporal VHR MS images

October 2005

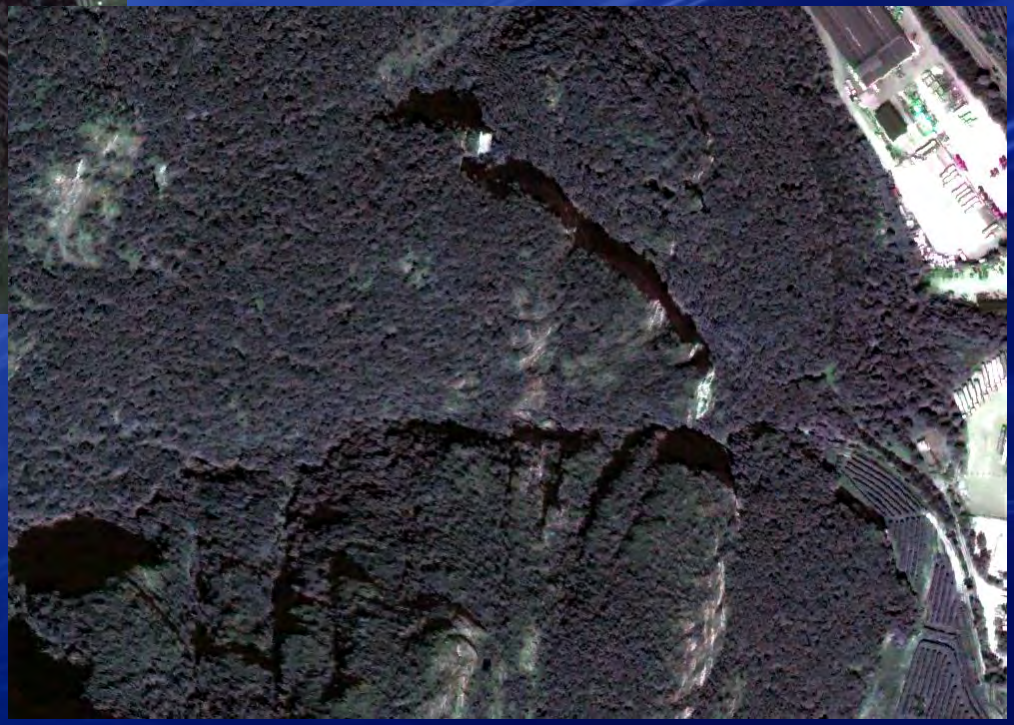
July 2006

Quickbird images of the city of Trento (Italy)

# CD in Multitemporal VHR MS images

October 2005

July 2006



Quickbird images of
the city of Trento (Italy)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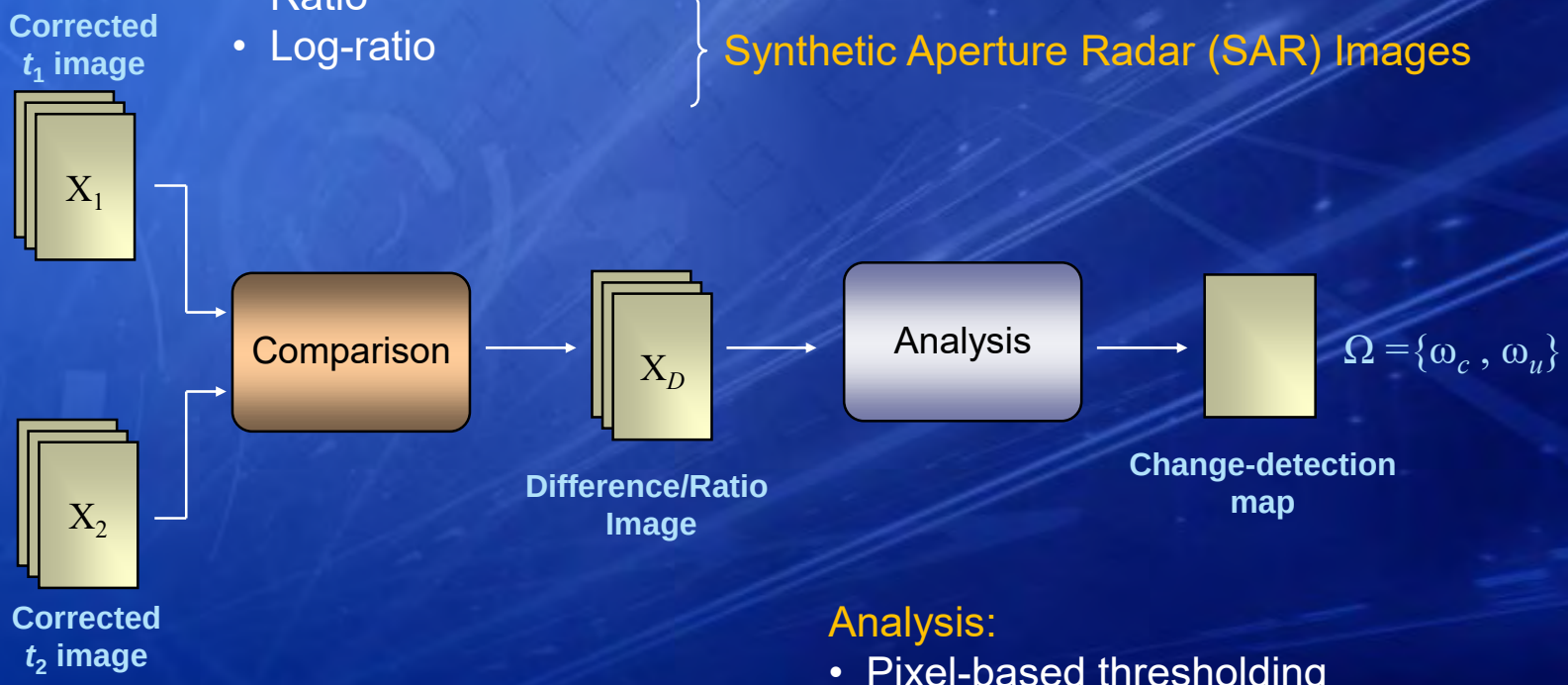
# Unsupervised CD: Typical Architecture

Comparison Operators:

- Difference
- Vector difference
- Ratio
- Log-ratio

Optical Images

Synthetic Aperture Radar (SAR) Images




Analysis:

- Pixel-based thresholding
- Context-based approaches

# CD in Multitemporal VHR Images: Example

Quickbird, October 2004 (true color composition)

Quickbird, July 2006 true color composition

Magnitude Difference Image

Pixel-Based Change Detection Map

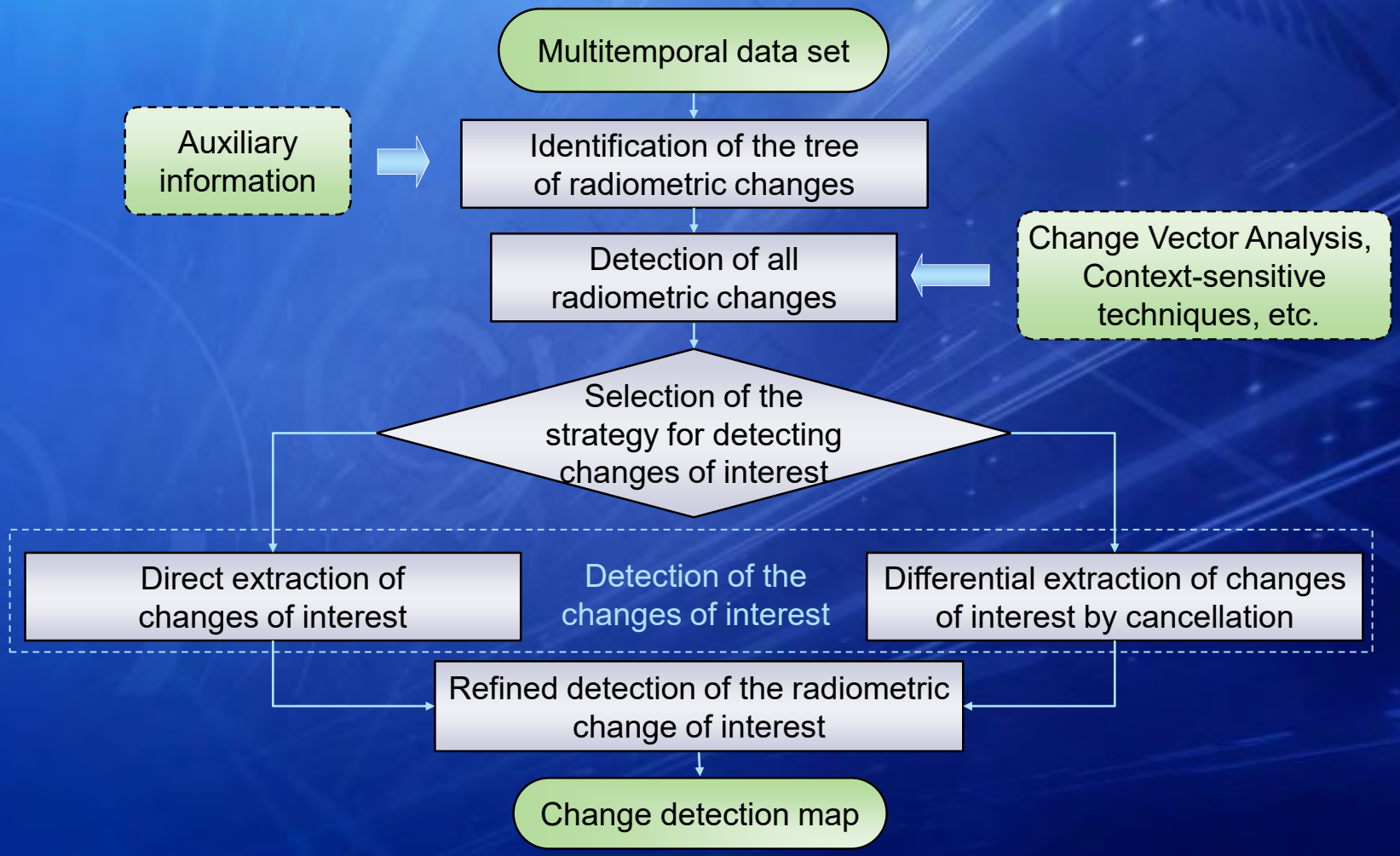
# CD in Multitemporal VHR images

Change detection in VHR Images should exploit a top-down approach to the definition of the processing architecture. This approach should [4]:

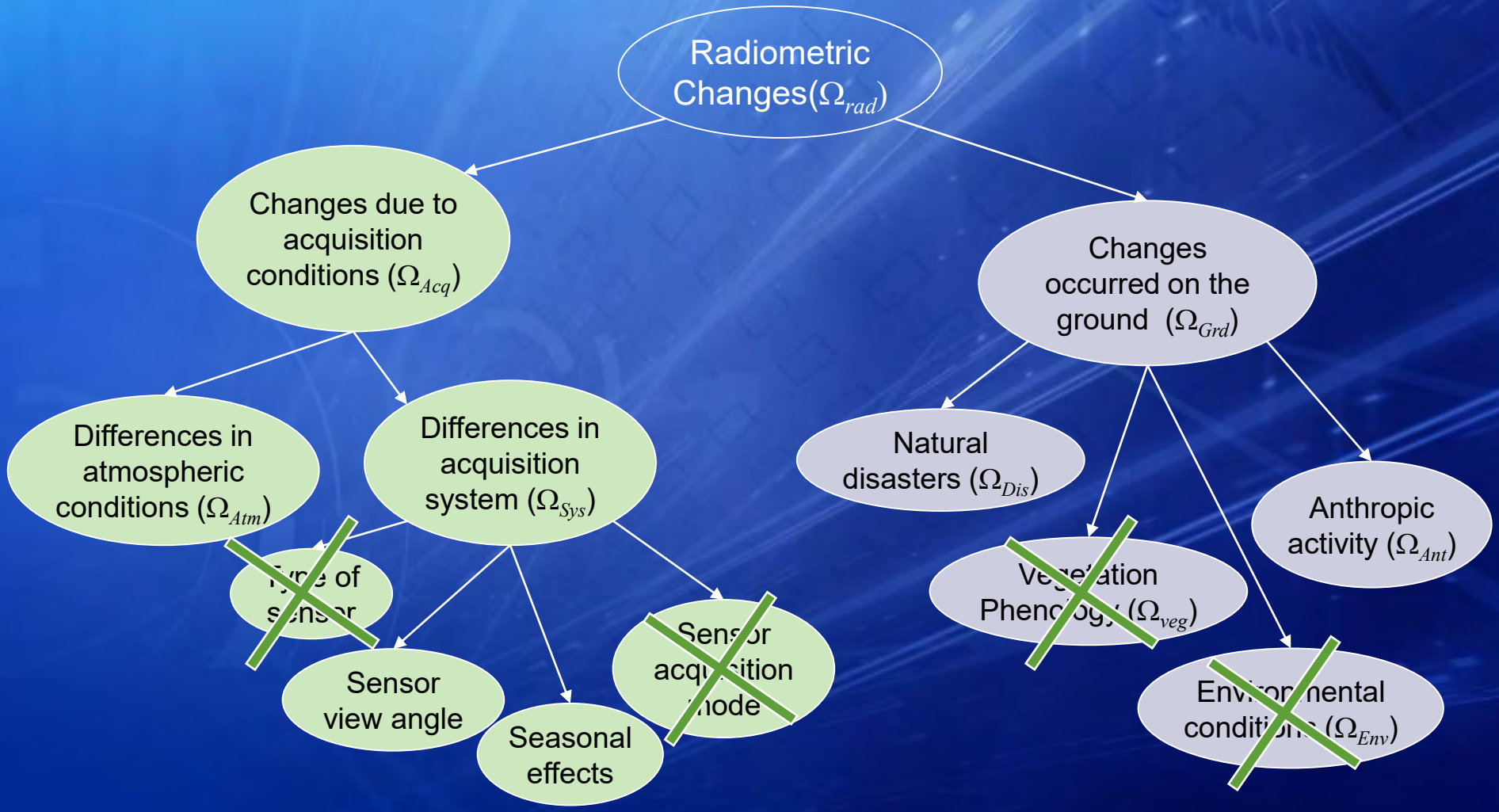
- ✓ explicitly model the presence of different radiometric changes on the basis of the properties of the considered images;
- ✓ extract the semantic meaning of changes;
- ✓ identify changes of interest with strategies designed on the basis of the specific application;
- ✓ exploit the intrinsic multiscale properties of the objects and the high spatial correlation between pixels in a neighborhood.

L. Bruzzone, F. Bovolo, "A Conceptual Framework for Change Detection in Very High Resolution Remote Sensing Images," *Proceedings of IEEE*, Vol. 101, pp. 609-630, 2013.

# CD in VHR MS Images: Architecture Design



# Identification of the Tree of Radiometric Changes





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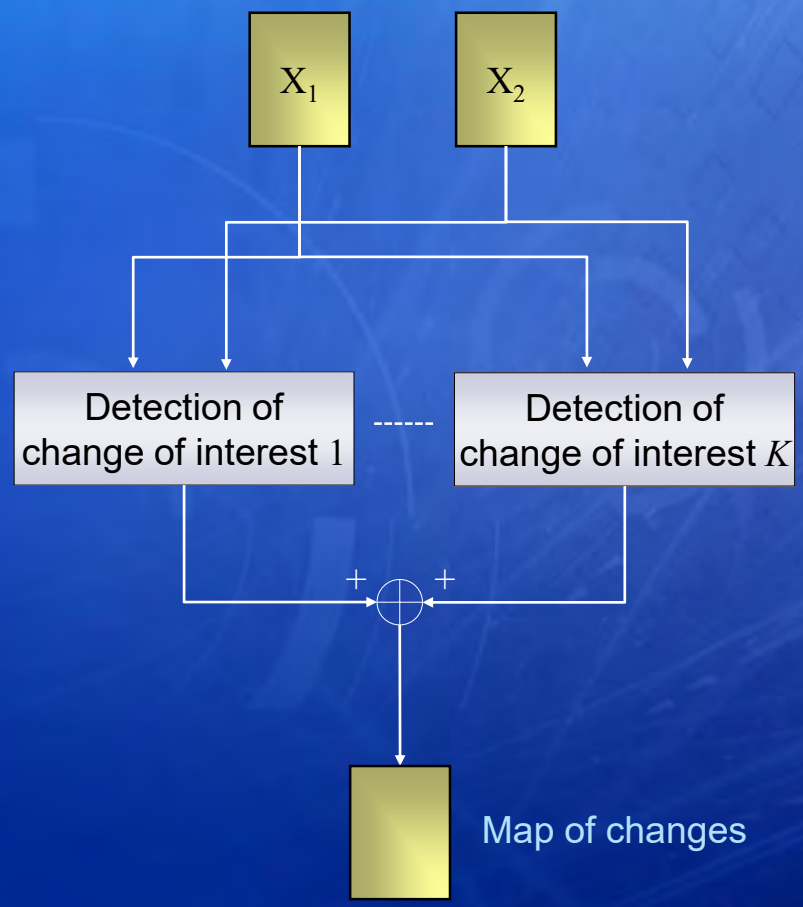
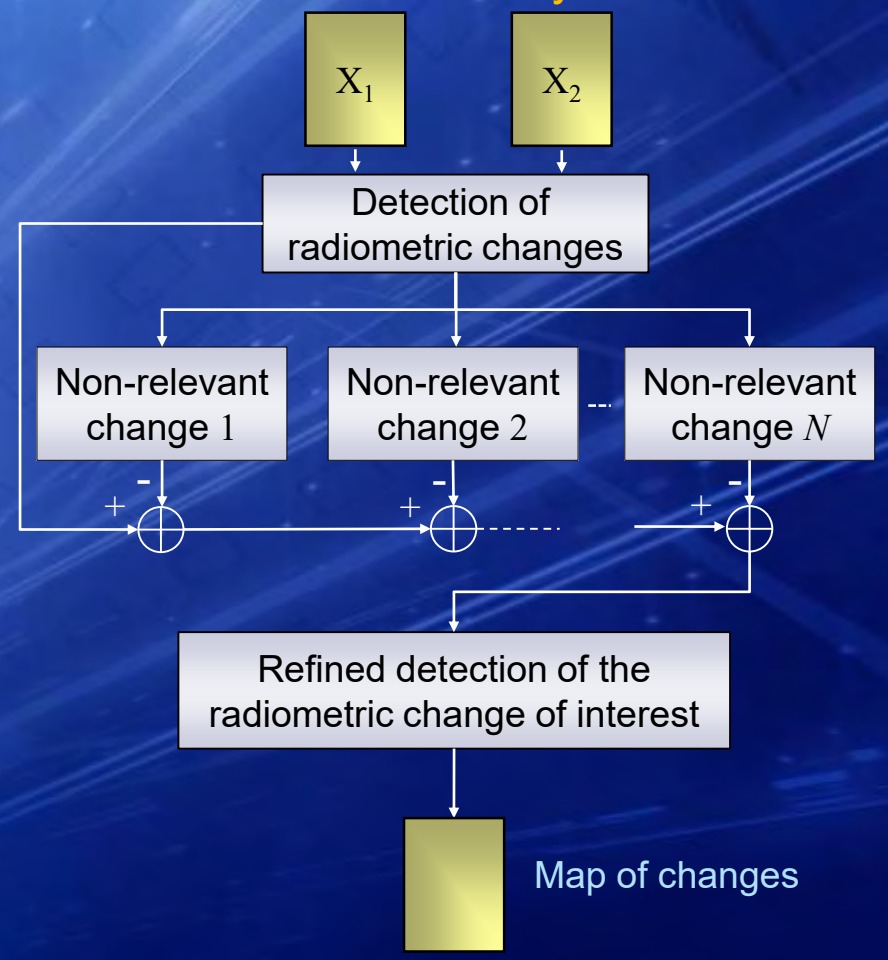
# Detection of Changes of Interest

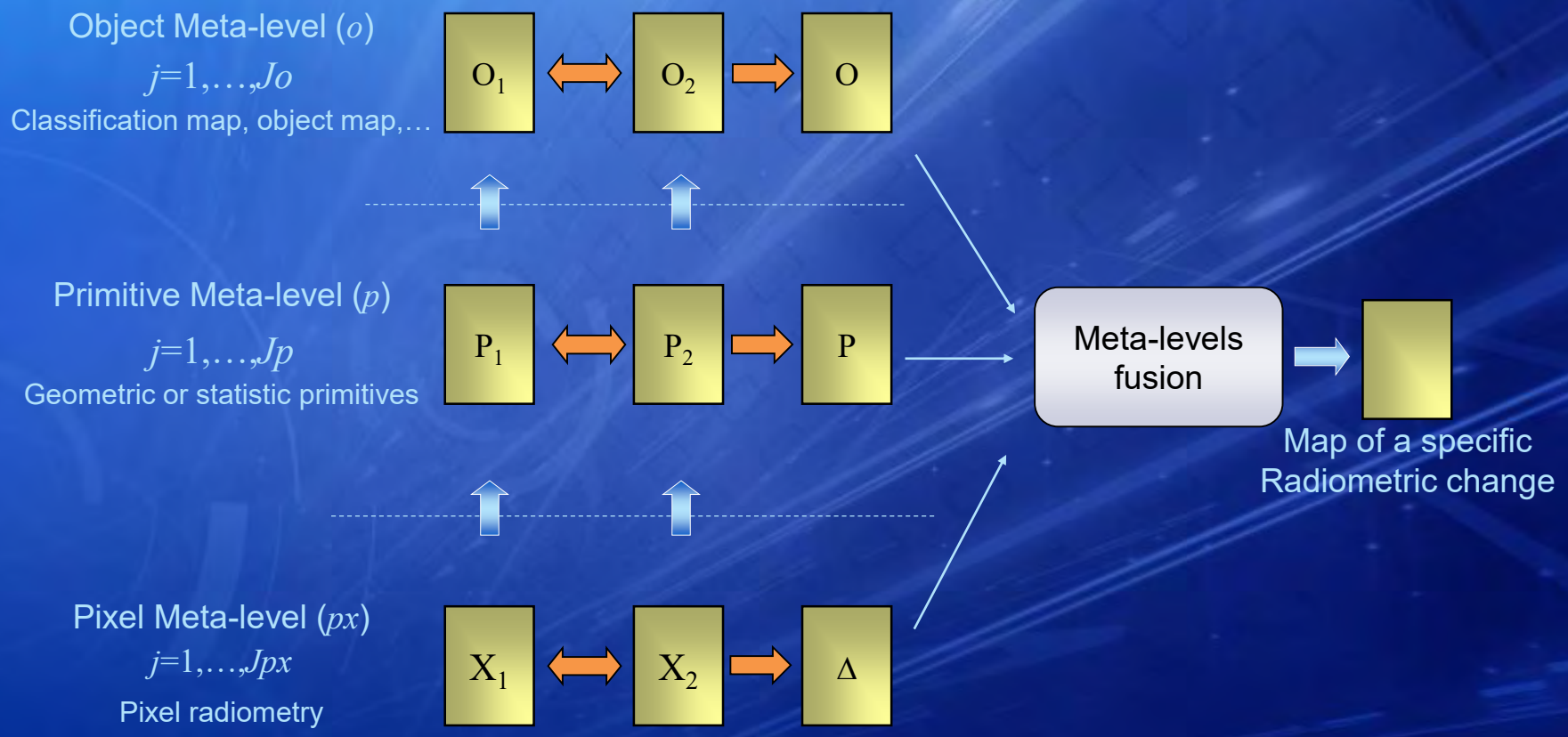
## Direct detection




## Differential detection by cancellation



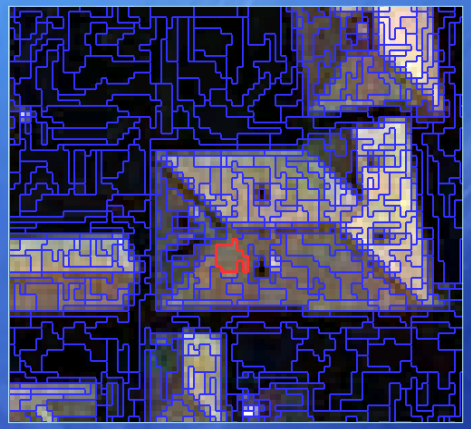
# Semantic of Changes: Multilevel Approach



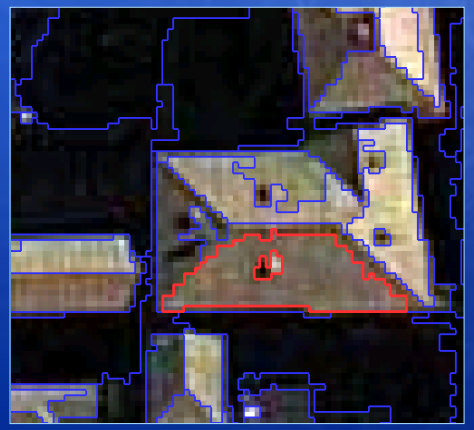

L. Bruzzone, F. Bovolo "A Conceptual Framework for Change Detection in Very High Resolution Remote Sensing Images," Proceedings of *IEEE*, Vol. 101, pp. 609-630, 2013.

# Example: Multilevel Object Characterization

Pixel Level

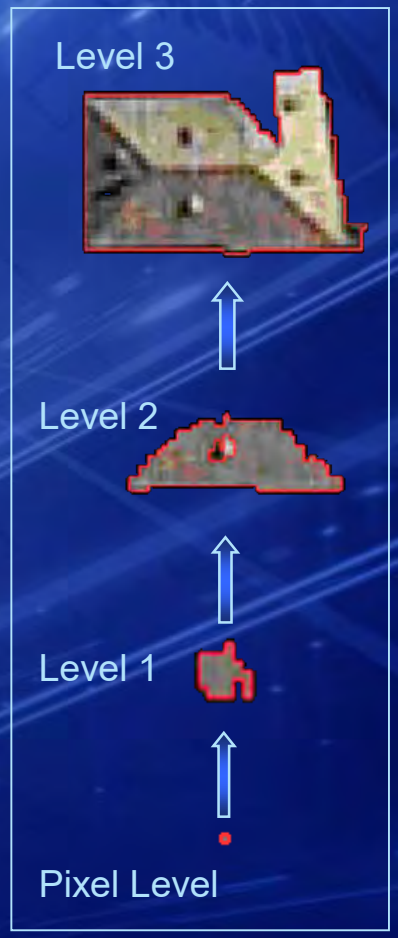


Level 1 ($L_1$)



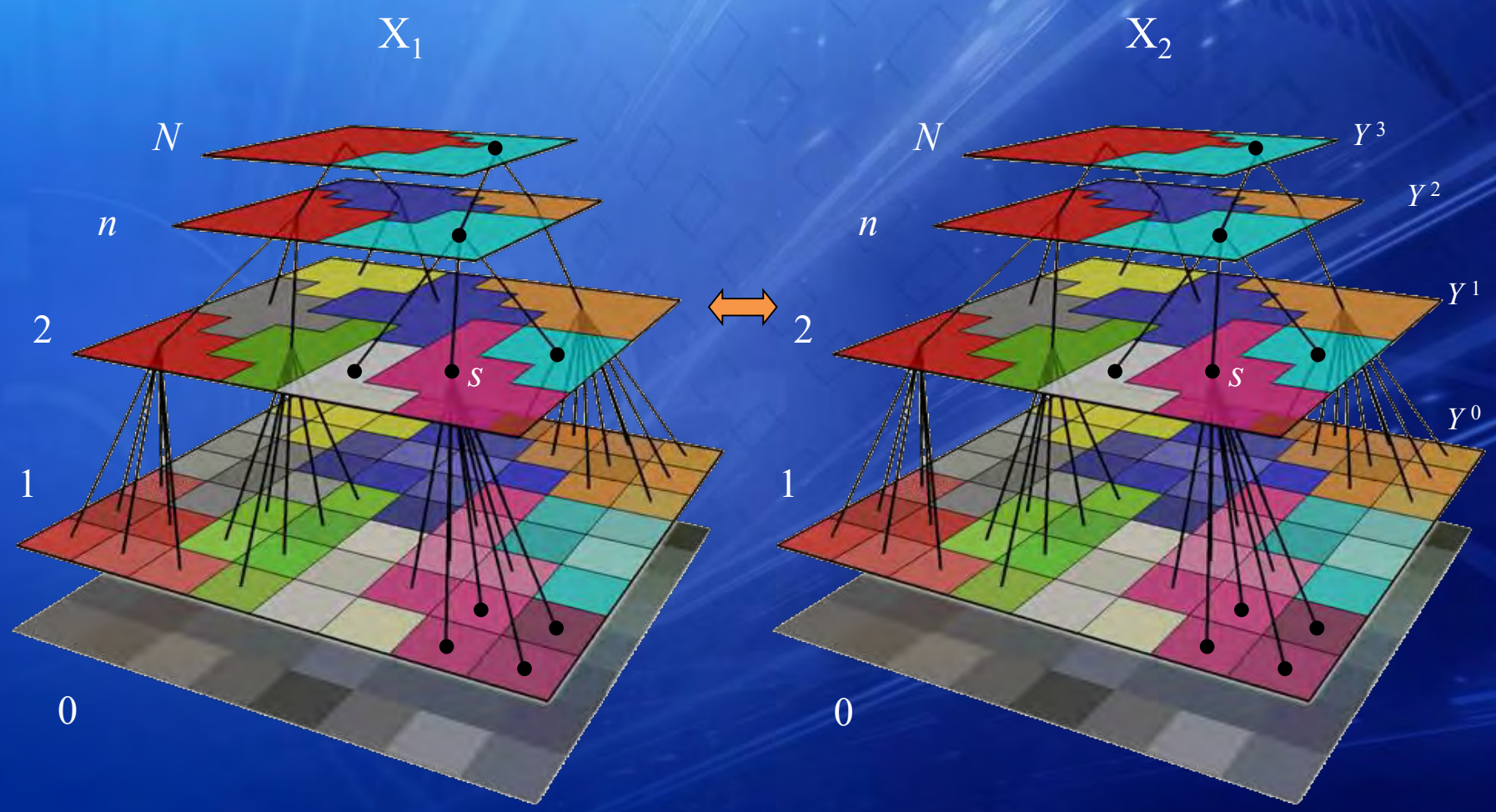
Level 2 ($L_2$)

Level 3 ($L_3$)




L. Bruzzone, L. Carlin, "A Multilevel Context-Based System for Classification of Very High Spatial Resolution Images", *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 44, No. 9, 2006, 2587-2600.

# Multilevel Multitemporal Representation



# Example: CD in VHR Optical Images

Study area: South part of Trento (Italy).

Multitemporal data set: portion (380×430 pixels) of two images acquired by the Quickbird satellite in October 2004 and July 2006.

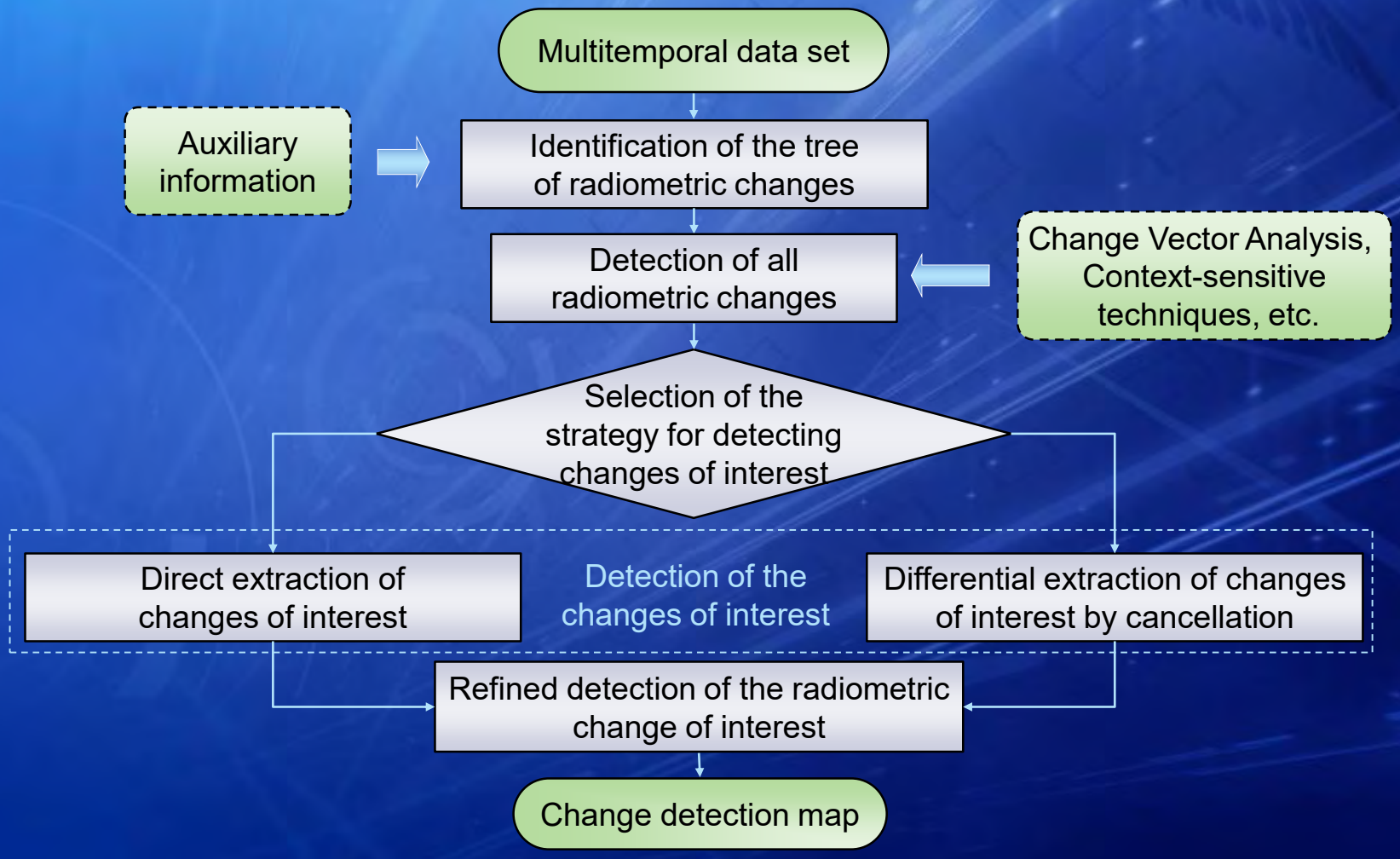
Causes of Change: changes on the ground, seasonal changes, registration noise.

October 2004

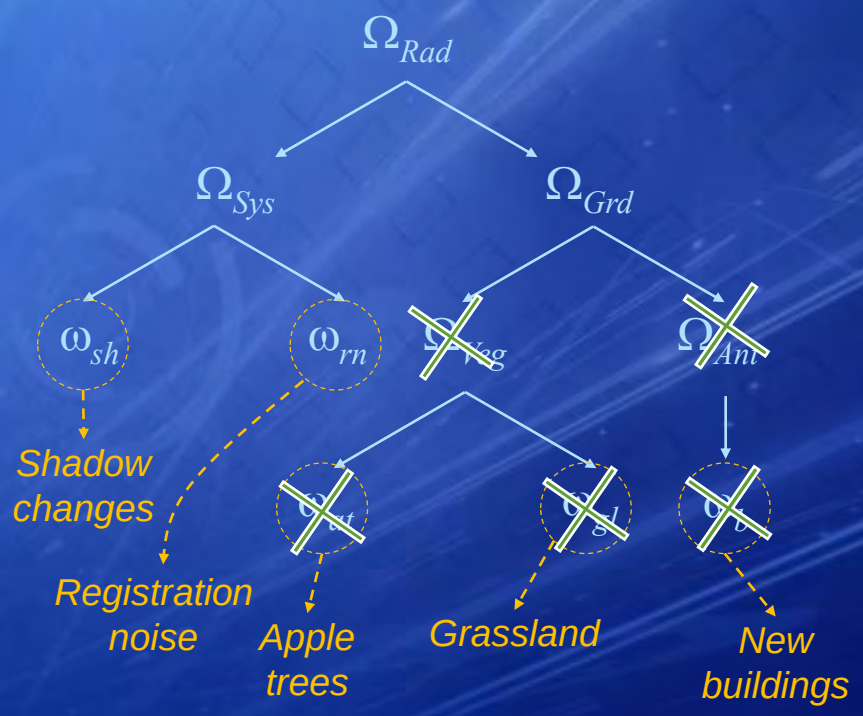
July 2006

Reference Map

# CD in VHR MS Images: Architecture Design

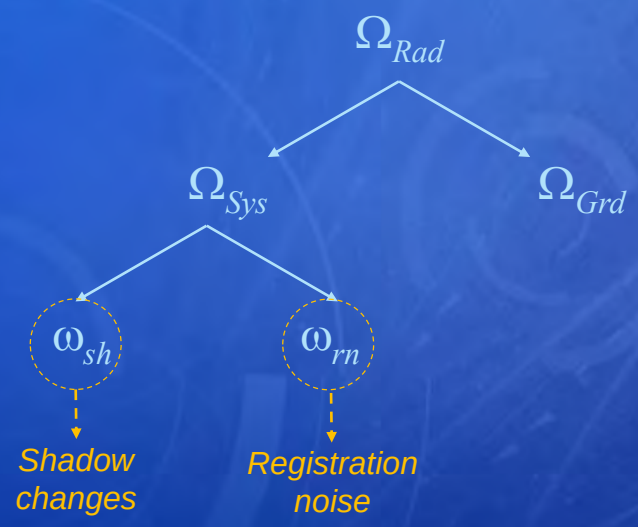


# Identification of the Tree of Radiometric Changes

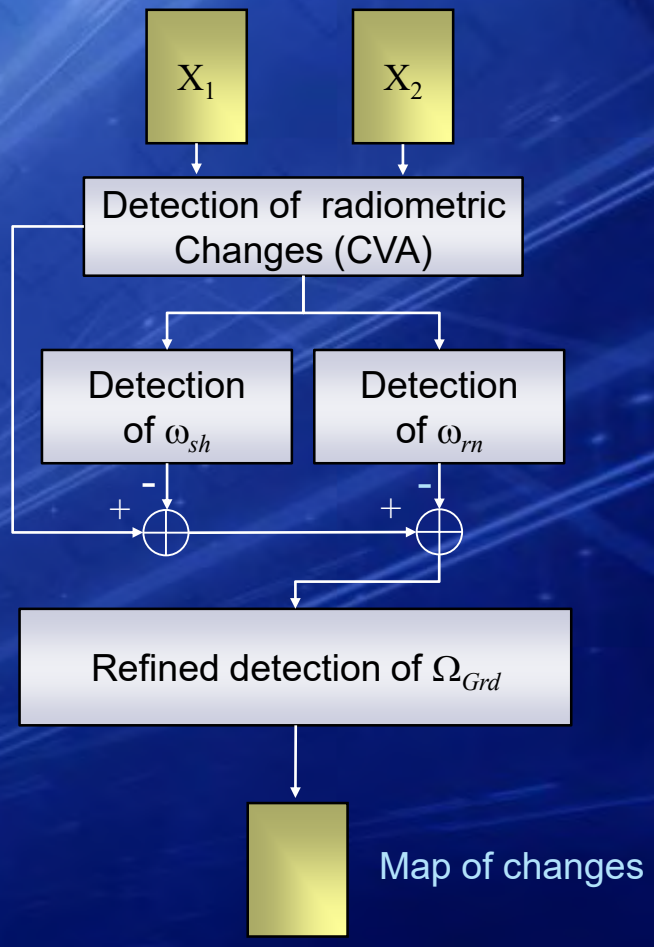


# Change Tree and Detection Strategy

## Identification of the tree of radiometric changes



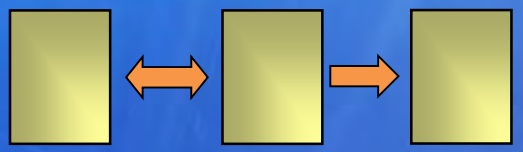

## Differential detection by cancellation



# Multilevel Representation of Radiometric Changes

Primitive Meta-level (*p*)

*Segmentation map*

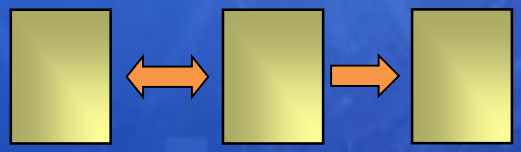


*Parcel map*

F. Bovolo, “A Multilevel Parcel-Based Approach to Change Detection in Very High Resolution Multitemporal Images,” IEEE Geoscience and Remote Sensing Letters, Vol. 6, No. 1, pp. 33-37, January 2009.

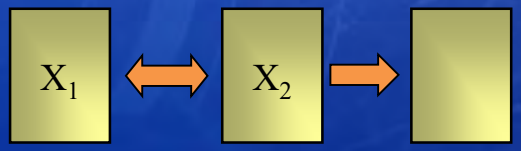
Pixel Meta-level (*px*)

*Shadow Index*



*Shadow change index*

V. J. D. Tsai, "A comparative study on shadow compensation of color aerial images in invariant color models," IEEE Trans. Geosci. Remote Sens., vol. 44, pp. 1661-1671, 2006.

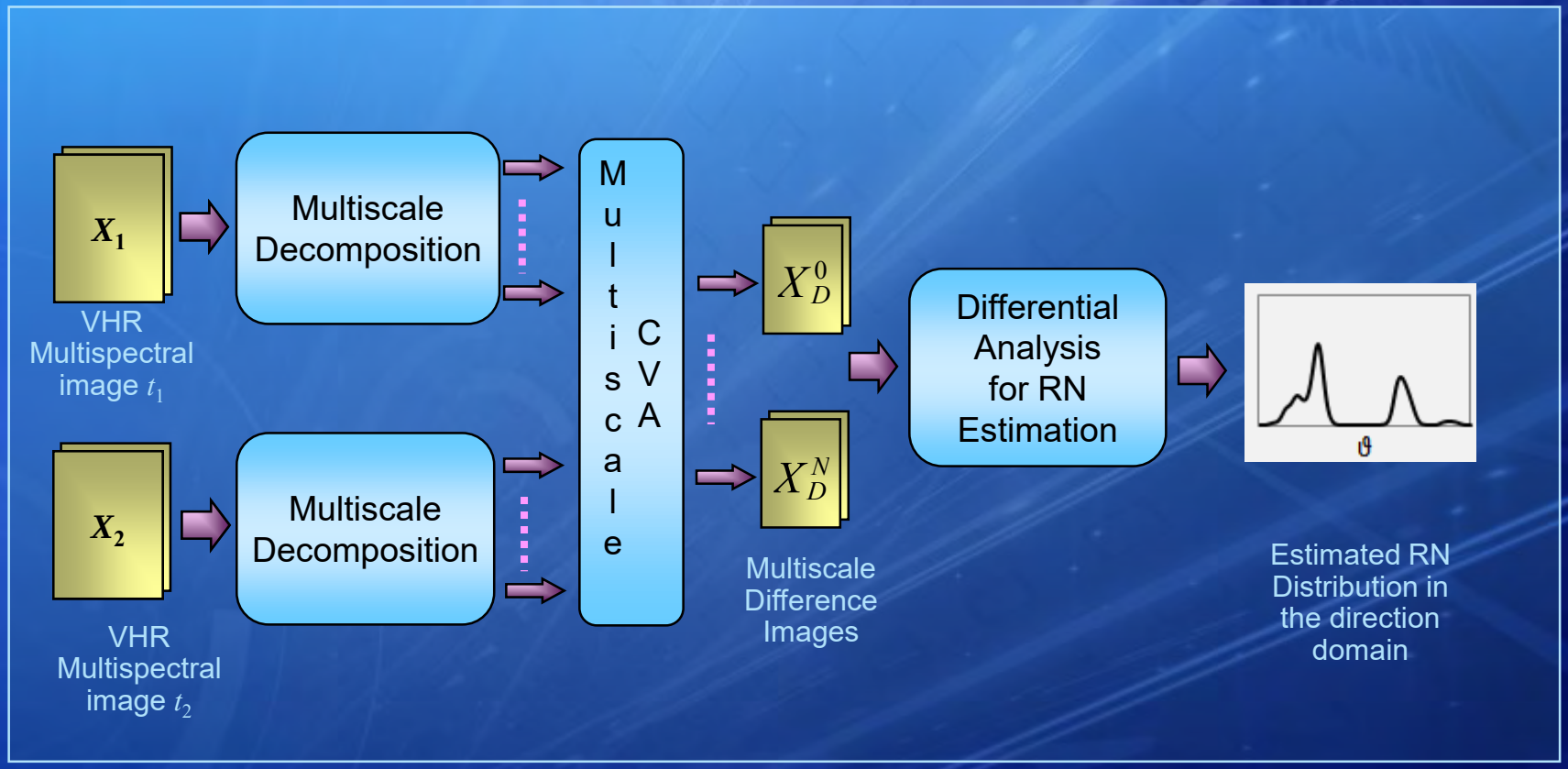



*Magnitude of multispectral change vectors*

L. Bruzzone and D. Fernández-Prieto, "Automatic Analysis of the Difference Image for Unsupervised Change detection," IEEE Trans. Geosci. Rem. Sens., vol. 38, pp. 1170-1182, 2000.

*Image radiometry*

# Detection of Registration Noise





F. Bovolo, L. Bruzzone, S. Marchesi, "Analysis and Adaptive Estimation of the Registration Noise Distribution in Multitemporal VHR Images," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 47, No. 8, 2009, pp. 2658-2671.

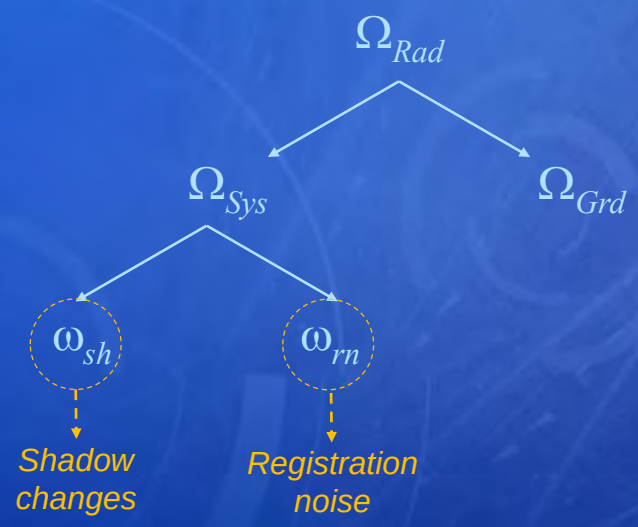
S. Marchesi, F. Bovolo, L. Bruzzone, "A Context-Sensitive Technique Robust to Registration Noise for Change Detection in VHR Multispectral Images", *IEEE Transactions on Image Processing*, Vol. 19, pp. 1877-1889, 2010.



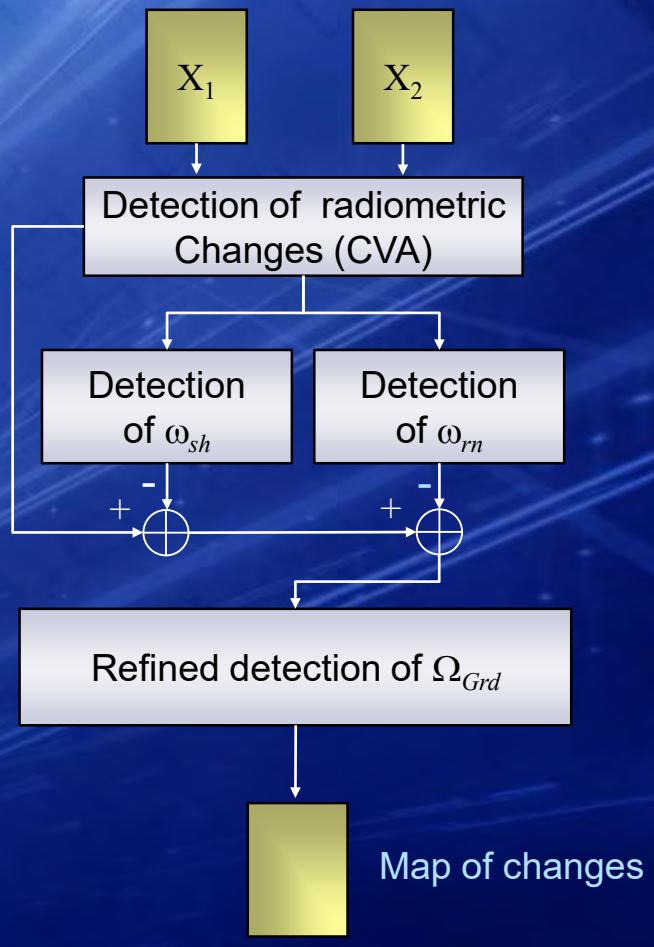

© Lorenzo Bruzzone

# Change Tree and Detection Strategy

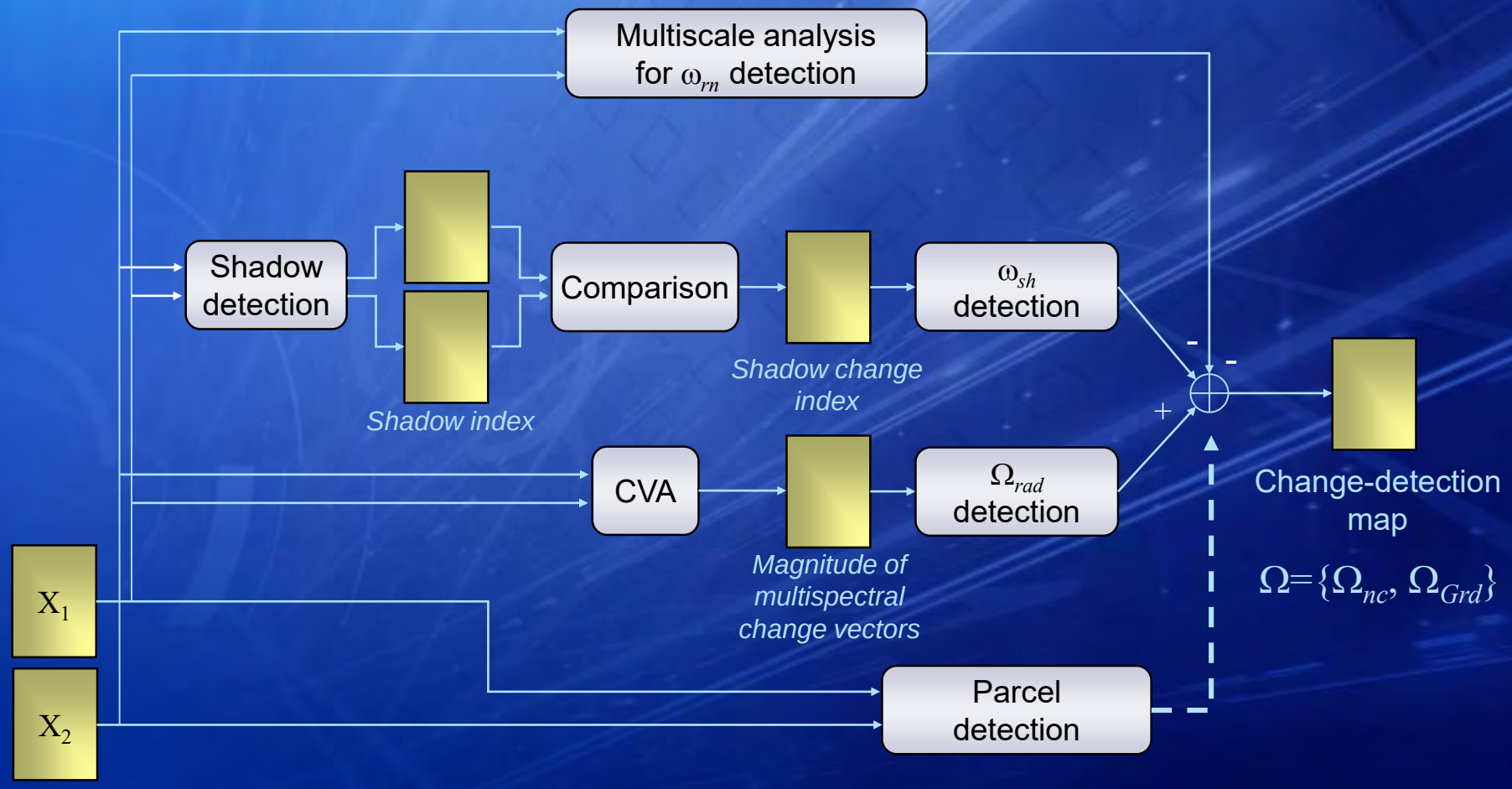
## Identification of the tree of radiometric changes



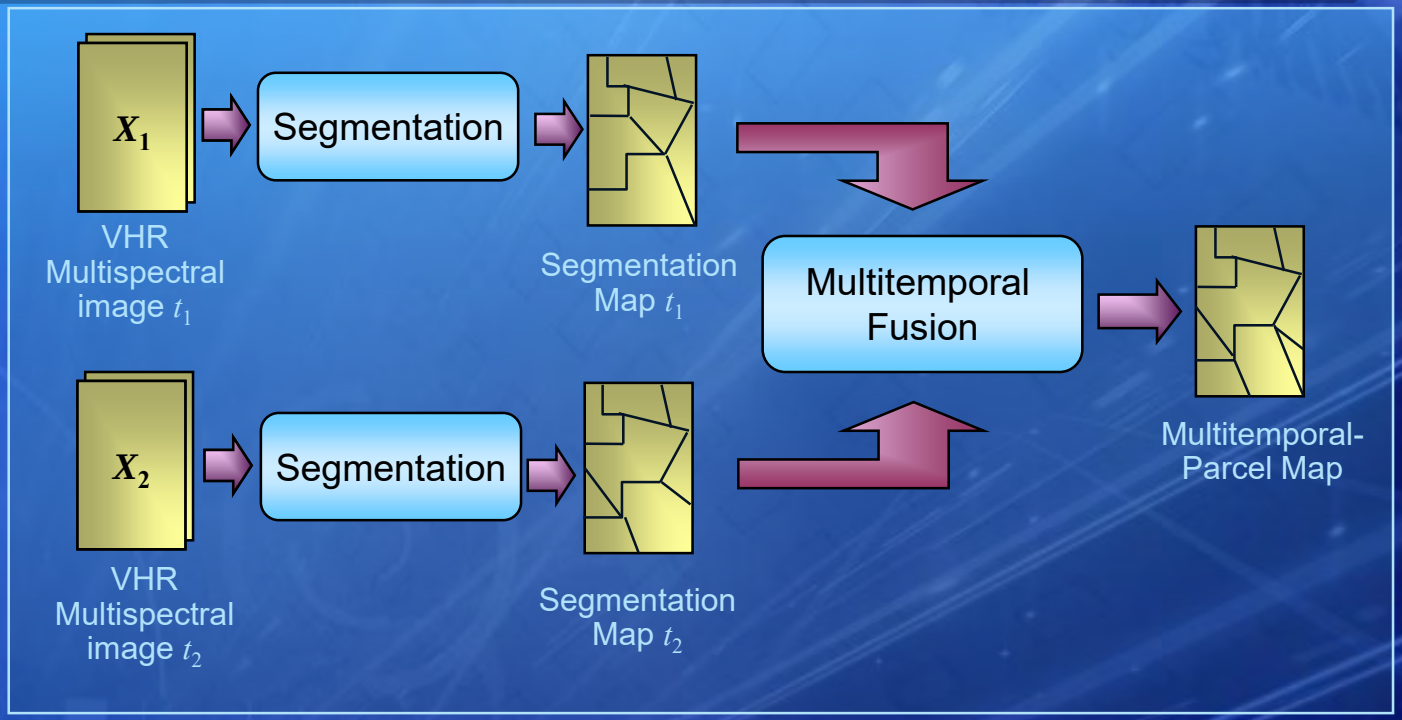

## Differential detection by cancellation

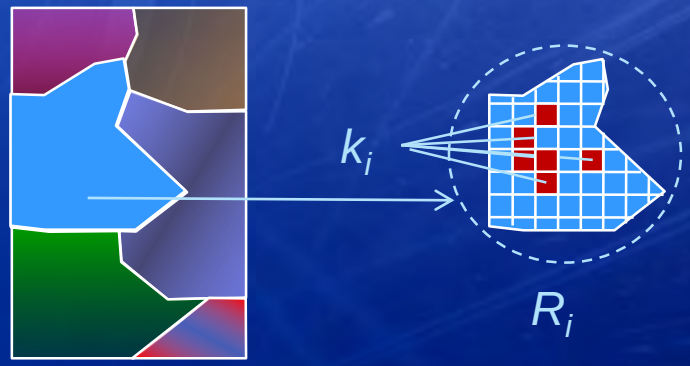


# Example: CD Architecture



# Parcel-Based Differencing




number of pixels $\in R_i$ that belong to a cell of RN or to $C_n$

$$R_i \in \begin{cases} \text{non-change} & \text{if } \frac{k_i}{n_i} \geq 0.5 \\ \text{change} & \text{otherwise} \end{cases}$$

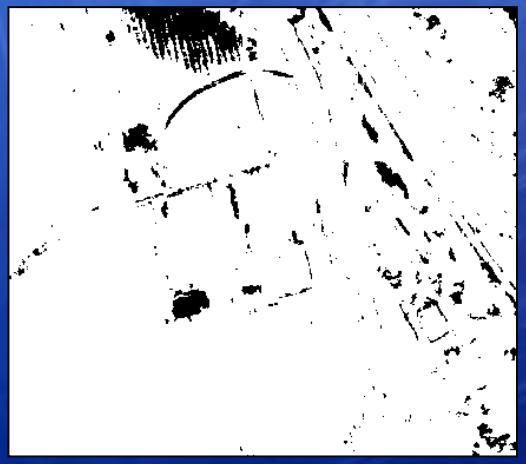
$n_i$: number of pixels $\in R_i$

# Example: Qualitative Results

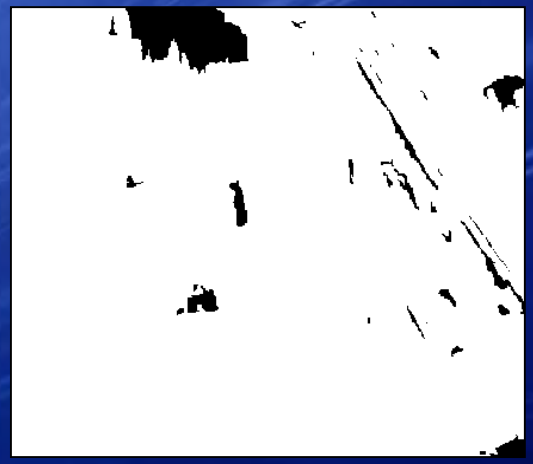
October 2005

July 2006

Reference Map



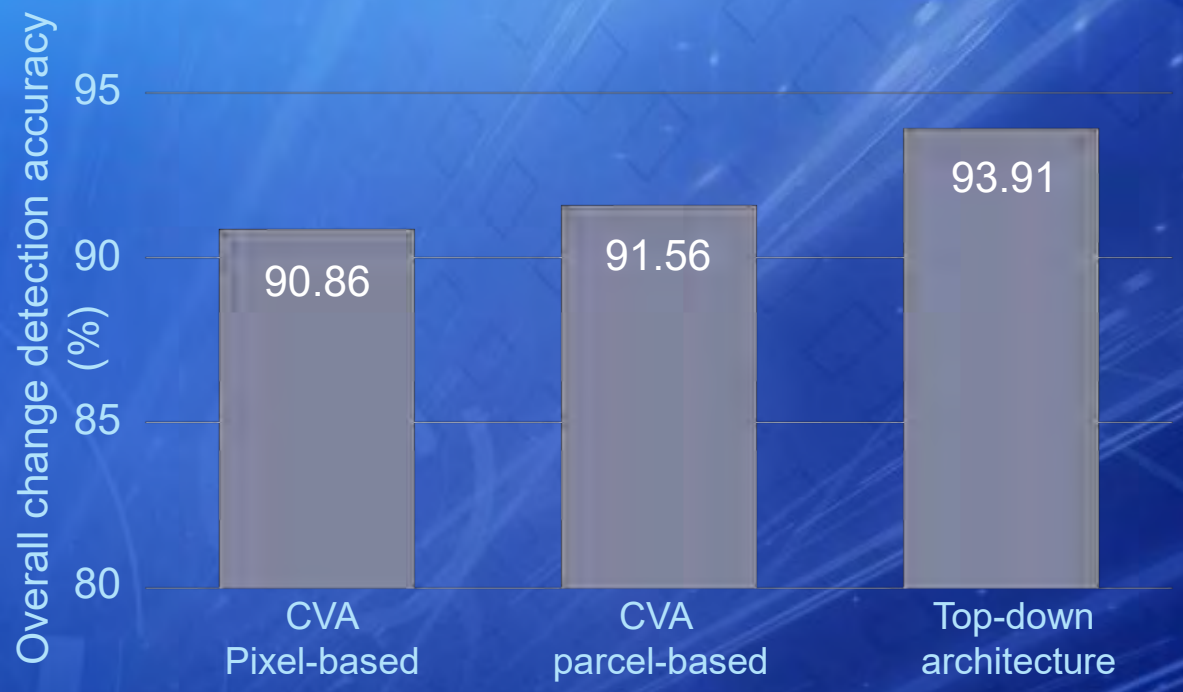
Change Detection Map
CVA Parcel Based



Change detection Map
Top-down Architecture


© Lorenzo Bruzzone

# Example: Quantitative Results



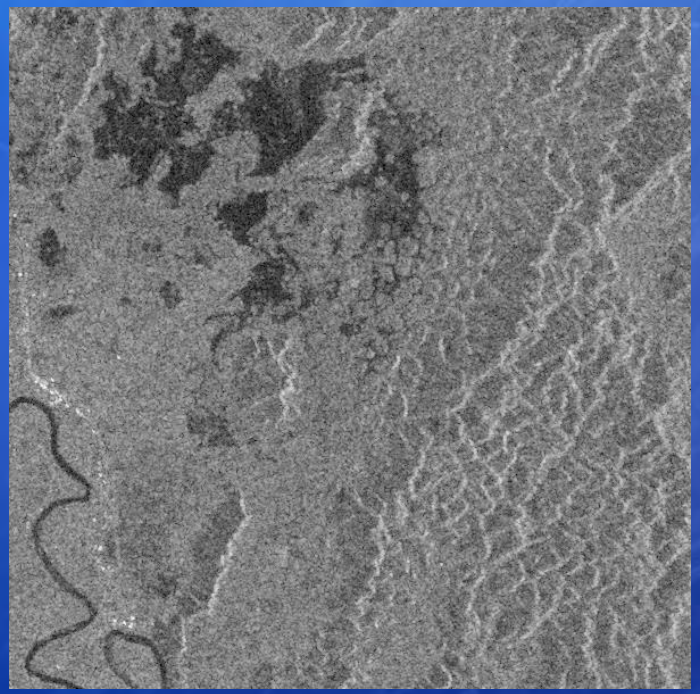

| Technique | False Alarms | Missed Alarms | Total Errors | Overall accuracy (%) |
|---|---|---|---|---|
| CVA pixel-based | 5005 | 9924 | 14929 | 90.86 |
| CVA parcel-based | 3537 | 10261 | 13798 | 91.56 |
| Top-down architecture | 1470 | 8480 | 9950 | 93.91 |

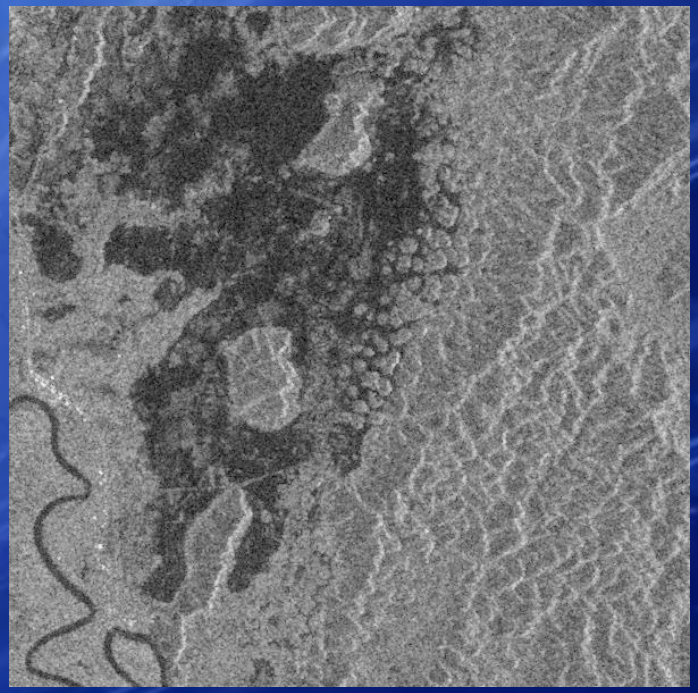
Remote Sensing Laboratory
Dept. of Information Engineering and Computer Science
University of Trento
Via Sommarive, 5, I-38123 Povo, Trento, Italy

# 5. Change Detection in Very High Resolution SAR Images

# Change Detection in Medium/High Resolution SAR Images

May 1999

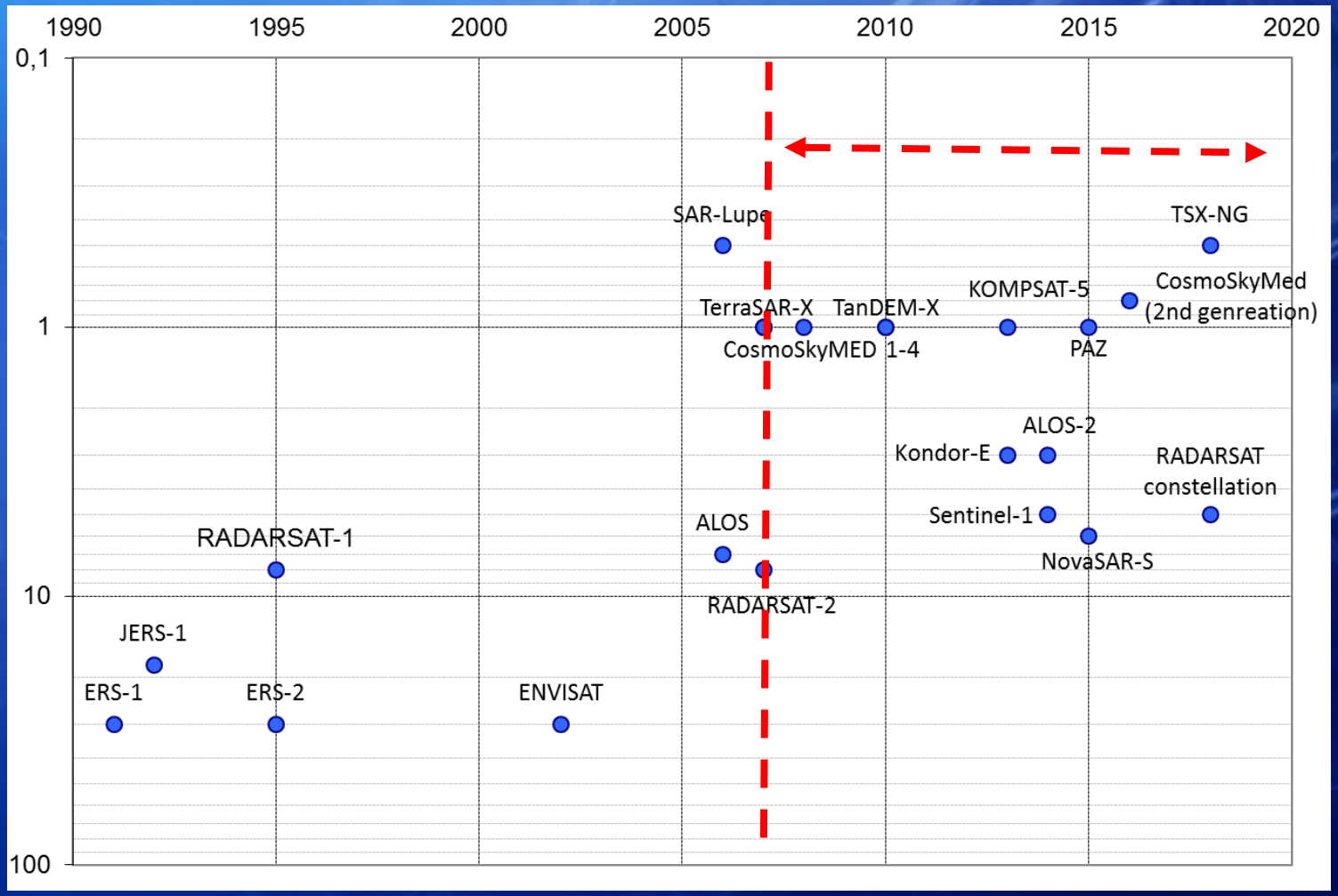




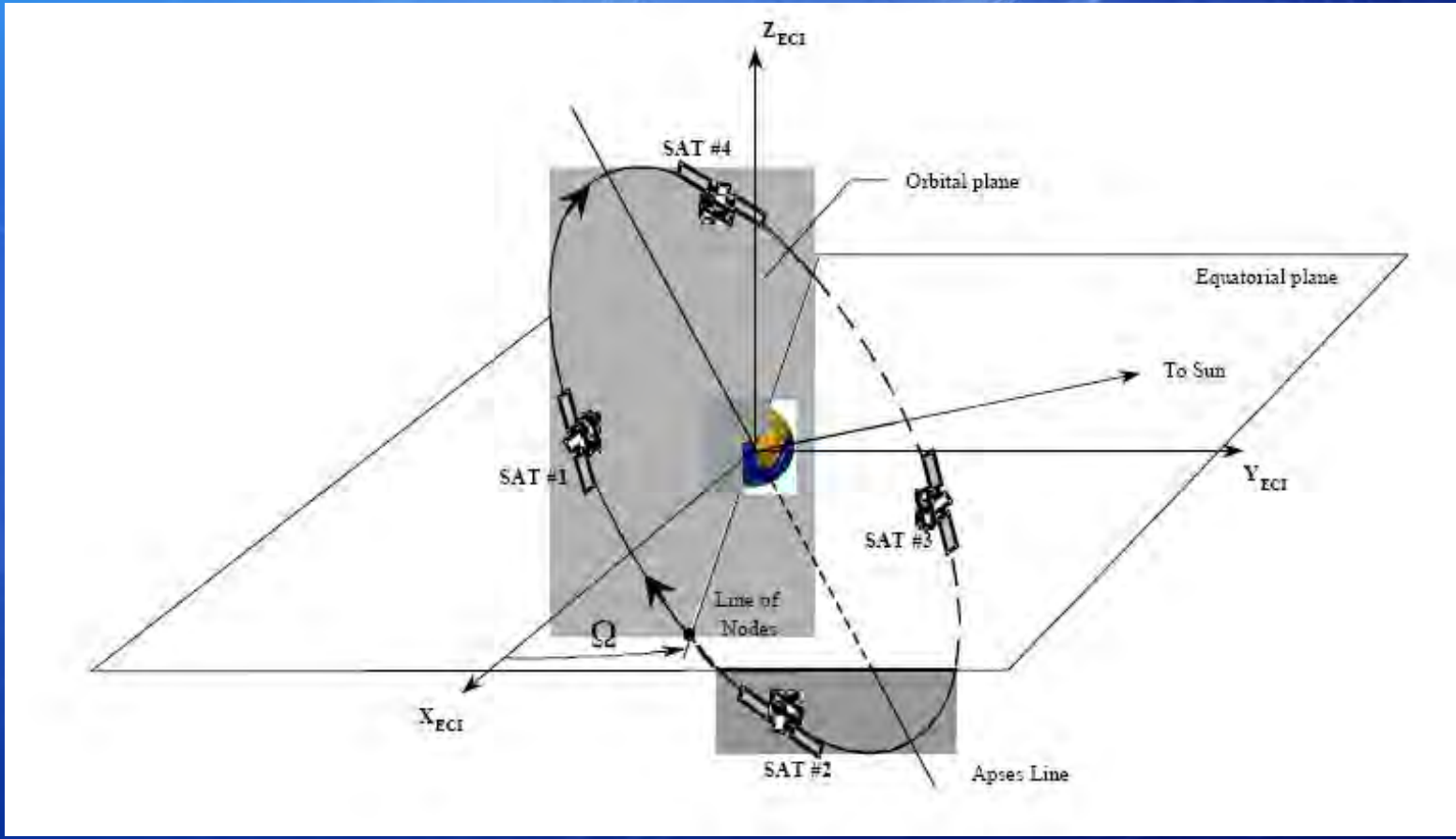
September 1999

ERS SAR images of a flood in the Cat-Tien National Park, Vietnam

# New Satellites with VHR SAR Sensors

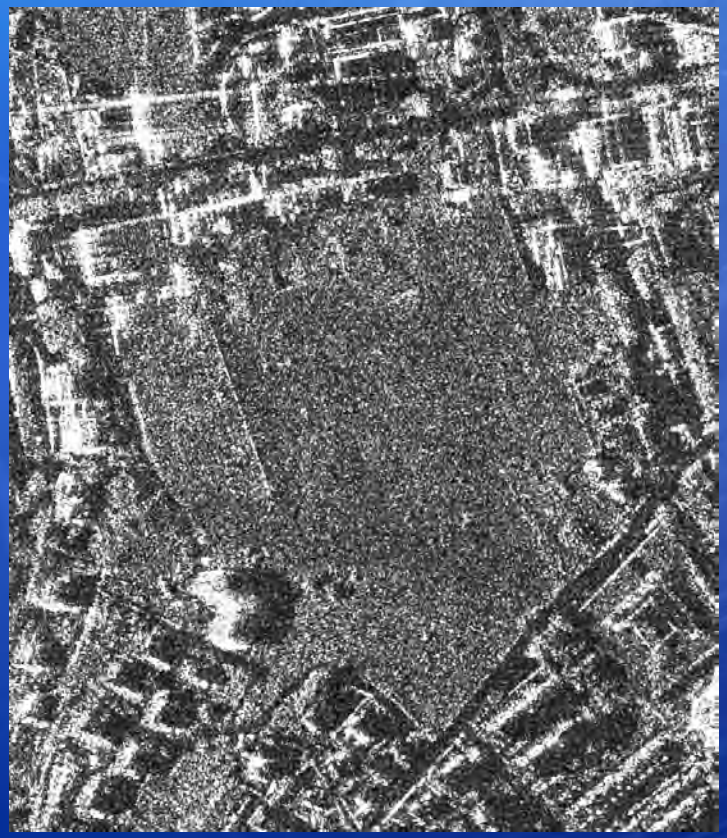


# COSMO-SkyMed Constellation



# Multitemporal SAR Images: New challenges

April 2009



September 2009

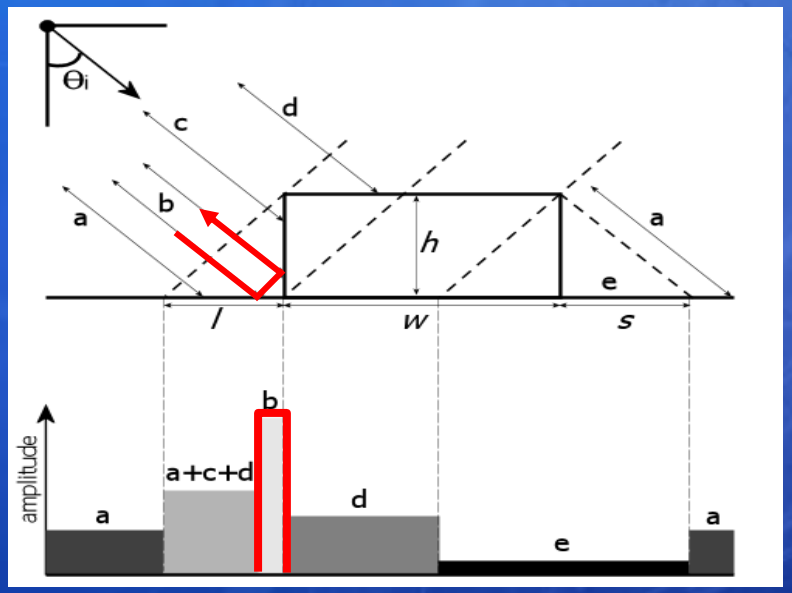
Comso-Skymed SAR Images of the Earthquake of L'Aquila, Italy

COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2010). All Rights Reserved.

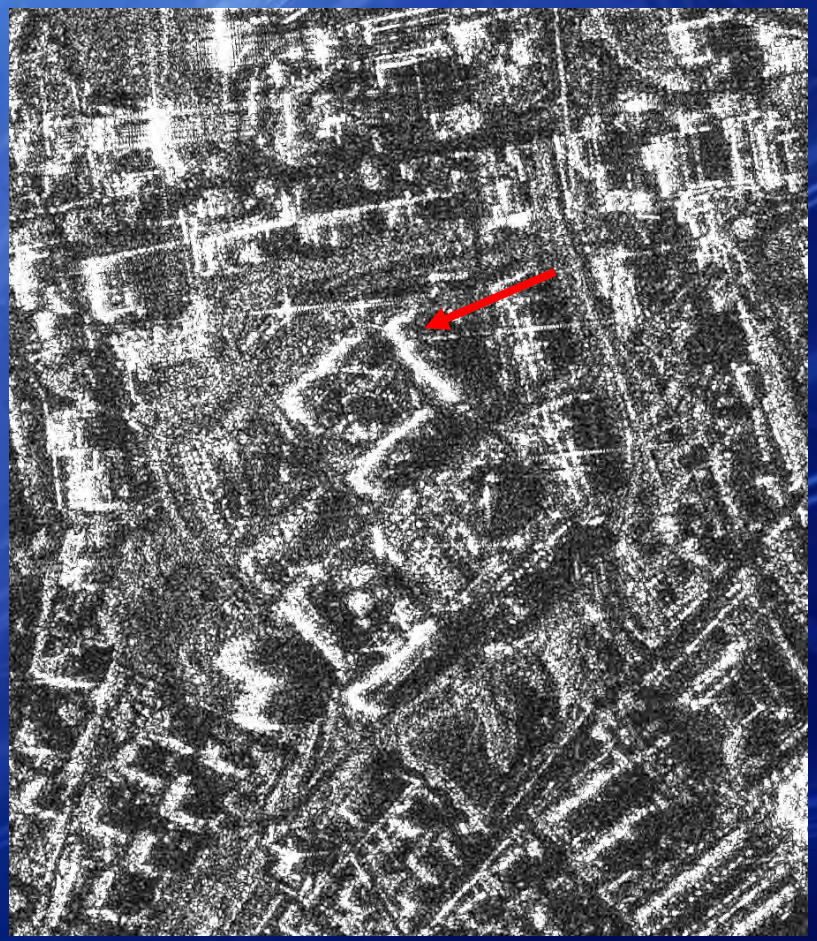
# CD in VHR SAR images

- ✓ In multitemporal SAR VHR images we have many sources of backscattering changes.
- ✓ Often backscattering changes associated with different sources exhibit characteristics similar to each other. They can be separated only by explicitly modeling the EM behavior of complex objects.
- ✓ To this end it is necessary to bridge the semantic gap between low level features and semantic information:
  - Modelling the interaction between the EM waves and the imaged objects;
  - Extracting the different object components with proper detectors;
  - Combining object components for identifying the objects and the possible changes in their state.

# Example: Building Detection in VHR SAR Images



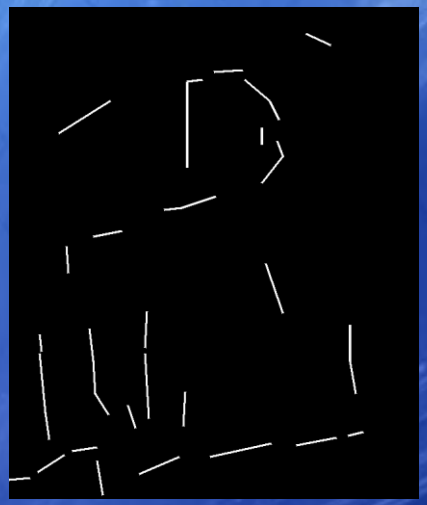

Building EM model



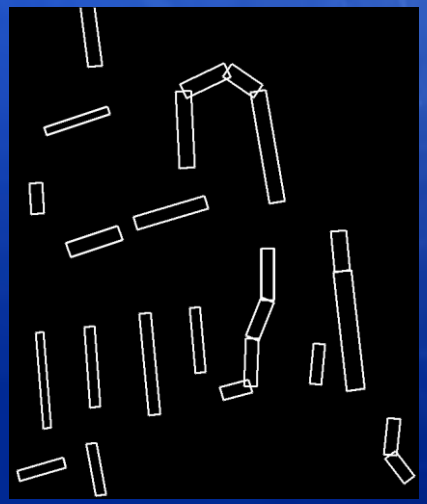
VHR satellite SAR image

# Building Detection: Primitives and Semantic

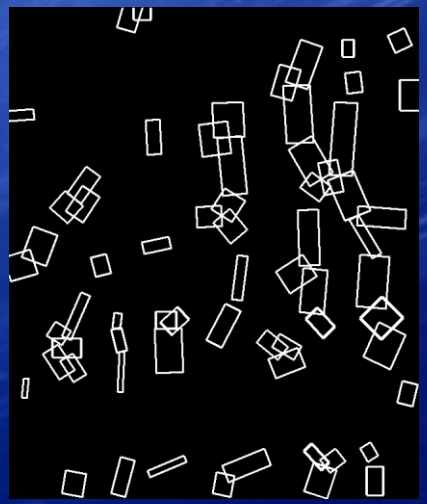
Despeckled image



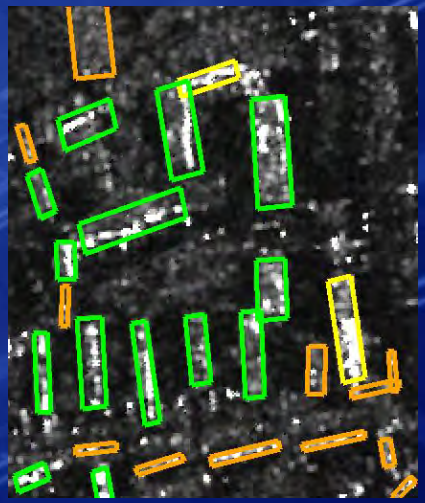
Detected lines



Detected bright areas



Detected shadow areas



Detected building fooprints

A. Ferro, D. Brunner, L. Bruzzone, "Automatic Detection and Reconstruction of Building Radar Footprints from Single VHR SAR Images", *IEEE Trans. on Geoscience and Remote Sensing*, 2012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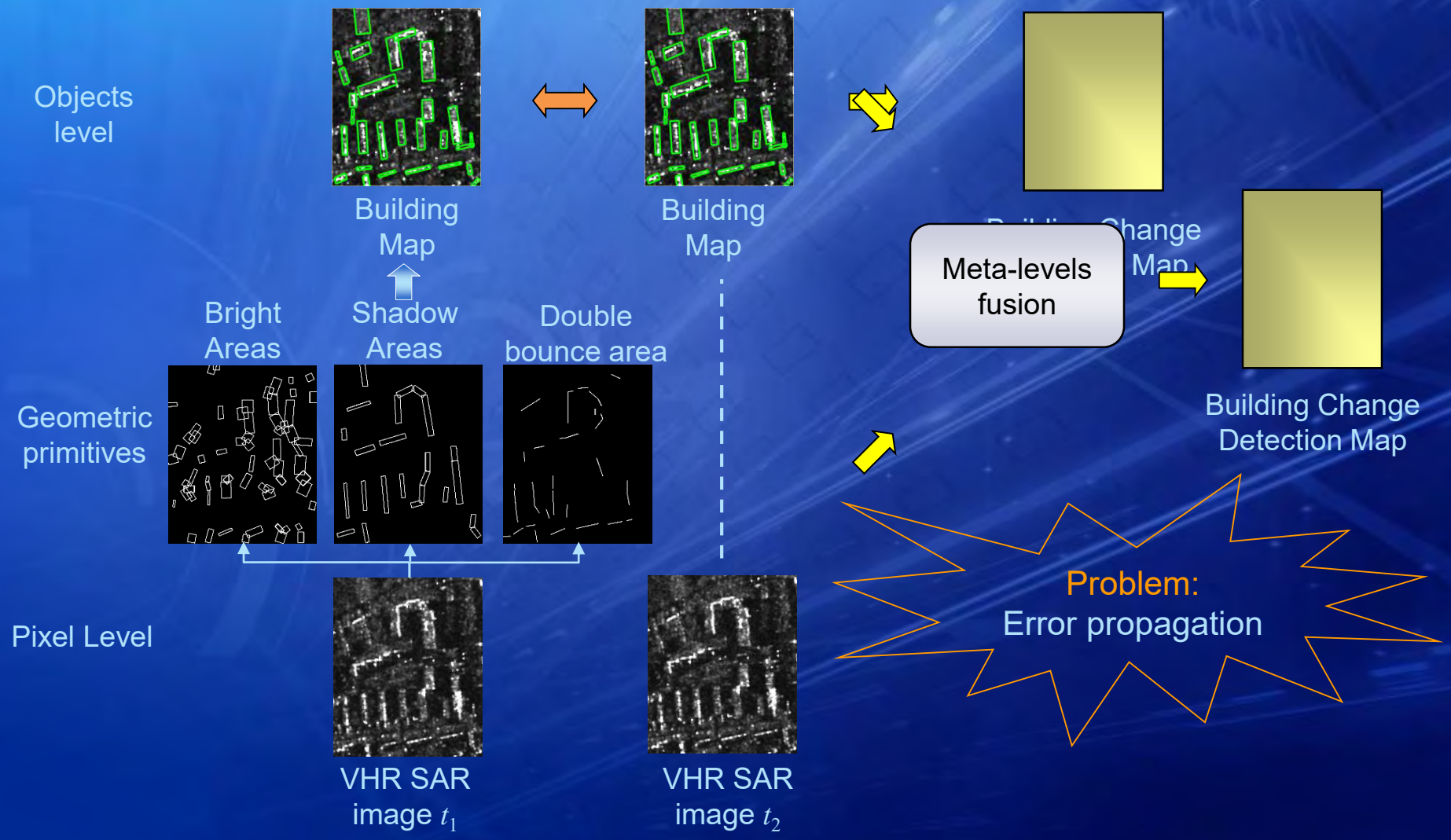
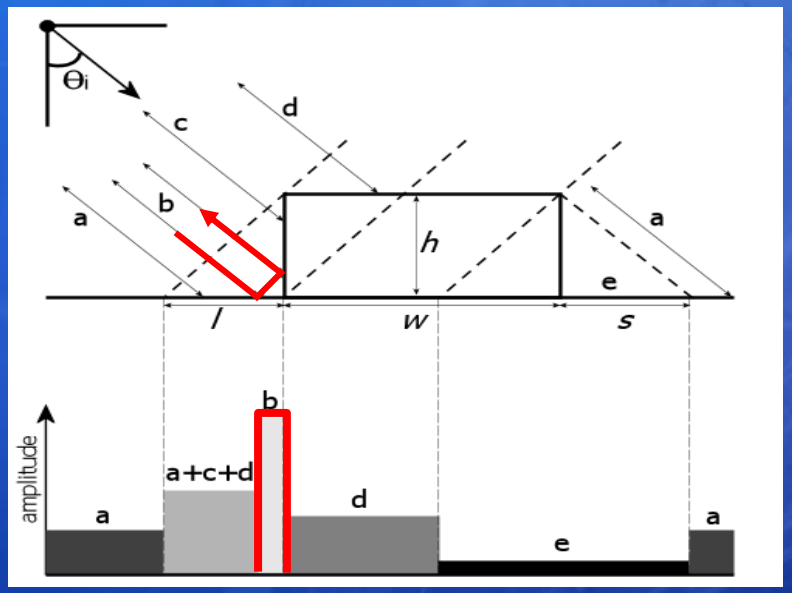
# Change Detection in VHR SAR Images

- ✓ Moving from object detection in single images to object change detection in multitemporal images increases the complexity of the information extraction.
- ✓ In order to define an effective general approach to change detection for VHR SAR images we have to:
  - Decompose the general complex problem in simpler hierarchical problems.
  - Exploit the intrinsic multiscale nature of objects present in VHR images.
  - Model the specific properties of expected changes for extracting the semantic meaning of backscattering changes.
  - Exploit the available prior information on the considered scenario.

# Example: Building Change Detection



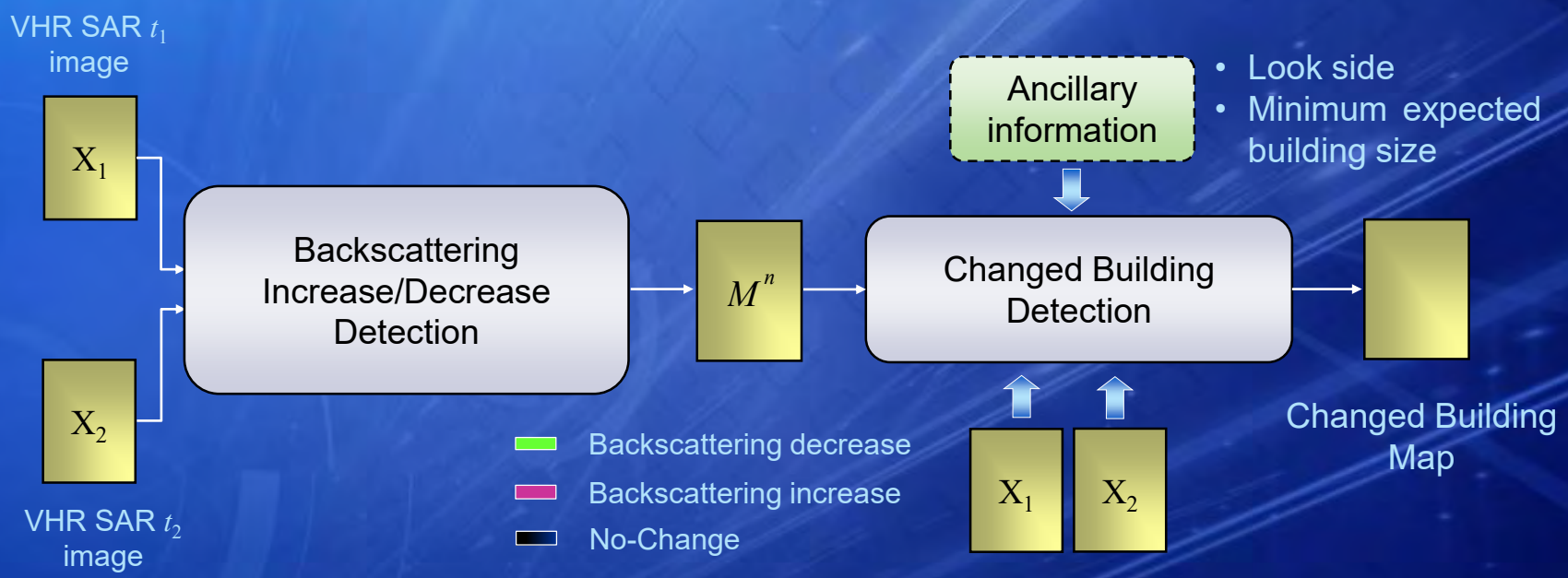
# Architecture for Building Change Detection




Building EM model

VHR satellite SAR image

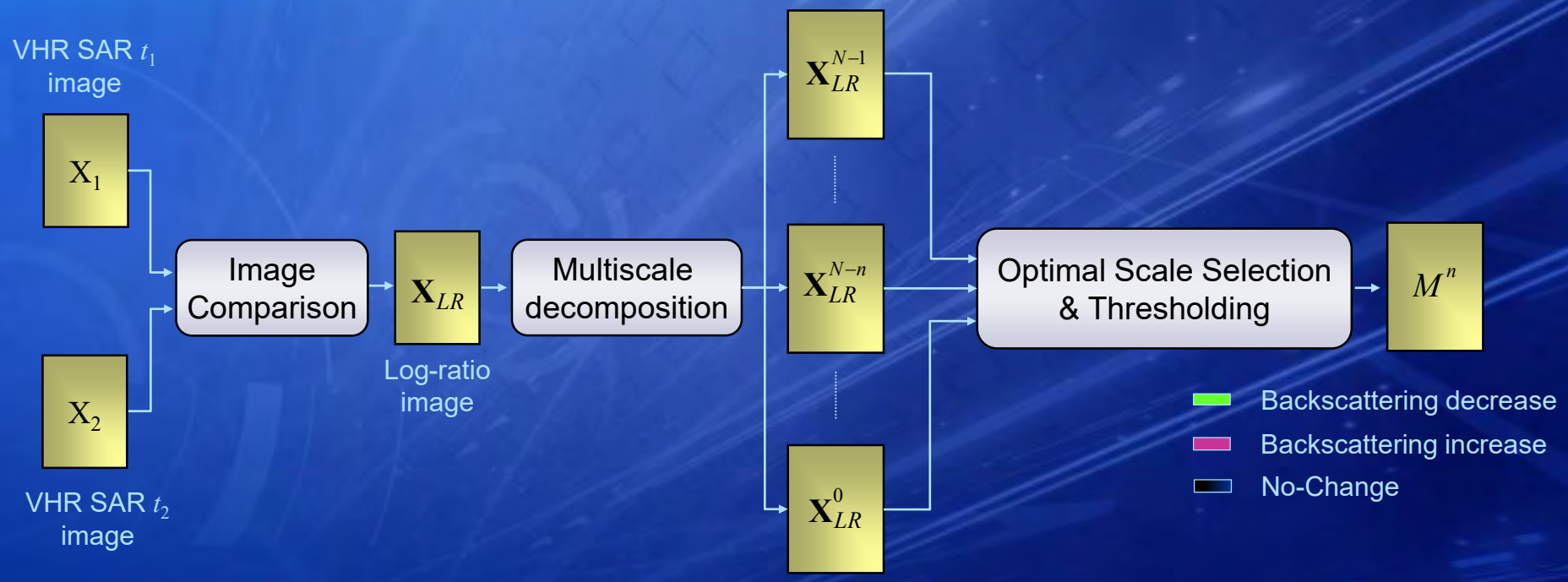
# Architecture for Building Change Detection




C. Marin, F. Bovolo, L. Bruzzone, Building Change Detection in Multitemporal Very High Resolution SAR Images, IEEE Transactions on Geoscience and Remote Sensing, Vol. 53, 2015, pp. 2664–2682.

# Architecture for Building Change Detection

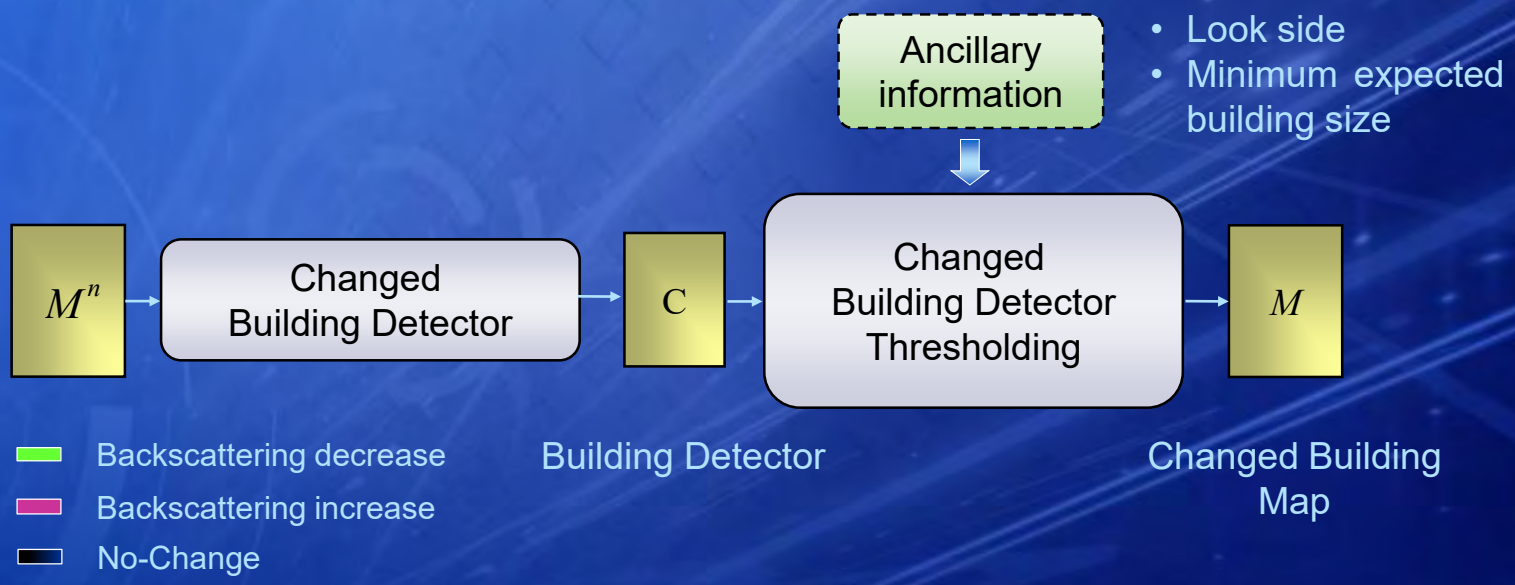
Goal: detect changes associated with increase and decrease in backscattering.



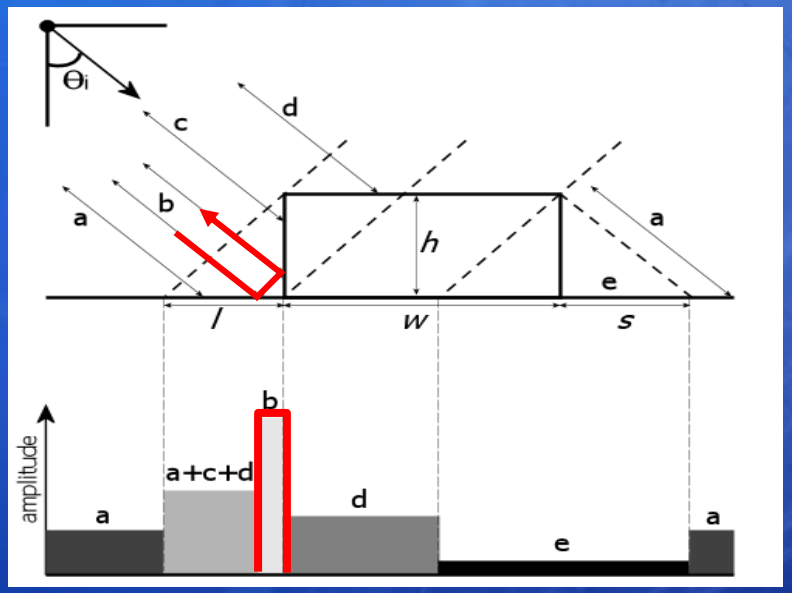

F. Bovolo, L. Bruzzone, "A Detail-Preserving Scale-Driven Approach to Unsupervised Change Detection in Multitemporal SAR Images", IEEE Transactions on Geoscience and Remote Sensing, 2005, Vol.43, No. 12, pp. 2963-2972, December 2005.

# Architecture for Building Change Detection

Goal: detect new/destroyed buildings.



# Architecture for Building Change Detection



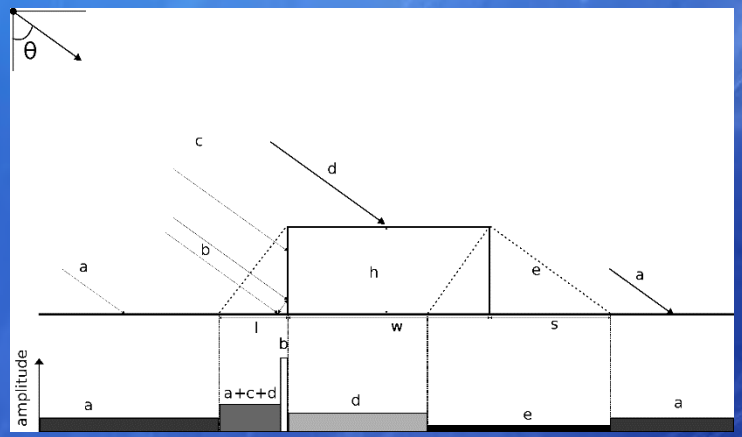

Building EM model

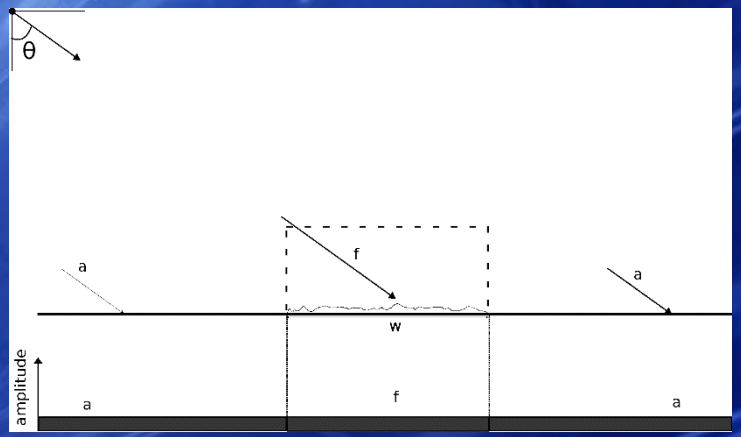
VHR satellite SAR image

# Architecture for Building Change Detection

- ✓ Scattering models for flat-roof buildings and bare land.

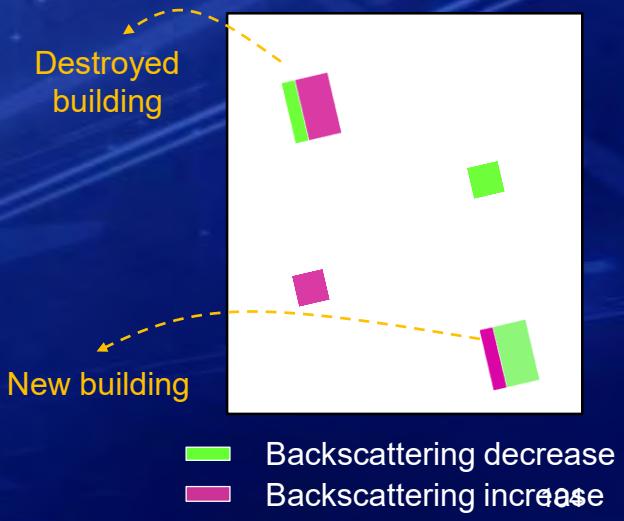
a) Ground return;
b) Double bounce;
c) Building wall;
d) Building roof;
e) Shadow;
a+c+d) Layover;
f) Bare soil.




- ✓ Changes in VHR SAR images imply increase or decrease of backscattering values.

- ✓ Changes in buildings (i.e., new/destroyed buildings) imply the generation of patterns of increase/decrease with specific proprieties.



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# Example: Damage Assessment

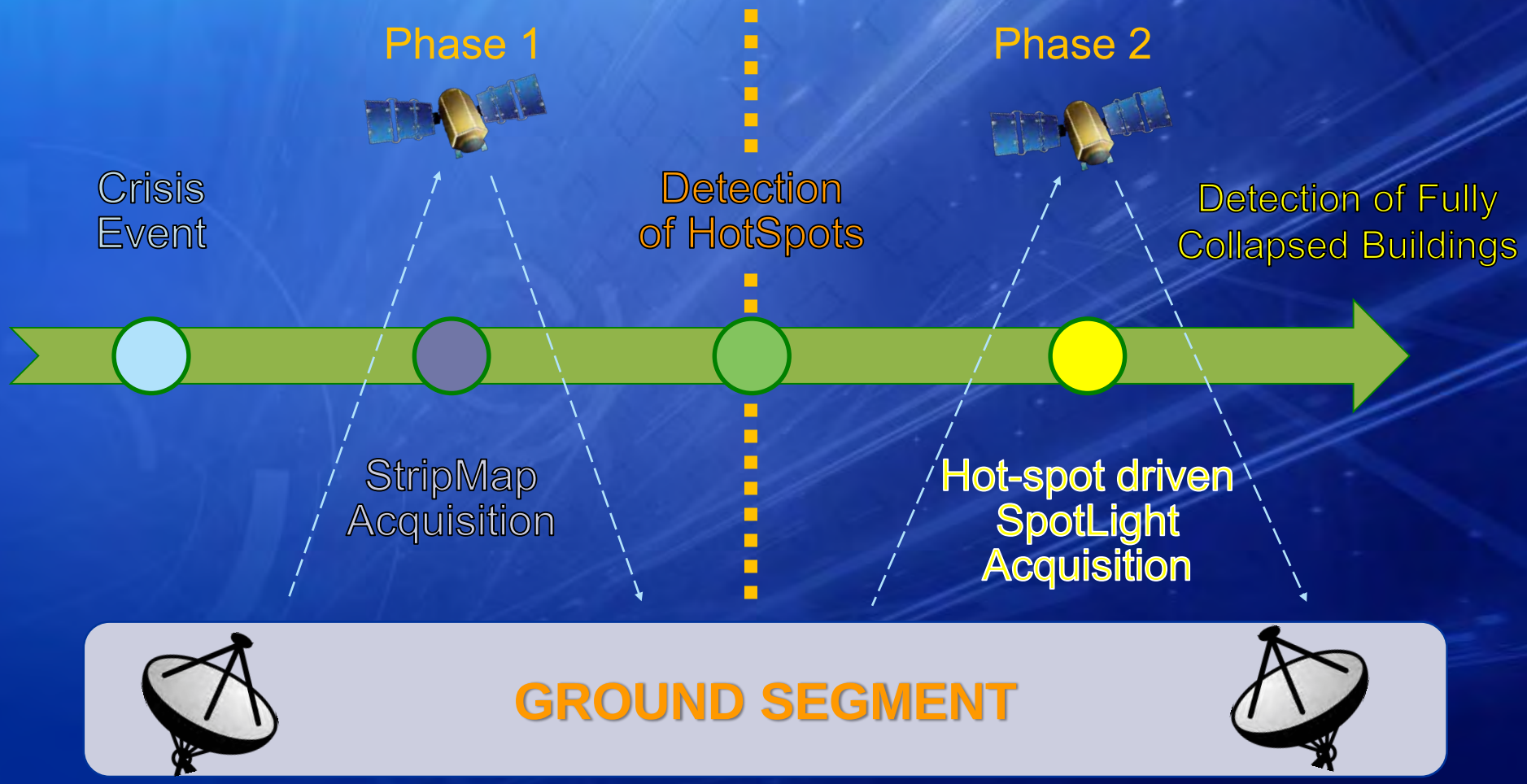
Satellite SAR systems COSMO-SkyMed, TerraSAR-X and TanDEM-X can regularly acquire data on the Earth with complementary acquisition modes:

- StripMap (SM): large swath, high to medium geometrical resolution;
- SpotLight (SL): very high geometrical resolution, smaller swath.

Data referred to TerraSAR-X imaging modes

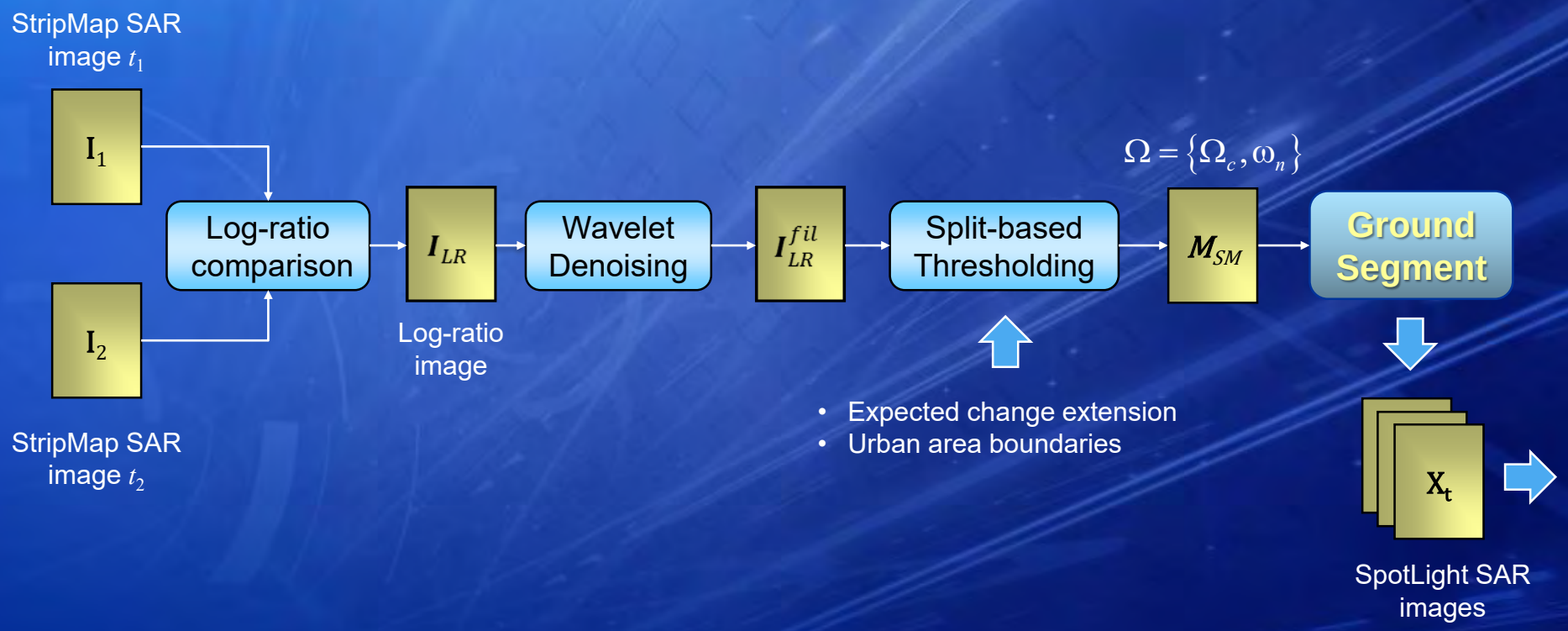
L. Bruzzone, C. Marin, F. Bovolo, “Damage Detection in Built-Up Areas Using SAR Images", in Encyclopedia of Earthquake Engineering, Eds. M. Beer, E. Patelli, I. Kougioumtzoglou and I. Siu-Kui Au, Springer Verlag.

# Example: Damage Assessment



# Damage Assessment: Hot Spot Detection

Phase 1: fast analysis of a large scene by using of StripMap mode acquisitions or data from other satellites (e.g., Sentinel 1) to detect changes in backscattering (hot-spots).

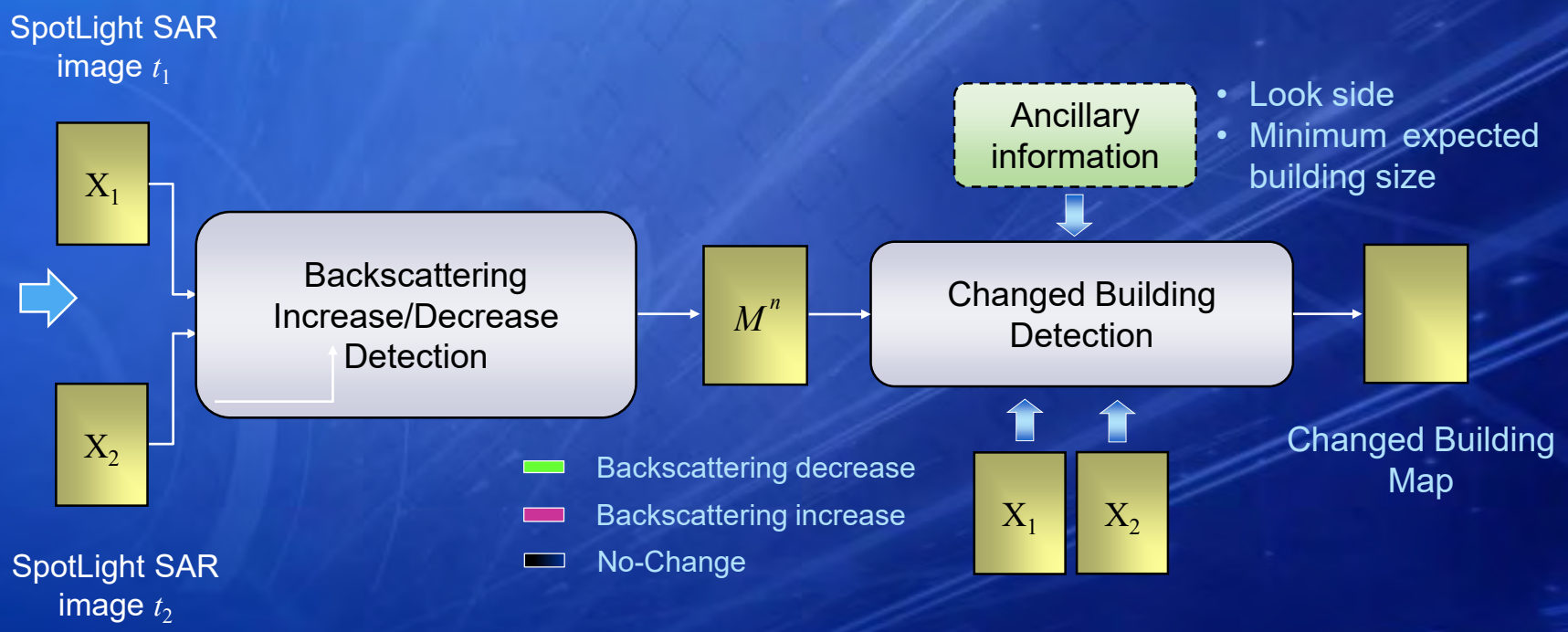



F. Bovolo, L. Bruzzone, "*A Detail-Preserving Scale-Driven Approach to Unsupervised Change Detection in Multitemporal SAR Images*", *IEEE Transactions on Geoscience and Remote Sensing*, 2005, Vol.43, No. 12, pp. 2963-2972, December 2005.

F. Bovolo and L. Bruzzone, "A split-based approach to unsupervised change detection in large-size multitemporal images: Application to tsunami-damage assessment," IEEE Trans. Geosci. Rem. Sens, vol. 45, no. 6, pp. 1658 –1670, 2007.

# Damage Assessment: Collapsed Building Detection

Phase 2: accurate detection of collapsed buildings by means of SpotLight mode acquisitions.




C. Marin, F. Bovolo, L. Bruzzone, Building Change Detection in Multitemporal Very High Resolution SAR Images, IEEE Transactions on Geoscience and Remote Sensing, Vol. 53, 2015, pp. 2664–2682.

# Example: L'Aquila (Italy) Earthquake

Data set: StripMap (CSK®) images acquired 5th April 2009 and 21st April 2009.

Optical image GeoEye Tele Atlas 2011
Google ©

April 05, 2009

RGB multitemporal composition
(R:04/21/2009, G:04/05/2009, B:04/21/2009)

April 21, 2009

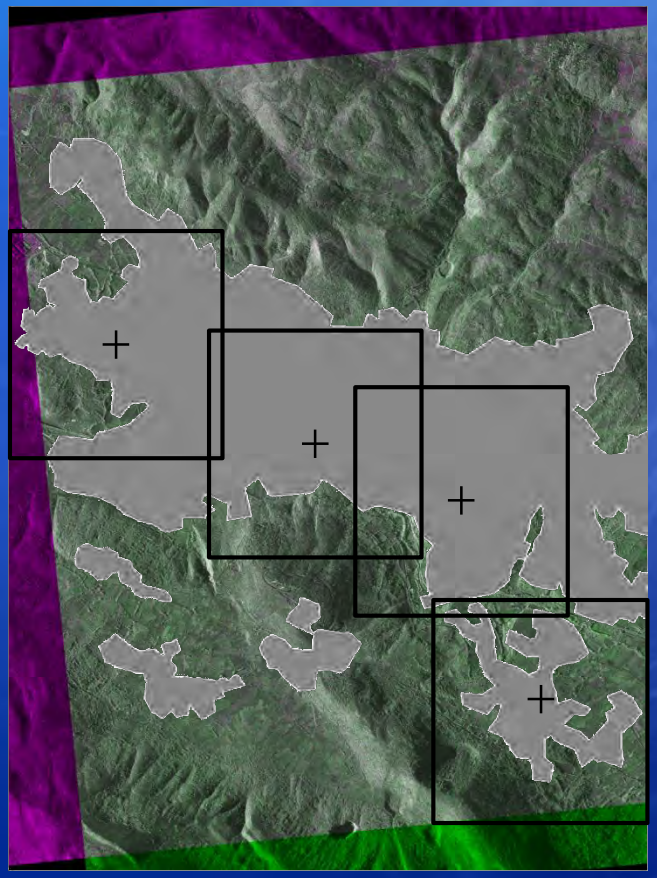
- 5m×5m resolution (Simulated)
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

Backscattering decrease
Backscattering increase
Unchanged areas

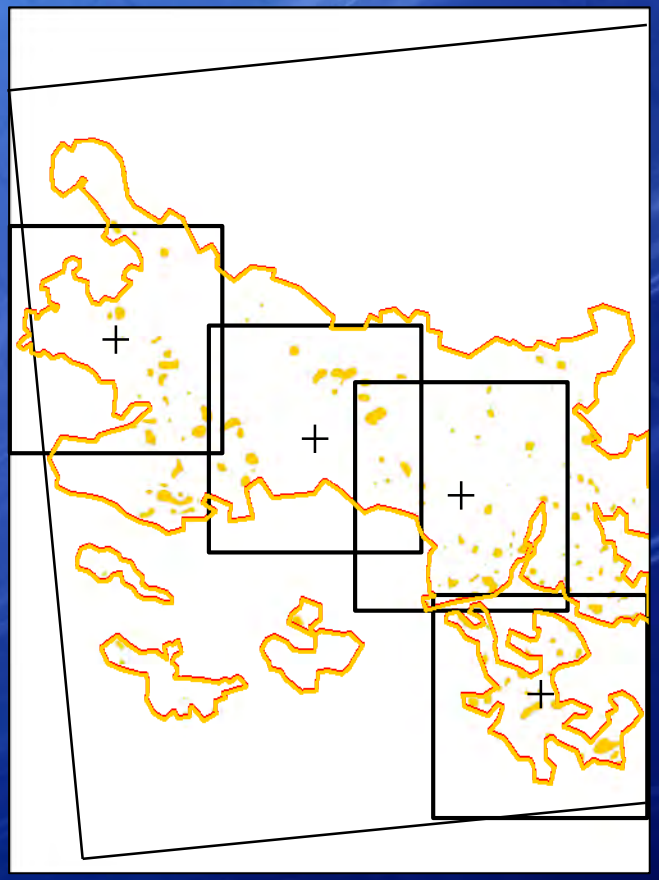
COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2009). All Rights Reserved.

# Example: L'Aquila (Italy) Earthquake

Wavelet Denoising performed at the 5th level; split-based thresholding (splits 64x64 pixels).



RGB multitemporal composition
(R:04/21/2009, G:04/05/2009, B:21/04/2009)



$M_{SM}^{R\,fil}$

- 5m×5m resolution (Simulated)
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

Backscattering decrease
Backscattering increase
Unchanged areas
Hot-spots

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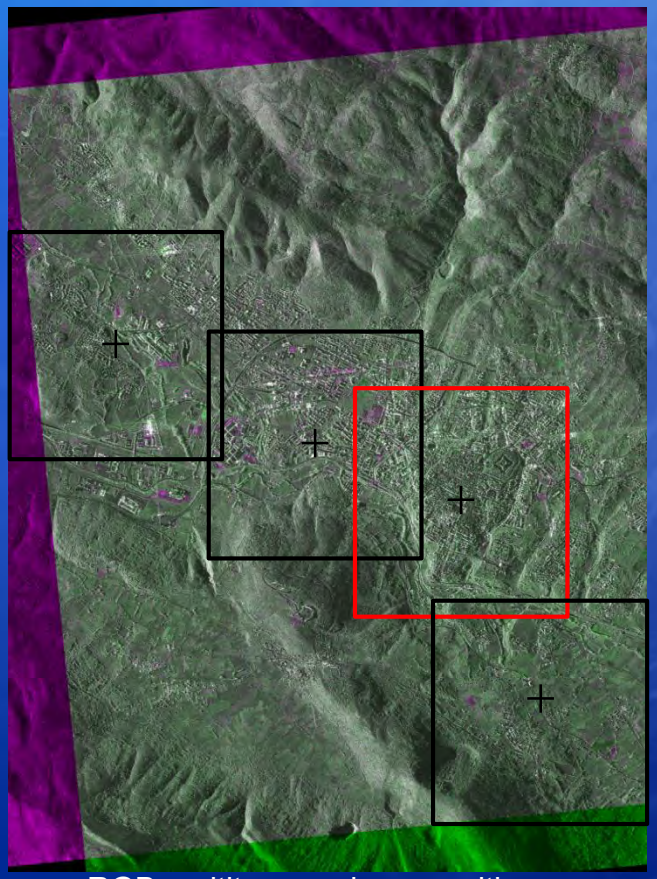
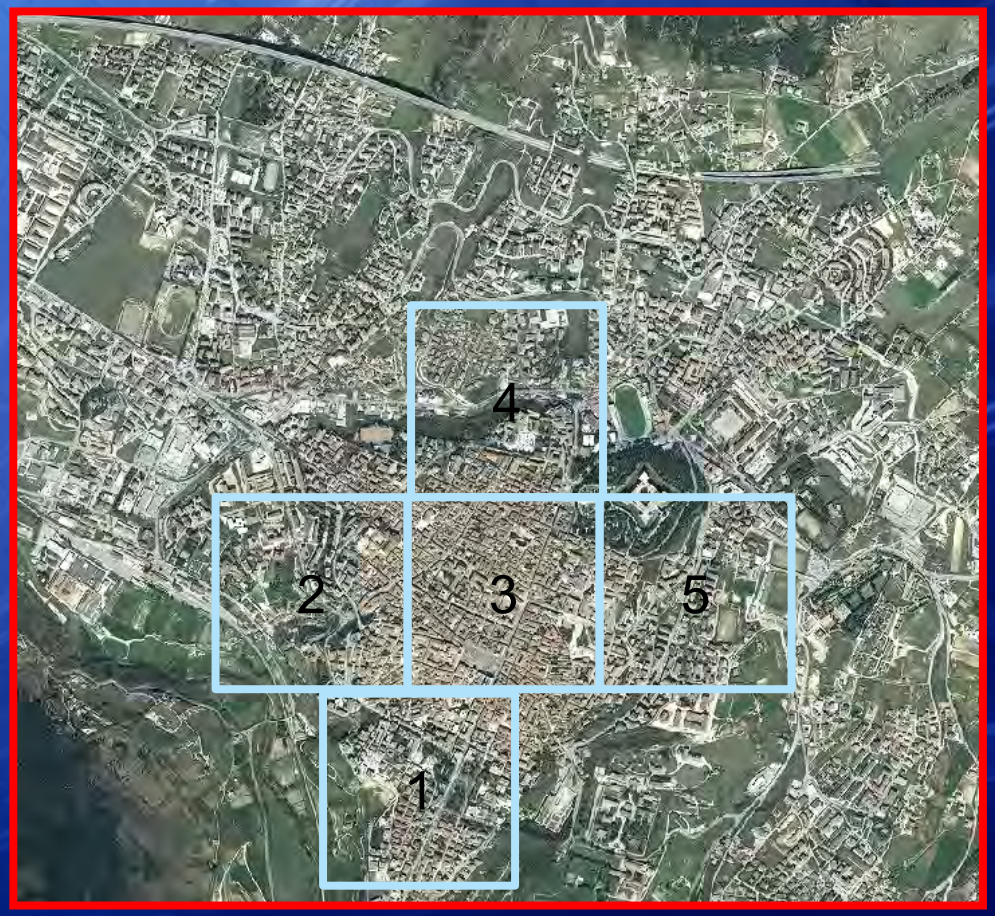
# Example: L'Aquila (Italy) Earthquake

Detection of relevant areas and acquisition of SpotLight images



RGB multitemporal composition
(R:04/21/2009, G:04/05/2009, B:21/04/2009)




Backscattering decrease  Backscattering increase  Unchanged areas

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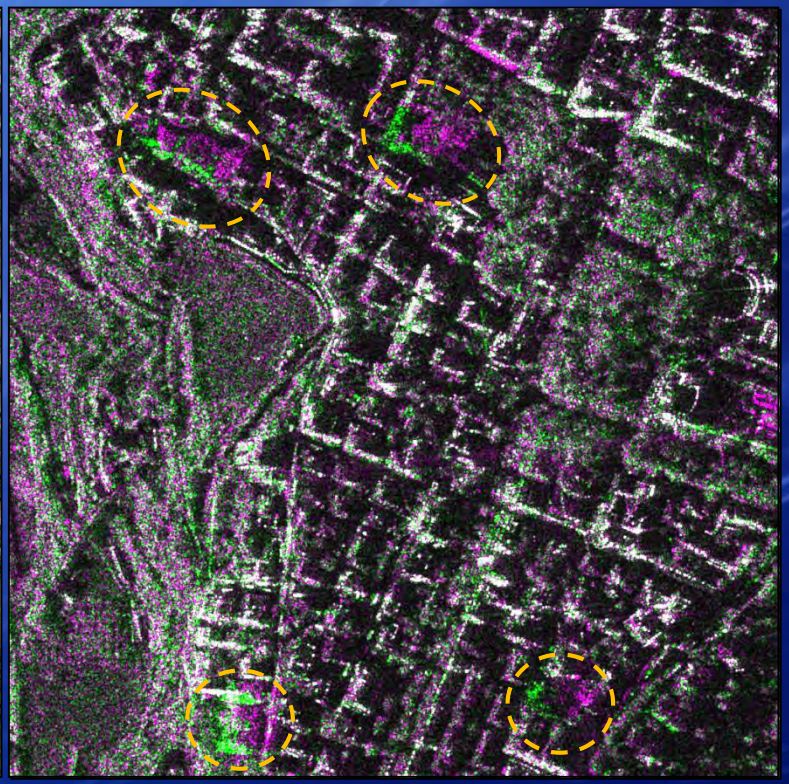
# Example: L'Aquila (Italy) Earthquake

Multitemporal data set: section (1024×1024 pixels) of two spotlight (CSK®) images acquired before (5th April 2009) and after (12th September 2009) the earthquake of L'Aquila (Italy, 6th April 2009).

Optical image: GeoEye, Tele Atlas 2011 Google ©

5th April 2009



RGB multitemporal composition (R:09/12/2009, G:04/05/2009, B:09/12/2009)

12th September 2009

- 1m×1m resolution
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

Backscattering decrease | Backscattering increase | Unchanged areas

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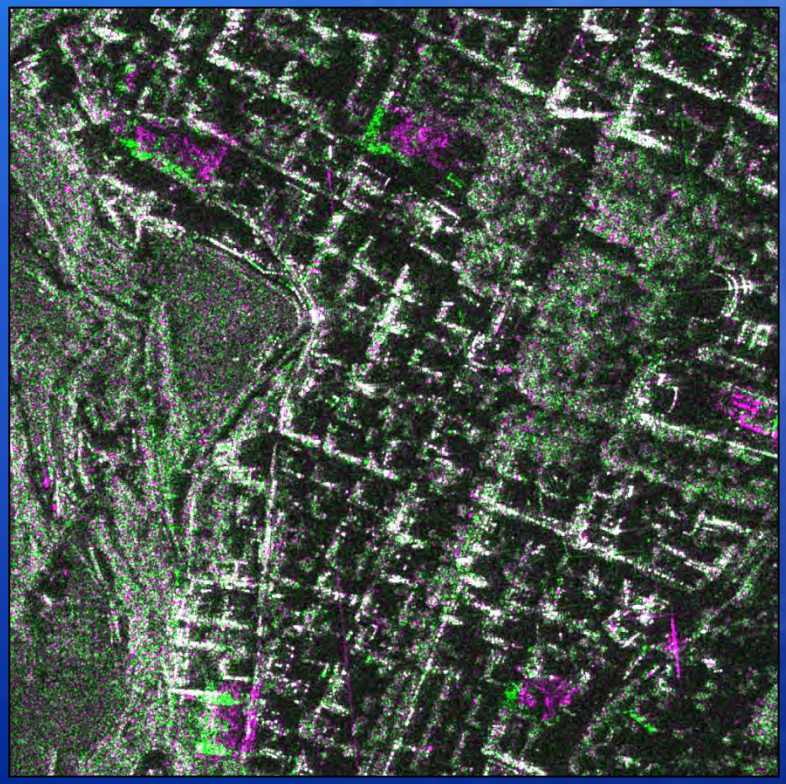
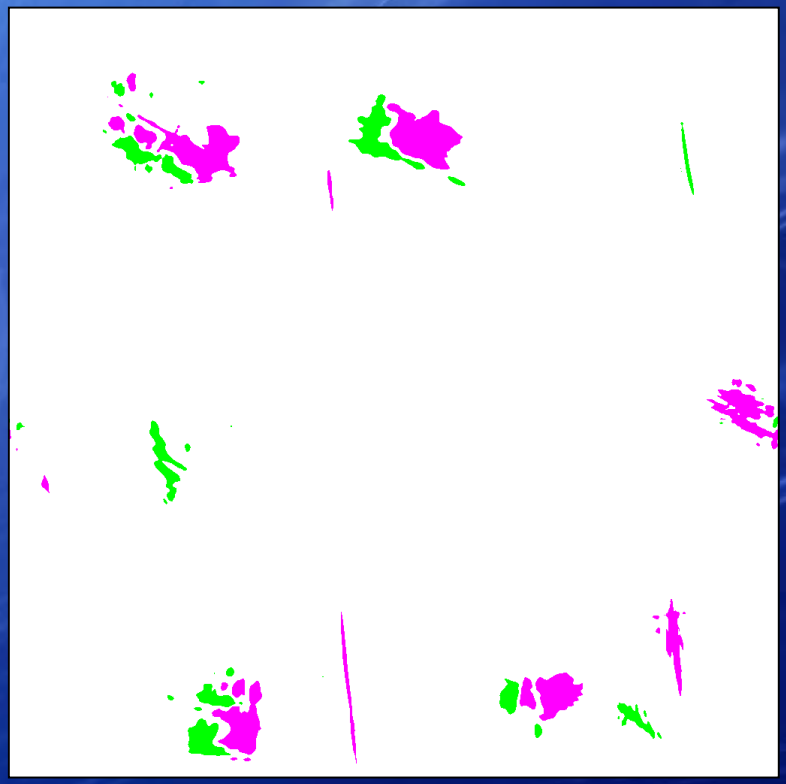
# Example: L'Aquila (Italy) Earthquake

Increase and decrease of backscattering performed automatically after Curvelet denoising.



RGB multitemporal composition
(R:09/12/2009, G:04/05/2009, B:09/12/2009)



$M_{SL}$

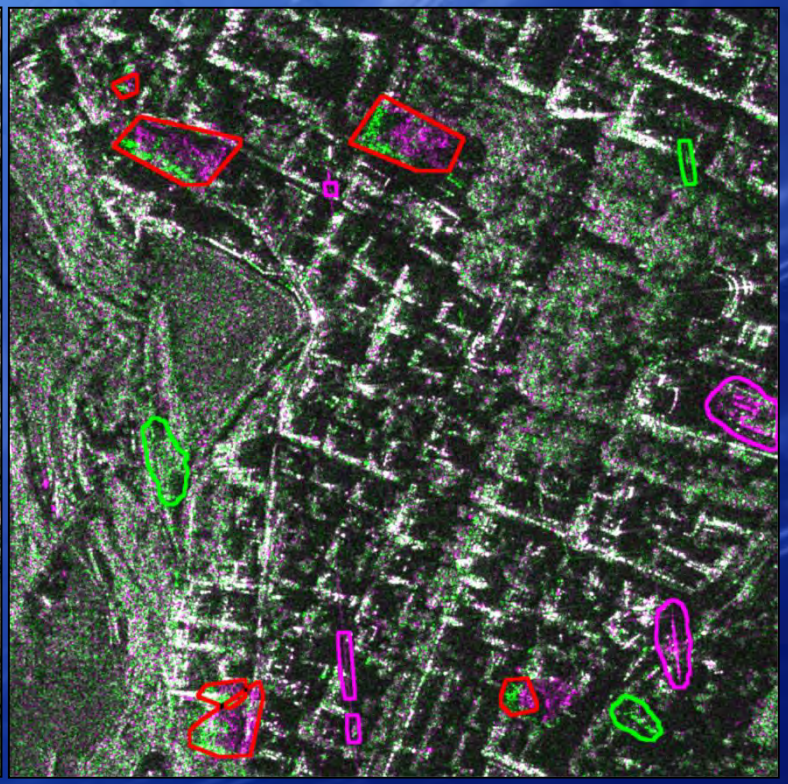
- 1m×1m resolution
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

Backscattering decrease  Backscattering increase  Unchanged areas

# Example: L'Aquila (Italy) Earthquake

Generation of the VHR building change detection map according to the output of fuzzy rules.

Optical image GeoEye, Tele Atlas 2011
Google ©



Overlay between RGB and the final buildings change detection map

- 1m×1m resolution
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

Backscattering decrease | Backscattering increase | Collapsed buildings

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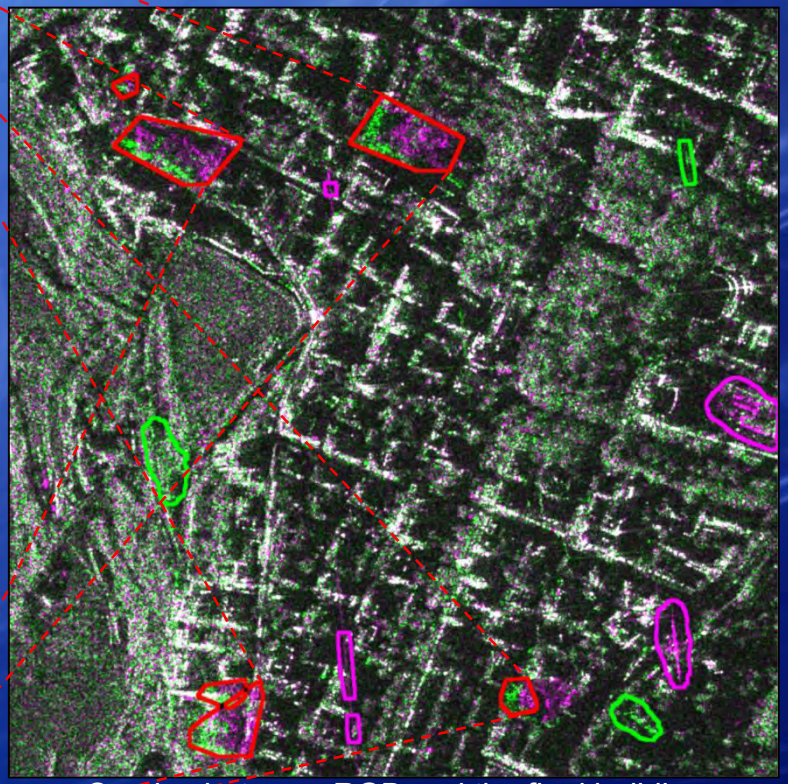
# Example: L'Aquila (Italy) Earthquake

Pre-Crisis Reference Image

Post-Crisis Reference Image

Optical image Pictometry International Corp © Microsoft Corporation ©

Backscattering decrease | Backscattering increase | Collapsed buildings



Overlay between RGB and the final buildings change detection map

- 1m×1m resolution
- X-band
- 1-look
- Amplitude
- HH-polarization
- 57-58 degree incidence angle
- Ascending orbit
- Right look
- CSKS1
- Calibrated
- Co-registered
- Geo-referred

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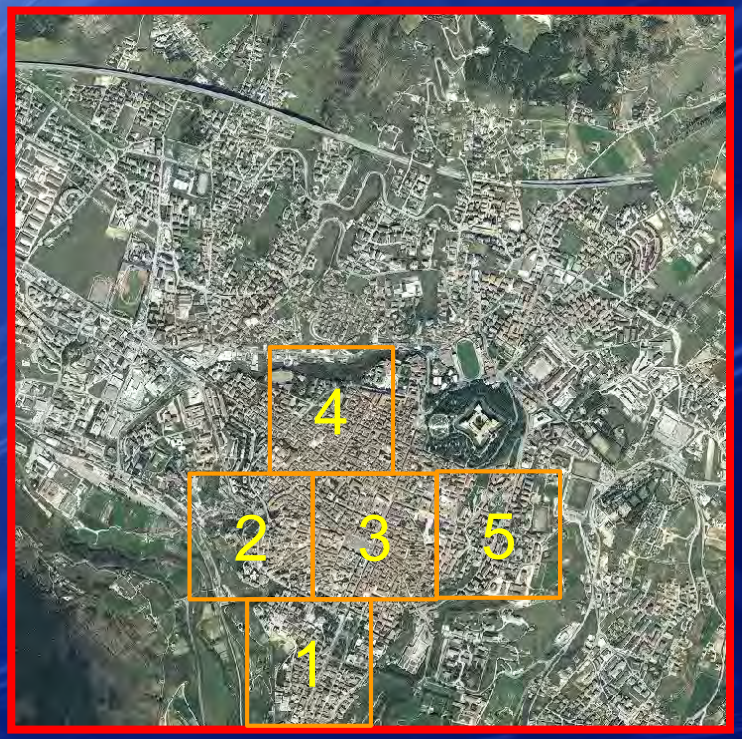
# Example: L'Aquila (Italy) Earthquake

| Area | Total # of buildings | Actually destroyed | Missed | False |
|---|---|---|---|---|
| 1 | 200 | 7 | 0 | 0 |
| 2 | 200 | 6 | 2 | 0 |
| 3 | 400 | 2 | 1 | 1 |
| 4 | 400 | 0 | 0 | 1 |
| 5 | 200 | 0 | 0 | 0 |
| Total | 1400 | 15 | 3 | 2 |



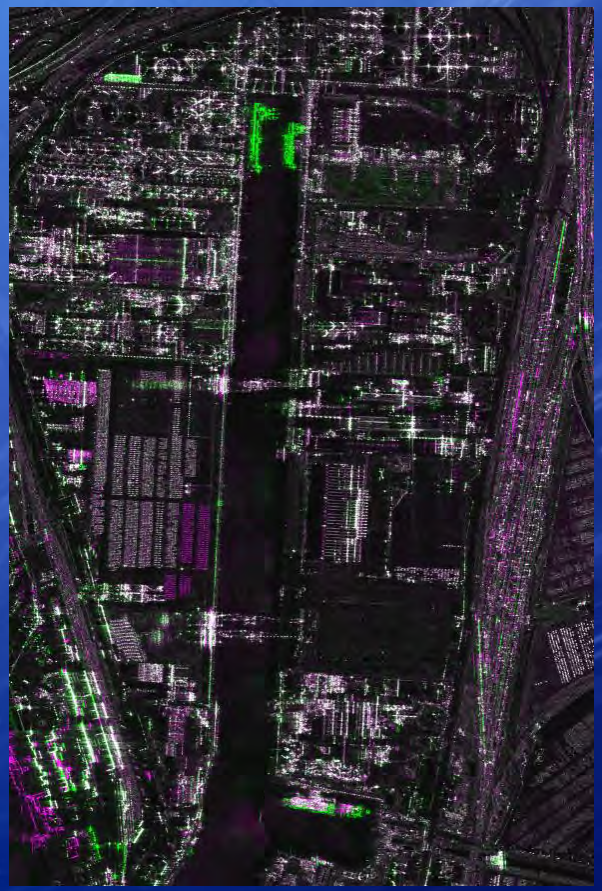

Reference about collapsed buildings derived from airborne orthophotos acquired after the earthquake available at www.regione.abruzzo.it/xcartografia/.

# Example: Commercial Port Surveillance (Livorno, Italy)

Data set: section (1920×2880) of 2 spotlight Cosmo-SkyMed (CSK®) images acquired 23rd & 24th April 2010.

Optical image GeoEye, Tele Atlas 2011
Google ©

23 April 2010



RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

24 April 2010

- 1m×1m resolution
- X-band
- 1-look
- Amplitude
- VV-polarization
- 25-26 degree incidence angle
- Descending orbit
- Right look
- CSKS2 & S3
- Calibrated
- Co-registered

Backscattering decrease
Backscattering increase
Unchanged areas

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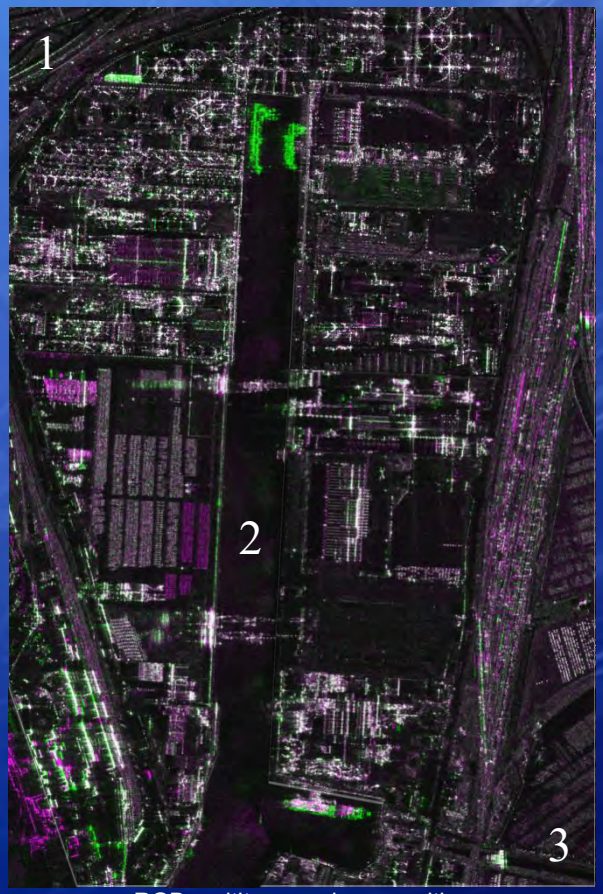
# Example: Commercial Port Surveillance (Livorno, Italy)

Data set: section (1920×2880) of 2 spotlight Cosmo-SkyMed (CSK®) images
Acquired 23rd & 24th April 2010.

Optical image GeoEye, Tele Atlas 2011
Google ©




RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

Prior knowledge on the scene

Areas of interest:

1 Chemical Terminal

2 Wet Dock

3 Cargo Terminal

Backscattering decrease
Backscattering increase
Unchanged areas

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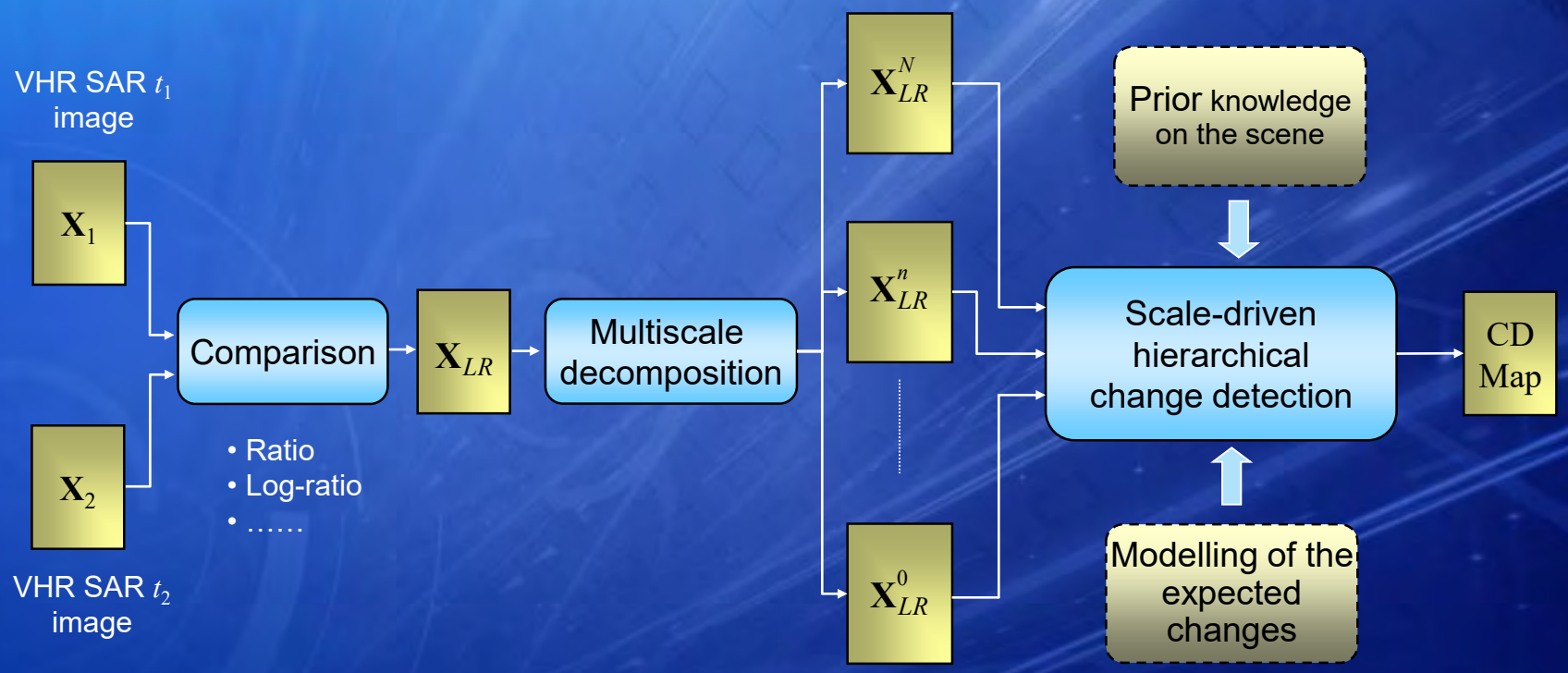
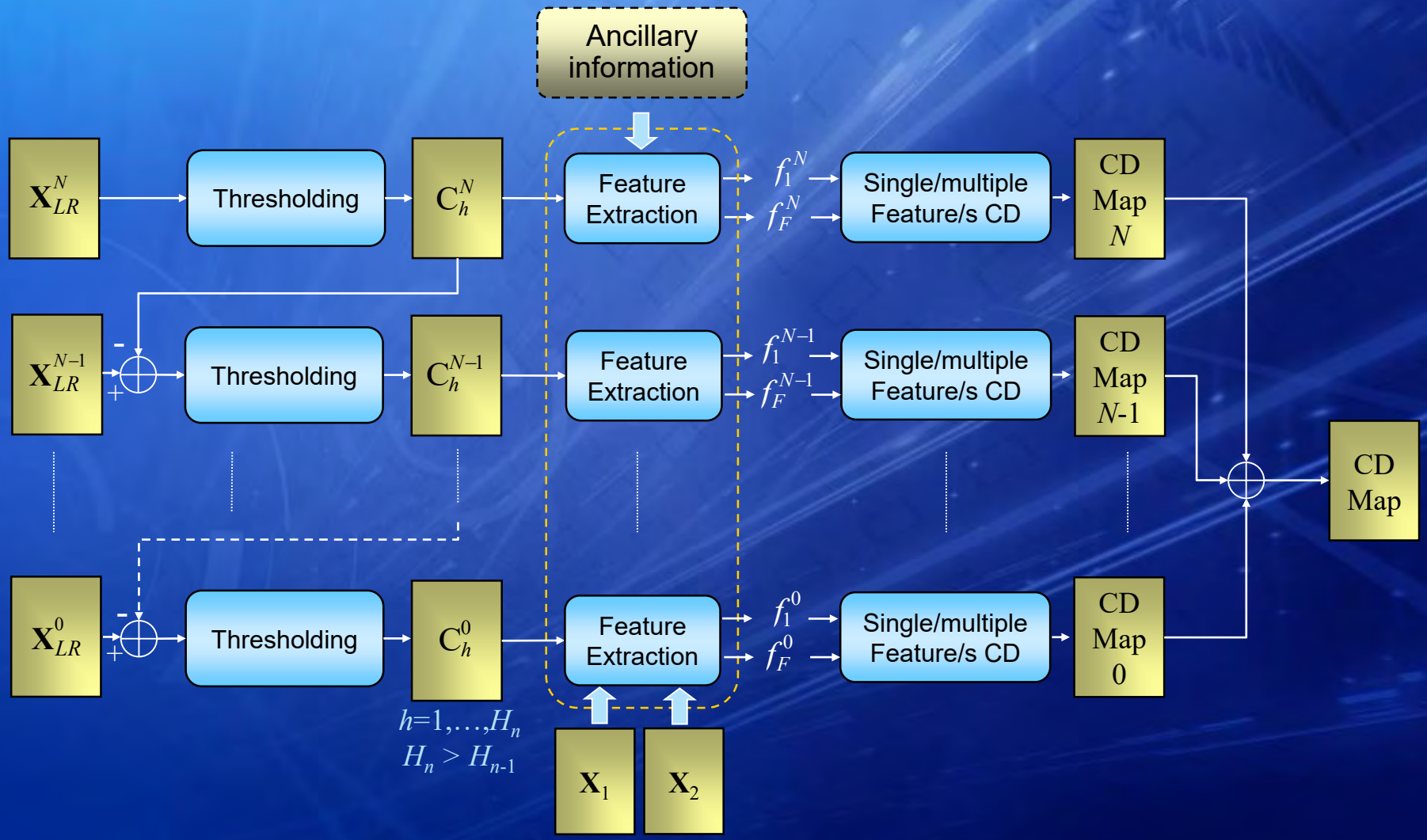
# Architecture for CD in Surveillance Applications



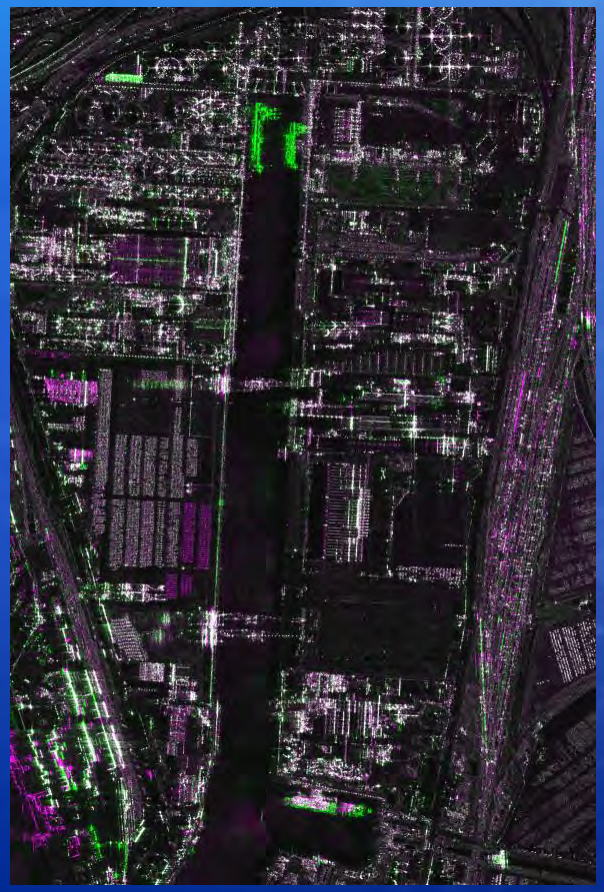

F. Bovolo, C. Marin, L. Bruzzone, "A Hierarchical Approach to Change Detection in Very High Resolution SAR Images for Surveillance Applications, *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 51, 2013, pp. 2042-2054.

# Architecture for CD in Surveillance Applications



# Example: Commercial Port Surveillance (Livorno, Italy)

COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2010). All Rights Reserved.



RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

$C_h^4$ $h=1,\ldots,H_4$, $H_4=166$

Multiscale decomposition of $\mathbf{X}_{LR}$ has been obtained by:

- ✓ 2D-SWT and 2D-ISWT with an 8-length *Daubechies* filter;
- ✓ $N$ = 5 resolution levels.

- Backscattering decrease
- Backscattering increase
- Unchanged areas
- Changed areas

# Example: Results on Cargo Terminal

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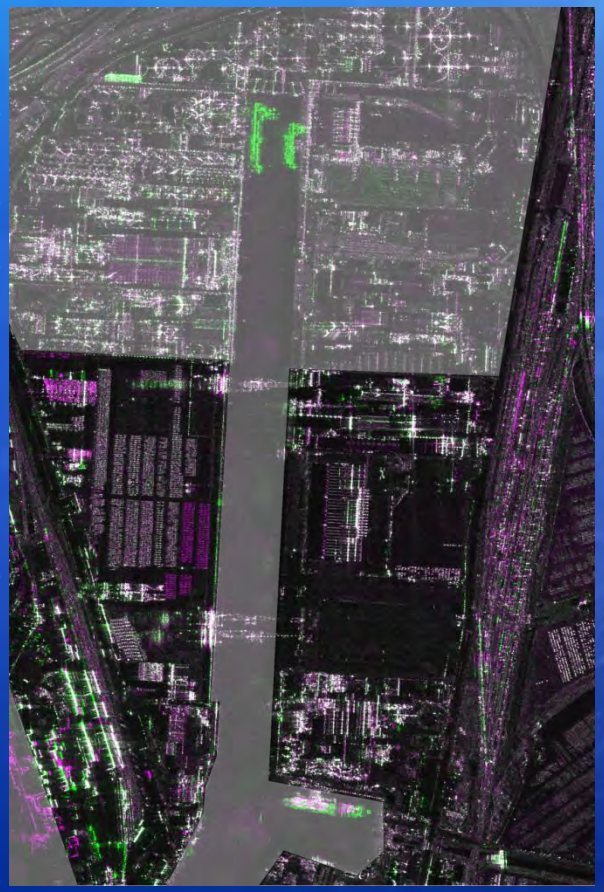


RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

## Changes of interest

- ✓ Movements of vehicles on duty in the terminal (e.g., truck, cars);
- ✓ Movements of containers.

ISO 6346 standard for containers

## Detector considered for containers

- ✓ Build a map of double bounce with a 20 feet length for $\mathbf{X}_1$ and $\mathbf{X}_2$ using [14].

Ratio line detector

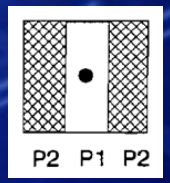
$$r = \min(r_{12}, r_{13})$$

Cross-correlation line detector

$$\rho = \min(\rho_{12}, \rho_{13})$$

Associative symmetrical sum

$$\sigma(r,\rho) = \frac{r\rho}{1 - r - \rho + 2r\rho'}$$

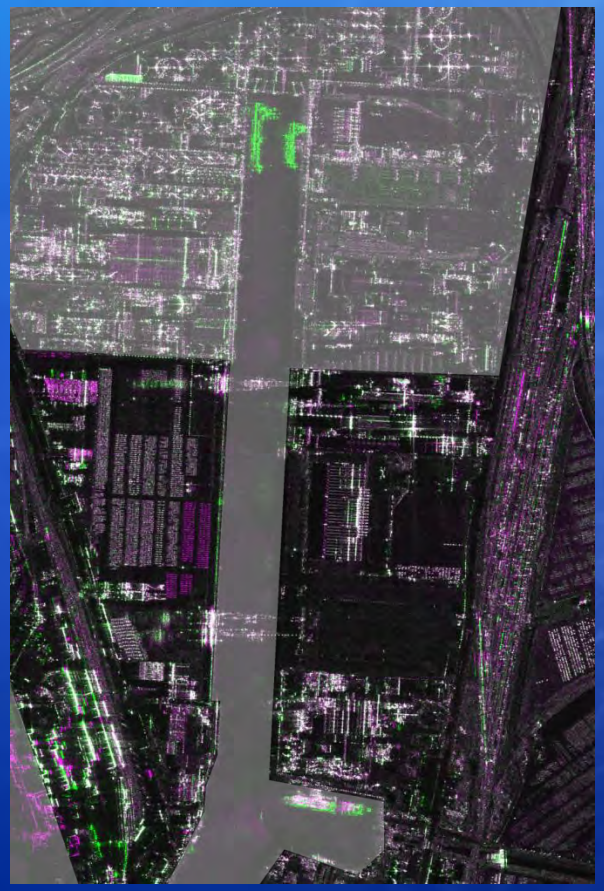



- ✓ Identify backscattering changes in double bounce regions threshoding their *Kullback-Leibler* distance.

F. Tupin, H. Maitre, J.-F. Mangin, J.-M. Nicolas,E. Pechersky, "Detection of linear features in SAR images: application to road network extraction," IEEE Trans. Geosci. Rem. Sens., vol.36, pp.434-453, 1998.

# Example: Results on Cargo Terminal

COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2010). All Rights Reserved.



RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

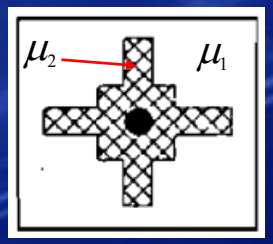
## Changes of interest

- ✓ Movements of vehicles on duty in the terminal (e.g., truck, cars);
- ✓ Movements of containers.

## Detector considered for car

- ✓ Build an isolated scatterers map for $\mathbf{X}_1$ and $\mathbf{X}_2$ using [15].

$$r_{PT} = 1 - \min\left(\frac{\mu_1}{\mu_2}, \frac{\mu_2}{\mu_1}\right)$$




- ✓ Compare the 2 maps according to the logical operator XOR.

A. Lopes, E. Nezry, R. Touzi, and H. Laur, "Structure detection and statistical adaptive speckle filtering in SAR images," *Int. J. Remote Sens.*, vol. 14, pp. 1735–1758, 1993.

# Example: Results on Car Movements in Cargo Terminal

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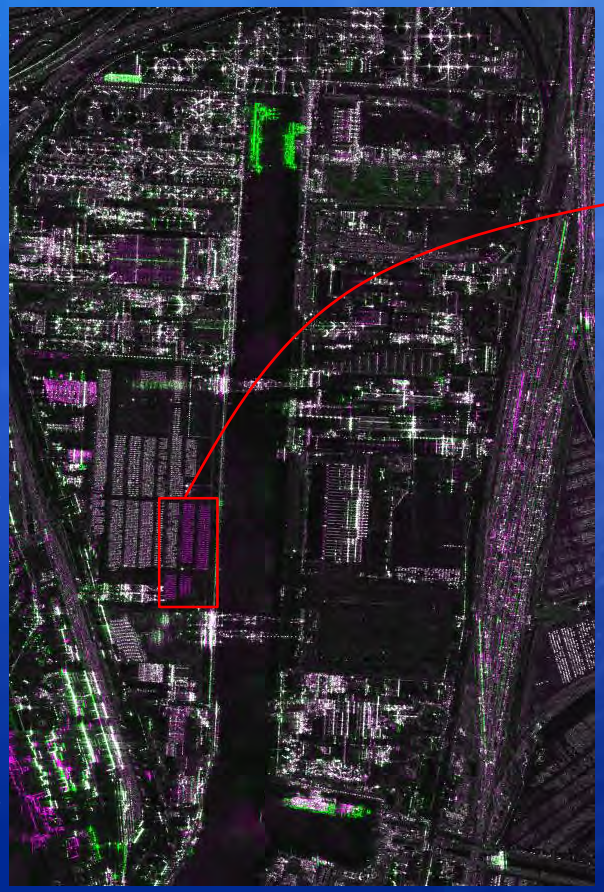
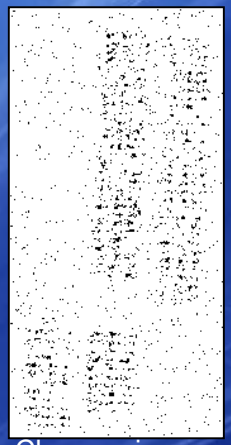
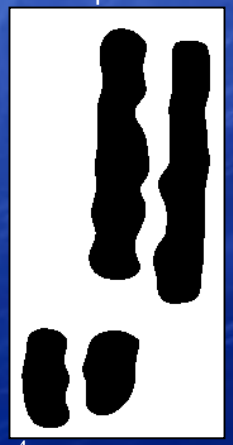


RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

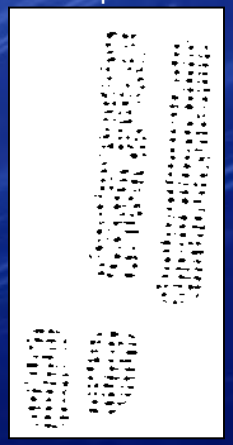
RGB multitemporal Composition



Changes in cars
(standard pixel based)



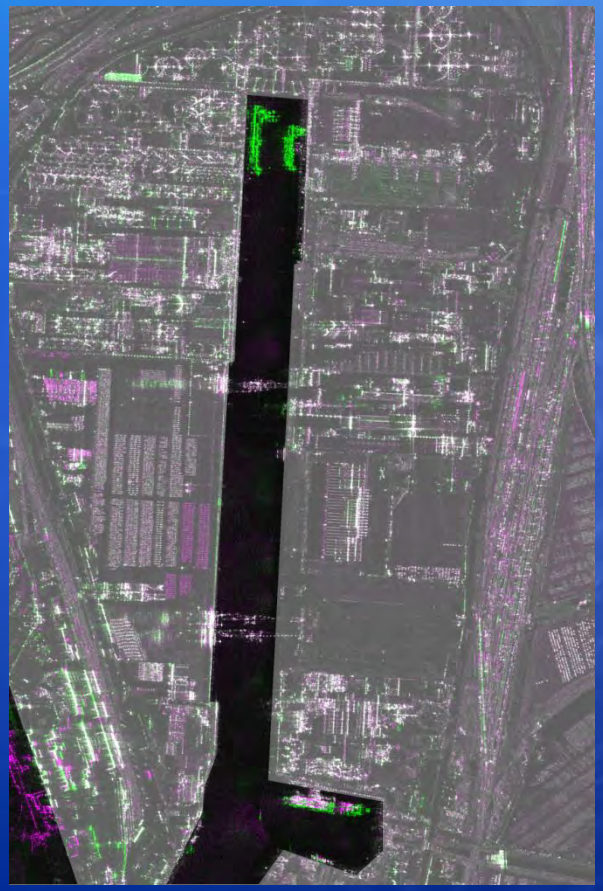
$C_{h^*}^4$ Map of changes



Changes in cars
(proposed method)

| Number of Changed Cars | |
|---|---|
| Estimated | 284 |
| Reference | 249 |

# Example: Results on Wet Dock



RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

## Changes of interest

- ✓ Movements of cargo ships.

## Detector considered

- ✓ Due to the expected size of cargo ships, only thresholding of the log-ratio image at the lowest resolution level $\mathbf{X}_{LR}^{4}$ is performed.

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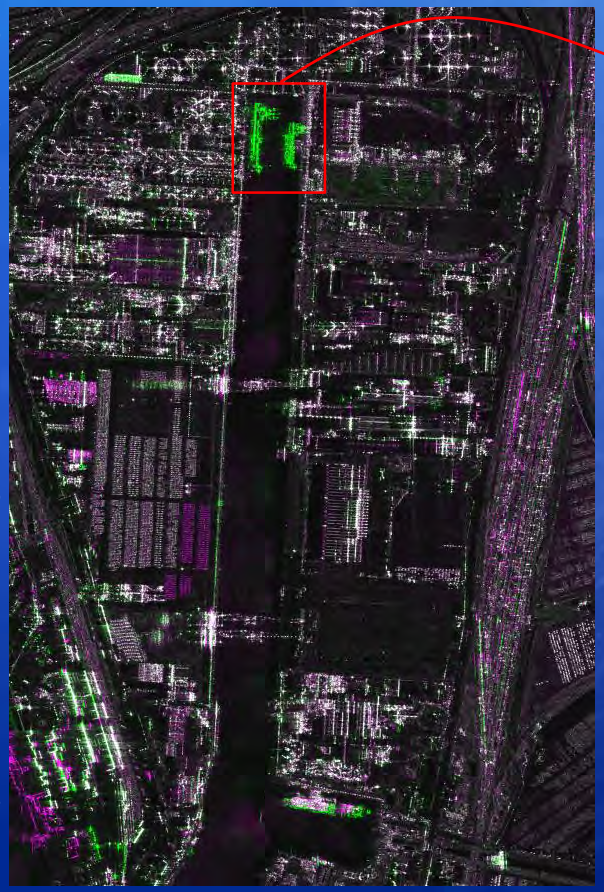
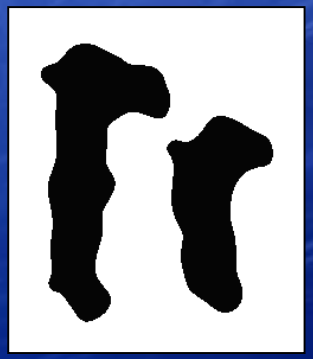
# Example: Cargo Ship Movement in the Wet Dock

COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana – (2010). All Rights Reserved.



RGB multitemporal composition
(R:04/24/2010, G:04/23/2010, B:04/24/2010)

RGB multitemporal
Composition



Changes in cargo ships
(Proposed method)

Aspect angle: 6 degrees

| Ships | Estimated Length | Reference Length |
|---|---|---|
| 1 | 117 m | 115 m |
| 2 | 85 m | 83 m |

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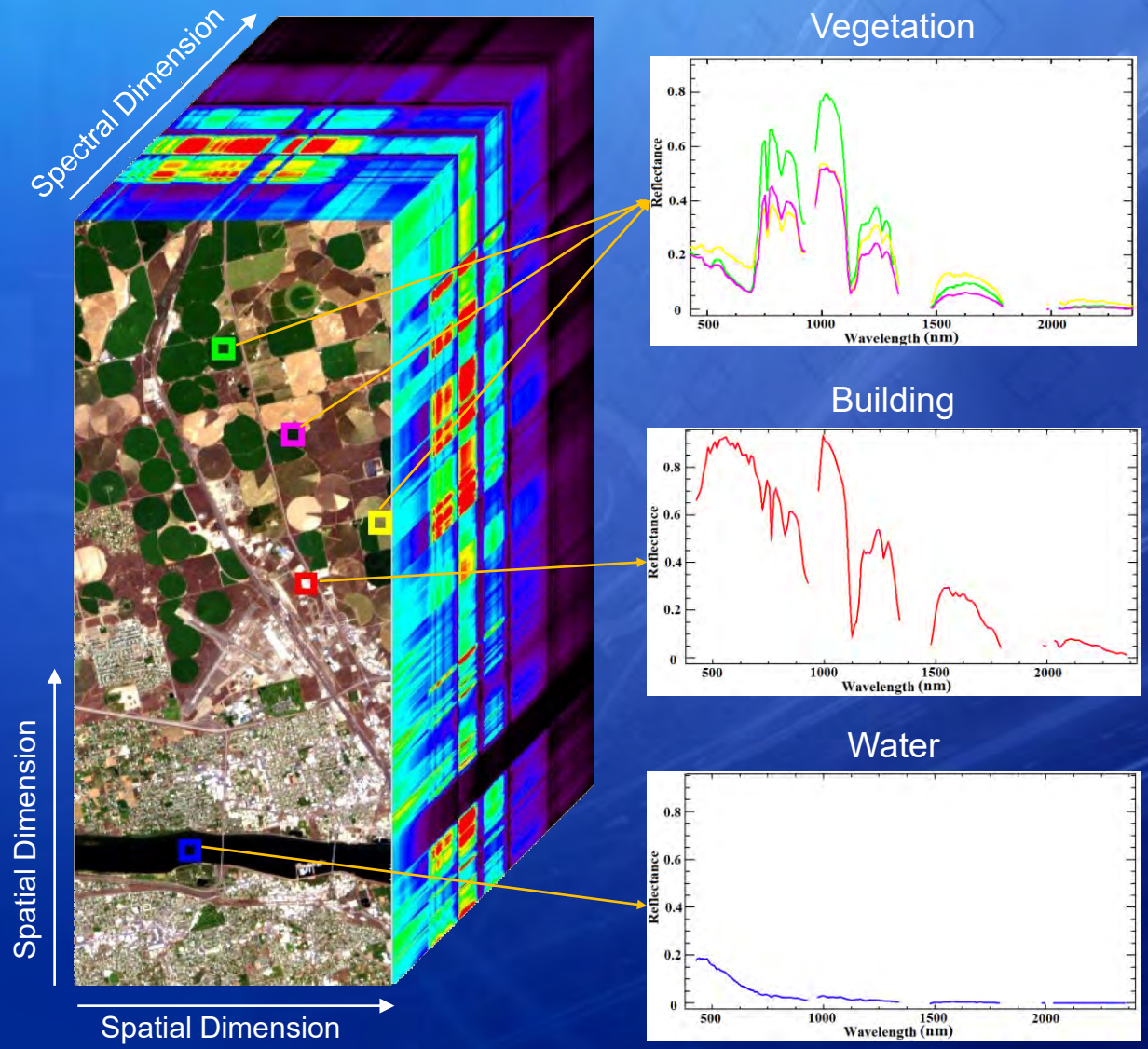
Dept. of Information Engineering and Computer Science
University of Trento
Via Sommarive, 5, I-38123 Povo, Trento, Italy

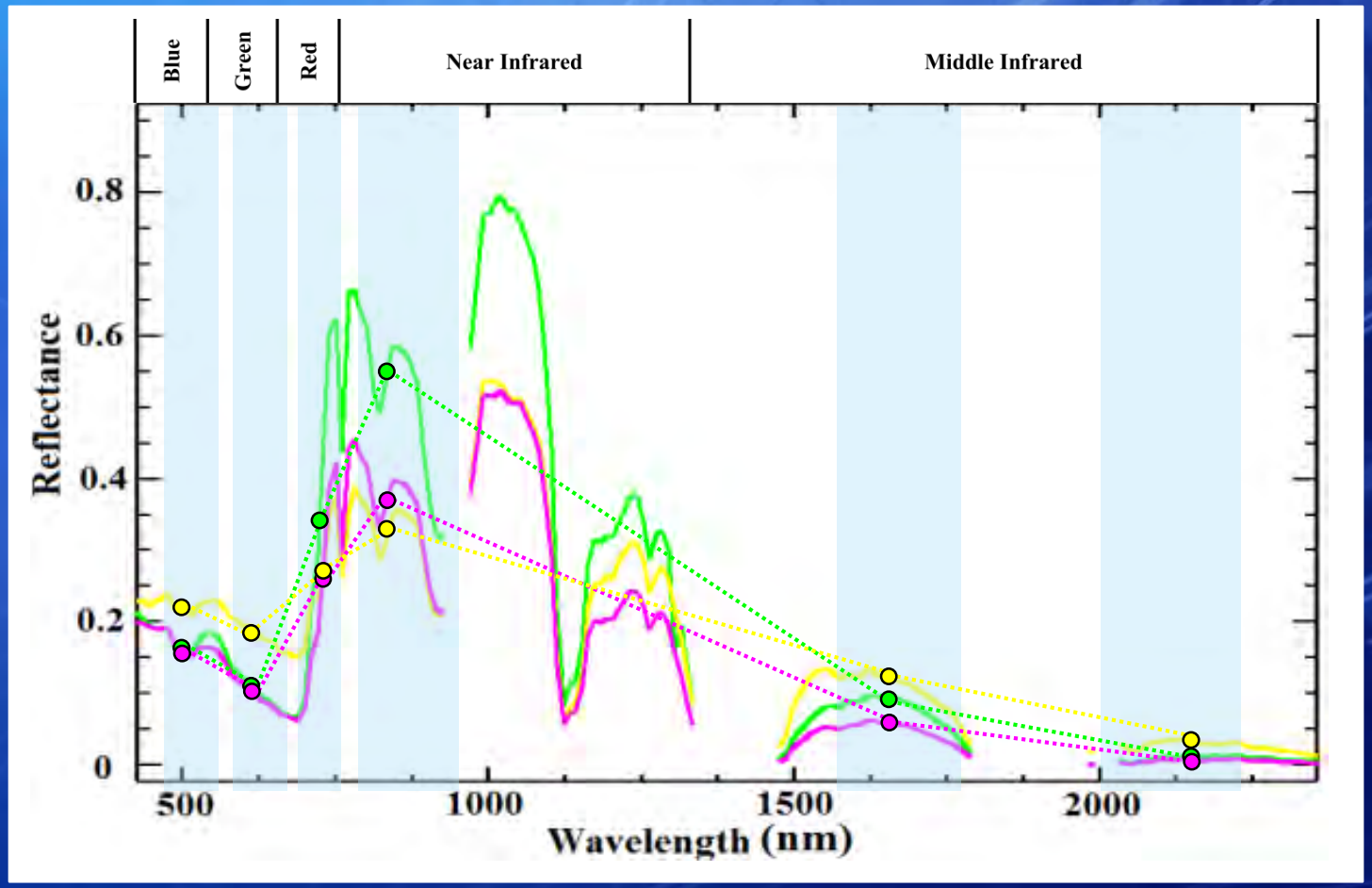
# 6. Change Detection in Hyperspectral Images

# Change Detection in Hyperspectral Images




- ✓ Hyperspectral sensors measure the solar reflected radiation in large number of narrow spectral intervals (e.g., 10nm).
- ✓ Fine spectral sampling better captures spectral signatures variations along the wavelength.

# Change Detection in Hyperspectral Images




Vegetation 1 Vegetation 2 Vegetation 3

Coarse multispectral bands

# Hyperspectral Satellite Missions

Source of data: IEEE GRSS Technical Committee

# Change Detection in Hyperspectral Images

- ✓ State-of-the-art change detection methods are mainly developed for multispectral images and do not explicitly handle the high dimensionality and the properties of hyperspectral images.

- ✓ Few existing methods applied to change detection in hyperspectral images mainly:
  - Compute binary change-detection maps (i.e., presence/absence of change) and seldom extract information about the kind of change.
  - Do not exploit the capability of hyperspectral sensors to capture subtle changes in the spectral signatures that are important for many applications.

# Change Detection in Hyperspectral Images

- ✓ CD methods for hyperspectral images should handle the challenging problems that arise due to the properties of HS images:
  - High dimensionality.
  - High level of noise and redundant information.
  - Increase of the sensitivity to the spectral variations.
  - More complex change representation and identification.

- ✓ Accordingly, effective and robust change representation, discovery and detection methods need to be developed for HS images.

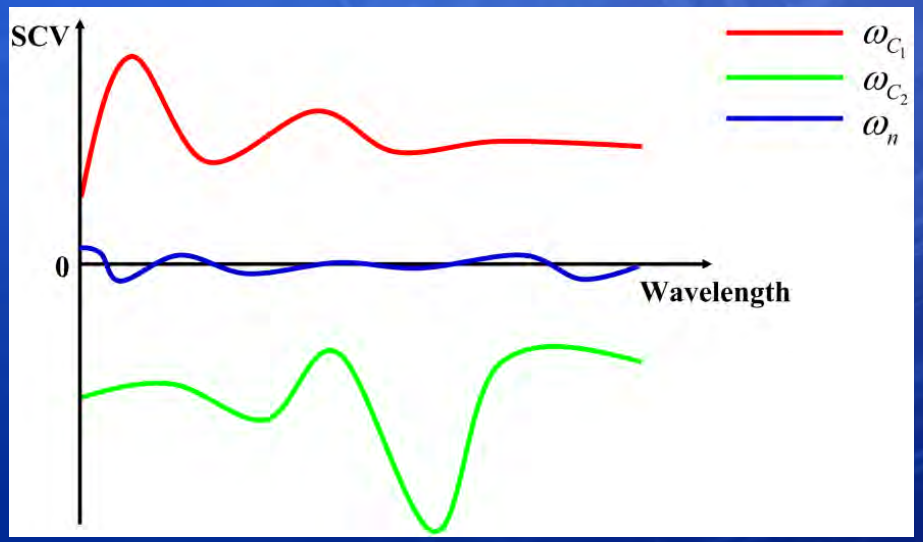
- ✓ Problem: what is a change in multitemporal hyperspectral images?

# Change Detection in Hyperspectral Images

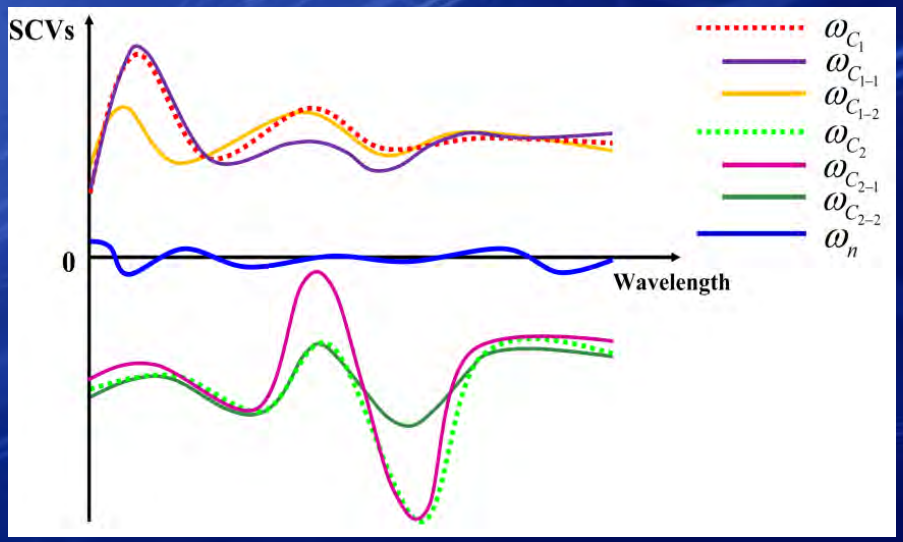
- ✓ Let us consider 2 hyperspectral images $X_1$ and $X_2$ acquired over the same geographical area at different times.
- ✓ Let us analyze the behaviors of the hyperspectral difference image:

$$X_D = X_2 - X_1$$

Major changes




Subtle changes



# Change Detection in Hyperspectral Images

- ✓ We can classify changes according to their the spectral behaviors in:
  - Major changes: the ones showing a large spectral difference;
  - Subtle changes: they are associated with a given major change and show a small, yet significant, spectral difference among each other.

- ✓ They may have different semantic meaning and, given a specific application, only a part of these changes may be relevant.

S. Liu, L. Bruzzone, F. Bovolo, P. Du, "Hierarchical Unsupervised Change Detection in Multitemporal Hyperspectral Images," IEEE Transactions on Geoscieance and Remote Sensing, Vol. 53, pp. 244 - 260, 2015.

# Change Detection in Hyperspectral Images

- ✓ Unsupervised change detection techniques in hyperspectral images should be able to identify both major and subtle changes. Then the user can select the changes of interest for the final change detection map.

- ✓ This can be addressed by using hierarchical techniques that:
  - Take advantage of the high spectral resolution;
  - Identify different kinds of major changes;
  - Separate subtle changes within the major change class.

S. Liu, L. Bruzzone, F. Bovolo, M. Zanetti, P. Du, "Sequential Spectral Change Vector Analysis for Change Detection in Multitemporal Hyperspectral Images," IEEE Transactions on Geoscience and Remote Sensing, Vol. 53, pp. 4363 – 4378, 2015.

S. Liu, L. Bruzzone, F. Bovolo, P. Du, "Unsupervised Multitemporal Spectral Unmixing for Detecting Multiple Changes in Hyperspectral Images," IEEE Transactions on Geoscience and Remote Sensing, Vol. 54, pp. 2733 - 2748, 2016.

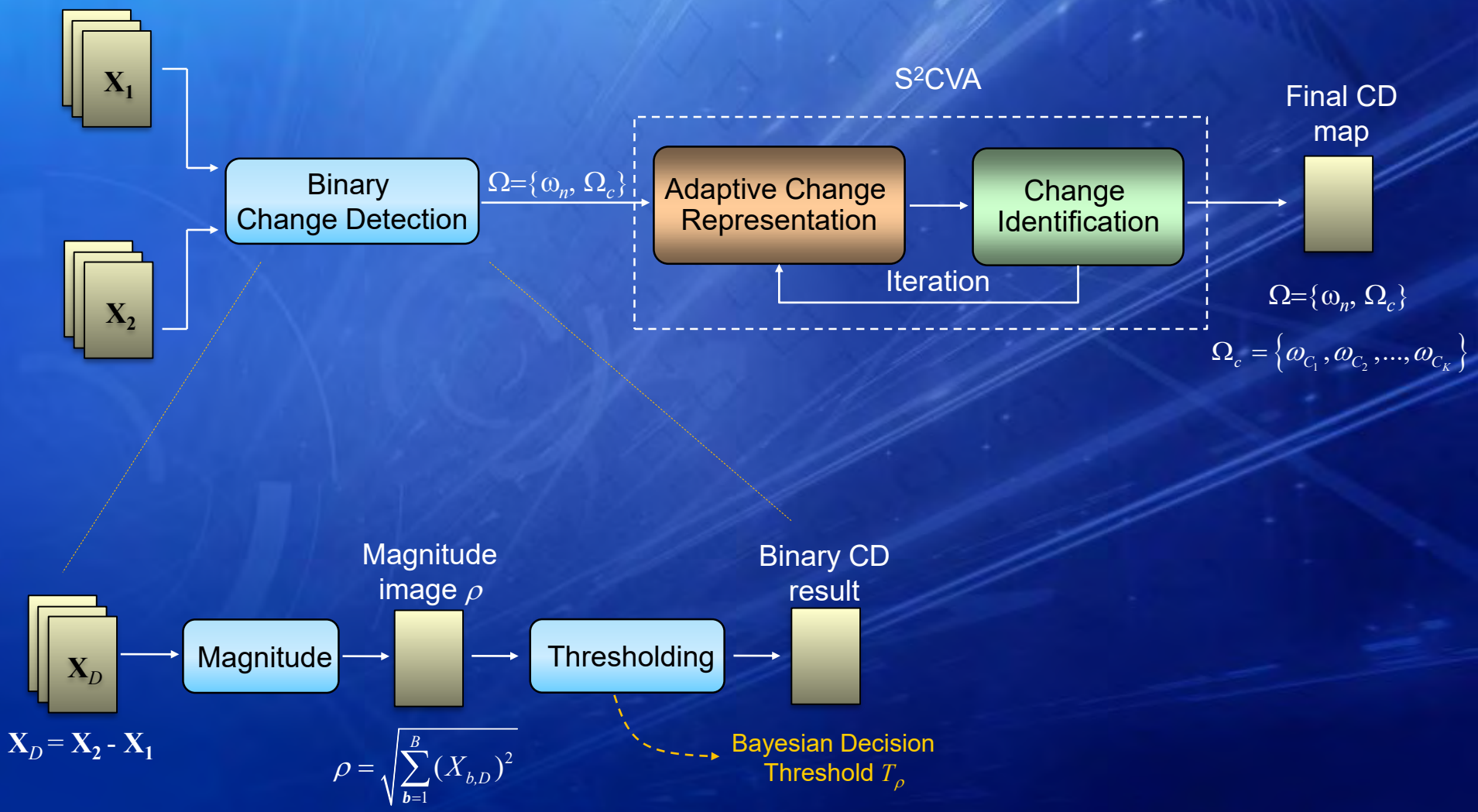
# Change Discovery and Representation

- ✓ Represent and discover multiple changes in multitemporal hyperspectral images by using an approach that exploits the intrinsic hierarchical nature of the problem.

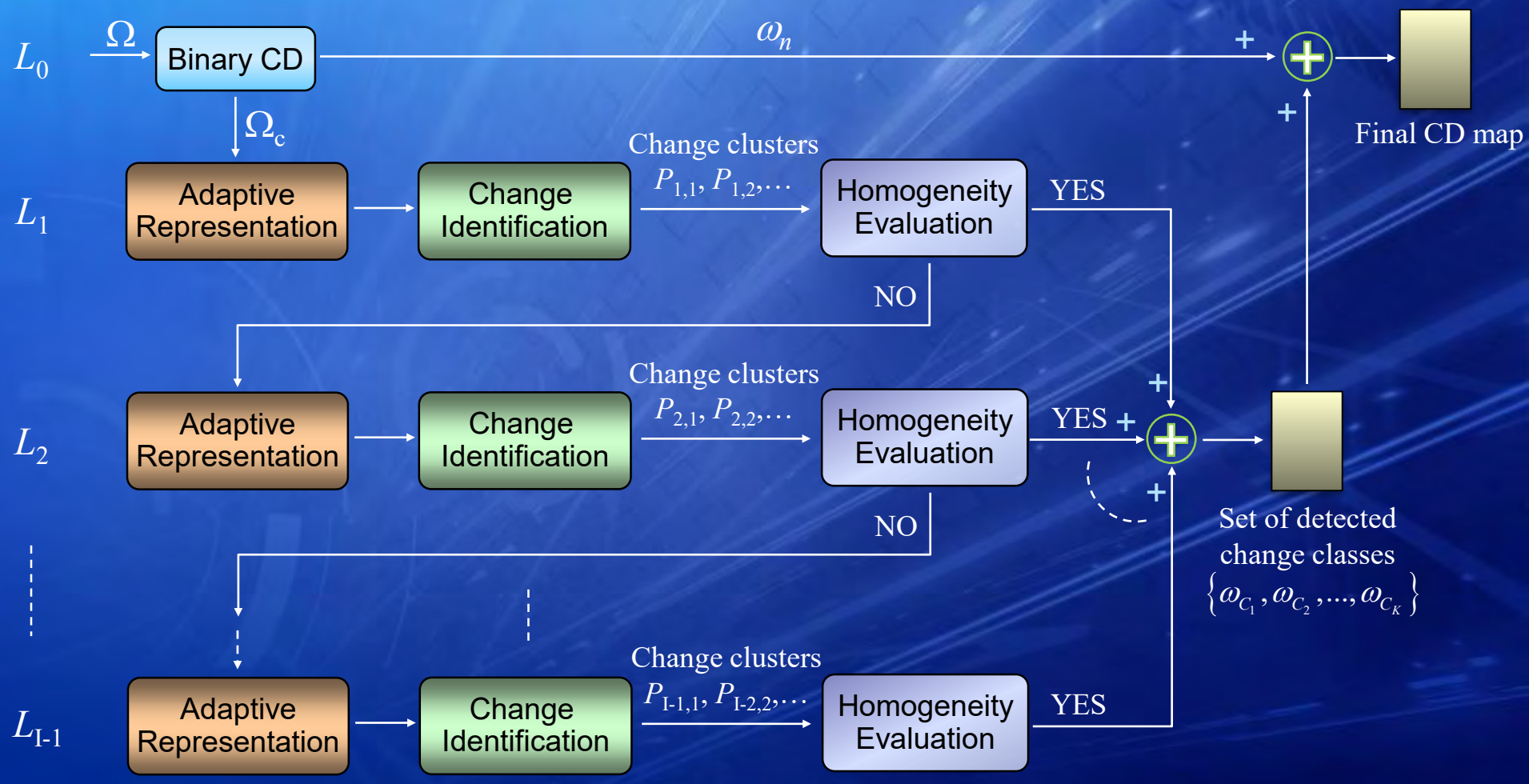
- ✓ The sequential spectral change vector analysis ($S^2CVA$) technique for change detection in hyperspectral images:
  - Automatically and adaptively represents different kinds of changes.
  - Uses a simple yet effective change identification scheme.
  - Is based on a sequential and interactive tool.
  - Is sensitive to the small variations of the spectral signature since it takes advantage of the high spectral resolution (i.e., subtle change).

S. Liu, L. Bruzzone, F. Bovolo, M. Zanetti, P. Du, "Sequential Spectral Change Vector Analysis for Change Detection in Multitemporal Hyperspectral Images," IEEE Transactions on Geoscience and Remote Sensing, Vol. 53, pp. 4363 – 4378, 2015.

# Change Discovery and Representation: S²CVA

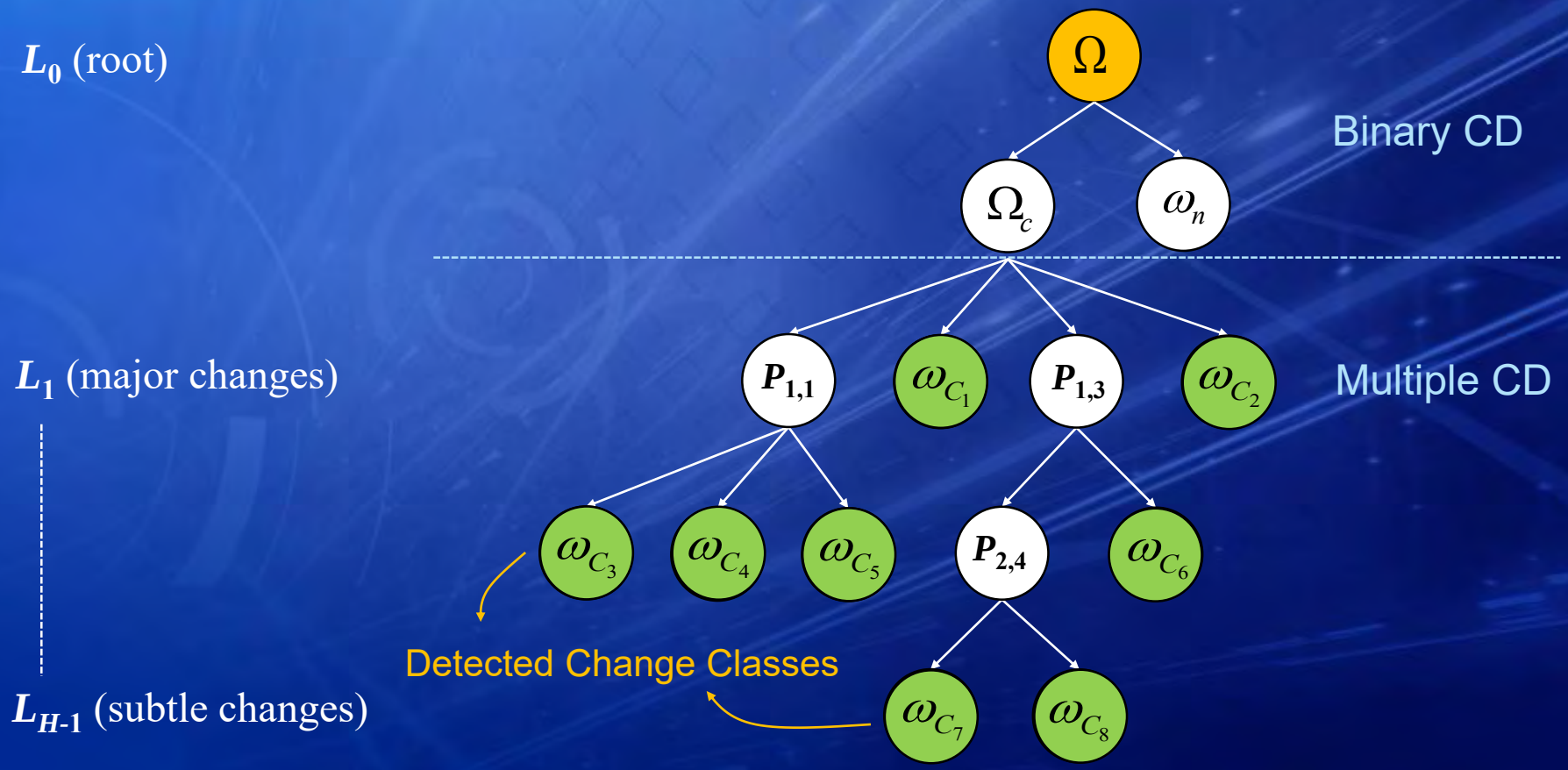


# Change Discovery and Representation: S²CVA



# Sequential Analysis

Sequential analysis results in the modeling of the change detection hyperspectral problem as a hierarchical tree.



# Example: Agriculture

$\mathbf{X}_1$, $\mathbf{X}_2$ : hyperspectral multitemporal images acquired by Hyperion in May 1, 2004 and May 8, 2007, Oregon.

Number of used spectral bands: 159 out of 242.

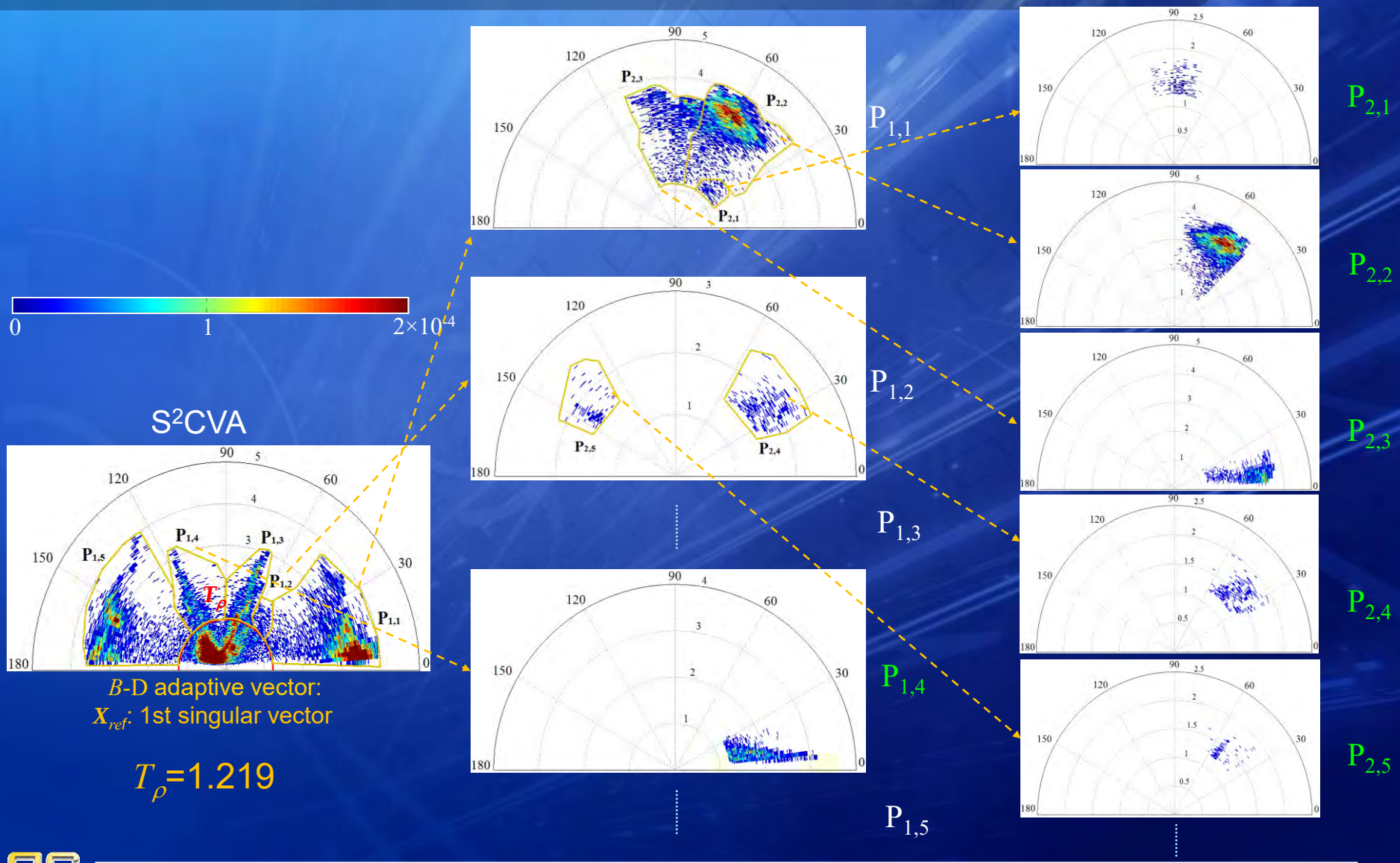
2004

2007

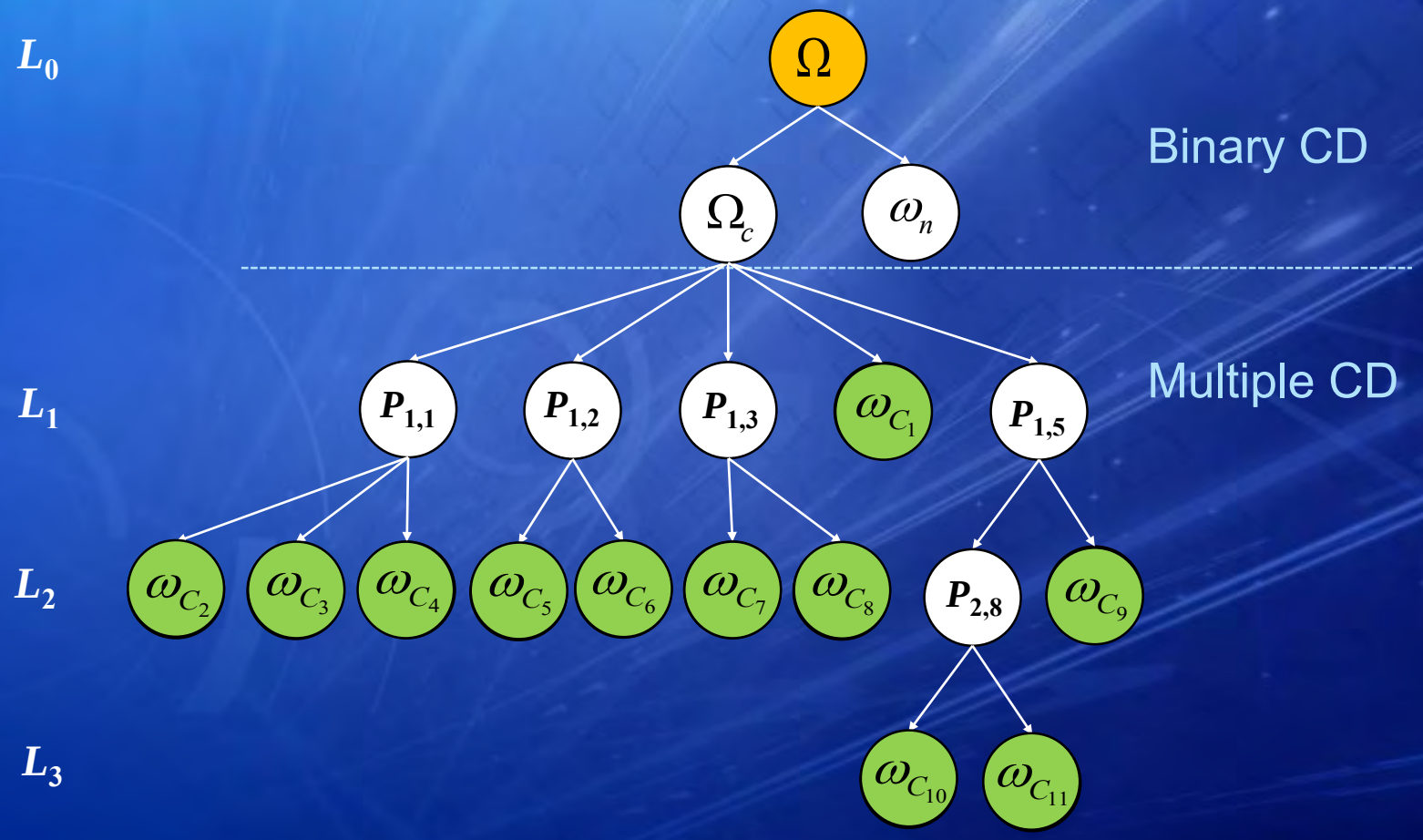
(R: 650.67nm, G: 548.92nm, B: 447.17nm)

False color composition of SCVs
(R: 1729.70nm, G: 1023.40nm, B: 752.43nm)

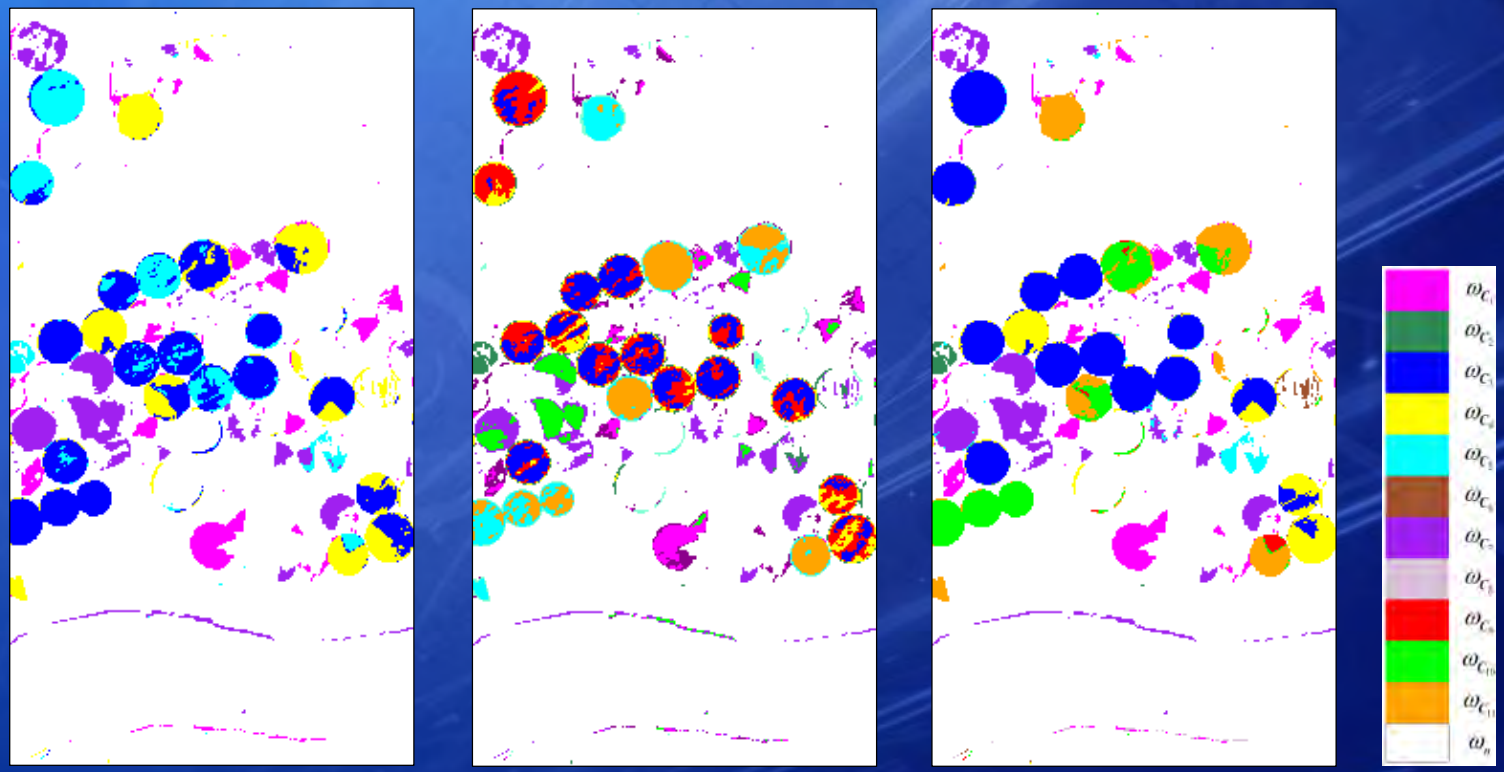
# Example: Agricultural Area



# Example: Agricultural Area



# Example: CD Maps



C²VA ($K$=5) *k*-means($K$=11) S²CVA($K$=11)

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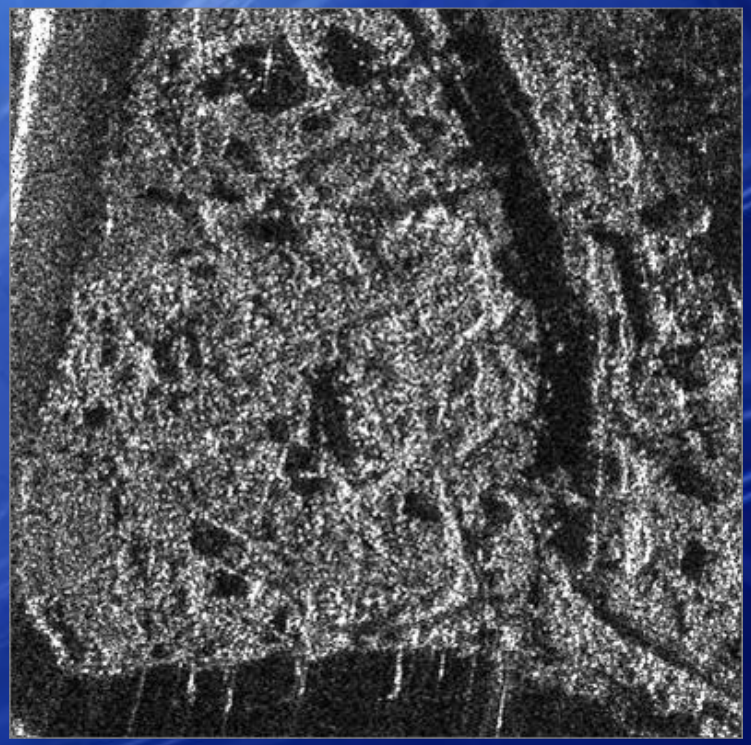
# 7. Change Detection in Multisensor/Multisource Images

# New challenges: Data Fusion

Quickbird image before earthquake

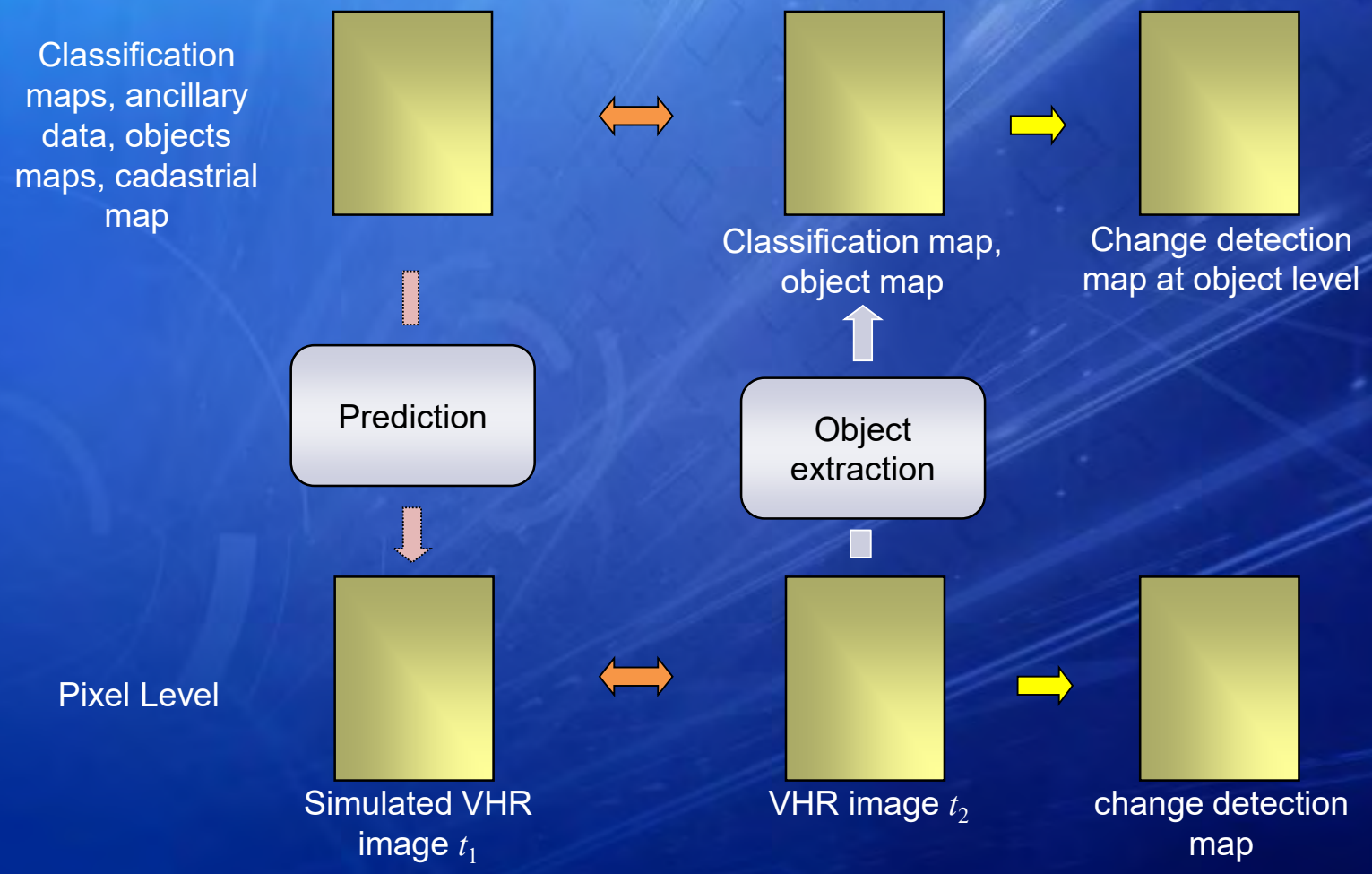


COSMO-Skymed image after earthquake

COSMO-SkyMed Product – ©ASI – Agenzia Spaziale Italiana (2010). All rights reserved.

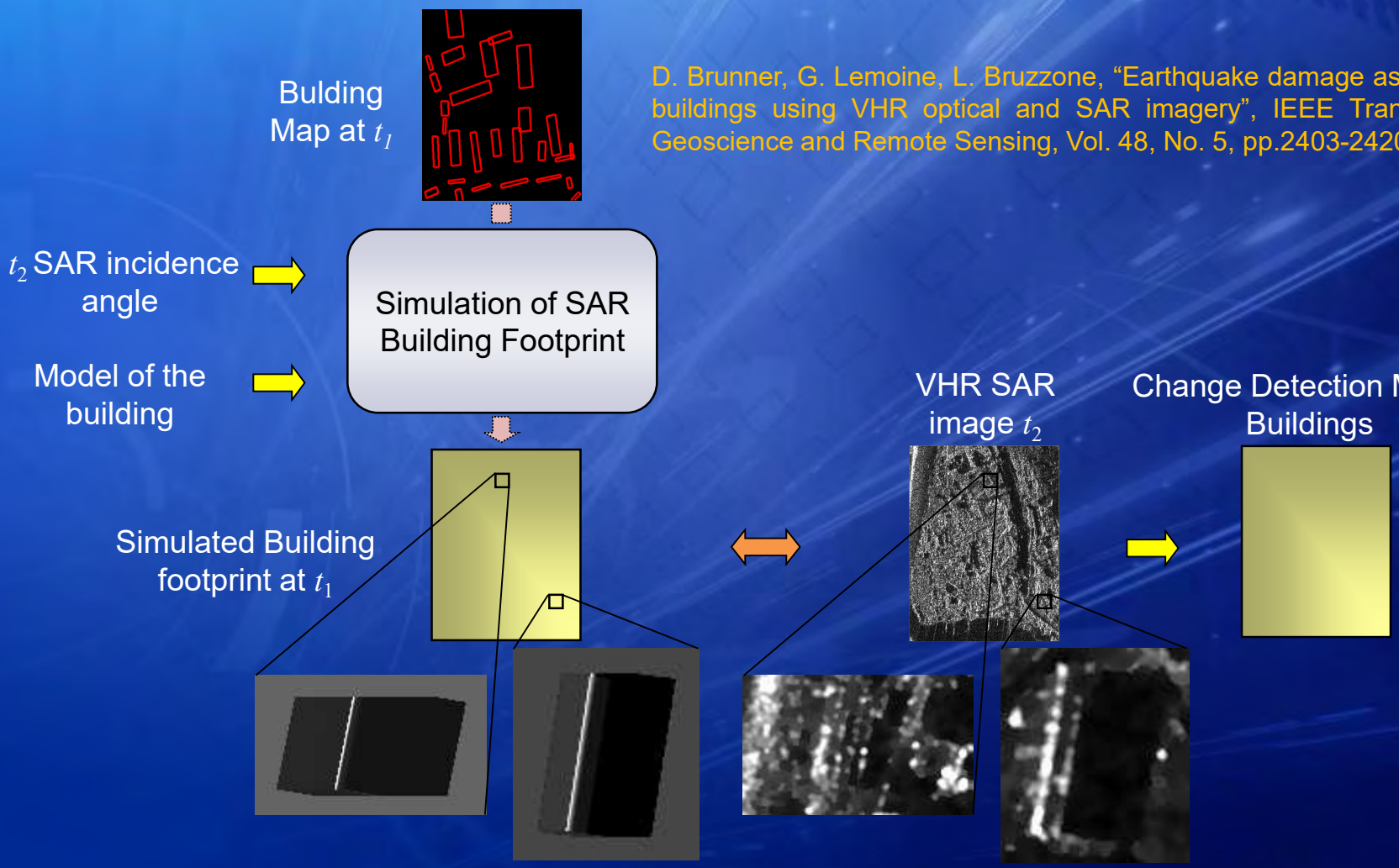
Earthquake of Sichuan province, China, May, 2008

# Top-Down/Bottom-Up Approaches



# CD in Multisource Data: Example

D. Brunner, G. Lemoine, L. Bruzzone, "Earthquake damage assessment of buildings using VHR optical and SAR imagery", IEEE Transactions on Geoscience and Remote Sensing, Vol. 48, No. 5, pp.2403-2420, 2010.



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# 8. Conclusion

# Conclusion

- ✓ Analysis and exploitation of time series and multitemporal images is a very important topic both from the methodological and the application perspective.

- ✓ Many methodological challenges are related to the properties of new satellite data that require the development of a new generation of multitemporal processing techniques for the analysis of:
  - VHR multispectral and SAR images.
  - Hyperspectral images.
  - LiDAR point clouds.
  - Long time series (data mining).

- ✓ These properties open the possibility to develop also new applications that exploit either the very high geometrical (e.g. analysis of single buildings) or spectral (e.g. detection of subtle changes) resolution and the increased revisit time (e.g. monitoring and surveillance application).

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