FUSION OF MULTITEMPORAL AND MULTIRESOLUTION REMOTE SENSING DATA AND APPLICATION TO NATURAL DISASTERS

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informatics mathematics

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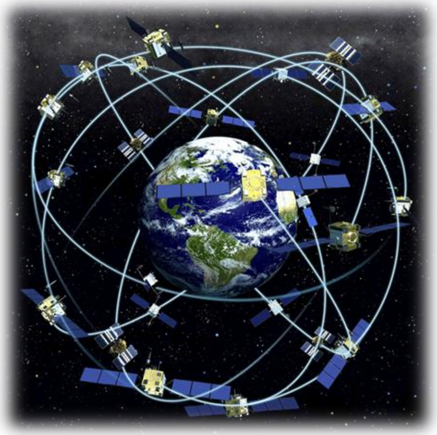
Introduction to the Research Activity

Problem Statement

Due to the huge number and the (short) revisit time of high resolution satellites



Huge amount of satellite images acquired at different resolution

valuable spatio-temporal information.

develop new methods to explore such big data

- Multi-resolution methods
- Multi-temporal methods

Objectives

- Supervised image classification
- General and sufficiently robust to different types of images at different dates.

Key points

- Focus on multi-resolution optical images
- extension to multi-temporal images

General applications

- Global detection of urban areas, that are critical w.r.t. populations (risk management).
- Infrastructure mapping. Mapping the water after a flooding.
- Land-cover or land-use maps after an earthquake.

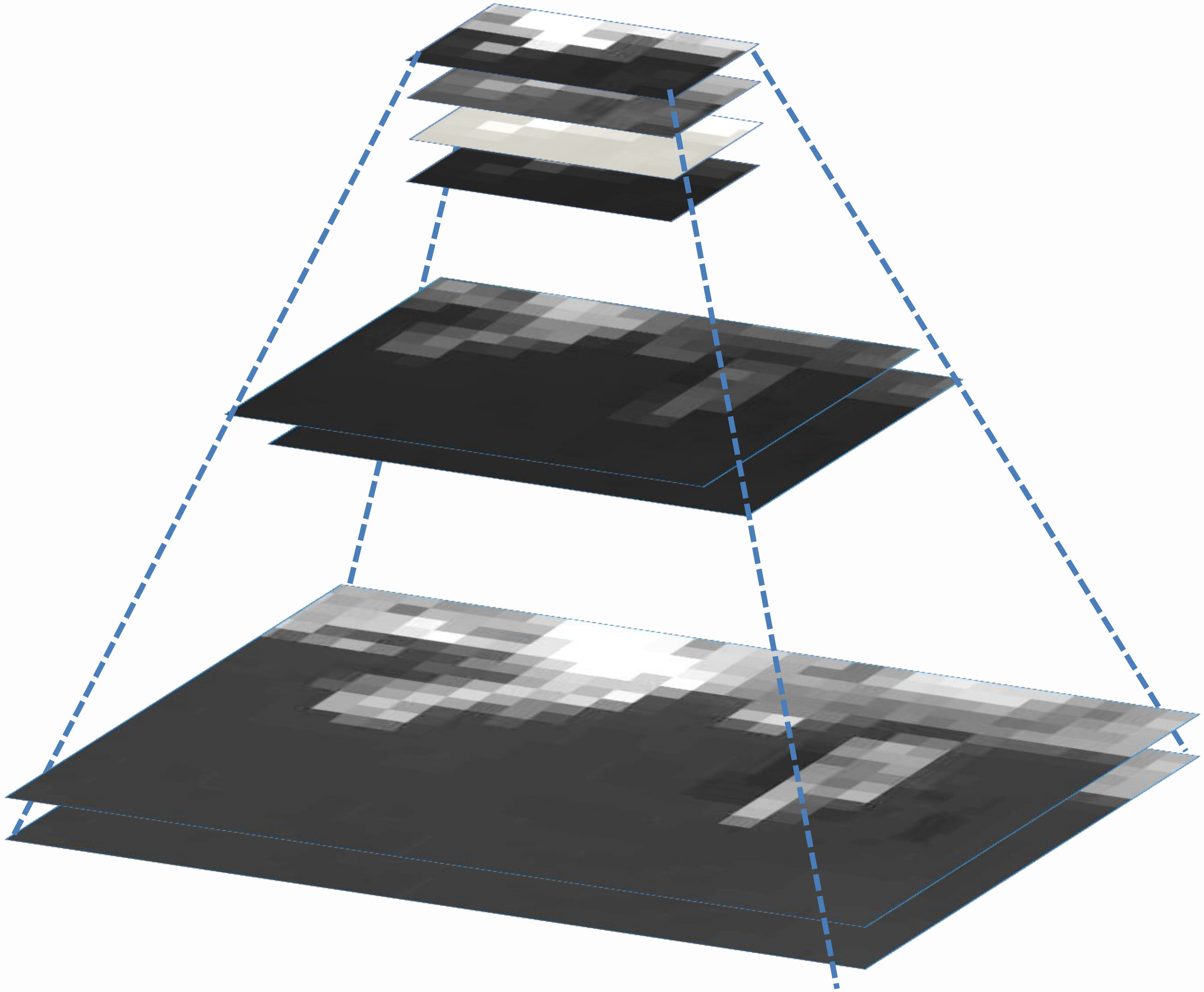
Proposed method

A novel hierarchical method to fuse multidate, multiresolution, and multiband remote sensing imagery for multitemporal classification purposes.

Contents

Contents

Pyramid Structure[1].



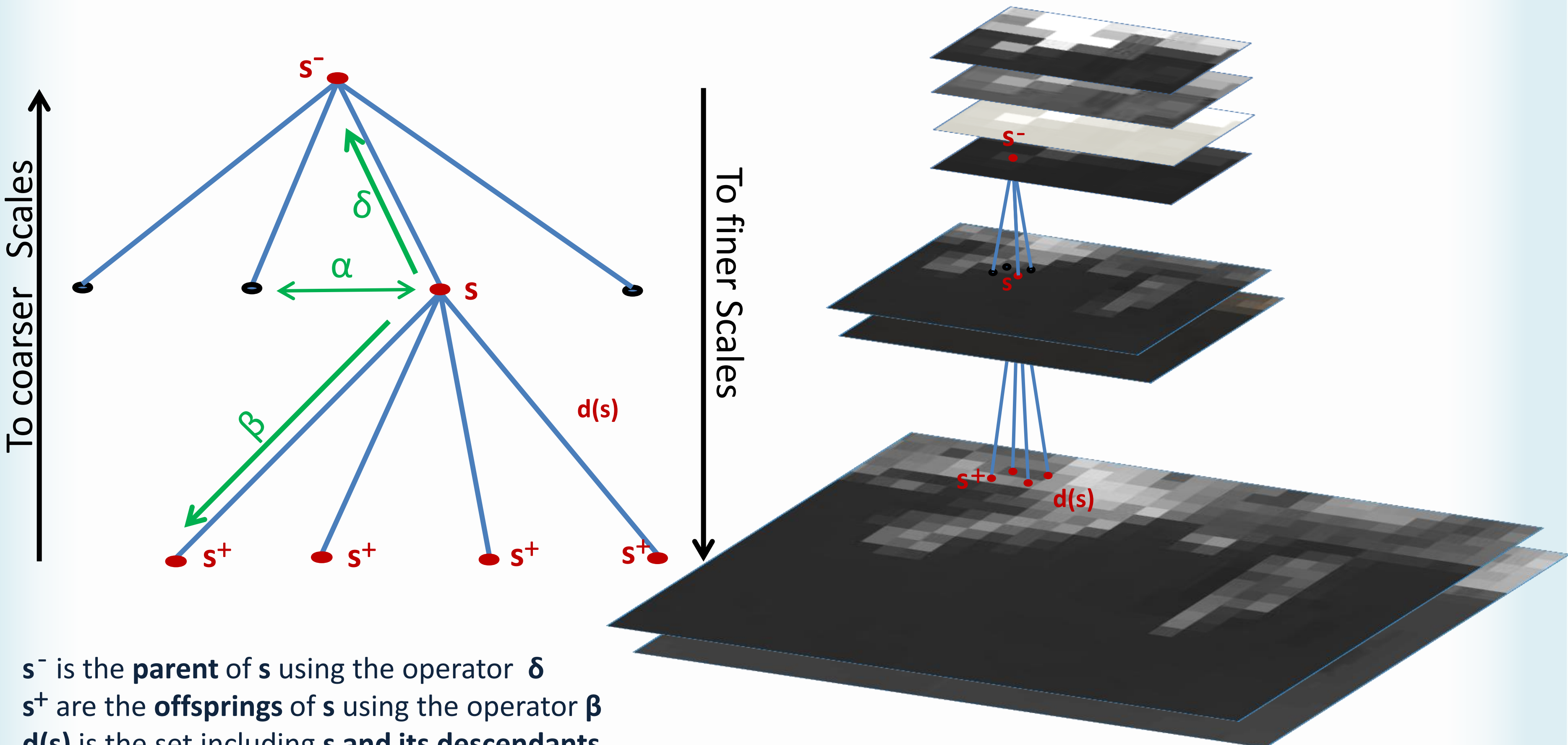
Images are organized according to their resolutions in a pyramid structure

[1] J. M. Jolion, A. Rosenfeld. *A Pyramid Framework for Early Vision: Multiresolutional Computer Vision.* Norwell, MA, USA: Kluwer Academic Publishers, 2004.

Quad-tree structure [2].

Operators on the quad-tree :

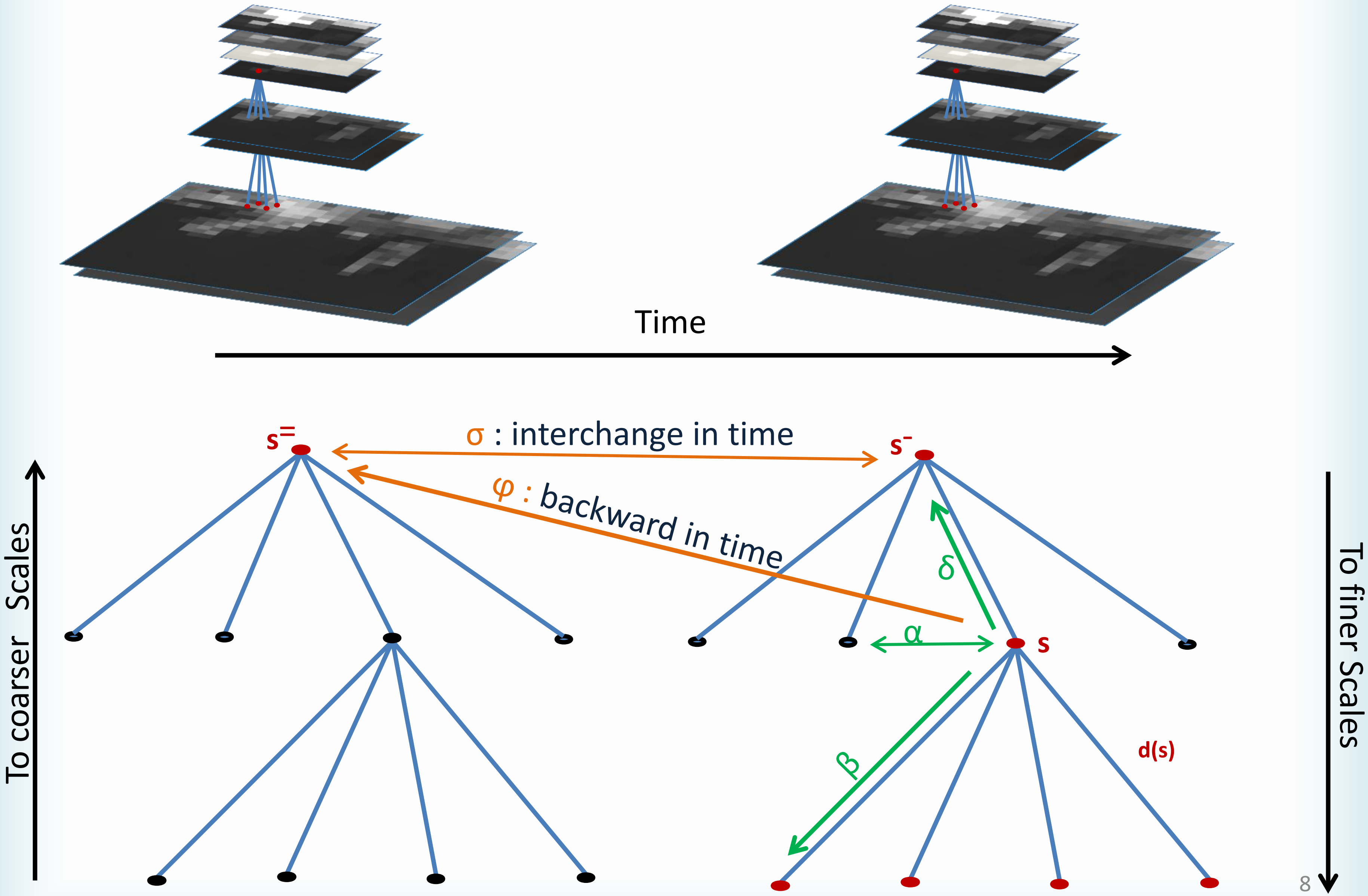
- δ : the backward shift (one-to-one operator)
- α : the interchange operator in the same scale
- β : the forward shift (one-to-four operator)



- s^- is the **parent** of **s** using the operator **δ**
- s^+ are the **offsprings** of **s** using the operator **β**
- **d(s)** is the set including **s and its descendants**

[2] M. Basseville, A. Benveniste, K. C. Chou, S. A. Golden, R. Nikoukhah, and A. S. Willsky, "Modeling and estimation of multiresolution stochastic processes,"IEEE Trans. Inform. Theory, vol. 38, pp. 766–784, Mar. 1992.

Proposed Multitemporal Quad-tree [3].



[3] Ihsen Hedhli, Josiane Zerubia, Gabriele Moser, Sebastiano B. Serpico. " Fusion of multitemporal and multiresolution remote sensing data and application to natural disasters". IGARSS, Jul2014, Québec, Canada.

Contents

Bayesian Formulation

In order to **classify** the image, **Y**, we consider the problem of **inferring** the "best" configuration of **X** (class labels).

The standard Bayesian formulation of this inference problem consists in **minimizing the average cost of an erroneous classification**.

$$\hat{x} = arg \min_{x \in \Omega} E[C(X,x)|Y = y]$$

where $C(X,x)$ is the cost of estimating the true classification, X, through the approximate classification, x. (Ω set of all possible configurations)

Considered cost function : **[4]**

$$C_{MPM}(X,x) = \sum_{s \in S} \delta(X,x)$$

Where $\delta(X,x)$ is 1 when $X = x$ and 0 otherwise.

The resulting Bayesian estimator is the **mode of posterior marginals (MPM)** estimator

$$\forall\, s \in S, \hat{x}_s = arg \max_{x_s \in \omega} P(x_s\,|y)$$

[4] Laferte, J.-M., Perez, P., and Heitz, F., "Discrete Markov modeling and inference on the quad-tree," IEEE Trans. Image Process. 9(3), 390-404 (2000).

Hierarchical Markovian Model

A non-iterative algorithm is developed to integrate an **exact estimator** of the mode of posterior marginals (MPM).

➡ The aim is to maximize recursively the posterior marginal at each site s.

$$\hat{x}_s = \arg\max_{x_s \in \omega} P(x_s \mid y)$$

Single date case

$$p(x_s \mid y) = \sum_{x_{s^-}} \left[\frac{p\left(x_s, x_{s^-} \mid y_{d(s)}\right)}{\sum_{x_s} p\left(x_s, x_{s^-} \mid y_{d(s)}\right)} \cdot p(x_{s^-} \mid y) \right] \quad [4]$$

Multidate case

$$p(x_s \mid y) = \sum_{x_{s^-}, x_{s^=}} \left[\frac{p\left(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)}\right)}{\sum_{x_s} p\left(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)}\right)} \cdot p(x_{s^-} \mid y)\, p(x_{s^=} \mid y) \right] \quad [5]$$

[4] Laferte, J.-M., Perez, P., and Heitz, F., “Discrete Markov modeling and inference on the quad-tree,” IEEE Trans. Image Process. 9(3), 390-404 (2000).

[5] Ihsen Hedhli, Josiane Zerubia, Gabriele Moser, Sebastiano B. Serpico. “ Fusion of multitemporal and multiresolution remote sensing data and application to natural disasters”. IGARSS, Jul2014, Québec, Canada.

Hierarchical Markovian Model

Single date case

$$\boxed{\hat{x}_s = \arg\max_{x_s \in \omega} P(x_s \mid y)}$$

$$p(x_s \mid y) = \sum_{x_{s^-}} \left[\frac{p\left(x_s, x_{s^-} \mid y_{d(s)}\right)}{\sum_{x_s} p\left(x_s, x_{s^-} \mid y_{d(s)}\right)} \cdot p(x_{s^-} \mid y) \right]$$

Calculate recursively the posterior marginal $p(x_s \mid y)$ while the probabilities $p\left(x_s, x_{s^-} \mid y_{d(s)}\right)$ are made available.

$$\underbrace{\frac{p(x_s \mid x_{s^-}) \cdot p(x_{s^-})}{p(x_s)} \cdot p\left(x_s \mid y_{d(s)}\right)}_{p\left(x_s, x_{s^-} \mid y_{d(s)}\right)}$$

1 **Prior**

2 **Posterior marginal**

3 **Transition Probabilities over scale**

Hierarchical Markovian Model

Multidate case

$$\boxed{\hat{x}_s = \arg\max_{x_s \in \omega} P(x_s \mid y)}$$

$$p(x_s \mid y) = \sum_{x_{s^-},\, x_{s^=}} \left[\frac{p\left(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)}\right)}{\sum_{x_s} p\left(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)}\right)} . p(x_{s^-} \mid y)\, p(x_{s^=} \mid y) \right]$$

Calculate recursively the posterior marginal $p(x_s \mid y)$ while the probabilities $p\left(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)}\right)$ are made available.

$$\overset{4}{p(x_s \mid x_{s^-}, x_{s^=})} . \frac{\overset{3}{p(x_{s^-} \mid x_{s^=})} . p(x_{s^=})}{p(x_s)\ \ 1} . \overset{2}{p\left(x_s \mid y_{d(s)}\right)}$$

1 Prior

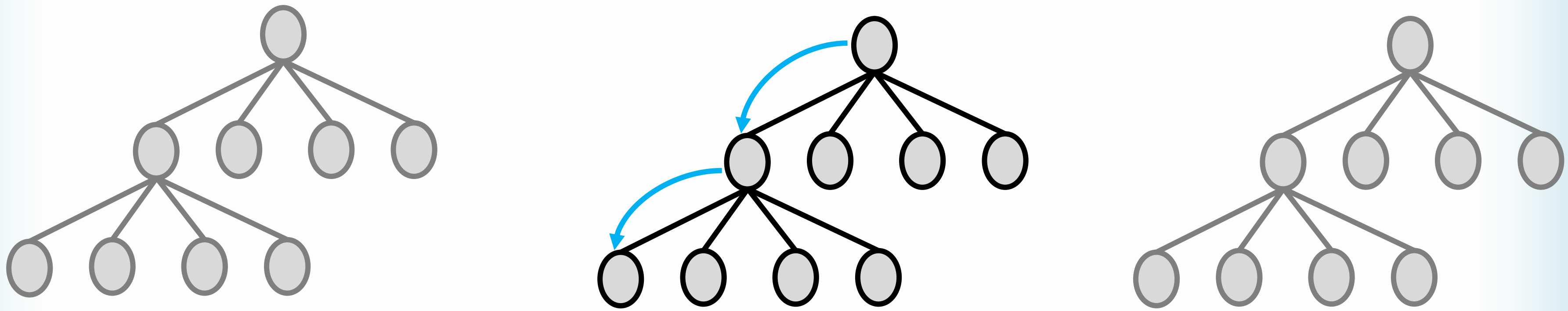
2 Posterior marginal

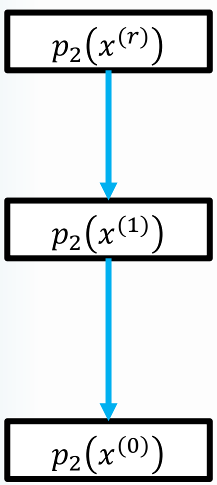
3, 4 Transition Probabilities over scale and time

These probabilities are calculated through an MPM algorithm runs in two passes on a quad tree, referred to as "bottom-up" and "top-down" passes.

Hierarchical Markovian Model

The Prior probabilities





Top-down

1 Prior $p\,(x_s) = \sum_{x_{s^-}} \left[\, p\,(x_s \mid x_{s^-}) .\, p\,(x_{s^-}) \right]$

Transition Probabilities over scale [6]

3 $$p\,(x_s \mid x_{s^-}) = \begin{cases} \theta & x_s = x_{s^-} \\ \dfrac{1-\theta}{M-1} & x_s \neq x_{s^-} \end{cases}$$

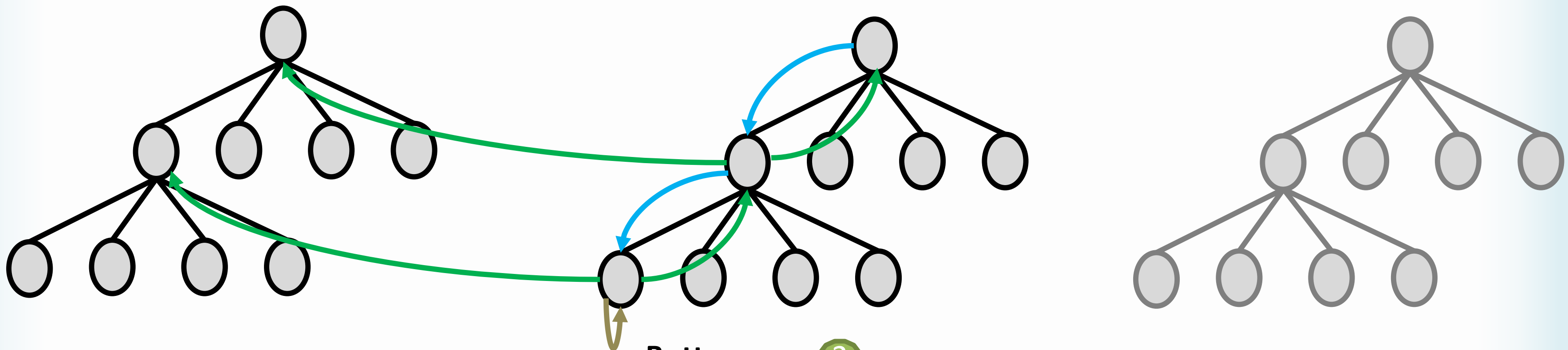
Transition Probabilities over scale and time

4 $$p\,(x_s \mid x_{s^-}, x_{s^=}) = \begin{cases} \theta & x_s = (x_{s^-} = x_{s^=}) \\ \varphi & x_s = (x_{s^-} \neq x_{s^=}) \\ \dfrac{1-\theta}{M-1} & x_s \neq (x_{s^-} = x_{s^=}) \\ \dfrac{1-2\varphi}{M-2} & x_s \neq (x_{s^-} \neq x_{s^=}) \end{cases}$$

[6] C. Bouman and M. Shapiro, "A multiscale image model for Bayesianimage segmentation," IEEE Trans. Image Processing, vol. 3, pp.162–177, Feb. 1994 f

Hierarchical Markovian Model

The Posterior marginal probabilities



Bottom-up 2

$p_2(x^{(r)})$

$p_2(x^{(1)})$

$p_2(x^{(0)})$

$p_2(x_r \mid y_{d(s)}) = p_2(x_r \mid y)$

$p_2\left(x_s^{(1)} \mid y_{d(s)}^{(1)}\right)$
$p_2\left(x_s, x_{s^-} x_{s^=} \mid y_s^{(1)}\right)$

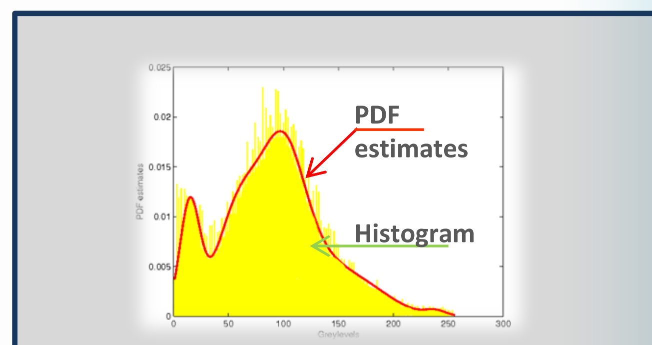
$p_2\left(x_s^{(0)} \mid y_s^{(0)}\right)$
$p_2\left(x_s, x_{s^-}, x_{s^=} \mid y_s^{(0)}\right)$

Initialisation : $p\,(x_s \mid y_s) \propto p\,(y_s \mid x_s).\, p\,(x_s)$

Posterior marginal [4]

$$p\,(x_s \mid y_{d(s)}) \propto p(y_s \mid x_s).\, p\,(x_s).\prod_{t \in s^+} \sum_{x_t} \left[\frac{p\,(x_t \mid y_{d(t)})}{p(x_t)}.\, p\,(x_t \mid x_s) \right]$$

Likelihood term estimated using Gaussian mixture

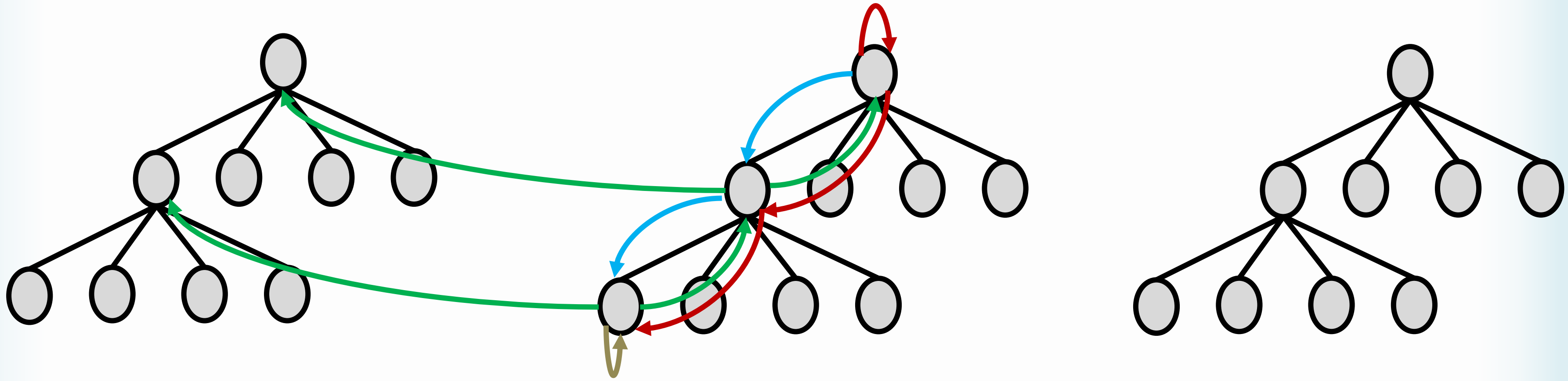


Urban area modeling

[4] Laferte, J.-M., Perez, P., and Heitz, F., "Discrete Markov modeling and inference on the quad-tree," IEEE Trans. Image Process. 9(3), 390-404 (2000).

Hierarchical Markovian Model

Maximisation step



$p_2\left(x^{(r)}\right)$

$p_2\left(x^{(1)}\right)$

$p_2\left(x^{(0)}\right)$

$p_2\left(x_r \mid y_{d(s)}\right) = p_2\left(x_r \mid y\right)$

$p_2\left(x_s^{(1)} \mid y_{d(s)}^{(1)}\right)$
$p_2\left(x_s\,, x_{s^-}\, x_{s^=} \mid y_s^{(1)}\right)$

$p_2\left(x_s^{(0)} \mid y_s^{(0)}\right)$
$p_2\left(x_s\,, x_{s^-}\,, x_{s^=} \mid y_s^{(0)}\right)$

$\hat{x}_r = \arg max_{x_r}\,[p\,(x_r \mid y)]$

$\hat{x}_s^{(1)} = \arg max_{x_r}\,[p\,\left(x_s^{(1)} \mid y\right)]$

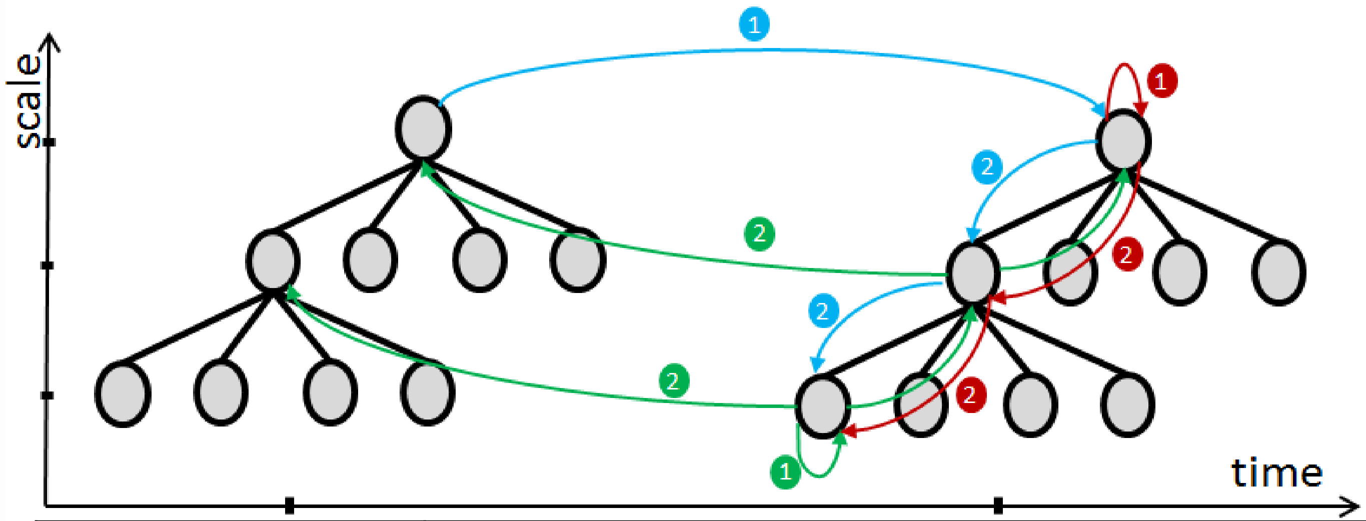
$\hat{x}_s^{(0)} = \arg max_{x_r}\,[p\,\left(x_s^{(0)} \mid y\right)]$

❖ **Need to maximize the posterior probability at the coarsest scale (top-down pass).**

❖ **Tool: modified Metropolis dynamics.** [7]

[7] **Kato, Z. Zerubia, J. and Berthod, M., "Satellite image classification using a modified Metropolis dynamics," IEEE International Conference on Acoustics, Speech, and Signal Processing, (ICASSP), Volume 3, 1992 .**

Summary: Recursive Passes on the Quad-tree



	initialisation ①	recursion ②
Top-down Prior $p(x_s)$	Potts MRF model	$p(x_s) = \sum_{x_{s^-}} [p(x_s \mid x_{s^-}).\, p(x_{s^-})]$
Bottom-up Partial Posterior $p(x_s \mid y_{d(s)})$	$p(x_s \mid y_s) \propto p(y_s \mid x_s).\, p(x_s)$	$p(x_s \mid y_{d(s)}) \propto p(y_s \mid x_s).\, p(x_s).\prod_{t\in s^+}\sum_{x_t}\left[\frac{p(x_t \mid y_{d(t)})}{p(x_t)}.\, p(x_t \mid x_s)\right]$
Top-down Posterior $p(x_s \mid y)$	$p(x_r \mid y_{d(r)}) = p(x_r \mid y)$	$p(x_s \mid y) = \sum_{x_{s^-}, x_{s^=}}\left[\frac{p(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)})}{\sum_{x_s} p(x_s, x_{s^-}, x_{s^=} \mid y_{d(s)})}.\, p(x_{s^-} \mid y)\, p(x_{s^=} \mid y)\right]$

Contents

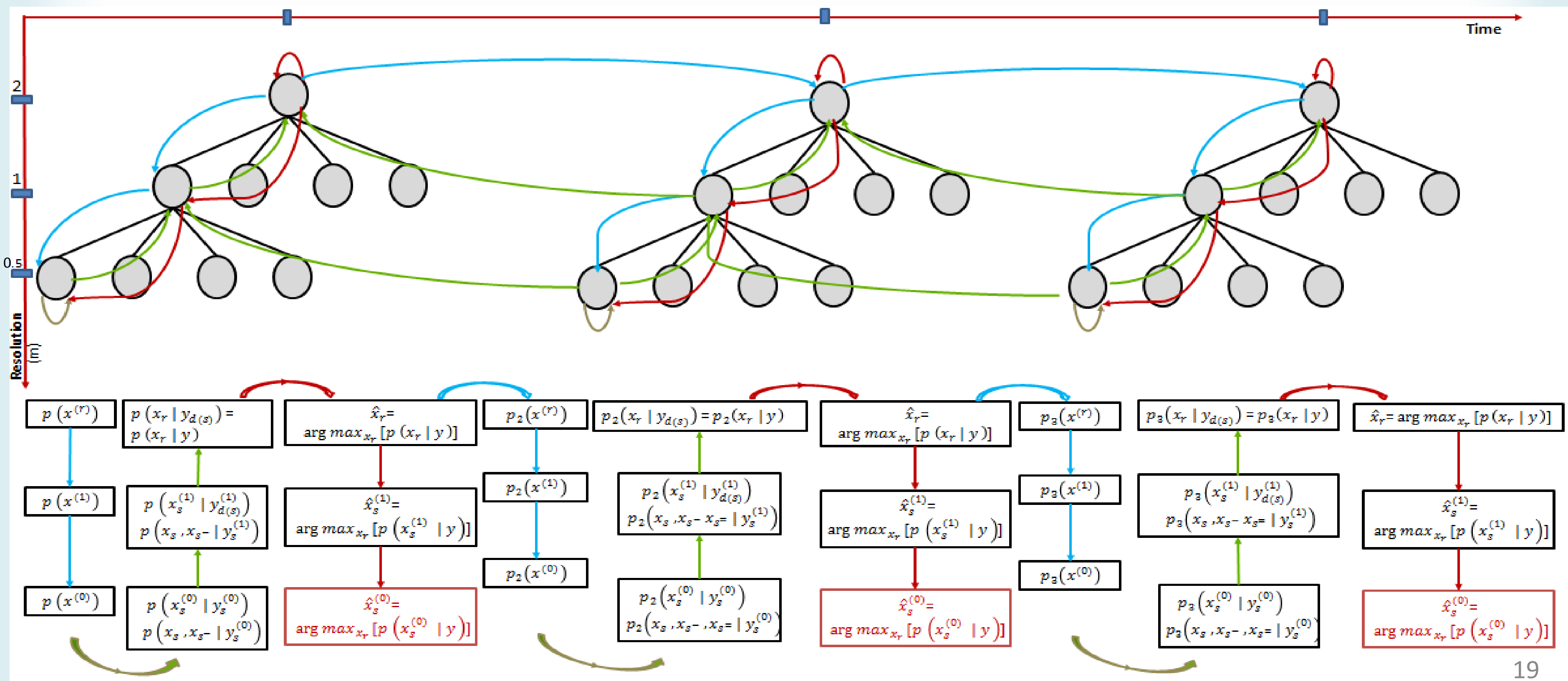
Hierarchical Markovian Model

Time series of panchromatic and multispectral Pléiades images acquired over Port-au-Prince (Haiti)

Port au Prince
Pléiades ©CNES (2011), distribution Airbus DS
- Panchromatic 0.7 m (resampled at 0.5 m)
- Multispectral 2.8 m (resampled at 2 m)

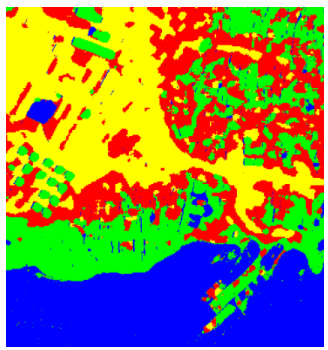
Port au Prince
Pléiades ©CNES (2012), distribution Airbus DS
- Pansharpened image (resampled at 0.5 m)

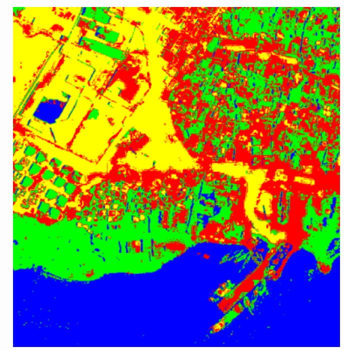
Port au Prince
Pléiades ©CNES (2013), distribution Airbus DS
- Panchromatic 0.7 m (resampled at 0.5 m)
- Multispectral 2.8 m (resampled at 2 m)



Experimental Results on Multitemporal Data

water
urban
vegetation
bare soil



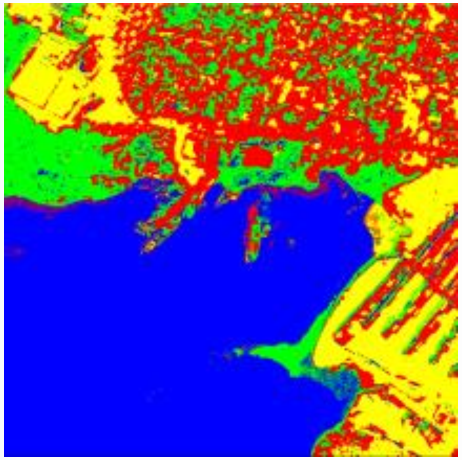


Classification map using monotemporal images

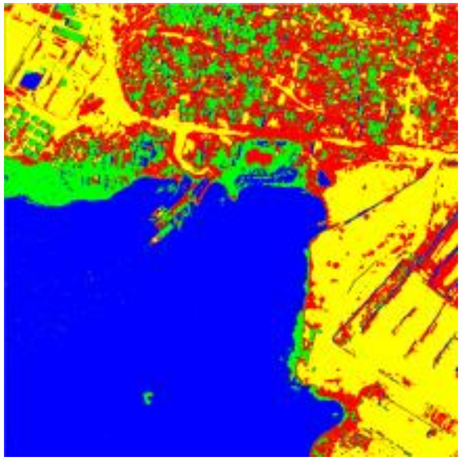
Classification map using time series images

		urban	water	vegetation	bare soil
GROUND TRUTH	**Urban**	**71.62 %**	14.19%	5.67 %	8.53 %
	Water	2.08%	**94.05 %**	2.38 %	1.48%
	vegetation	1.26%	1.04%	**96.69 %**	1.1 %
	Bare soil	3.94%	2.15%	1.07 %	**92.82 %**
	Overall accuracy	**88,79 %**			

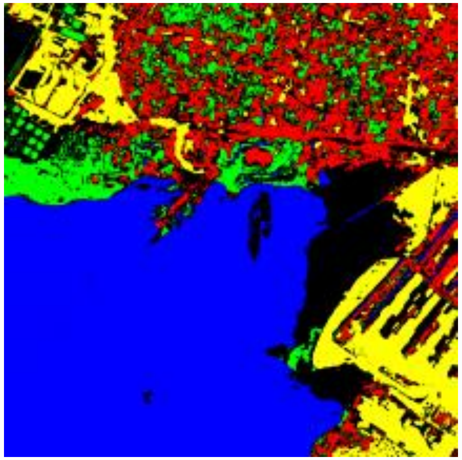
Confusion matrix for the Port-au-Prince dataset.



Classification map for 2012, obtained through the proposed cascade method using images acquired in 2011 and 2012



Classification map for 2013, obtained through the proposed cascade method using all images (15 images in total).



Change map derived from the classification result of the proposed method (change is indicated in black).

Conclusion

❖Satisfying classification results obtained through the proposed Markovian method.

❖Details provided by the multitemporal hierarchical model.

Perspectives

Further experimental validation with more spatially detailed ground truth on Haïti (provided by SERTIT, France in the near future)

Propose a new hierarchical model in order to :

❖Use a different number of classes at each level of the pyramid.
❖Update of the model according to the update of the ground truth made by SERTIT in collaboration with CNES
❖Extend to multisensor optical-radar imagery