KAL-Haïti

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# Classification supervisée et détection de changements à partir d'images d'*Haïti* à haute résolution (*CSK/GeoEye ou CSK/Pleiades*) par utilisation de méthodes Markoviennes.

# Supervised classification and change detection from high resolution (CSK / GeoEye or CSK / Pleiades) images from *Haïti* using Markovian methods.


Presented by

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# Introduction



## Objectives

- Supervised image classification
- Change detection (using 2 dates or temporal series)
- General and sufficiently robust to different types of images.

## Key points

- Focus on (single-pol) radar (SAR) imagery
- extension to multi-sensor  data (CSK/ GeoEye or CSK/Pleiades).

## General applications

- Global detection of urban areas, that are critical w.r.t. populations (risk management).
- Infrastructures mapping.

...

## Optical imagery

Port au Prince (GeoEye) © GeoEye

•Here considered as an additional information to SAR. ( *0.5 m)*

## SAR imagery

Port au Prince (CSK) © ASI

•All-weather conditions.

•SAR amplitude.

•SpotLight ( *1m), StripMap ( 2.5m), PingPong (10m).*

•Challenge: Speckle noise.

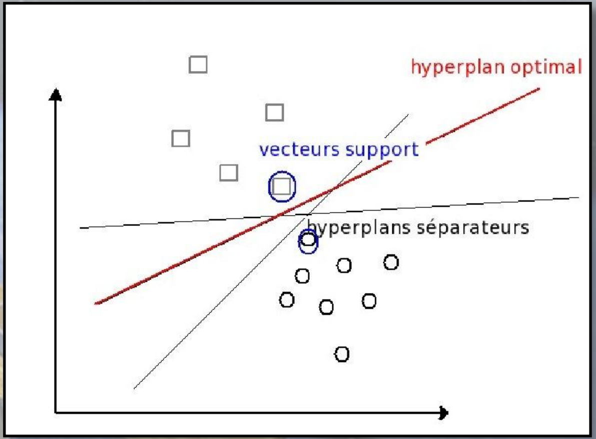
# Supervised classifiers



## Support Vector Machine (SVM)[1]

•Well-chosen projections to reformulate the classification problem as a resolution of quadratic optimization problem, maximizing the distance between the separating border and the closest learning samples.

•Extension to nonlinear classification through kernel functions.




## K-nearest neighbors (K-NN)

•Used to model the probability density functions.

•Integrated in a MRF model.

•Supervised estimation of the probability of a given pixel by using a majority vote on the *K-nearest (distance rule) known* pixels.

•*K estimated by cross validation.*

**[1]** V. Vapnik, [The Nature of Statistical Learning Theory], Springer, 2*nd edition, (2000).*

# Supervised classifiers



## Proposed methods

**2 supervised contextual classifiers based on MRF :**

- **MRF with textural features**
- **Hierarchical MRF integrating a prior update**

## Contributions of A.Voisin (PhD), V. Krylov (Post-Doc)

**2 supervised contextual classifiers :**

- **Shared learning:** statistical modeling of the input images, by using **adapted finite mixtures** and ***d-variate copulas.***
- **Integration of the statistics in Markovian models:** MRF with **textural features**, and hierarchical MRF integrating a **prior update**

**[2]** A. Voisin, G. Moser, V. Krylov, S. B. Serpico, and J .Zerubia, "Classification of very high resolution SAR images of urban areas by dictionary-based mixture models, copulas and Markov random fields using textural features," in [Proc. of SPIE Symposium on Remote Sensing], 78300O (2010).

**[3]** A. Voisin, V. Krylov, G. Moser, S. B. Serpico, and J .Zerubia, "Multichannel hierarchical image classification using multivariate copulas", in [Proc. of IS&T/SPIE Electronic Imaging], 82960K (2012).

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1 **Joint PDF**

- ❖Marginal PDF modeling
- ❖Joint PDF modeling

2 Single-scale Markovian model

3 Hierarchical Markovian model

4 Experimental results

5 Conclusion and Perspectives

# Copulas : Overview

The reflectivity in SAR and optical bands are very different from each other

How to address the complicated problem of SAR + optical PDF modeling ?

1. First, estimate the marginal class-conditional statistics of each SAR/optical channel separately via distinct finite mixtures.
2. then, model the joint PDF through copulas.[4]

A copula is a kind of distribution function. Copulas are used to describe the dependence between random variables.

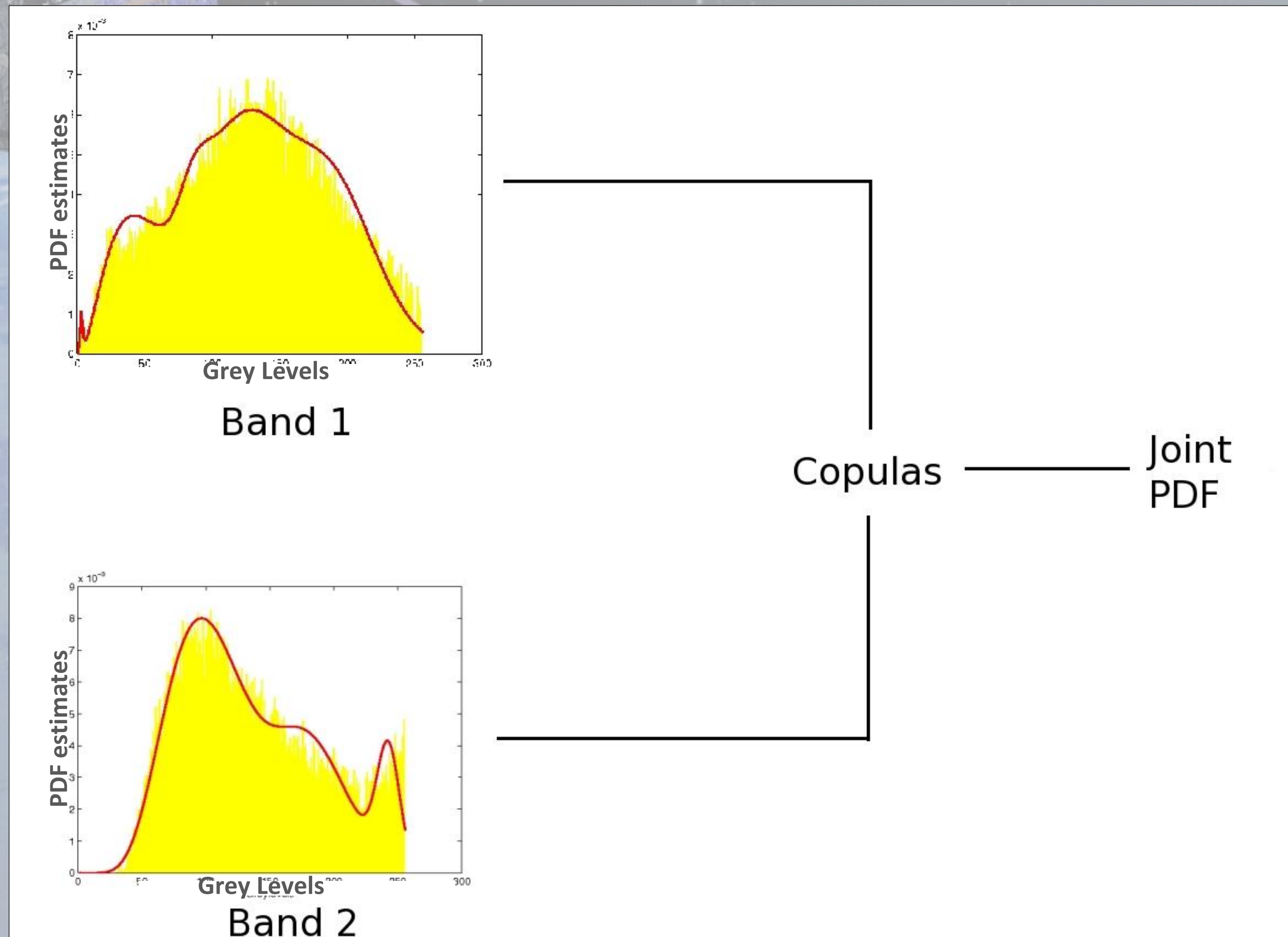
| Copula | $C(u_1, \dots, u_d)$ | $\theta(\tau)$ | $\tau$ interval |
| --- | --- | --- | --- |
| Clayton | $\left[\left(\sum_{i=1}^{d} u_i^{-\theta}\right) - d + 1\right]^{-1/\theta}$ | $\theta = \frac{2\tau}{1-\tau}$ | $\tau \in ]0; 1]$ |
| AMH (Ali-Mikhail-Haq) | $\frac{\prod_{i=1}^{d} u_i}{1-\theta \prod_{i=1}^{d}(1-u_i)}$ | $\tau = \frac{3\theta-2}{3\theta} - \frac{2}{3}\left(1-\frac{1}{\theta}\right)^2 \ln(1-\theta)$ | $\tau \in [-0,182; \frac{1}{3}]$ |
| Gumbel | $\exp\left(-\left[\sum_{i=1}^{d}(-\ln u_i)^{\theta}\right]^{1/\theta}\right)$ | $\theta = \frac{1}{1-\tau}$ | $\tau \in [0; 1]$ |

In order to maximize flexibility in the proposed method, a dictionary approach is adopted for copula modeling

[4] Nelsen, R. B., [An introduction to copulas], Springer, New York, 2nd ed. (2006).

# Joint PDF : Overview

**For each class *m, and at each resolution (multi-resolution case):* Build a joint PDF.**




***Note :** the two bands may come from multiple polarizations (e.g., CSK pingpong) and/or multiple sensors (e.g., CSK stripmap and GeoEye).*

## Marginal PDF modeling

For each input image, we want to estimate the distributions of each class $m \in [1; M]$. The PDF $f_m^{(j)}(\mathbf{y}^{(j)})$ of the $j^{th}$ input band, $j \in [1; d]$, is modeled via **finite mixtures**:

$$f_m^{(j)}(\mathbf{y}^{(j)}) = p_m^{(j)}(\mathbf{y}^{(j)}|\omega_m) = \sum_{i=1}^{K^{(j)}} P_{mi}^{(j)} p_{mi}^{(j)}(\mathbf{y}^{(j)}|\theta_{mi}^{(j)})$$

$\mathbf{y}^{(j)}$ is a greylevel

$P_{mi}^{(j)}$ are the mixing proportions such that $\sum_{i=1}^{K} P_{mi}^{(j)} = 1$

$\theta_{mi}^{(j)}$ is the set of parameters of the $i^{th}$ PDF mixture component of the $m^{th}$ class

mi is the i-th component of the mixture that models the class m

## Advantages of finite mixtures

❖ Unimodal density does not accurately model SAR amplitude statistics given their heterogeneity.

❖ Each component (of the sum) may reflect the contribution of the different materials.

# Marginal PDF modeling: Optical image case

**Gaussian distribution** is a usually accepted model for optical imagery:

$$p_{mi}(\mathbf{y}|\theta_{mi}) = \frac{1}{\sqrt{2\pi\sigma^2_{mi}}} \exp\left[-\frac{(\mathbf{y}-\mu_{mi})^2}{2\sigma^2_{mi}}\right], \quad \text{with } \theta_{mi} = \{\mu_{mi}, \sigma^2_{mi}\}.$$

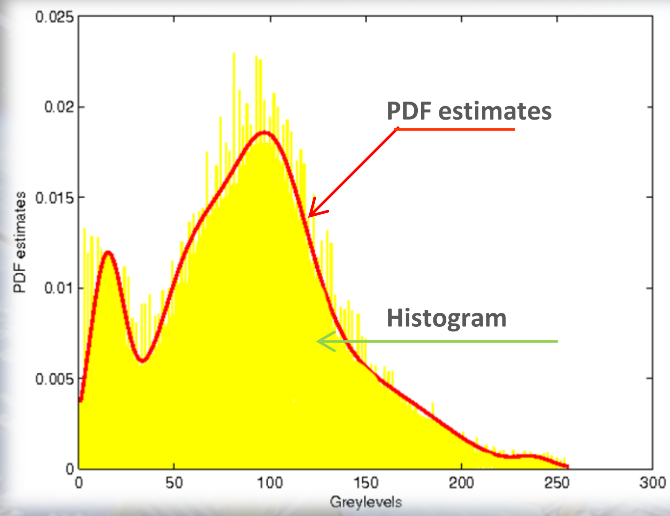
The parameters $P_{mi}$, $\theta_{mi}$ are estimated within a SEM* algorithm .

* Stochastic Expectation Maximization algorithm [5]

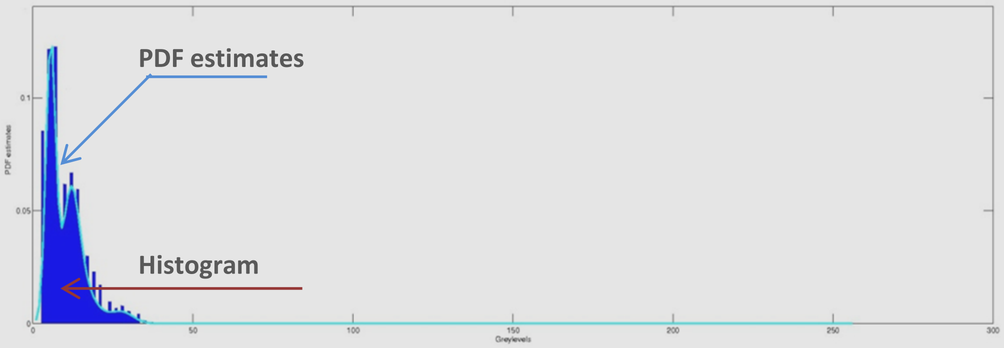
[5] G. Celeux, D. Chauveau, and J. Diebolt, "Stochastic versions of the EM algorithm: an experimental study in the mixture case," Journal of Statistical Computation and Simulation, 55(4), 287-314 (1996).

# Experimental validation

Port au Prince (©GeoEye)
(0.5 m)




Urban area modeling




Water modeling

## Marginal PDF modeling: SAR image case[6]

$P_{mi}$, $\theta_{mi}$ and K are estimated within a SEM algorithm combined with the method of log-cumulants. Best family chosen through ML.

| Family | Probability density function | MoLC equations |
|---|---|---|
| **Generalized Gamma** | $p_{mi}(y\|\theta_{mi}) = \frac{\nu_{mi}}{\sigma_{mi}\Gamma(\kappa_{mi})}\left(\frac{y}{\sigma_{mi}}\right)^{\kappa_{mi}\nu_{mi}-1}\exp\left\{-\left(\frac{y}{\sigma_{mi}}\right)^{\nu_{mi}}\right\}$ | $\kappa_1 = \Psi(\kappa)/\nu + \ln\sigma$<br>$\kappa_2 = \Psi(1,\kappa)/\nu^2$<br>$\kappa_3 = \Psi(2,\kappa)/\nu^3$ |
| Log-normal | $p_{mi}(y\|\theta_{mi}) = \frac{1}{\sigma_{mi}y\sqrt{2\pi}}\exp\left[-\frac{(\ln y - m_{mi})^2}{2\sigma_{mi}^2}\right]$ | $\kappa_1 = m$<br>$\kappa_2 = \sigma^2$ |
| Weibull | $p_{mi}(y\|\theta_{mi}) = \frac{\eta_{mi}}{\mu_{mi}^{\eta}}y^{\eta_{mi}-1}\exp\left[-\left(\frac{y}{\mu_{mi}}\right)^{\eta_{mi}}\right]$ | $\kappa_1 = \ln\mu + \Psi(1)\eta^{-1}$<br>$\kappa_2 = \Psi(1,1)\eta^{-2}$ |
| Nakagami | $p_{mi}(y\|\theta_{mi}) = \frac{2}{\Gamma(L_{mi})}(\lambda_{mi}L_{mi})^{L_{mi}}\,y^{2L_{mi}-1}\exp\left(-\lambda_{mi}L_{mi}y^2\right)$ | $2\kappa_1 = \Psi(L) - \ln\lambda L$<br>$4\kappa_2 = \Psi(1,L)$ |

## Modified SEM algorithm - Settings

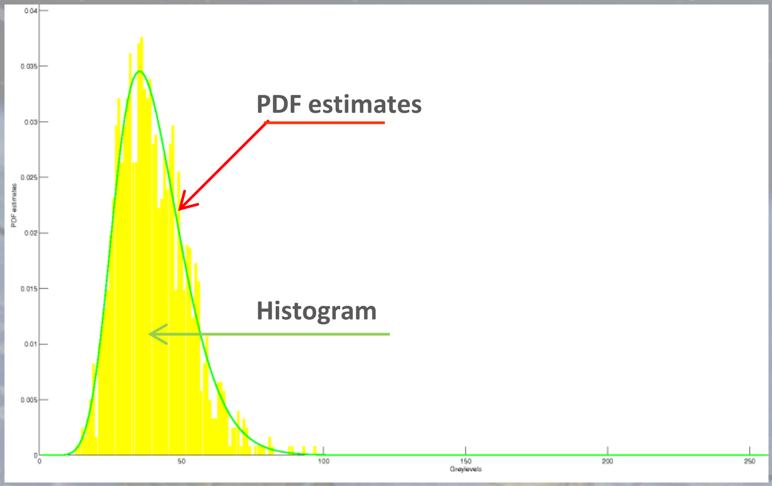
- **Initialization: *Kmax = 6.***
- **Stop criterion: Maximum number of iterations reached**

**[6]** Krylov, V., Moser, G., Serpico, S. B., and Zerubia, J., “Supervised high resolution dual polarization SAR image classification by finite mixtures and copulas,” IEEE J-STSP, 5(3), 554-566 (2011).

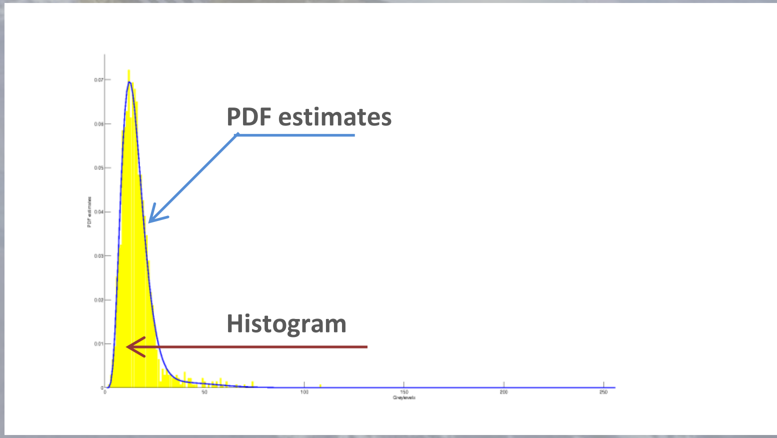
# Experimental validation

**Port au Prince (CSK) © ASI**

SpotLight ( *1m*), *StripMap ( 2.5m)*
*PingPong (10m).*




**Urban area modeling**




**Water modeling**

## General presentation

- Classification of multi-band, single-resolution acquisitions into *M classes.*
- Contextual information via MRF.
- Use the Bayesian formulation:

$$p_m(x = \omega_m | y) \propto p(x) \times p_m(y | x = \omega_m)$$

**X, Y** random variables and $\omega_m \in [1, M]$

# Prior probabilities

For each class $m \in [1, M]$ (Gibbs):

$$p(x_s) = \frac{\exp(-U(x_s = \omega_m))}{\sum_{j=1}^{M} \exp(-U(x_s = \omega_j))}$$

Potts model:

$$U(x_s, \beta) = \sum_{s' \in S} \left[ -\beta \sum_{s : \{s, s'\} \in C} \delta_{x_s = x'_s} \right]$$

where

$$\beta > 0 \quad \text{and} \quad \delta_{x_s = x_{s'}} = \begin{cases} 1, & \text{if } x_s = x_{s'} \\ 0, & \text{otherwise} \end{cases}$$

$s$ and $s'$ belong to the same clique $C$.

## Optimization

❖Need to maximize the posterior probability to find the labels.

❖Here: **minimization of the energy function:**

$$H(x = \omega_m | y, \beta) = \sum_{t \in S} \left[ -\log p_m(y_t | x_t = \omega_m) - \beta \sum_{s:\{s,t\} \in C} \delta_{x_s = x_t} \right]$$

**Tools:**

❖**Modified Metropolis dynamics.**[7]

❖**Graph-cuts.**

**[7]** Berthod, M., Kato, Z., Yu, S., and Zerubia, J., “Bayesian image classification using Markov random fields,” Image and Vision Computing 14(4), 285-295 (1996).

# Textural features [8]

**Problem:** often limited class discriminability in single-pol SAR amplitudes.

**Aim:** Improve the classification accuracy by integrating some additional information: textural features.

- ❖ Urban area discrimination.
- ❖ Well-adapted textural feature: Haralick's Grey Level Co-occurrence Matrix (GLCM) variance.[9]

**Principle :** Moving $w \times w$ *window, and estimation of the value* of the central pixel by using its neighborhood (calculation of spatial second-order statistics).

[8] Voisin, A., Moser, G., Krylov, V., Serpico, S. B., and Zerubia, J., "Classification of very high resolution SAR images of urban areas by dictionary-based mixture models, copulas and Markov random fields using textural features," in [Proc. of SPIE Symposium on Remote Sensing], 78300O (2010).
[9] R. M. Haralick, K. Shanmugam and I. Dinstein, "Textural features for image classification," IEEE TRans. Syst., Man, Cybern. 3(6), 610-621 (1973).

## Experimental settings

- **Number of classes M fixed by the user.**
- **MRF β parameter manually fixed ( β between 1.3 and 3.7).**
- **Windows of size w = 5 for textural feature extraction.**
- **Ground truth sets represent 5% of the whole image.**

1 Joint PDF

2 Single-scale Markovian model

3 **Hierarchical Markovian model**

- ❖ Model presentation
- ❖ Transition probabilities
- ❖ Prior probability

4 Experimental results

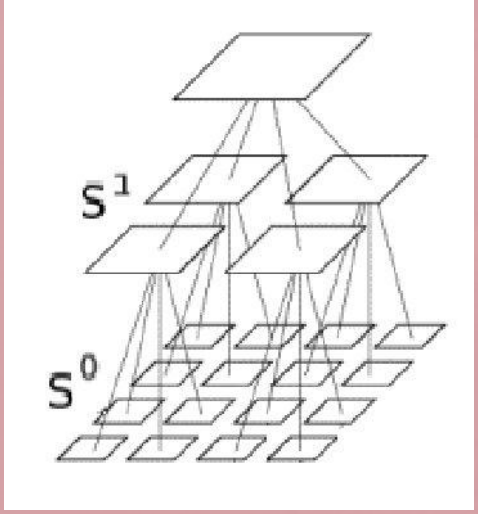
5 Conclusion and Perspectives

## Considered DATA

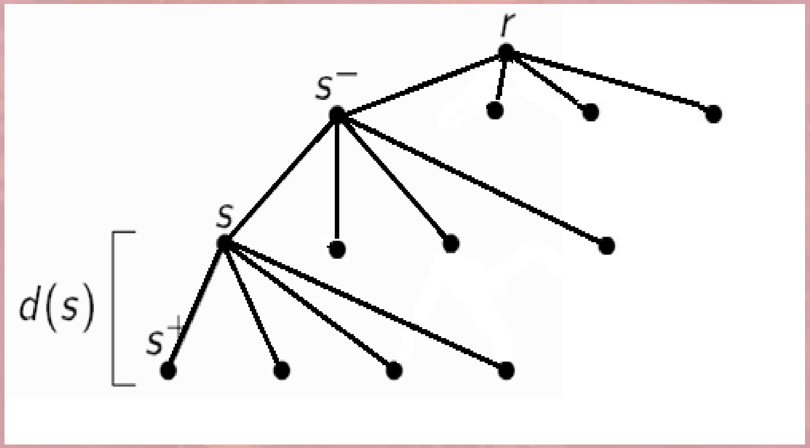
- Classification of coregistered mono-/multi-band, multi-resolution and/or multi-sensor (SAR, optical) acquisitions into $M$ *classes*
- **Hierarchical graph**: use multi-resolution data.
- **Flexible** enough to take into account different kinds of statistics (multi-sensor data).

# Notations

**The novelty in this work is in keeping the multi-resolution aspect by integrating the multisensor data in an explicit hierarchical Markovian model, based on a quad-tree structure.**




Hierarchical model (quad-tree)




Quad-tree notations

# General presentation: Hierarchical method [10]

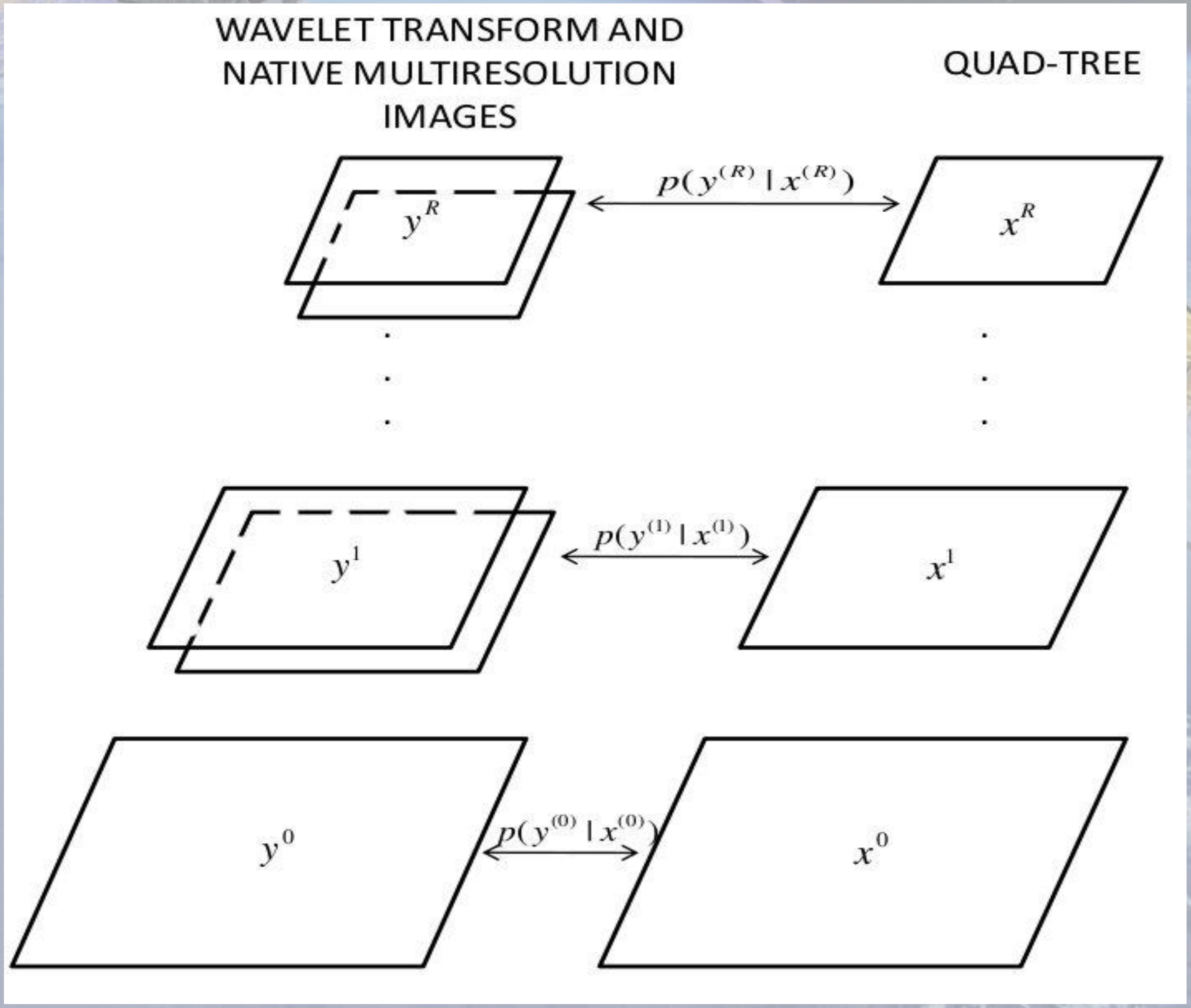
❖**Classification**: **Estimate the labels *X at the finest resolution* (here, level 0) given all the observations.**

❖**Quad-tree structure**: **causality that allows to use a non-iterative algorithm.**

❖**MPM (marginal posterior mode)** **penalizes the errors according to their number and the scale at which they occur.**

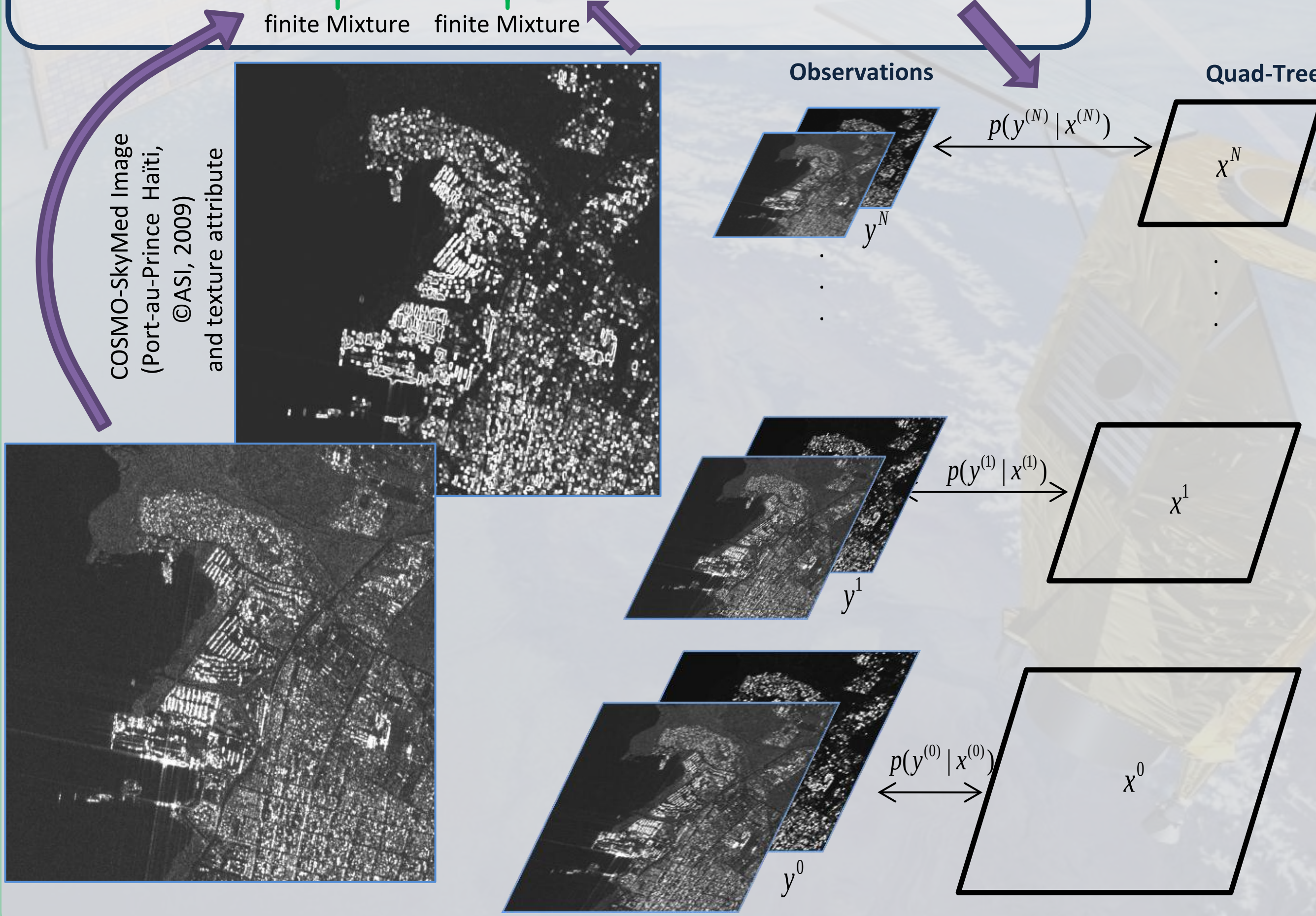
**[10]** Laferte, J.-M., Perez, P., and Heitz, F., "Discrete Markov modeling and inference on the quad-tree," IEEE Trans. Image Process. 9(3), 390-404 (2000).

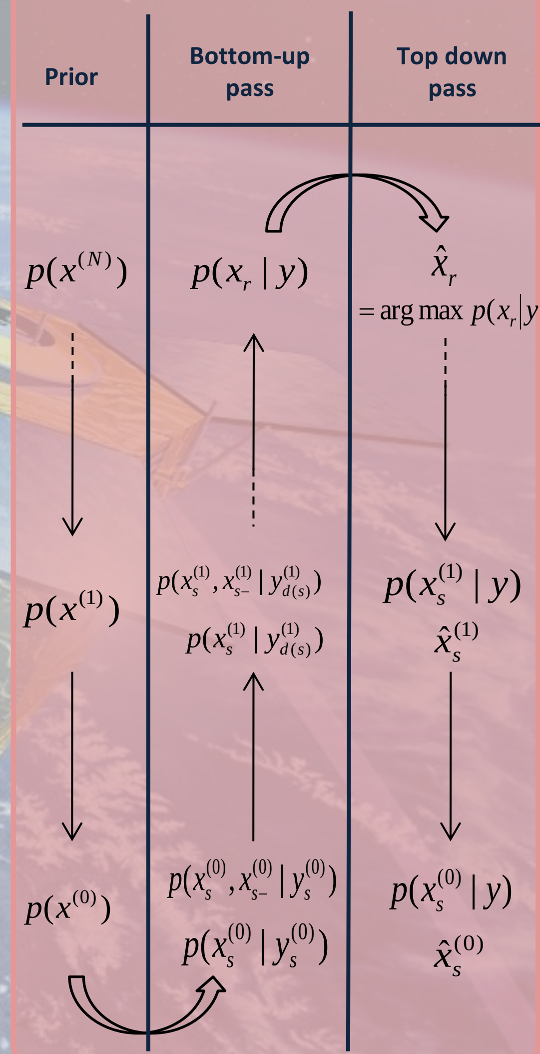
**Wavelet transforms** are used in the proposed method to **generate multiscale features** and a **hierarchical MRF-based approach** is defined **to fuse** the extracted **multiscale information** and generate the output classification map.



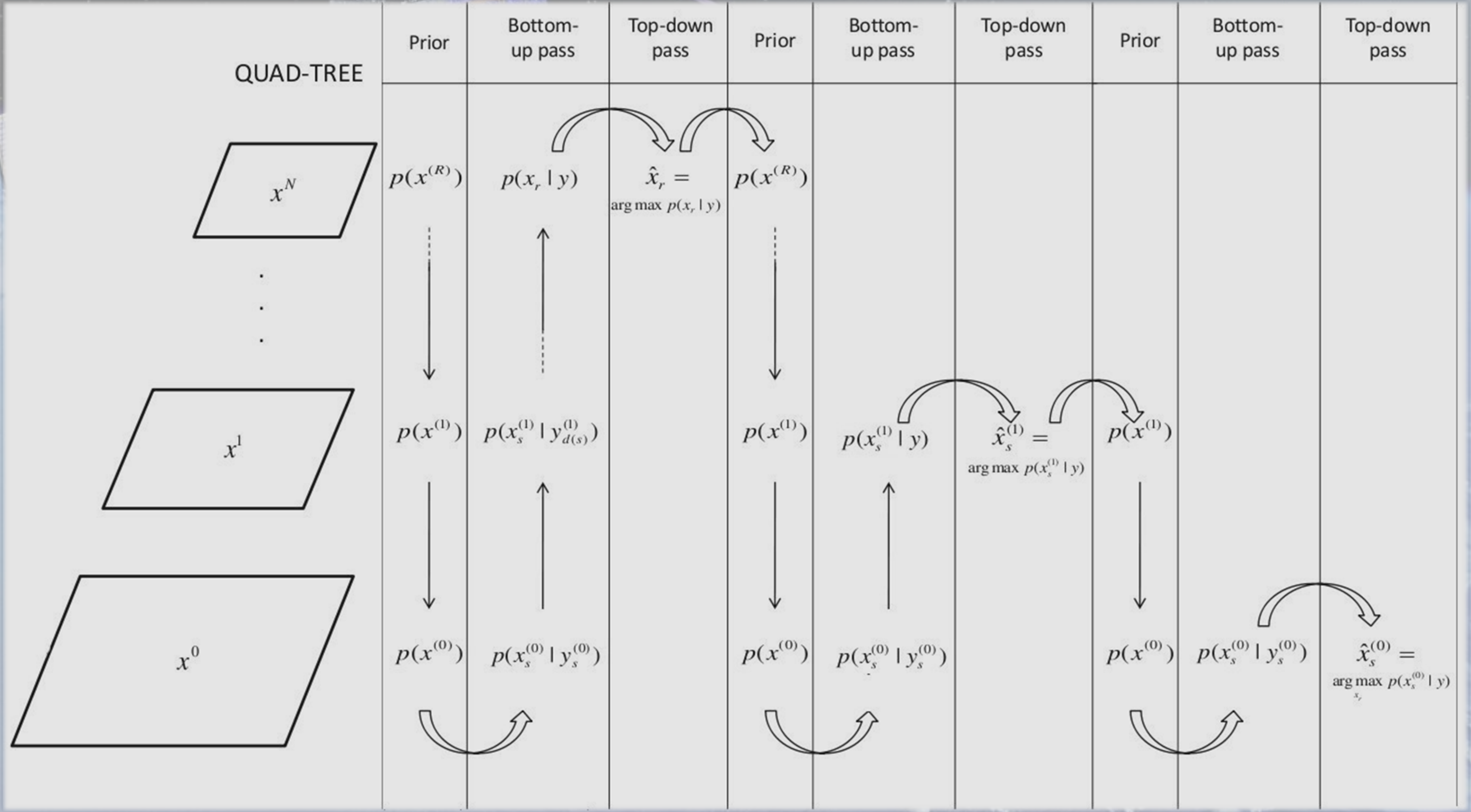
# Initial marginal posterior mode (MPM) scheme

$$p_m(y^{(n)}|x_m^{(n)}) = \underbrace{p_{1m}(y_1^{(n)}|x_m^{(n)})}_{\text{finite Mixture}}.\underbrace{p_{2m}(y_2^{(n)}|x_m^{(n)})}_{\text{finite Mixture}}\frac{\partial^2 C_m^*\left(F_{1m}(y_1^{(n)}|x_m^{(n)}), F_{2m}(y_2^{(n)}|x_m^{(n)})\right)}{\partial y_1^{(n)}\partial y_2^{(n)}}$$



# Global scheme - prior update[11]




**[11]** A. Voisin, V. Krylov, G. Moser, S.B. Serpico and J. Zerubia, "Classification of Very High Resolution SAR Images of Urban Areas Using Copulas and Texture in a Hierarchical Markov Random Field Model," IEEE Geoscience and Remote Sensing Letters, 10(1), 96-100 (2013).

## Optimization

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

❖ Tool: modified Metropolis dynamics.

## Posterior probability

Expression of the partial posterior probability (bottom-up pass):

$$p(x_s|y_{d(s)}) = \frac{1}{Z} p(y_s|x_s) p(x_s) \prod_{t \in s^+} \sum_{x_t} \left[ \frac{p(x_t|y_{d(t)})}{p(x_t)} p(x_t|x_s) \right]$$

Thus, we need to define the prior probabilities, the transition probabilities. The likelihood has already been defined (joint PDF at each level of the tree).

# Transition probabilities [12]

For all sites s ∈ S and all scales n ∈ [0; R – 1], R corresponding to the root

$$p(x_s = \omega_m | x_{s^-} = \omega_k) = \begin{cases} \theta_n, & \text{if } \omega_m = \omega_k \\ \frac{1-\theta_n}{M-1}, & \text{otherwise} \end{cases}.$$

With $\theta_n > 1/M$

The transition probabilities determine the hierarchical MRF since they represent the causality of the statistical interactions between the different levels of the tree.

# Prior probabilities

Prior probabilities at the coarsest level: Updated. Prior probability at level n in [0; R – 1]:

$$p(x_s^n) = \sum_{x_{s^-}^n} p(x_s^n | x_{s^-}^n) p(x_{s^-}^n).$$

**[12]** Bouman, C. and Shapiro, M., "A multiscale random field model for Bayesian image segmentation," IEEE Trans. Image Process. 3(2), 162-177 (1994).

# General presentation: Example of multisensor data classification

**Example of classification result for a multi-sensor acquisition over the Port au-Prince quay (Haiti).**

SAR image ( ©ASI, 2010) (2.5 *m)*

Optical image (©GeoEye, 2010) (0.625 *m)*

Hierarchical MRFbased classification (optical+ SAR)

## Experimental settings

- Number of classes M fixed by the user.
- $\Theta_n = 0.85$ (transition probability).
- For native single-resolution images, the multi-resolution acquisitions are obtained by wavelet transform (Daubechies[12] and Haar) on R = 3 levels.

## Multi-sensor acquisition of Port-au-Prince (Haiti)

2 coregistered images of the quay of Port-au-Prince (Haiti):

- A single-polarized COSMO-SkyMed SAR image ( ©ASI,2010), HH polarization, StripMap acquisition mode (2*.5 m* pixel spacing), geocoded, single-look of 320 × *400 pixels.*
- A pan-sharpened (1-band) GeoEye acquisition (©GeoEye, 2010, 0*.625 m pixel spacing) of 1280 × 1600 pixels.*

**[12]** I. Daubechies, “Orthonormal bases of compactly supported wavelets,” Communications on Pure and Applied Mathematics, 41(7), 909-996 (1988).

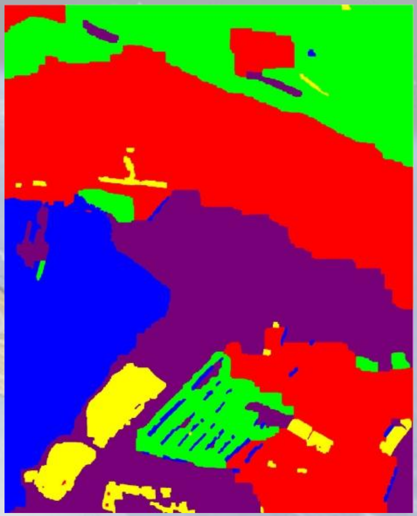
# General presentation: Example of multisensor data classification

**Classification results, 5 classes: water, urban, vegetation, sand, and containers.**

Optical image
(©GeoEye, 2010) 0.625 *m*

K-means

Hierarchical
MRF-based classifier



Single-scale MRF

| | Port-au-Prince, Haiti | | | | | | |
|---|---|---|---|---|---|---|---|
| | water | urban | vegetation | sand | containers | overall | Time Exec |
| Proposed SAR+optical | 100% | 75.24% | 87.16% | 98.89% | 49.31% | **82.12%** | ≈30 min |
| Single-scale MRF | 100% | 100% | 81.42% | 99.94% | 59.62% | **88.20%** | ≈6 min |
| K-means | 100% | 39.01% | 91.19% | 82.32% | 6.54% | **57.30%** | |

**Experiments were conducted on an Intel Xeon quad-core(2.40 GHz and 12-MB cache) 18-GB-RAM 64-bit Linux system. SAR image (320x400) and optical image (1280x1600).**

## Conclusion

❖ Urgent need of more data with ground trouth on Haïti (Both CSK and Pleiades) to validate the proposed methods.

❖Satisfying classification results obtained by using these Markovian methods. (Smoothing effect of the MRF. )

❖Details provided by the hierarchical MRF.

❖Selection of the best method according to the user.

## Perspectives

❖ Extension of the previous methods to :
  - ❖Change detection
  - ❖Satellite image time series analysis

❖Extension of the copula dictionary

# Acknowledgments

We would like to thank :

- The Direction Générale de l'Armement (DGA, France) and Institut National de Recherche en Informatique et Automatique (INRIA, France) for the partial financial support.
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- GeoEye Inc. And Google crisis response for providing the GeoEye images.
- The Centre National d'Etudes Spatiales (CNES, France) for providing Pleiades data in the near future.


# Thank you For your attention

*For more information : https://team.inria.fr/ayin/*
*And previously https://www-sop.inria.fr/ariana/*