CLASSIFICATION OF VHR SAR IMAGES OF URBAN AREAS BY DICTIONARY-BASED MIXTURE MODELS, COPULAS AND MARKOVIAN MODELS USING TEXTURAL FEATURES

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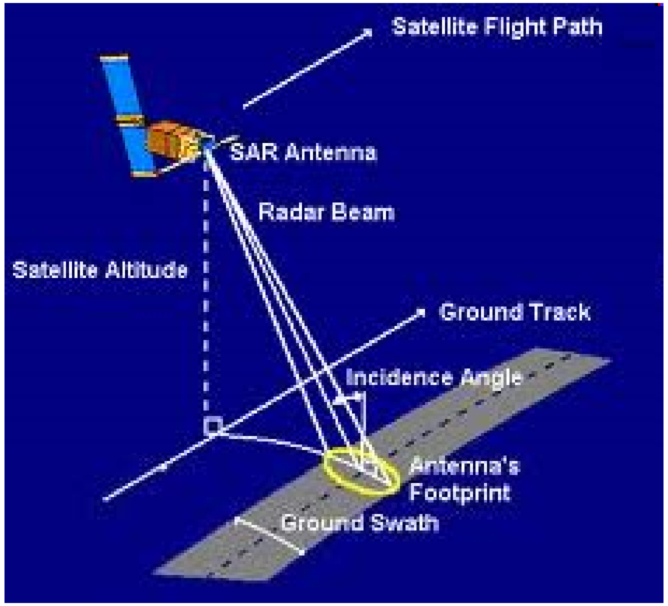
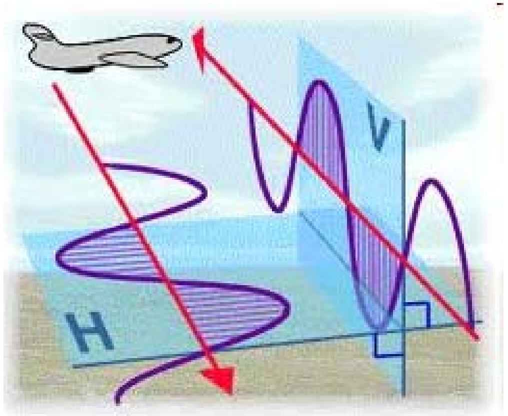
INTRODUCTION

- Synthetic Aperture Radar (SAR): active imagery





INTRODUCTION

- Example of SAR image: Port-au-Prince quay (©ISA, 2009)

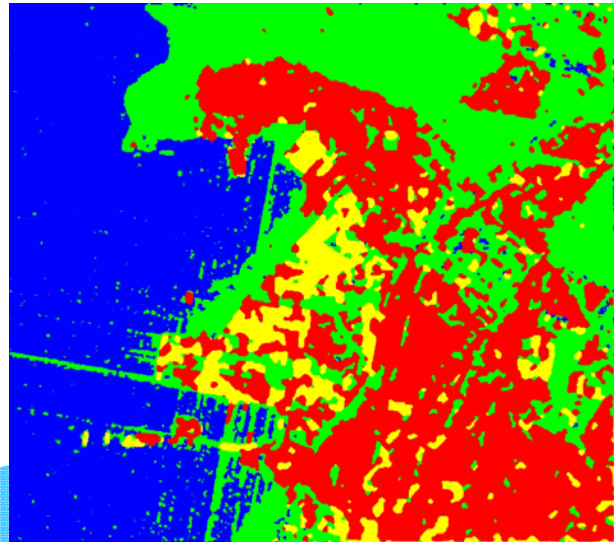
INTRODUCTION

- Synthetic Aperture Radar (SAR): good properties
  - Risk management
- Very high resolution (VHR) SAR data (up to metric resolution)
  - Speckle [Oliver 98]
  - Heterogeneity
- Supervised classification of VHR single-channel SAR amplitude images
  - Methods: bags-of-features [Yang 09], SVM, etc.
  - Proposed method: statistical modeling + Markov random fields (MRFs)

CLASSIFICATION

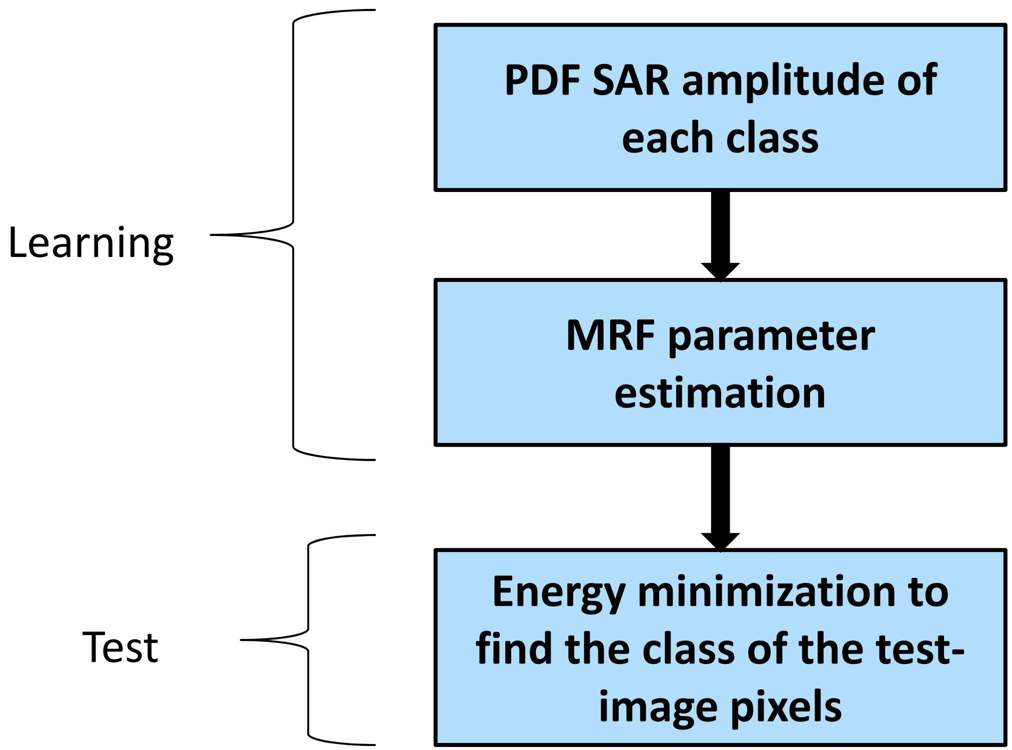
- Supervised classification
  - 1 learning image
  - 1 test image

- M classes (e.g.: water, vegetation, urban)



CLASSIFICATION USING MRF METHOD

[Moser 10]



CLASSIFICATION USING MRF METHOD

[Moser 10]

Learning

PDF SAR amplitude of each class

↓

MRF parameter estimation

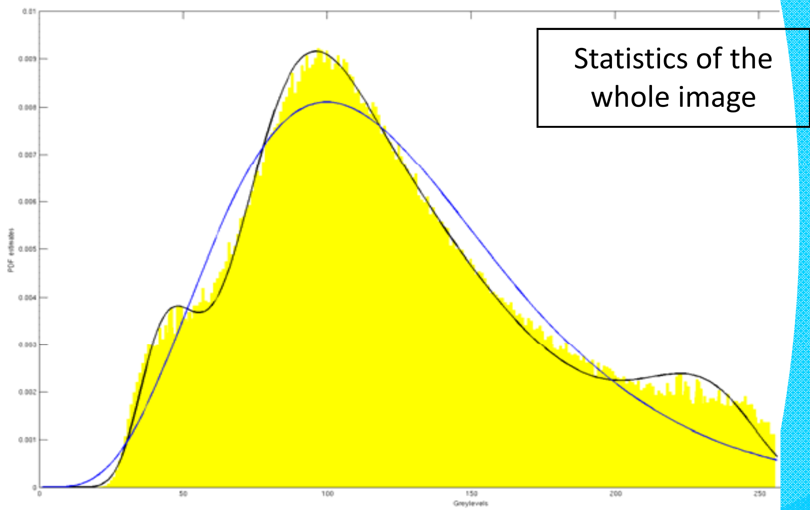
↓

Test

Energy minimization to find the class of the test-image pixels

DSEM - RESULTS

Terra SAR-X image of Roshenheim (Germany) (©Infoterra, 2008)



DSEM

Dictionary-based **S**tochastic **E**xpectation **M**aximization

- Heterogeneity of SAR images
  - Single probability density function (PDF) doesn't accurately model SAR amplitude statistics
  - Model the SAR amplitude PDF by a FMM (Finite Mixture Model)

$$p(r|\theta) = \sum_{k=1}^{K} P_k . p_k(r|\theta_k)$$

DSEM - ALGORITHM

$$p(r|\theta) = \sum_{k=1}^{K} P_k . p_k(r|\theta_k)$$

- Estimation of:
  - K: number of components
  - $p_k(r|\ \theta_k)$: k^{th} PDF family component
  - Parameters of the k^{th} component (θ_k and P_k)

with $\sum_{k=1}^{K} P_k = 1$ $\qquad 0 \leq P_k \leq 1$

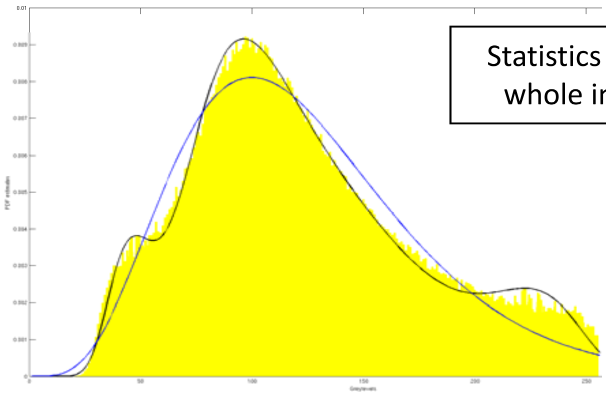
- Data incompleteness
  - $r = \{r_1, \ldots, r_N\}$ belongs to which statistical population?

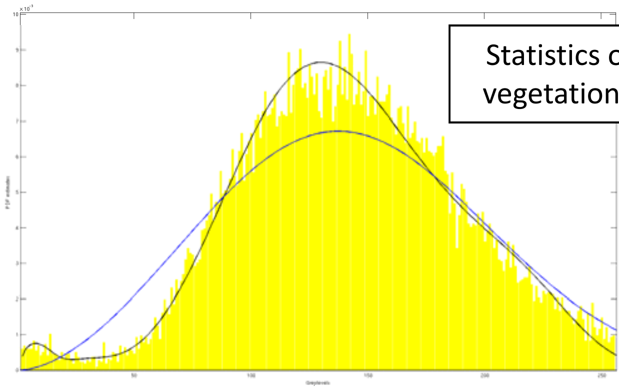
⇨ Unsupervised context

DSEM - RESULTS

Terra SAR-X image of Roshenheim (Germany) (©Infoterra, 2008)

COSMO-Skymed image of Cavallermaggiore (Italy) (©ISA, 2008)

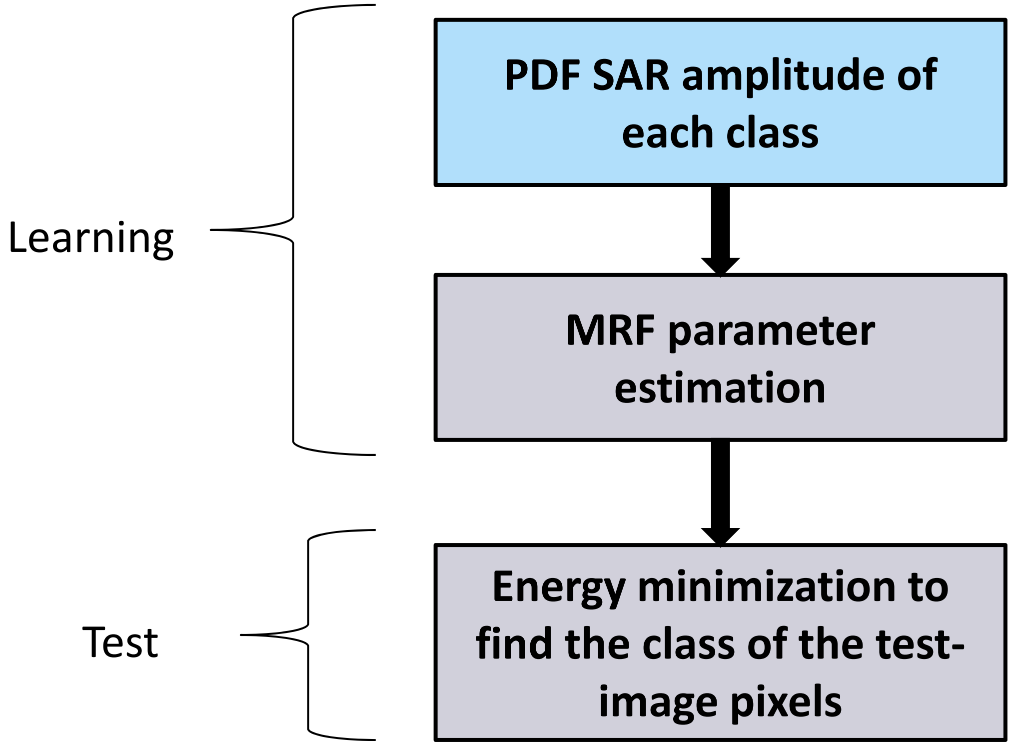




Model	KS distance
GGamma	0.022
DSEM 4: GGamma, Naka, LogN, Weib.	0.007

Model	KS distance
Weibull	0.053
DSEM 4: LogN, Naka (2), Weib.	0.011

CLASSIFICATION USING MRF METHOD



CLASSIFICATION - MRF

- MRF: robustness against speckle and contextual information [Besag 86, Dubes 89, Fjortoft 03]
- Anisotropic second-order neighborhood system
- Gibbs distribution [Besag 74, Geman 84]: Local characteristic (conditional proba) for each class m $\in [1;M]$

$$p_s(\omega_m | x^{(s)}) = P(x_s = \omega_m | x^{(s)}) = \frac{P\left(x_s = \omega_m, x^{(s)}\right)}{P\left(x^{(s)}\right)} = \frac{e^{-H(x_s = \omega_m, x^{(s)})}}{\sum_{j=1}^{M} e^{-H(x_s = \omega_j, x^{(s)})}}$$

  - Potts model: $H(x_s, x^{(s)}, \beta) = \sum_{s \in S} \left(-\ln(PDF) - \beta . \sum_{s' : \{s,s'\} \in C} \delta_{x_s = x_{s'}} \right)$

- Pseudo-logLikelihood $\ln(PL(x|\beta)) = \ln\left[\prod_{cliques\_s} p_s(\omega_m | x^{(s)}) \right]$

TEXTURAL FEATURE

- Problematic: Single – pol. SAR images
- Find a 2nd channel to improve the accuracy

→ Textural features

COSMO-Skymed image of Cavallermaggiore (Italy) (©ISA, 2008)

Semi-Variogram [Chen 04]

Grey-Level Co-occurrence Matrix (GLCM) variance [Haralick 73]

CLASSIFICATION - METHOD

[Moser 10]

PDF SAR amplitude of each class and each channel

$$p_m(y|\omega_m) = p_{1m}(y_1|\omega_m).p_{2m}(y_2|\omega_m)\frac{\partial^2 C_m^*\left(F_{1m}(y_1|\omega_m),F_{2m}(y_2|\omega_m)\right)}{\partial y_1 \partial y_2}$$

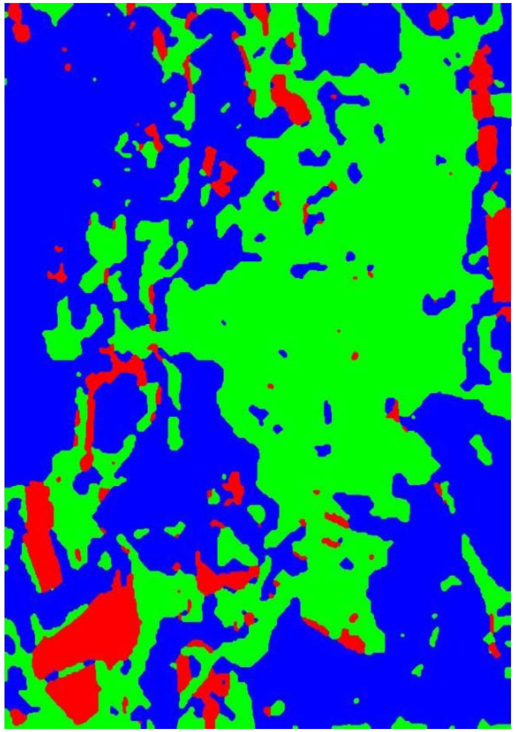
MRF parameter estimation

Test

Energy minimization to find the class of the test-image pixels

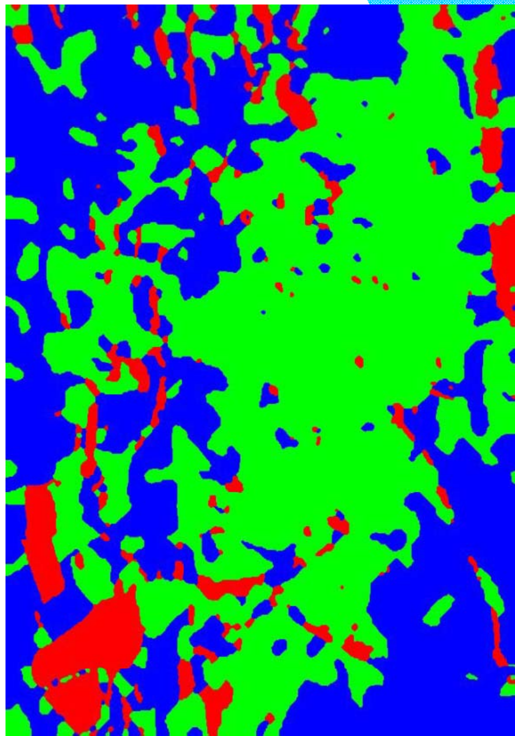
RESULTS

CoDSEM (GLCM)



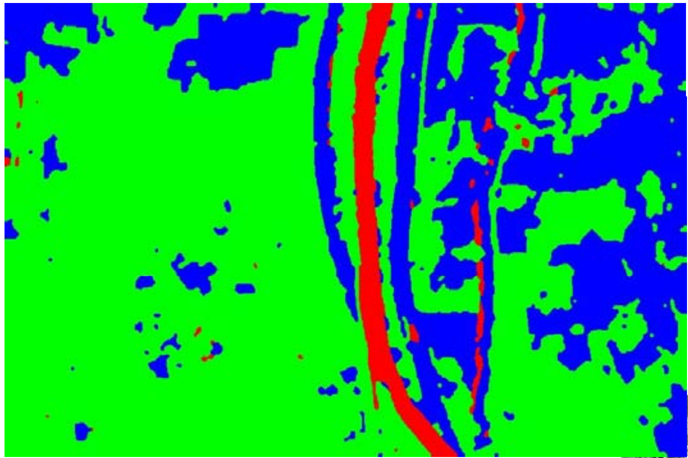
COSMO-Skymed image of Cavallermaggiore (Italy) (©ISA, 2008)

DSEM-MRF



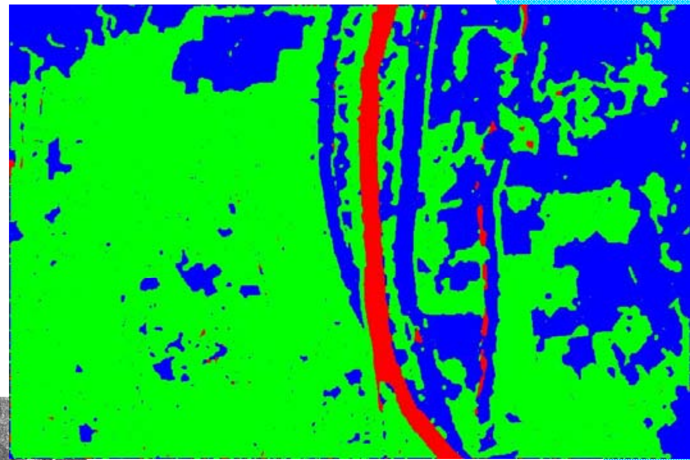
	Water	Urban	Vegetation	Overall
DSEM-MRF	**99.14 %**	98.88 %	84.65 %	94.22 %
K-NN-MRF	96.72 %	96.09 %	99.92 %	97.58 %
CoDSEM (Semivar.)	98.37 %	**98.91 %**	**100 %**	**99.09 %**
CoDSEM (GLCM)	98.62 %	98.42 %	**100 %**	**99.01 %**

RESULTS



CoDSEM (GLCM)

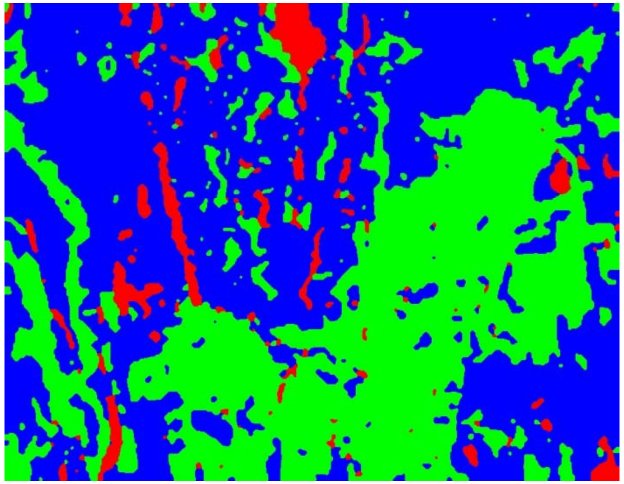
TerraSAR-X image of Rosenheim (Germany) (©Infoterra, 2008)



K-NN-MRF

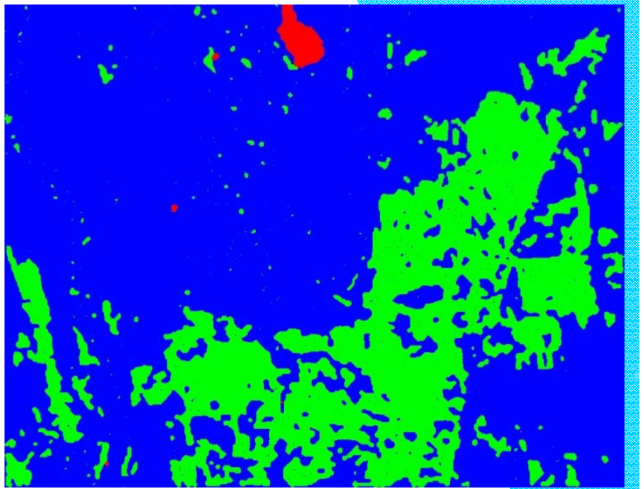
	Water	Urban	Vegetation	Overall
DSEM-MRF	**92.95 %**	98.32 %	81.33 %	90.87 %
K-NN-MRF	90.56 %	98.49 %	**94.99 %**	**94.68 %**
CoDSEM (GLCM)	91.28 %	**98.82 %**	93.53 %	94.54 %

RESULTS



CoDSEM (GLCM)

COSMO-Skymed image of Racconigi (Italy)
(©ISA, 2008)



K-NN-MRF

	Water	Urban	Vegetation	Overall
DSEM-MRF	**91.51 %**	**91.83 %**	68.31 %	83.88 %
K-NN-MRF	51.81 %	80.19 %	**99.00 %**	77.00 %
CoDSEM (GLCM)	88.66 %	91.60 %	87.04 %	**89.10 %**

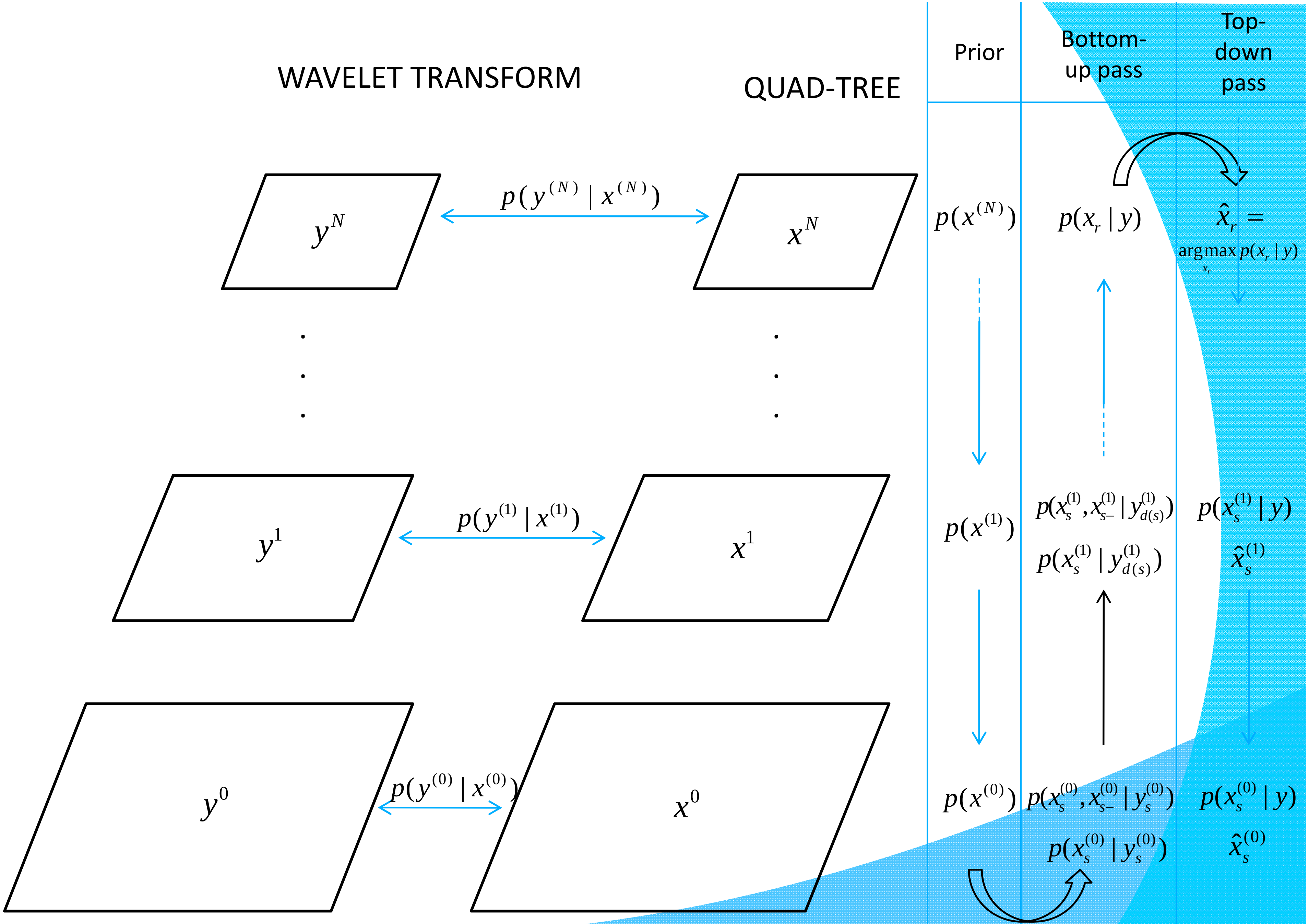
CLASSIFICATION USING HIERARCHICAL MRF

[Laferté 00]

PDF SAR amplitude of each class at each resolution	Prior information at root

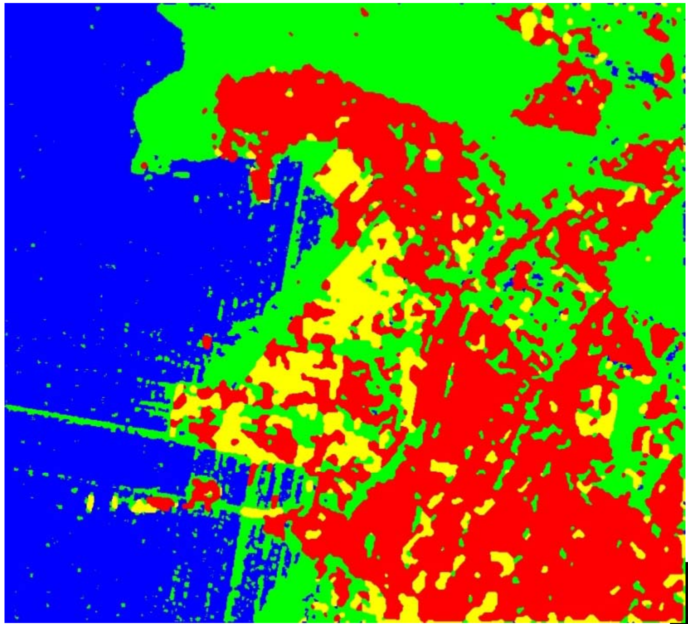
↓

Hierarchical MRF
MPM criterion applied on a quadtree



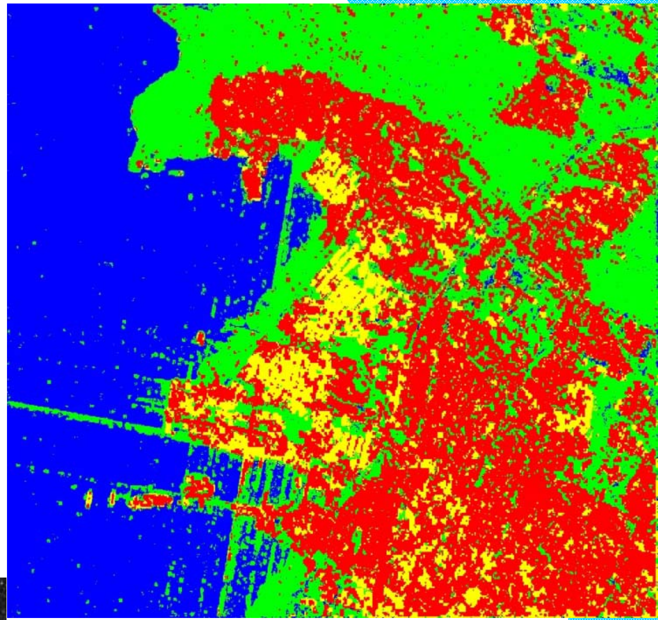
WAVELET TRANSFORM
QUAD-TREE
Prior
Bottom-up pass
Top-down pass
y^N
$p(y^{(N)} \mid x^{(N)})$
x^N
$p(x^{(N)})$
$p(x_r \mid y)$
$\hat{x}_r = \arg\max_{x_r} p(x_r \mid y)$
y^1
$p(y^{(1)} \mid x^{(1)})$
x^1
$p(x^{(1)})$
$p(x_s^{(1)}, x_{s-}^{(1)} \mid y_{d(s)}^{(1)})$
$p(x_s^{(1)} \mid y_{d(s)}^{(1)})$
$p(x_s^{(1)} \mid y)$
$\hat{x}_s^{(1)}$
y^0
$p(y^{(0)} \mid x^{(0)})$
x^0
$p(x^{(0)})$
$p(x_s^{(0)}, x_{s-}^{(0)} \mid y_s^{(0)})$
$p(x_s^{(0)} \mid y_s^{(0)})$
$p(x_s^{(0)} \mid y)$
$\hat{x}_s^{(0)}$

RESULTS



CoDSEM-MRF

COSMO-SkyMed image of Port-au-Prince (Haiti) (©ASI, 2009)



CoDSEM-MPM

	Water	Urban	Vegetation	Containers	Overall
CoDSEM-MRF	97.59 %	**96.84 %**	**99.56 %**	83.84 %	**94.45 %**
CoDSEM-MPM	97.58 %	90.23 %	98.16 %	**84.22 %**	92.55 %

CONCLUSIONS

- Algorithms validated in the application: urban/land/water separation on several single-pol. SAR images
- Difficulty of choosing the best method (depending on the final application)
- Possible improvements:
  - More sophisticated texture-extraction techniques
  - Prior knowledge of the hierarchical model + Potential modifications of this model

THANKS FOR YOUR ATTENTION

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