UNIVERSITÀ DEGLI STUDI
DI GENOVA

Change detection approach for the monitoring of the recovery phase in the aftermath of a disaster. The example of Haiti RO

Andrea De Giorgi[1], Giorgio Boni[1], Gabriele Moser[1], Sebastiano Serpico[1], Giuseppe Squicciarino[2], Anna Rita Pisani[3], Deodato Tapete[3], Simona Zoffoli[3]

[1] University of Genoa, Genoa, Italy
[2] Cima Research Foundation, Savona, Italy
[3] Italian Space Agency, Rome, Italy

Outline

- Introduction
  - Addressed problem and Project overview
  - Change detection methodologies
- The proposed approach
  - Key ideas of Region-based and Markov random fields
  - Proposed energy function
- Experimental results
  - Experiments on 10 m resolution data
  - Experiments on 2 m resolution data
- Conclusion

Introduction

Research activity framed within the project "Committee on Earth Observation Satellites – Disaster Risk Management "(CEOS-DRM)

- Contribution to the activity of CEOS Working Group on Disasters (Recovery Observatory and GEO-DARMA pilot);
- Development of change detection methodologies for the environmental monitoring of the recovery phase after disasters;
- Special focus on both radar and optical sensors (COSMO-SkyMed and Plèiades data);
- Case study: aftermath of Hurricane Matthew, which struck the southwest department of Haiti in October 2016 leading to more than 1000 lives lost and to severe damage to buildings, forests, and agriculture.

Change detection methodologies

- Multitemporal fusion at the feature level
  - multitemporal information extracted through the generation of new features able to emphasize changes in the data set;
  - mainly related to unsupervised detection approaches;
  - mostly (almost always) single-sensor;
  - final product usually limited to binary "change vs. no-change" case.

- Multitemporal fusion at the decision level
  - higher semantic level analysis;
  - explicit characterization of the typology of occurred changes;
  - mainly related to supervised (possibly semi-supervised) approaches;
  - especially relevant for detailed post-analysis (e.g., monitoring, recovery analysis).

Proposed methodological approach

Data set: multitemporal, very high resolution (VHR), multisensor imagery

Objective:

Formalize the change-detection problem through a multitemporal supervised classification approach for multisensor optical/SAR data taking advantage from the temporal and spatial information associated with the images

Key approaches:

- Multiscale region-based concepts
- Markov random field (MRF) modeling

Proposed methodological approach

Region-based approach:

- characterization of the geometrical structure associated with VHR images;
- takes advantage of both fine-scale and coarse-scale spatial behaviors through multiple segmentation maps at different spatial scales.

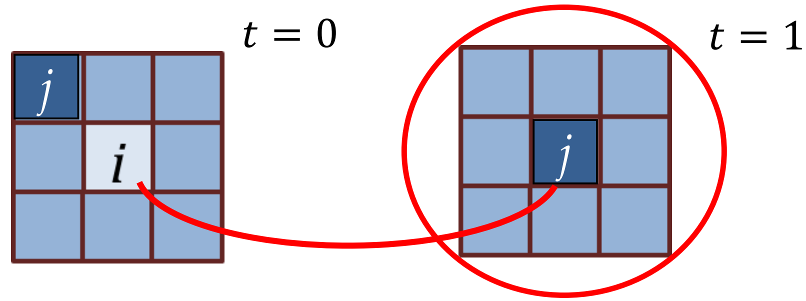
MRFs:

- major families of (undirected) probabilistic graphical models;
- naturally formalize global Bayesian decision criteria;
- capability to fuse together data belonging to different sources;
- integration of spatial context and temporal correlation associated with images acquired at different dates on the same area;
- classification through minimum-energy rules.

UNIVERSITÀ DEGLI STUDI DI GENOVA

Proposed MRF energy function

The contextual spatial information related to each image, the temporal correlation between the images, and the multiscale information provided by the set of segmentation maps are fused together as a linear combination of different energy contributions:



$$U\left(\mathcal{Y}_0, \mathcal{Y}_1 | S_0, S_1\right) = -\sum_{t=0}^{1}\left[\underbrace{\sum_{i \in I}\sum_{q=1}^{Q} \alpha_{qr} \ln P\left(s_{iqt} | y_{it}\right)}_{\text{Energy contribution related to each segmentation map}} \underbrace{- \beta_t \sum_{i \sim j} \delta\left(y_{it}, y_{jt}\right)}_{\text{Spatial-contextual energy contribution associated with the image on each date}} \underbrace{+ \gamma_t \sum_{i \bowtie j} P\left(y_{it} | y_{j,1-t}\right)}_{\text{Temporal energy term (transaction probability matrix) across the acquisition dates}}\right]$$

Proposed MRF energy function

- Represented by the Probability Mass Function (PMF) of the considered segment labels conditioned to the thematic classes
- Estimation is based on a relative frequency approach
- Requires as input classification maps obtained from the acquired image

$$U\left(\mathcal{Y}_0, \mathcal{Y}_1 | S_0, S_1\right) = -\sum_{t=0}^{1}\left[\underbrace{\sum_{i\in I}\sum_{q=1}^{Q}\alpha_{qt}\ln P\left(s_{iqt}|y_{it}\right)}_{\text{Energy contribution related to each segmentation map}} - \underbrace{\beta_t\sum_{i\sim j}\delta\left(y_{it}, y_{jt}\right)}_{\text{Spatial-contextual energy contribution associated with the image on each date}} + \underbrace{\gamma_t\sum_{i\bowtie j}P\left(y_{it}|y_{j,1-t}\right)}_{\text{Temporal energy term (transaction probability matrix) across the acquisition dates}}\right]$$

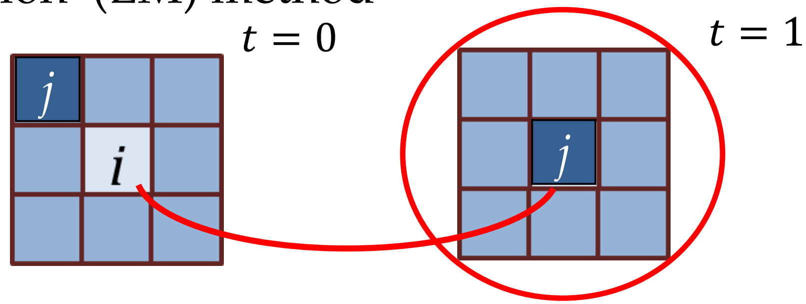
Proposed MRF energy function

The Potts model is adopted with a second order neighborhood system

$$U\left(\mathcal{Y}_0, \mathcal{Y}_1 | S_0, S_1\right) = -\sum_{t=0}^{1}\left[\underbrace{\sum_{i \in I}\sum_{q=1}^{Q}\alpha_{qt}\ln P\left(s_{iqt}|y_{it}\right)}_{\text{Energy contribution related to each segmentation map}} - \underbrace{\beta_t\sum_{i\sim j}\delta\left(y_{it}, y_{jt}\right)}_{\text{Spatial-contextual energy contribution associated with the image on each date}} + \underbrace{\gamma_t\sum_{i \bowtie j}P\left(y_{it}|y_{j,1-t}\right)}_{\text{Temporal energy term (transaction probability matrix) across the acquisition dates}}\right]$$

Proposed MRF energy function

Given the pixelwise posterior probability of the class labels, the estimation of the transition probabilities is performed through the expectation-maximization (EM) method



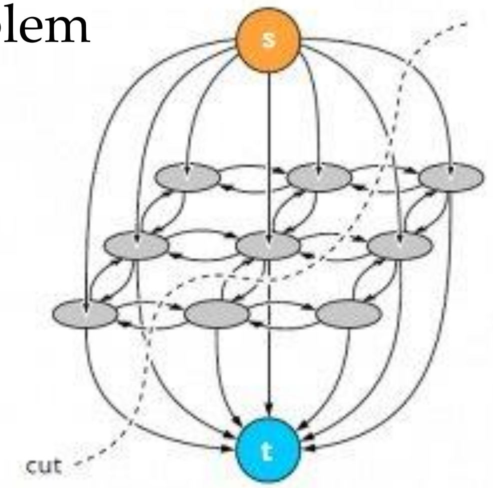
$$U\left(\mathcal{Y}_0, \mathcal{Y}_1 | S_0, S_1\right) = -\sum_{t=0}^{1}\left[\underbrace{\sum_{i\in I}\sum_{q=1}^{Q}\alpha_{qt}\ln P\left(s_{iqt}|y_{it}\right)}_{\text{Energy contribution related to each segmentation map}} - \underbrace{\beta_t\sum_{i\sim j}\delta\left(y_{it}, y_{jt}\right)}_{\text{Spatial-contextual energy contribution associated with the image on each date}} + \underbrace{\gamma_t\sum_{i\bowtie j}P\left(y_{it}|y_{j,1-t}\right)}_{\text{Temporal energy term (transaction probability matrix) across the acquisition dates}}\right]$$

Proposed methodological approach

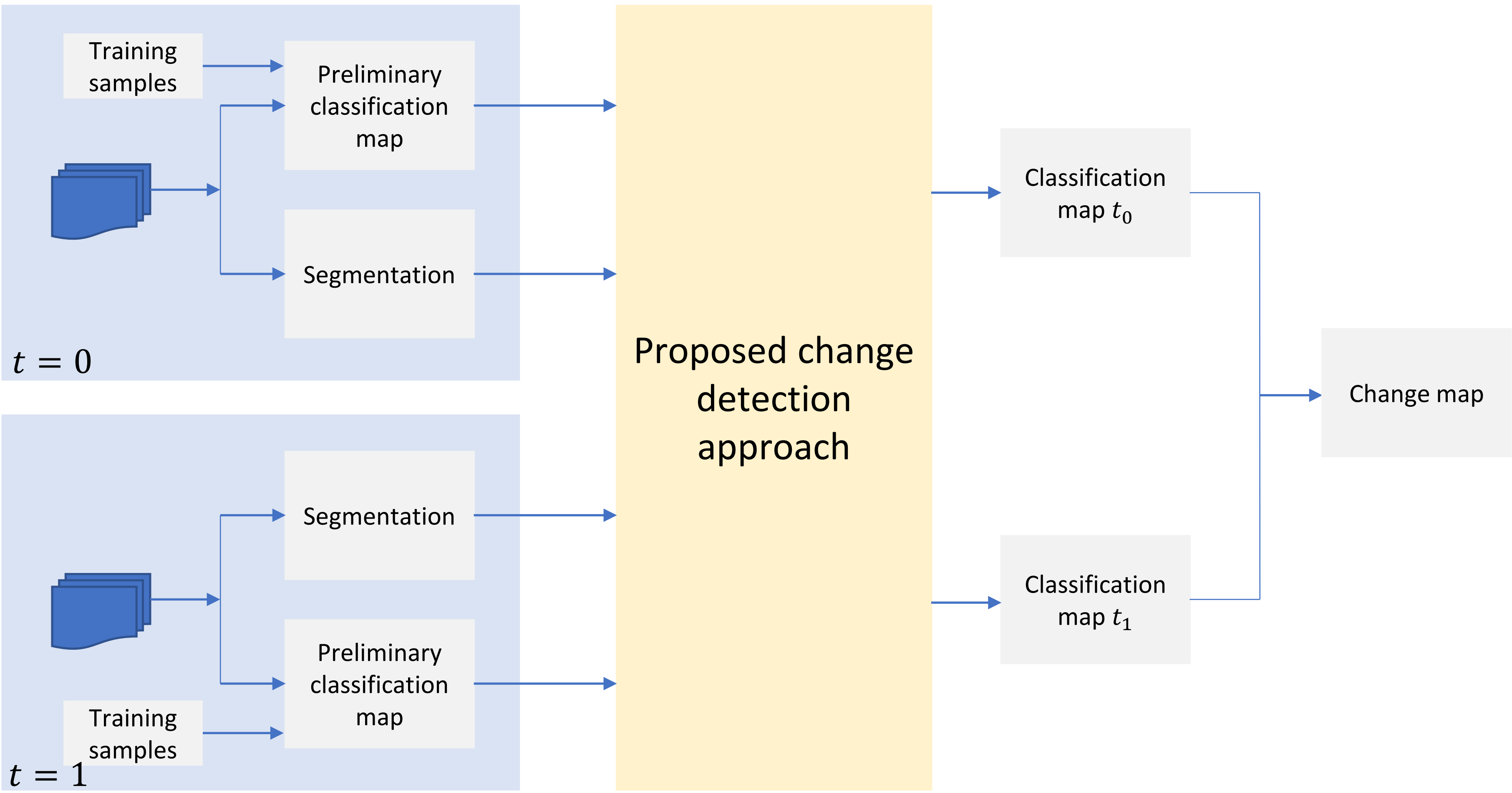
- **Parameter estimation:**

  The estimation of the weights (α, β, γ) of each energy contribution is performed through the method presented in (De Giorgi et al., 2015), which is based on a mean square error approach and on the sequential minimal optimization (SMO) algorithm.

- **Energy minimization by graph cut:**
  - energy minimization as a maximum flow problem
  - global minimum for binary classification
  - “strong” local minimum in the multiclass case



Proposed methodological approach



Examples of results

- Data set acquired during 2016 and 2017

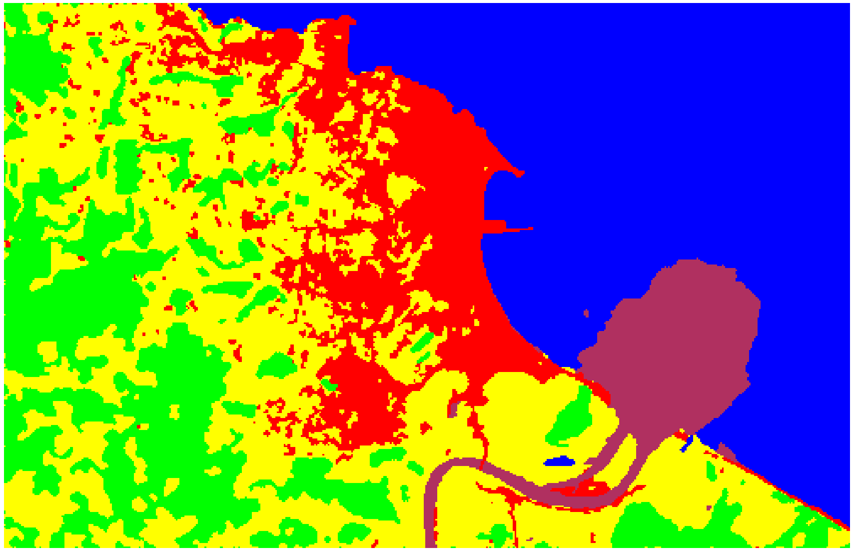
Jérémie_2016:

- Pansharpened Pléiades multispectral acquisition date 7/10/2016 (few days after Hurricane Matthew), 4 channels, native resolution: 2m for multispectral channels and 0.5 m for the panchromatic channel)

Jérémie_2017":

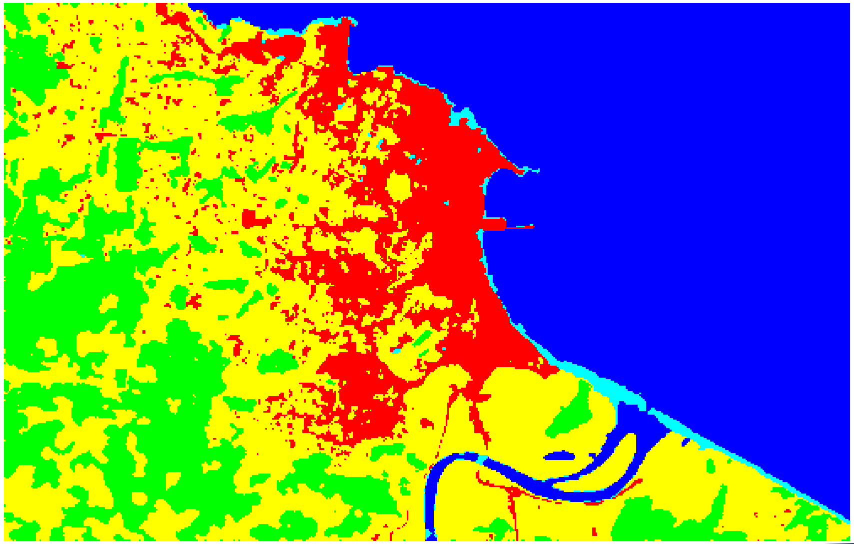
- Pléiades multispectral, acquisition date 18/10/2017, 4 channels, resolution 2 m;
- COSMO-SkyMed Spotlight, acquisition date 2/12/2017, resolution 1 m

Examples of results (10m resolution)



Jérémie_2016: classification map obtained from the application of the proposed algorithm; Producer Accuracy (PA) and Overall Accuracy (OA)

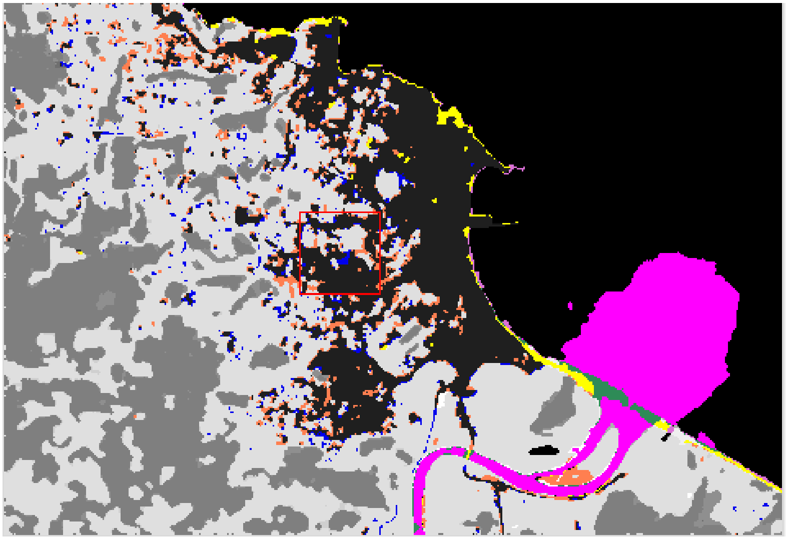
		PA
WATER		100%
URBAN		100%
TALL VEG		96,70%
LOW VEG		95,50%
MUDDY WATER		100%
	OA	98,40%



Jérémie_2017: classification map obtained from the application of the proposed algorithm; Producer Accuracy (PA) and Overall Accuracy (OA)

		PA
WATER		97.4%
URBAN		100%
TALL VEG		100%
LOW VEG		97%
BARE SOIL		100%
	OA	99%

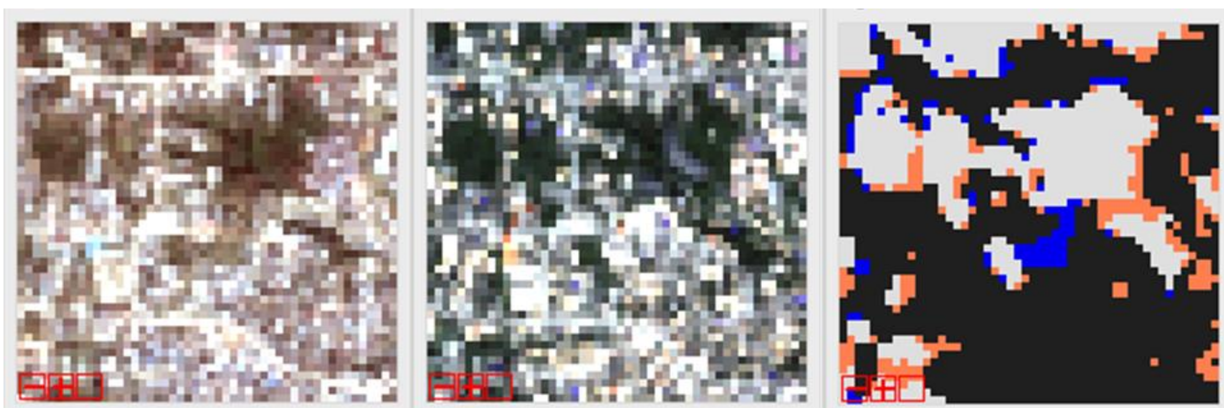
Examples of results (10m resolution)



Change-map derived from the application of the proposed method

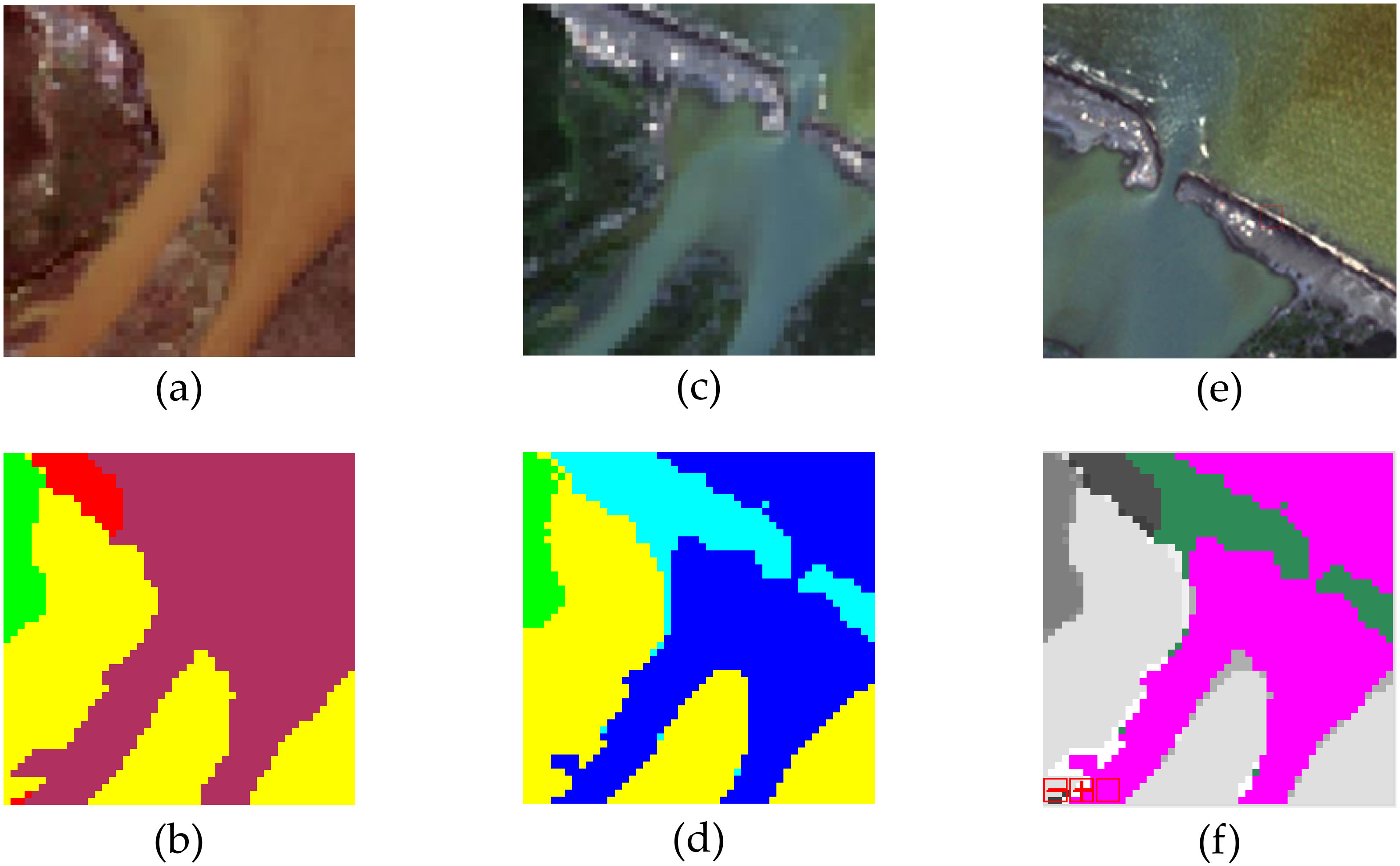
Highlighted transition:

MUDDY WATER - WATER	
MUDDY WATER - BARESOIL	
URBAN - BARE SOIL	
WATER - BARE SOIL	
URBAN - LOW VEG	
LOW VEG - URBAN	



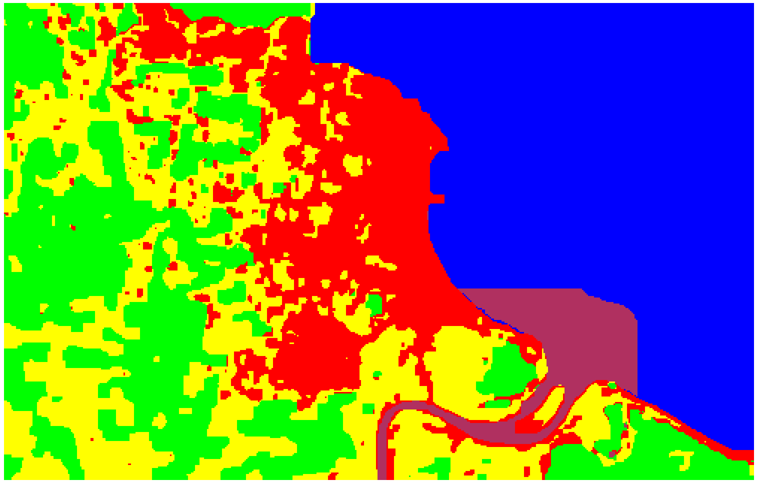
Detail: Urban area. RGB composition Jérémie_2017 (left), RGB composition Jérémie_2016 (center) and change-map (right) Gray scale visualization in the change-map is related to no-change transitions.

Examples of results (10m resolution)

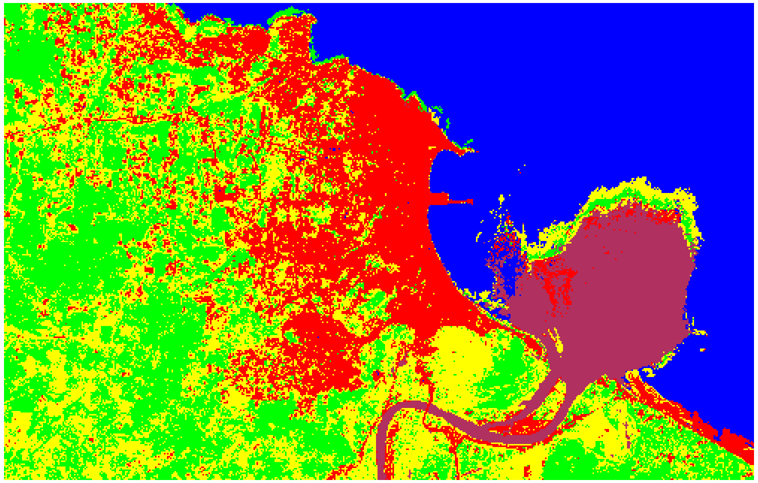


Detail: Mouth of the river Grande Anse. RGB composition Jérémie_2016 (a), classification map Jérémie_2016 (b), RGB composition Jérémie_2017 (c), classification map Jérémie_2017 (d), RGB composition Jérémie_2017 - 2m resolution (e), and change map (f)

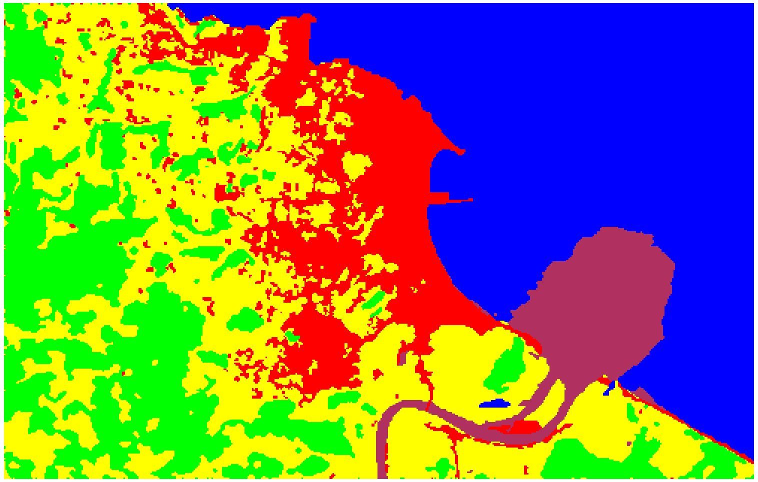
Examples of results (10m resolution)



Jérémie_2016: Classification map generated through MSVC-GC



Jérémie_2016: Classification map generated through RF

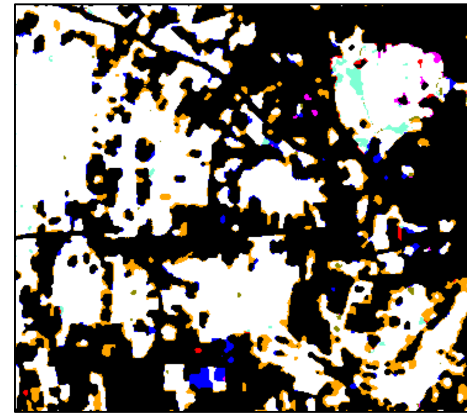


Jérémie_2016: Classification map obtained through the proposed approach

Examples of results (2m resolution)

Urban area of Jeremie_2016, RGB composition

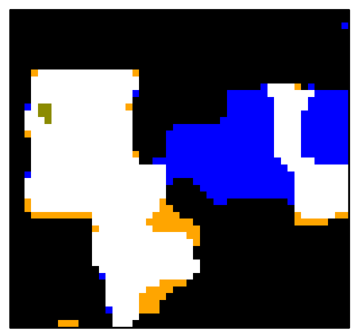
Urban area of Jeremie_2017, RGB composition



Obtained Change-map

(a)

(b)



(c)

URBAN - VEG	
URBAN - GRASS	
VEG - URBAN	
VEG - GRASS	
GRASS - URBAN	
GRASS - VEG	

Detail: Urban area of Jerèmie. RGB composition Jérémie_2016 (a), RGB composition Jérémie_2017 (b), and change map (c). Gray scale visualization in the change-map is related to no-change transitions.

Conclusions

- Change detection and identification of land cover classes and land cover transitions
- Characterization of the typology of the occurred changes
- High Overall Accuracy on the test set
- Applicability to images characterized by an arbitrary probability distribution function
- Significant improvement wrt the initial classification map used for the PMF estimation
- Limited sensitivity to the number of segmentation maps used

References

- Felzenszwalb, P. F., & Huttenlocher, D. P. (2004). Efficient graph-based image segmentation. International journal of computer vision, 59(2), 167-181.
- Moser, G., & Serpico, S. B. (2008, July). Classification of high-resolution images based on MRF fusion and multiscale segmentation. In Geoscience and Remote Sensing Symposium (IGARSS), 2008 IEEE International (Vol. 2, pp. II-277). IEEE.
- De Giorgi, A., Moser, G., Poggi, G., Scarpa G., & Serpico S.B. (2018, July). Very high resolution optical image classification using watershed segmentation and a region-based kernel. In Geoscience and Remote Sensing Symposium (IGARSS), 2018 IEEE International.
- Moser, G., & Serpico, S. B. (2013). Combining support vector machines and Markov random fields in an integrated framework for contextual image classification. IEEE Transactions on Geoscience and Remote Sensing, 51(5), 2734-2752.
- Ghamisi, P., Maggiori, E., Li, S., Souza, R., Tarablaka, Y., Moser, G., ... & Serpico, S. B. (2018). New Frontiers in Spectral-Spatial Hyperspectral Image Classification: The Latest Advances Based on Mathematical Morphology, Markov Random Fields, Segmentation, Sparse Representation, and Deep Learning. *IEEE Geoscience and Remote Sensing Magazine*, *6*(3), 10-43.
- De Giorgi, A., Moser, G., & Serpico, S. B. (2015, July). Parameter optimization for Markov random field models for remote sensing image classification through sequential minimal optimization. In Geoscience and Remote Sensing Symposium (IGARSS), 2015 IEEE International (pp. 2346-2349).
- Bruzzone, L., Prieto, D. F., & Serpico, S. B. (1999). A neural-statistical approach to multitemporal and multisource remote-sensing image classification. IEEE Transactions on Geoscience and remote Sensing, 37(3), 1350-1359.
- Kato, Z., & Zerubia, J. (2012). Markov random fields in image segmentation. Foundations and Trends® in Signal Processing, 5(1–2), 1-155.