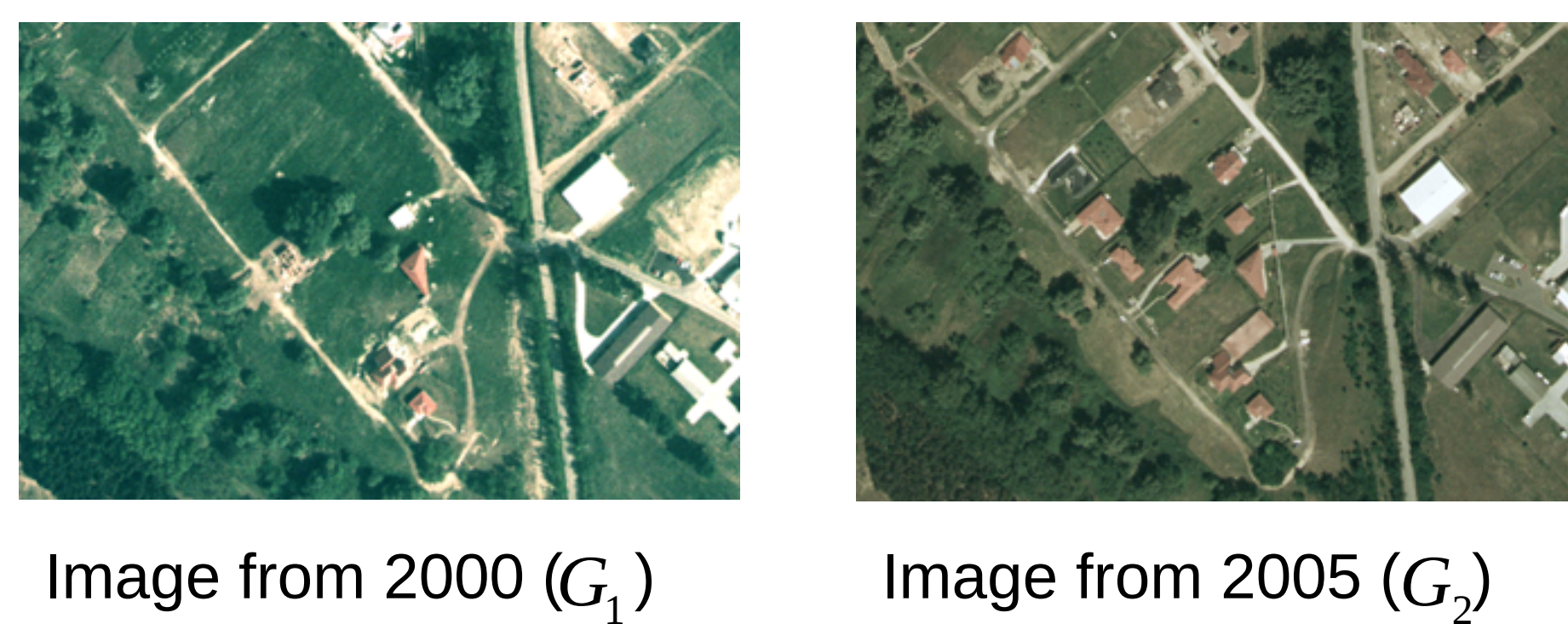


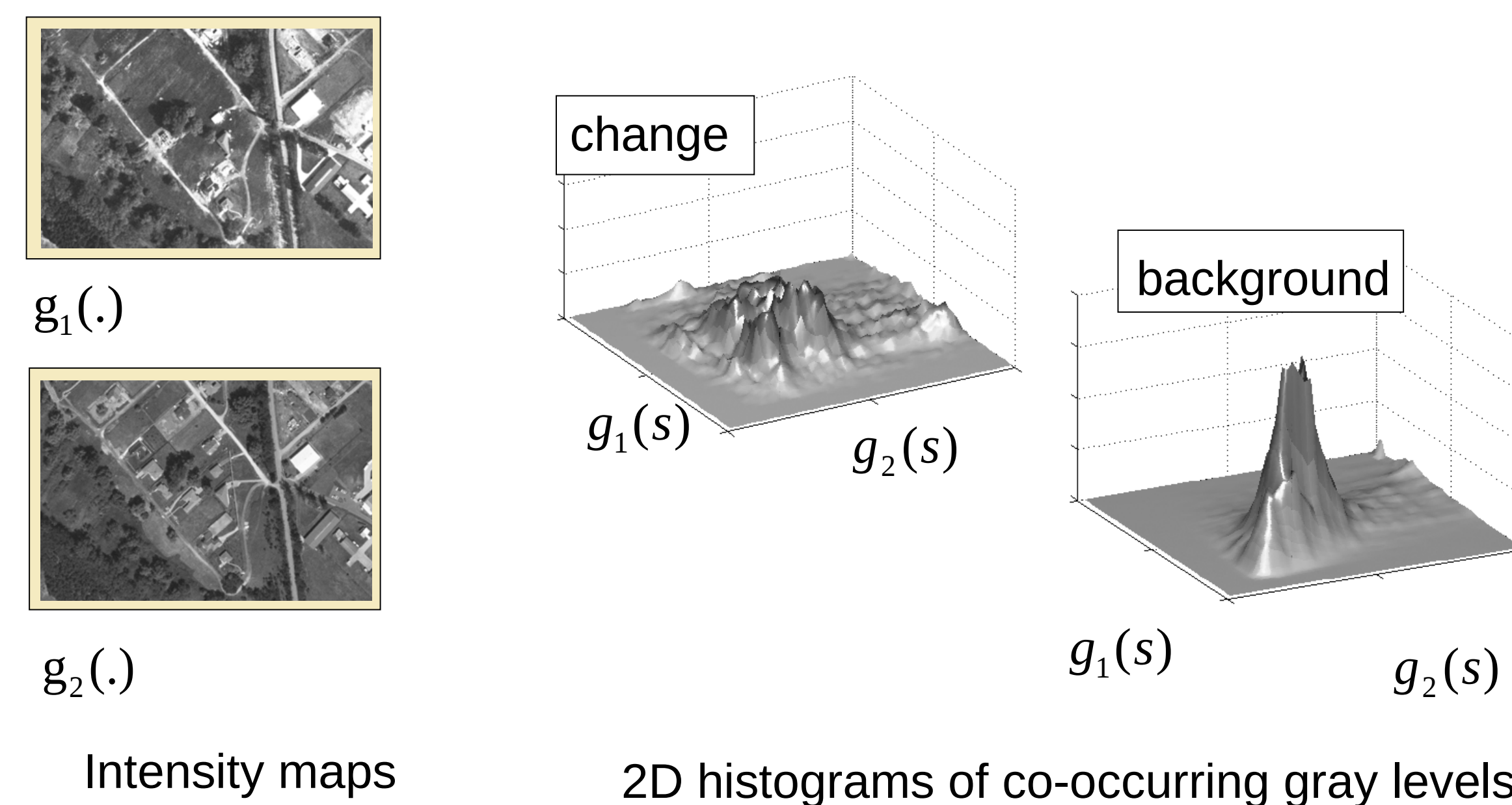
1. Introduction and Research Goals

- Change detection in optical aerial image pairs
 - new built-up regions, building operations
 - planting of trees, fresh plough-lands
 - groundwork before building-over etc
- Large time differences (many years) → different seasons, illumination conditions, vegetations etc.
- Input - preliminary registered orthophotos:



2. Global Statistics of Intensity Co-occurrences

- Feature vector of pixel s : pair of intensity values of s in the two images: $\bar{g}(s) = [g_1(s), g_2(s)]^T$



- Multi-Gaussian Intensity-based (MGI) change detection: ‘change’ class is modeled by a 2D uniform pdf, while ‘background’ with a mixture of Gaussians in the $\bar{g}(s)$ feature space

$$P(\bar{g}(s) | ch) \equiv u$$

$$P(\bar{g}(s) | bg) = \sum_{i=1 \dots K} \kappa_i \cdot N(\bar{g}(s), \mu_i, \Sigma_i)$$

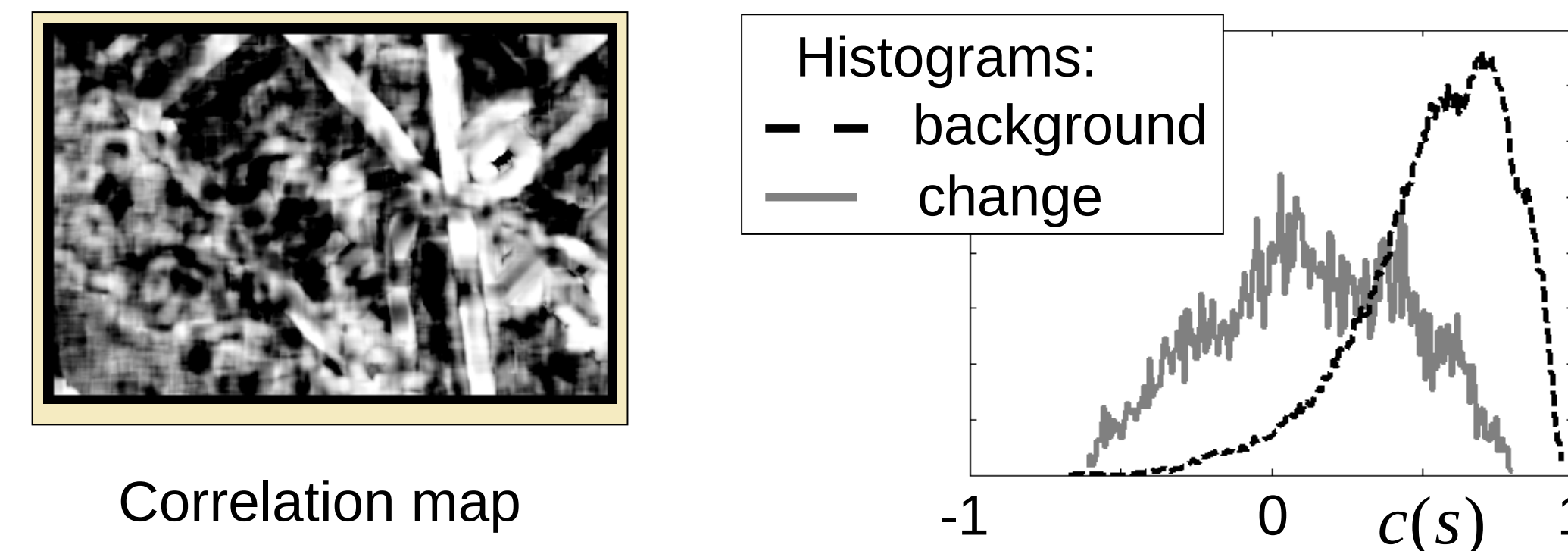
ML change map



Weak point of MGI: false changes in textured regions

3. Local Block Correlation

- $c(s)$: correlation of the $v \times v$ neighborhoods of pixel s in G_1 resp. G_2



- ‘change’ and ‘background’ classes are modeled by different Gaussian densities in the $c(s)$ feature space.

$$P(c(s) | ch) = N(c(s), \mu_{ch}, \sigma_{ch})$$

$$P(c(s) | bg) = N(c(s), \mu_{bg}, \sigma_{bg})$$

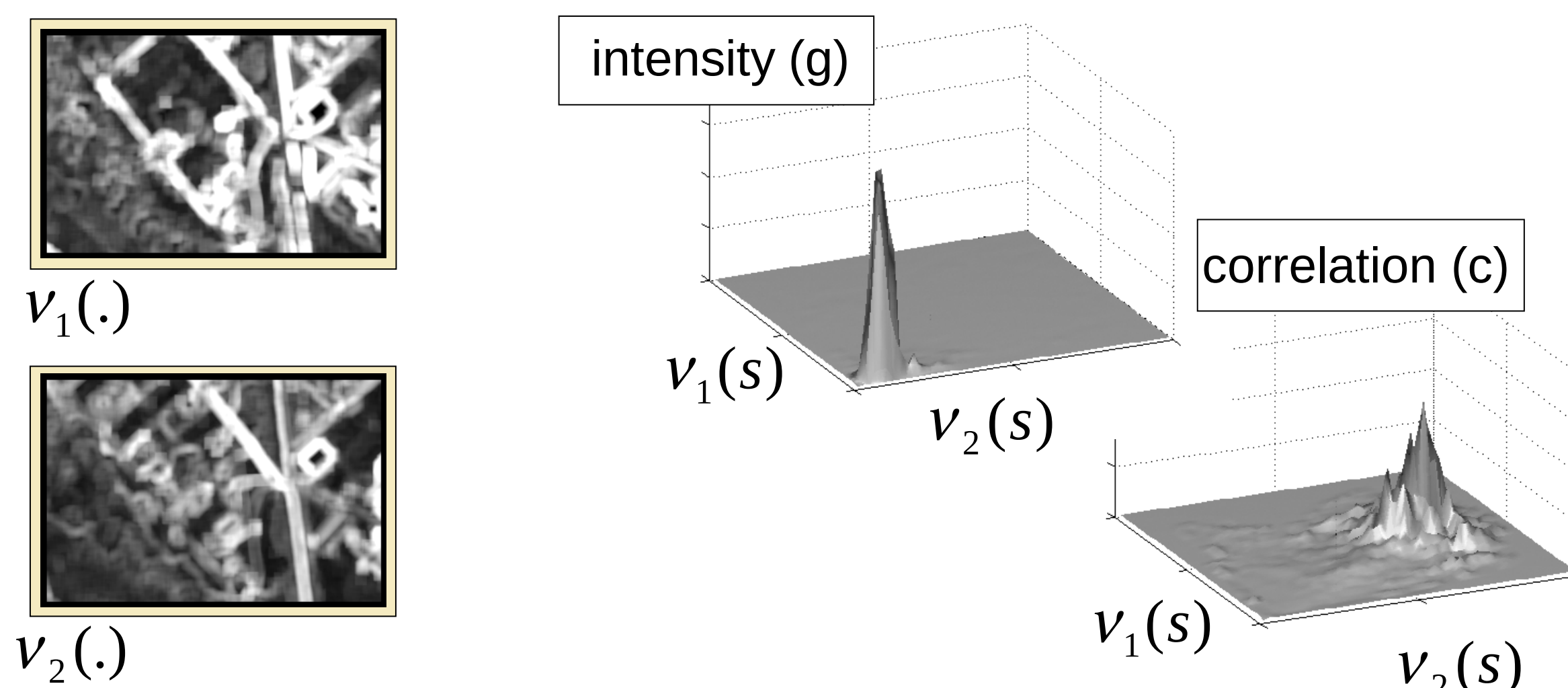
ML change map



Weak point of correlation-based classification: false changes in homogenous regions

4. Feature Selection

- Evidence: intensity feature should be used in low contrasted, while correlation feature in high contrasted image regions.
- Indicator feature: local intensity variances $\bar{v}(s) = [v_1(s), v_2(s)]^T$



Contrast (variance) maps

Reliability histograms of the intensity respectively correlation features as a function of local contrast

$$P(\bar{v}(s) | g) = N(\bar{v}(s), \mu_g, \Sigma_g)$$

$$P(\bar{v}(s) | c) = N(\bar{v}(s), \mu_c, \Sigma_c)$$

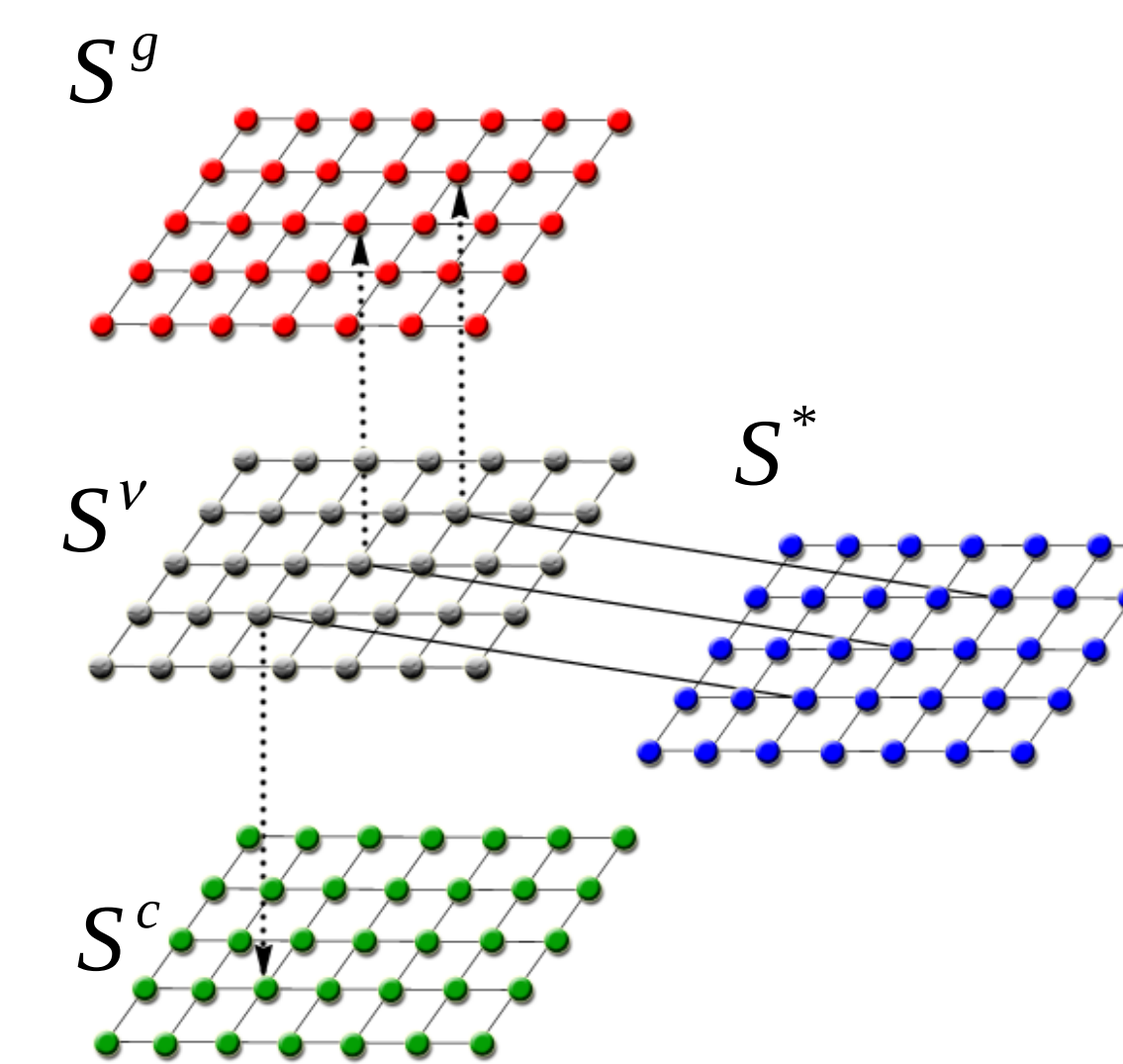
ML feature selection



Contrast-based feature selection-map (red regions: correlation feature preferred)

5. Four-Layer Mixed Markovian Segmentation Model

- Robust MRF-like segmentation model for the feature integration schema
- Multi-layer approach to jointly handle the 3 feature-maps and the final change map
- Feature selection requires dynamically changing links in the graph



Regular layers:

- S^g, S^c : change masks based on the $\bar{g}(s)$ resp. $c(s)$ features
- S^* : combined layer – output change mask

Address layer:

- S^v : switch layer: providing configurable, data-driven inter-layer connections

Node labels: $\omega(s^i)$

Interactions and clique potentials

- Singletons: data-label consistency
- Intra-layer cliques V_{C_2} : smooth label maps
- Inter-layer cliques V_{C_3} : label fusion

- Output label-map by global energy optimization:

$$\hat{\omega} = \arg \min \left\{ \sum_{s \in S} -\log P(\bar{g}(s) | \omega(s^g)) + \sum_{s \in S} -\log P(\bar{v}(s) | \omega(s^v)) + \sum_{s \in S} -\log P(c(s) | \omega(s^c)) + \sum_{i; \{s, r\} \in C_2} V_{C_2}(\omega(s^i), \omega(r^i)) + \sum_{s \in S} V_{C_3}(\omega(s^*), \tilde{\omega}(s^v)) \right\}$$

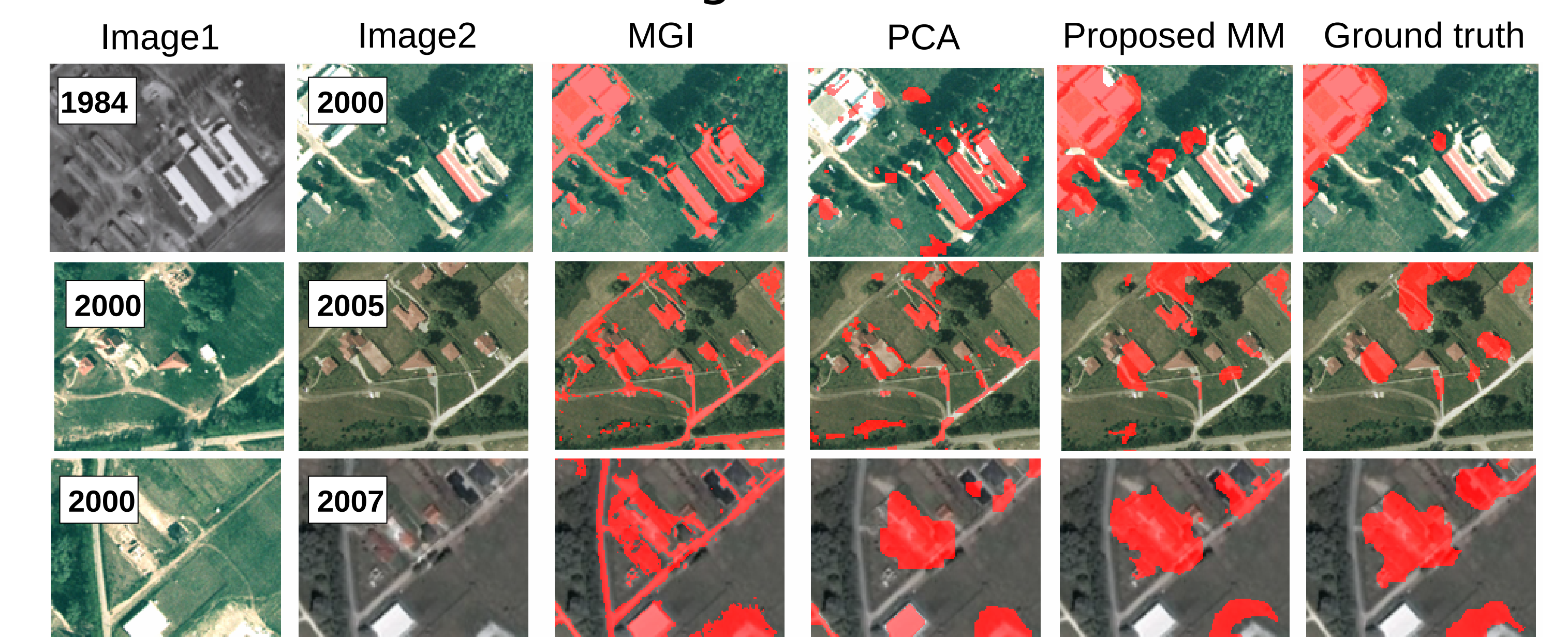
Output change mask



Ground truth changes



6. Results and Concluding Remarks



- Fast, not object-specific, robust regarding image quality ☺
- Less efficient at high resolution and in the presence of high parallax ☹
- Acknowledgement: MUSCLE Shape Modeling E-Team and Josiane Zerubia (INRIA)