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A Multiresolution Fusion Framework based on Probabilistic Graphical Modeling for Burnt zones mapping from satellite and UAV imagery

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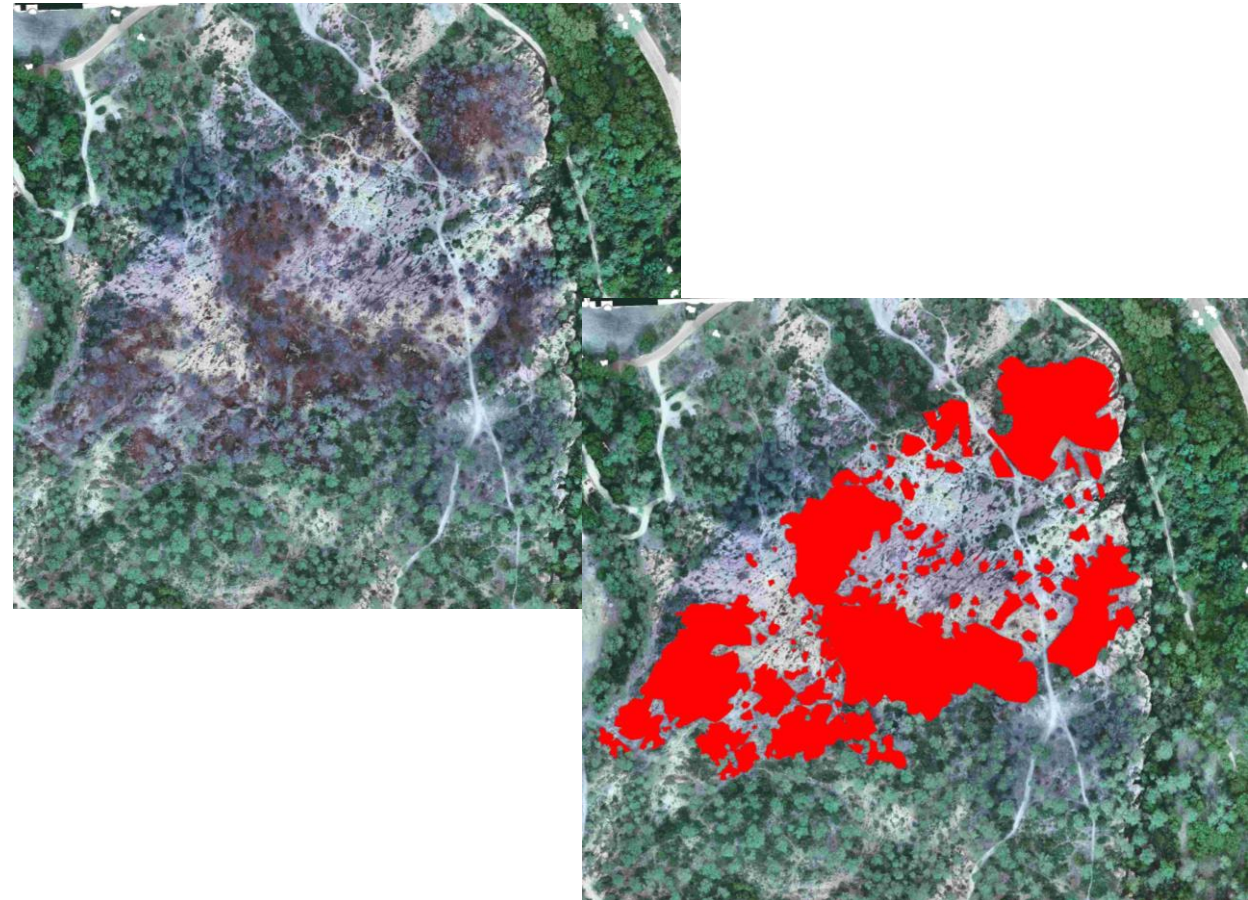
Outline

- The addressed problem
- Proposed framework
- Experimental results
- Conclusion

The addressed problem

Increasing occurrence of wildfires, amplified by the changing climate conditions and drought, has significant impacts on natural resources, ecosystem responses, and climate change

- Burnt area mapping is crucial not only to prevent further damage but also to manage the area itself



The addressed problem

Availability of **multimodal information**:

- **UAV**-based systems:
 - ❑ **Pros**: high flexibility, low-cost, low altitude, **extremely high spatial resolution**
 - ❑ **Cons**: small area coverage, complex scene background, and susceptibility to forest cover
- **Satellite**-based monitoring
 - ❑ **Pros**: large-scale wildfire assessment due to its wide **coverage** and **revisit time**
 - ❑ **Cons**: suffers from aerosol and cloud occlusions

Multisensor images possibly contain **complementary information** → need for **multimodal information fusion** techniques

The proposed solution

Two different methods combining **stochastic modeling, decision fusion, machine** and **deep learning** were developed

- to address the **huge ratio** between the resolutions of the available input image sources (e.g., 1:500, 1:1000)

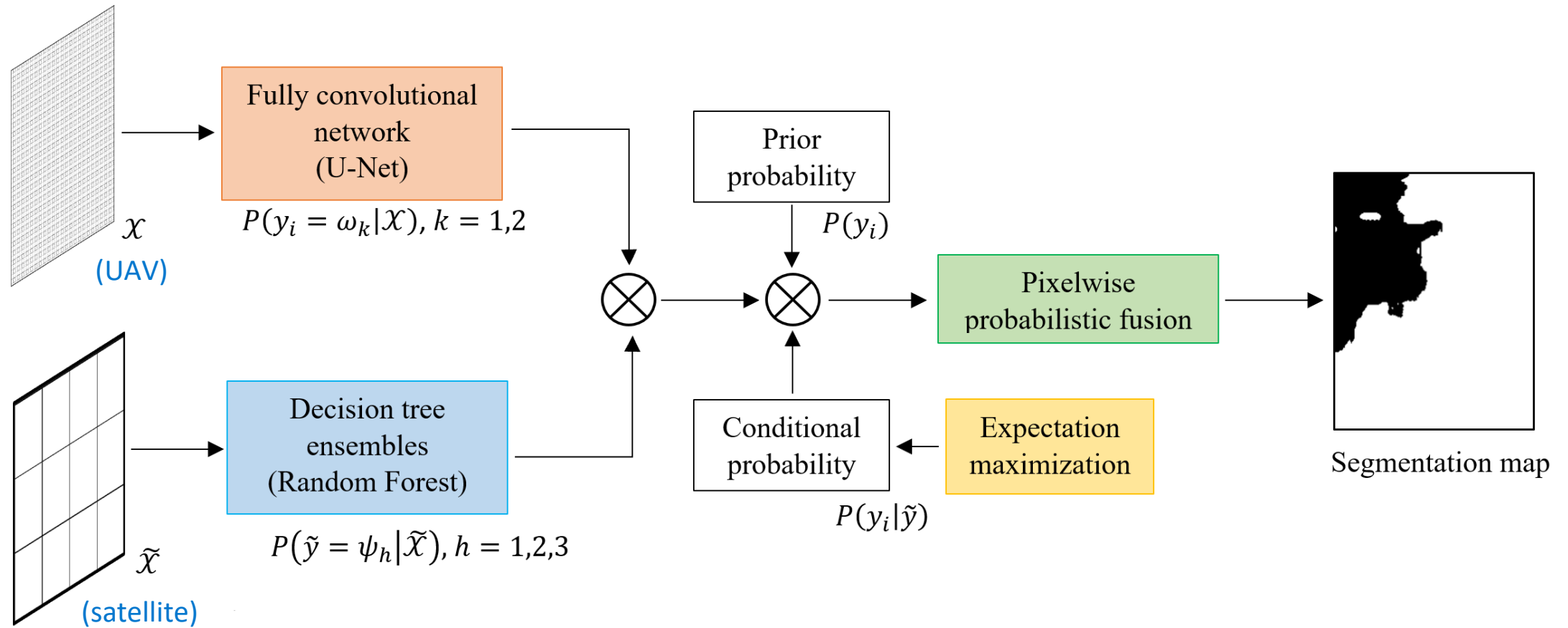
- ① **Pixelwise probabilistic fusion** of the multiscale information.
- ② **Probabilistic graphical fusion** in a partially regular quadtree graph topology through the MPM criterion

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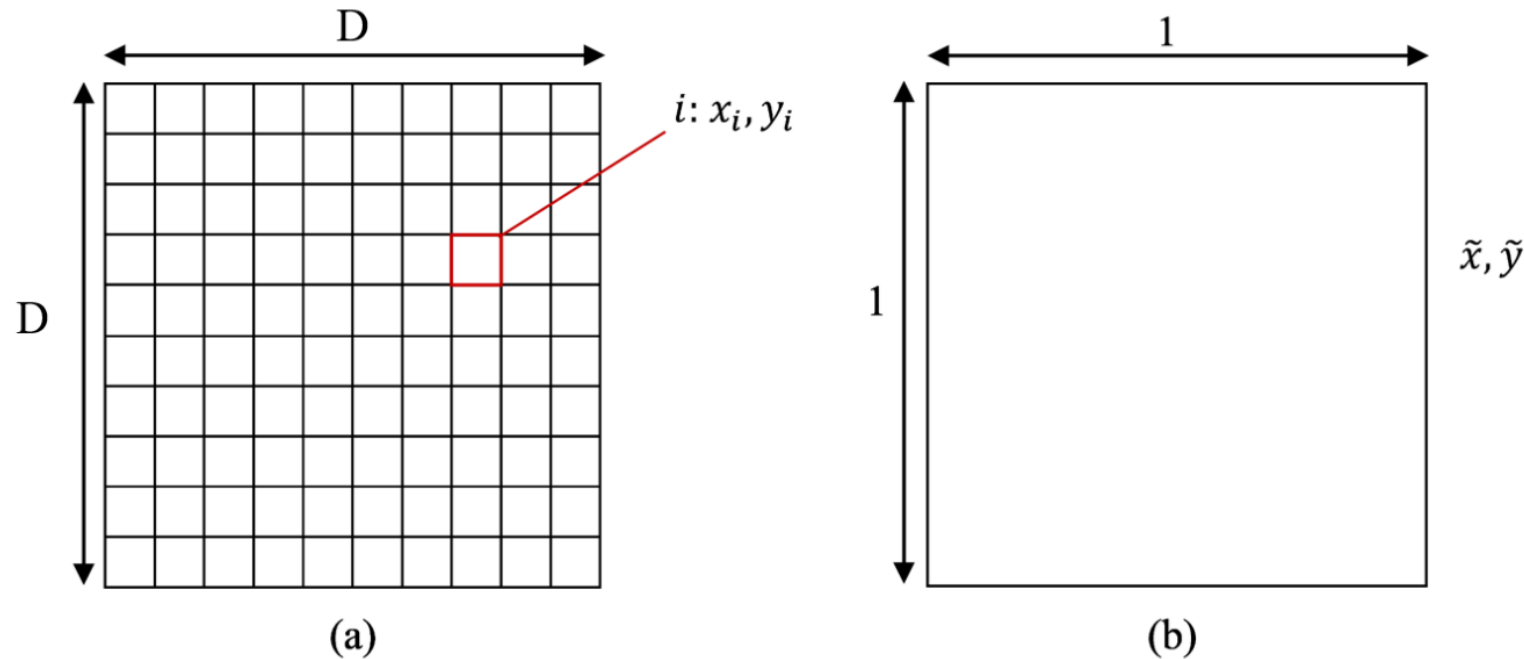
Proposed framework

Solution 1: Pixelwise probabilistic fusion



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The idea is to extract the thematic information contained in the two acquisitions collected by the different sensors (at very different spatial resolutions and with generally different spectral bands) separately, and perform a **posterior probability pixelwise decision fusion**



Pixel grid of (a) the finer and (b) the coarser resolution images.

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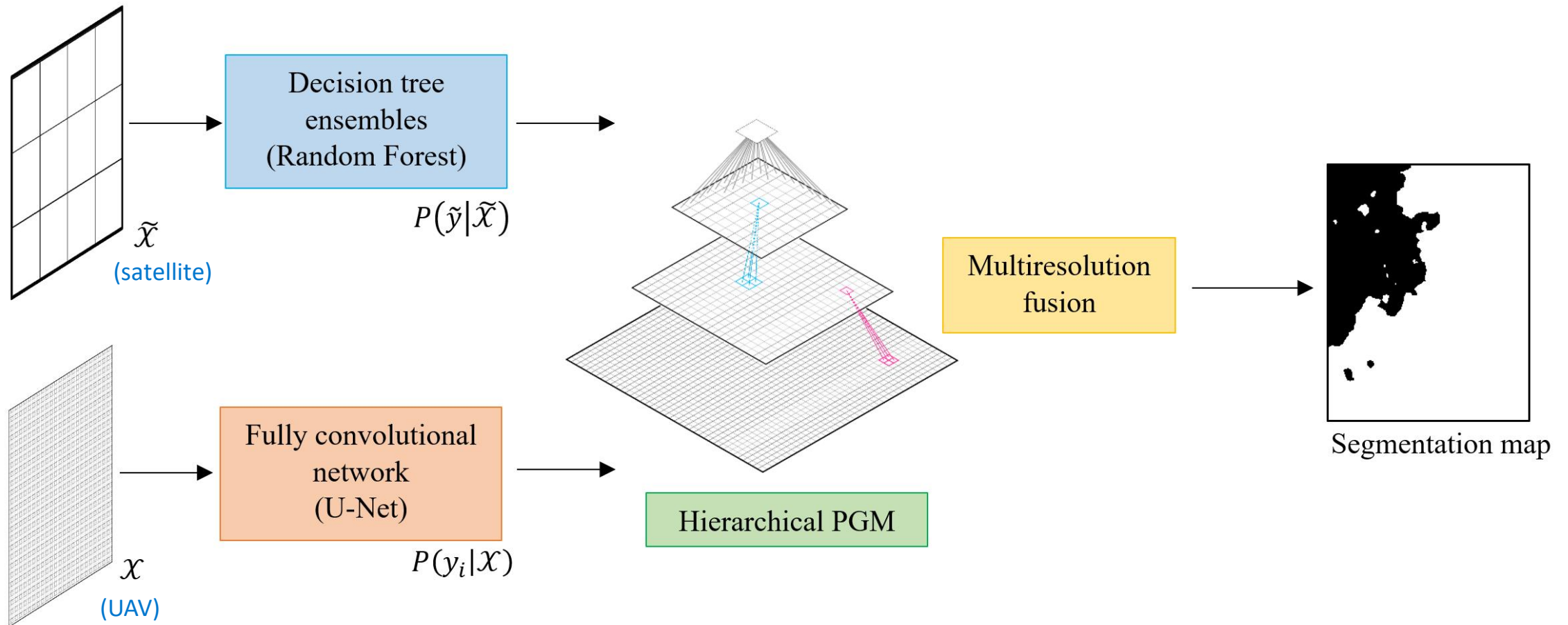
$$P(y_i|X, \tilde{x}) \propto \sum_{\tilde{y} \in \tilde{\Omega}} P(y_i|X) P(\tilde{y}|\tilde{x}) \frac{P(y_i|\tilde{y})}{P(y_i)},$$

$y_i \backslash \tilde{y}$	Burnt	Non-burnt	Partially burnt
Burnt	$1 - \epsilon_1$	ϵ_2	α
Non-burnt	ϵ_1	$1 - \epsilon_2$	$1 - \alpha$

X , $D \times D$ patch in the finer resolution image
 x_i, y_i , feature vector and the class label of the i th pixel of X
 \tilde{x}, \tilde{y} , feature vector and the class label of the coarser-resolution pixel
 Ω set of classes on the finer resolution lattice
 $\tilde{\Omega}$ set of classes on the coarser resolution lattice

Conditional probability. The parameters are estimated automatically with the expectation-maximization (EM) algorithm.

Solution 2: Multiresolution fusion through hierarchical PGM



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Fuse the multiresolution information through a **pyramidal tree structure**, where the information is inserted at its **native resolution**. The **hierarchical PGM** is formulated over a partially irregular quadtree.

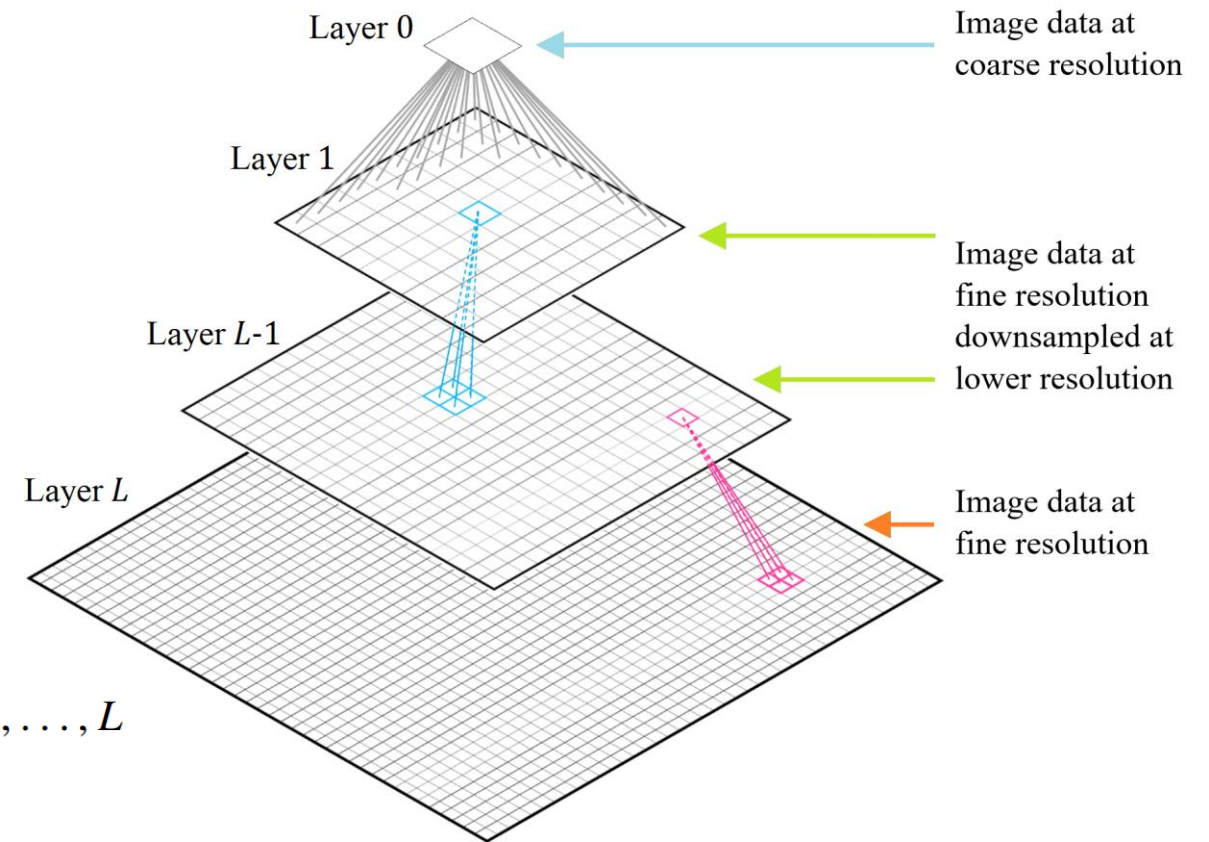
$$P(y_i) = \sum_{\tilde{y} \in \tilde{\Omega}} P(y_i | \tilde{y}) P(\tilde{y})$$

$$P(y_i | x_i^d) \propto P(y_i | x_i) \prod_{t \in i^+} \sum_{y_t \in \Omega} \frac{P(y_t | x_t^d) P(y_t | y_i)}{P(y_t)},$$

$$P(y_i | y_i^c, x_i^d) \propto \frac{P(y_i | x_i^d) P(y_i | y_{i-}) P(y_{i-})}{P(y_i)^{n_i}}$$

$$P(y_i | \mathcal{X}, \tilde{x}) = \sum_{y_i^c \in \Omega^{n_i}} P(y_i^c | y_i, x_i^d) P(\tilde{y} | \mathcal{X}, \tilde{x}), \quad i \in S^1$$

$$P(y_i | \mathcal{X}, \tilde{x}) = \sum_{y_i^c \in \Omega^{n_i}} P(y_i^c | y_i, x_i^d) P(y_{i-} | \mathcal{X}, \tilde{x}), \quad i \in S^\ell, \ell = 2, 3, \dots, L$$



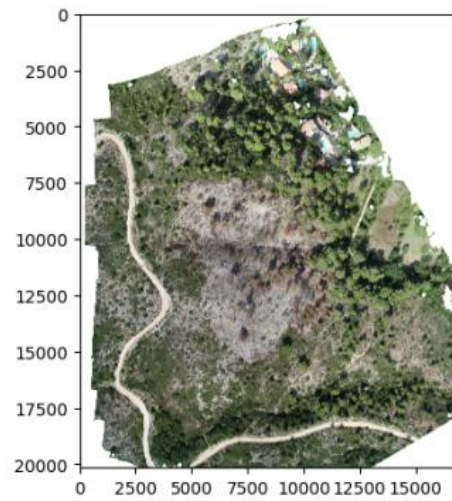
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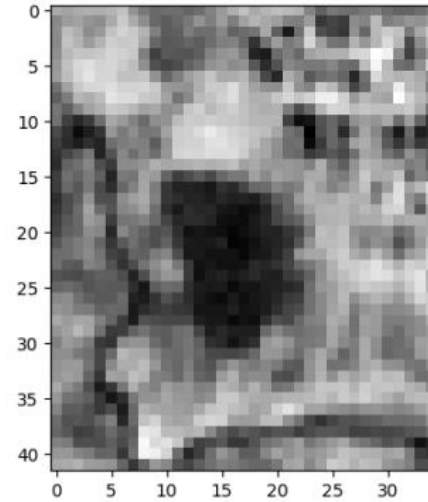
Experimental results

Dataset (La Destrousse, PACA, France)

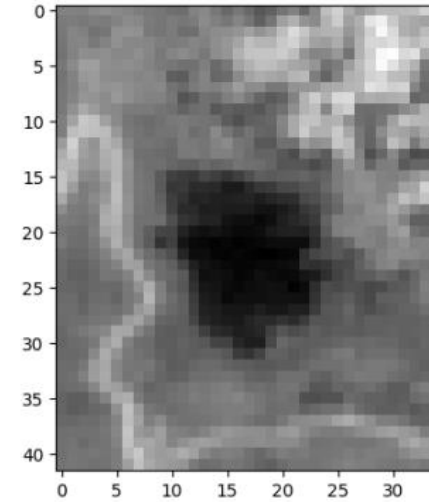
13



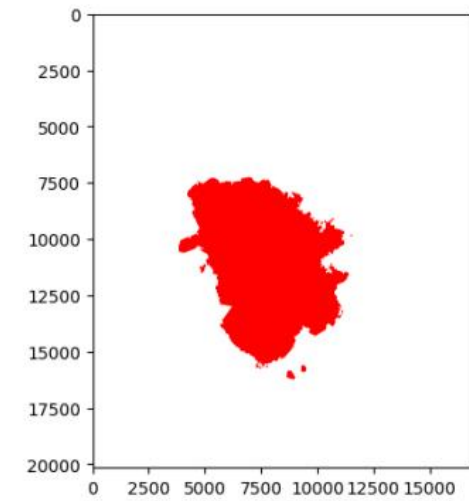
*Drone
image (2
cm)*



*Sentinel-2
NDVI (10 m)*



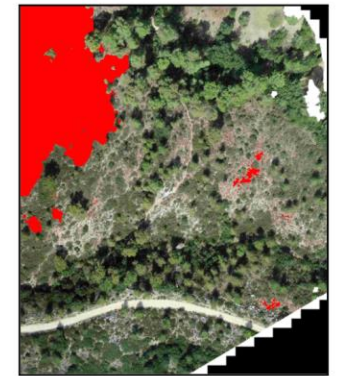
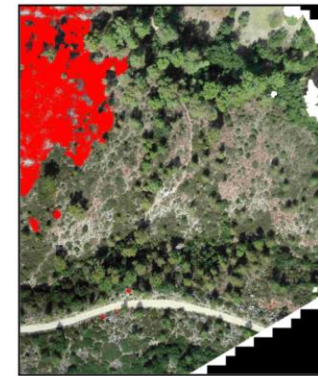
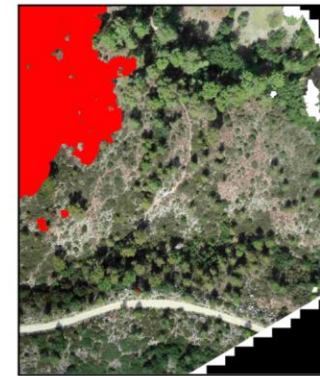
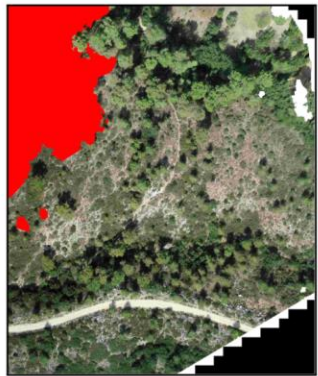
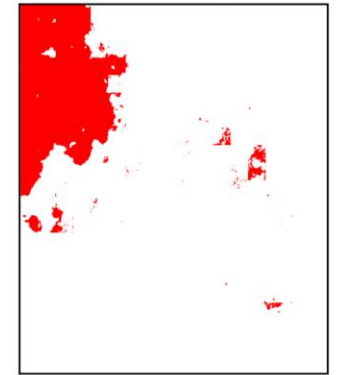
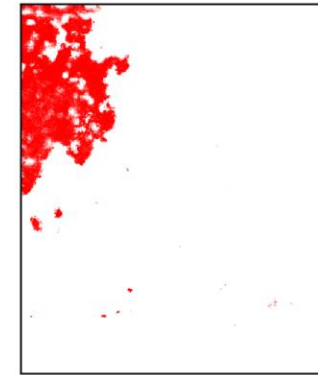
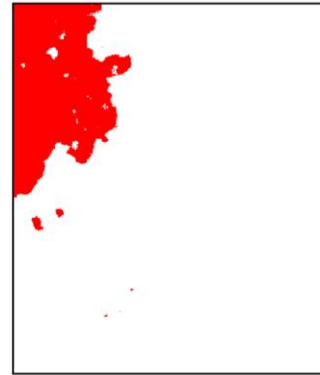
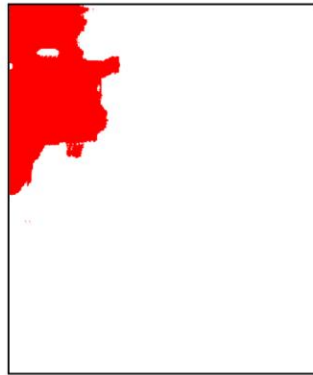
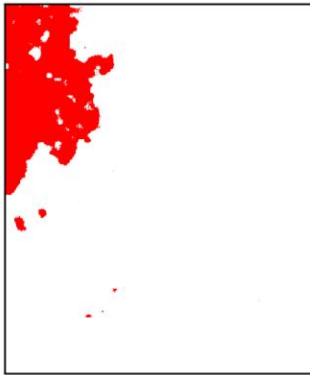
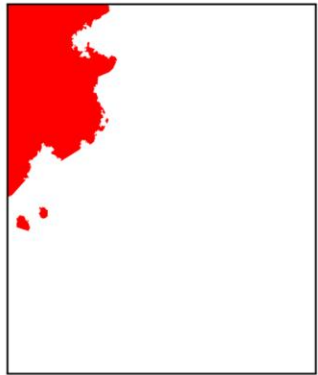
*Sentinel-2 NIR
(10 m)*



*Ground truth
(2 cm)*

- **Drone** image (2 cm) acquired by INRAE, Aix-en-Provence, shortly after the fire of **11 July 2018**.
- **Sentinel-2** image (10 m) of **14 July 2018**.
- The **GT boundaries** (2 cm) of the burnt area were found using a canopy height model (**CHM**).
- In this case, $D = 480$.

Experimental results



GT

U-Net

1st prop. method2nd prop. methodDL based fusion
(based on CNNs)DBINet
(based on CNNs and ViT)

Experimental results

Architecture	False alarm rate	Missed alarm rate	Overall error rate
*U-Net (on UAV)	0.28	10.81	1.61
*RF (on Sentinel-2)	0.27	20.34	3.17
DL multires. fusion	0.19	27.08	3.51
First proposed method	0.48	8.55	1.47
Second proposed method	0.19	7.43	1.17
*DBINet (on UAV)	1.01	6.29	1.66
DBINet (on Sentinel-2)	0.69	12.45	2.15

*O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Med. Image Comput. Comput. Assist. Interv.*, ser. LNCS, vol. 9351. Springer, 2015.

*L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

*W. Fang, Y. Fu and V. S. Sheng, "Dual Backbone Interaction Network for Burned Area Segmentation in Optical Remote Sensing Images," in *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1–5, 2024.

Conclusion and perspectives

Two **multiresolution probabilistic fusion** methods were proposed for the **challenging case** of **UAV** and **satellite images**

- for the **semantic segmentation** of zones affected by **forest fires**
- **extreme multiresolution** task, resolution ratio between the input image sources is of the order of the **hundreds**
- **automatic parameter optimization** through **EM**
- the experimental validation confirms the potential of the combination of FCN architectures with PGMs on appropriate graphs.

Future work will involve

- application to different case studies related to forest fires with data acquired by **different sensors** and at **different resolutions**
- integration with **transfer learning** to apply it to fire image data characterized by **different features** and associated with **different geographical areas**

Thank you for your attention!



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