# Fully convolutional and feedforward networks for the semantic segmentation of remotely sensed images

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# Outline





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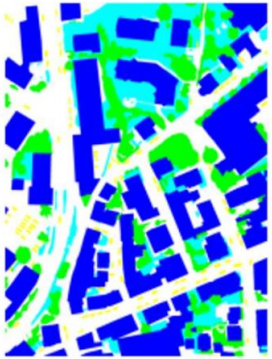
# 01

# Introduction

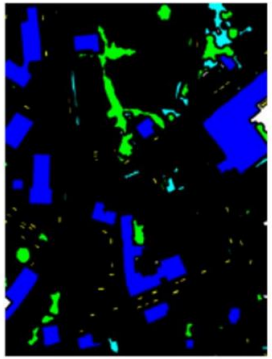
# The addressed problem

**The development of a supervised method for the semantic segmentation – or dense image classification – of remote sensing images at very high resolution (VHR) is a challenging problem**

- **Models based on deep learning (e.g., fully convolutional networks, FCNs) are capable to reach accurate classification results**
  - **however**, these models need **large datasets** which require **high efforts** in annotation and most often are **not available**
  - their **performances worsen** in case of **scarce ground truth (GT)**



*Original GT*



*GT used to train the model*

# The addressed problem

**FCNs extract information at different spatial resolutions**

- the use of the spatial details at the finest resolutions and the robustness to noise plus outliers at the coarsest has proven to improve the classification results
- stochastic models such as probabilistic graphical models (PGMs) are flexible and powerful approaches which can extract information from multiscale data for labeling purposes
- several approaches that combine DL and PGMs have been studied in order to improve the accuracy of the classification results by capturing the interactions between pixels

# Proposed solution

**The method in [1] was extended with the addition of fully connected neural networks (NNs) at different convolutional blocks of the FCN**

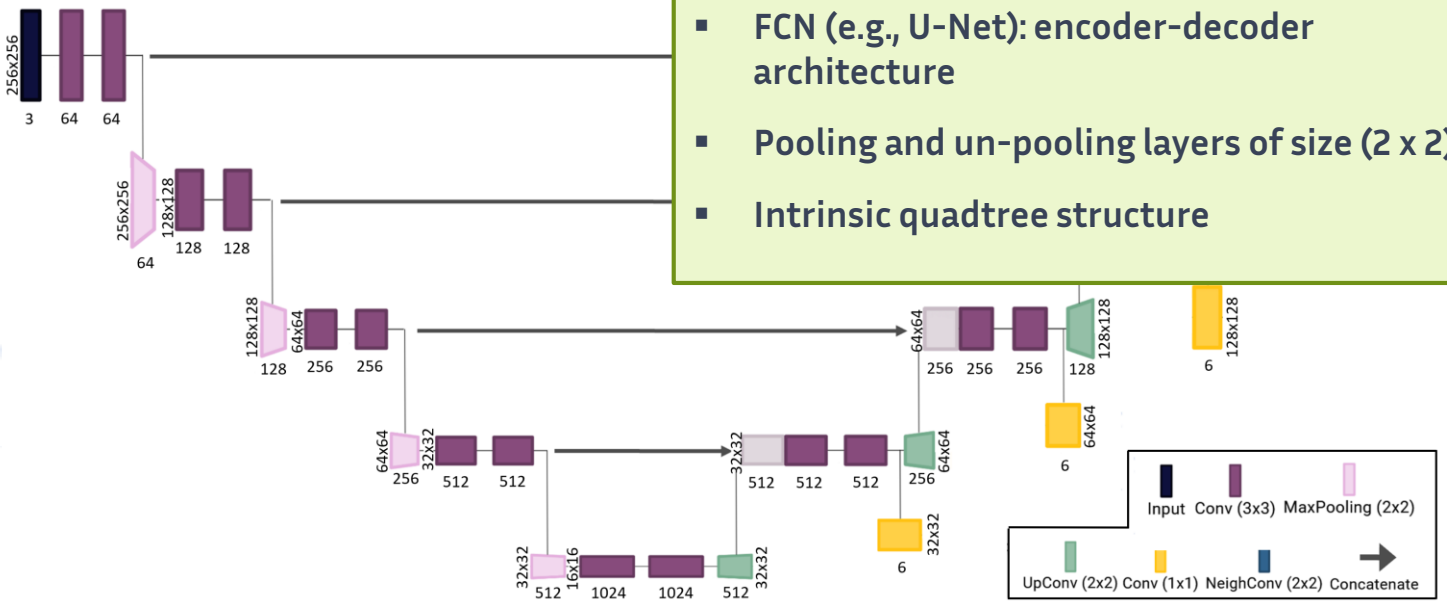
- **Architecture capable of integrating multiscale data without the need of ensemble learning techniques, thus making the approach end-to-end.**
- **Spatial-contextual information is favored in this framework, through**
  - a supplementary convolutional layer modeling the interactions between neighboring pixels at the same resolution.
  - an additional loss term which allows to integrate spatial information between neighboring pixels.

[1] M. Pastorino, G. Moser, S. B. Serpico, and J. Zerubia, "Semantic segmentation of remote sensing images through fully convolutional neural networks and hierarchical probabilistic graphical models," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 60, pp. 1–16, 2022.

# 02

# Proposed framework

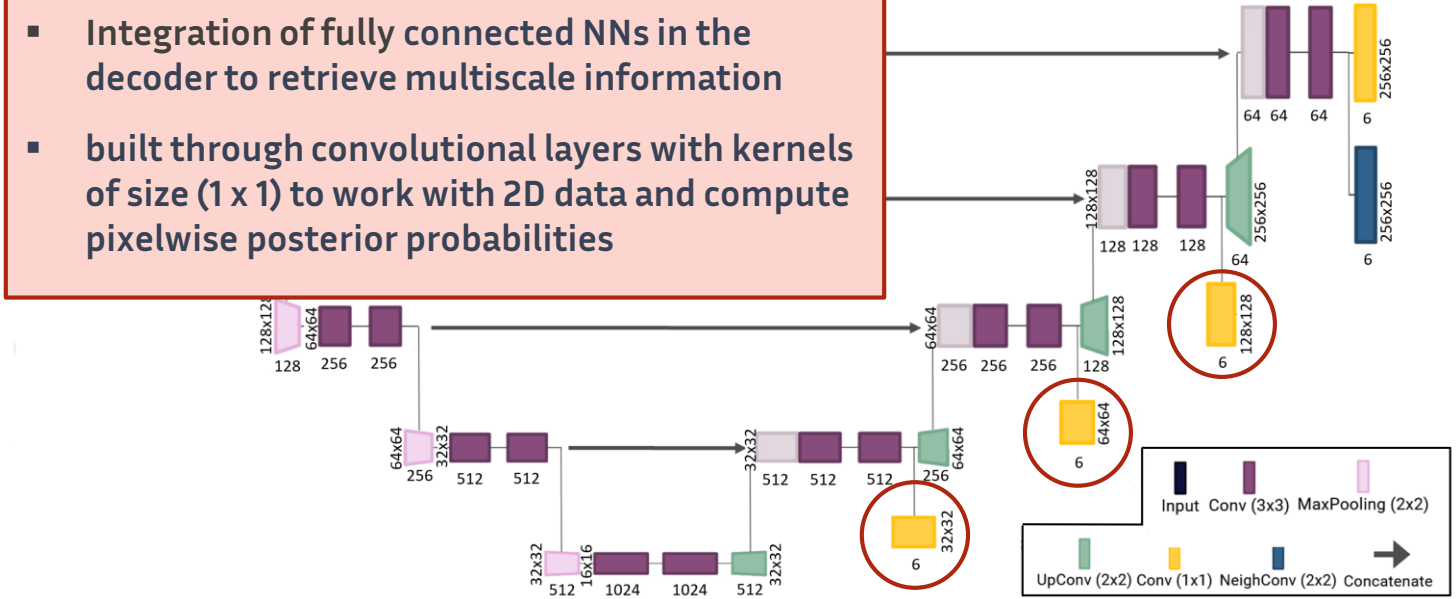
# Overall architecture




- FCN (e.g., U-Net): encoder-decoder architecture
- Pooling and un-pooling layers of size (2 x 2)
- Intrinsic quadtree structure

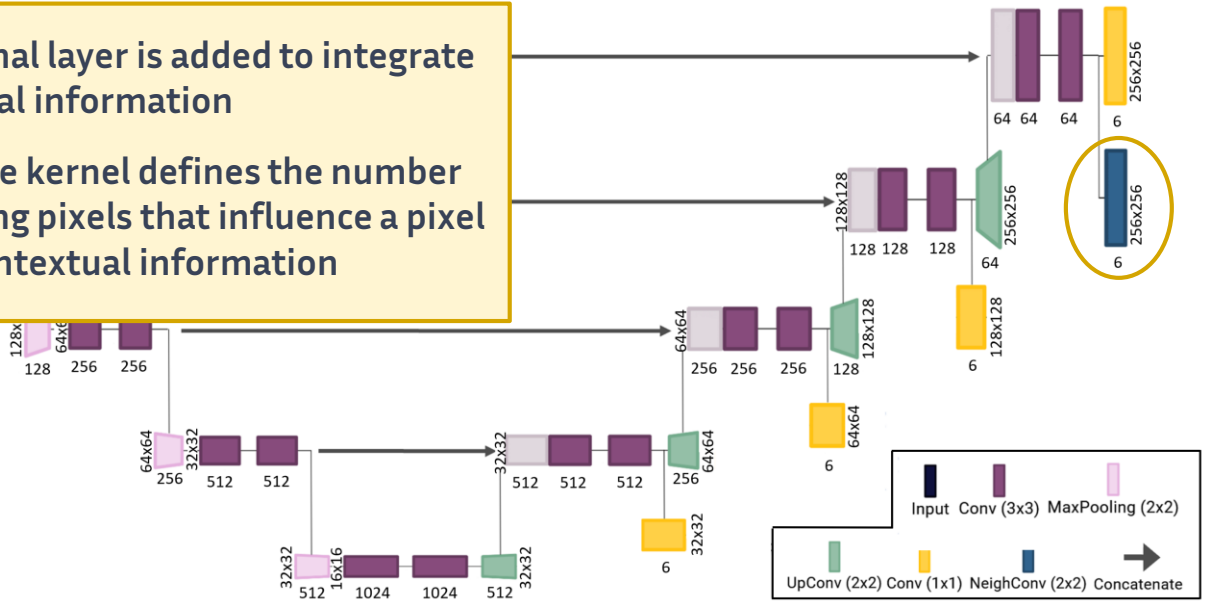
# Overall architecture

- Integration of fully connected NNs in the decoder to retrieve multiscale information
- built through convolutional layers with kernels of size (1 x 1) to work with 2D data and compute pixelwise posterior probabilities



# Overall architecture

- a convolutional layer is added to integrate further spatial information
- the size of the kernel defines the number of neighboring pixels that influence a pixel → spatial-contextual information



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# Loss function

weighting factor for imbalanced training data

$$\mathcal{L}_u = -\frac{1}{L}\sum_{l=1}^{L}\sum_{k=0}^{M-1}\frac{\widehat{P}_{max}}{\widehat{P}_k}\sum_{i\in S^l} t_{ik}\log(p_{ik}), p_{ik} = \frac{\exp(z_{ik})}{\sum_{n=0}^{M-1}\exp(z_{in})}$$

$$\mathcal{L}_p = -\sum_{a=1}^{W_L}\sum_{b=1}^{H_L}\sum_{k=0}^{M-1} t_{ik}\log\left(\sum_{j=0}^{D-1}\sum_{q=0}^{D-1} h_{j,q}\cdot p_{(a-j,b-q),k}\right)$$

$$\mathcal{L} = \mathcal{L}_u + \mathcal{L}_p$$

$M$ number of classes

$L$ number of resolutions

$H_L, W_L$ height, width of the pixel grid

$p_{ik}$ estimated output probability that pixel $i$ belongs to class $k$

$(z_{i1}, \dots, z_{ij})$ prediction vector

$\widehat{P}_k$ prior probability of the $k$ −th class

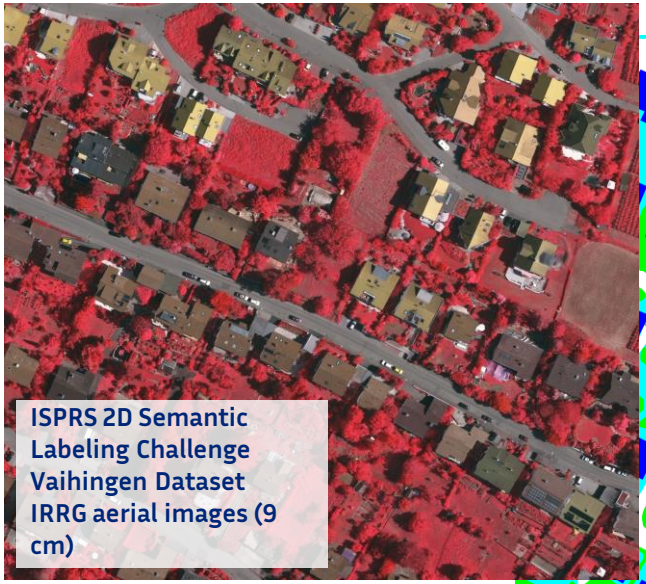
$h_{j,q}$ weight of the kernel of size $D \times D$

# 03

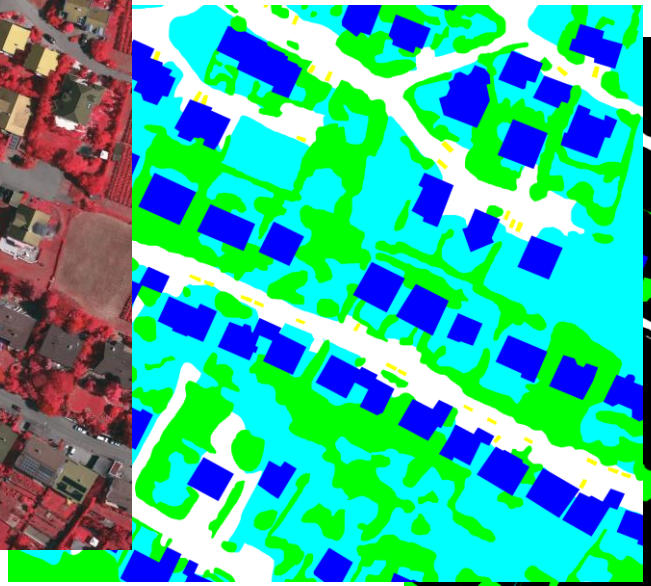
# Experimental results

# Dataset

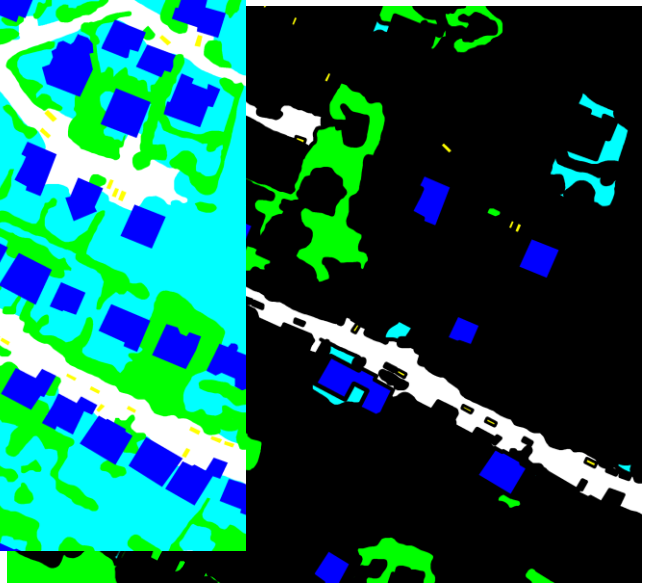
| | | |
|---|---|---|
| Buildings | Roads | Vegetation |
| Trees | Cars | Clutter |
| Unlabeled | | |




*Aerial image*



*Original GT*



*Scarce GT used to train the model*

https://www2.isprs.org/commissions/comm2/wg4/benchmark/



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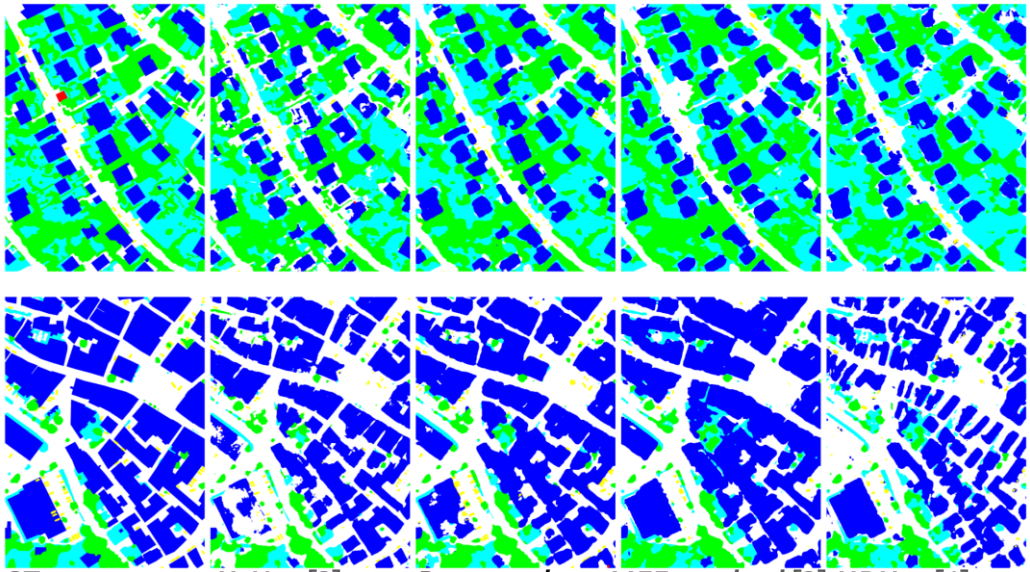
# Results




[2] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Med. Image Comput. Comput. Ass. Interv.*, ser. LNCS, vol. 9351. Springer, pp. 234–241, 2015.
[3] S. Liu, C. He, H. Bai, Y. Zhang, and J. Cheng, "Light-weight attention semantic segmentation network for high-resolution remote sensing images," in *2020 IGARSS*, pp. 2595–2598, 2020.
[4] K. Sun, B. Xiao, D. Liu, and J. Wang, "Deep high-resolution representation learning for human pose estimation," in *2019 CVPR*, pp. 5686–5696, 2019.

# Results (full images)

| | Architecture | buildings | impervious surf. | low vegetation | trees | cars | OA | recall | prec | F1 |
|---|---|---|---|---|---|---|---|---|---|---|
| Full GT | U-Net [2] | 0.86 | 0.91 | 0.79 | 0.90 | **0.86** | 0.89 | 0.87 | 0.85 | 0.86 |
| | MFF method [3] | **0.96** | **0.93** | 0.71 | 0.89 | 0.61 | 0.89 | 0.82 | **0.88** | 0.85 |
| | HRNet [4] | 0.89 | 0.89 | 0.50 | 0.89 | 0.81 | 0.79 | 0.80 | 0.81 | 0.81 |
| | **Proposed method** | **0.96** | 0.91 | **0.80** | **0.91** | 0.81 | **0.91** | **0.88** | 0.87 | **0.88** |
| Scarce GT | U-Net [2] | 0.87 | **0.93** | 0.64 | **0.87** | 0.76 | 0.82 | 0.81 | 0.84 | 0.83 |
| | MFF method [3] | **0.94** | 0.82 | 0.65 | 0.85 | 0.60 | 0.81 | 0.78 | 0.83 | 0.80 |
| | HRNet [4] | 0.84 | 0.75 | **0.82** | 0.69 | 0.49 | 0.77 | 0.72 | 0.79 | 0.75 |
| | **Proposed method** | **0.94** | 0.78 | 0.80 | **0.87** | **0.90** | **0.86** | **0.86** | **0.85** | **0.86** |

[2] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Med. Image Comput. Comput. Ass. Interv.*, ser. LNCS, vol. 9351. Springer, pp. 234–241, 2015.
[3] S. Liu, C. He, H. Bai, Y. Zhang, and J. Cheng, "Light-weight attention semantic segmentation network for high-resolution remote sensing images," in *2020 IGARSS*, pp. 2595–2598, 2020.
[4] K. Sun, B. Xiao, D. Liu, and J. Wang, "Deep high-resolution representation learning for human pose estimation," in *2019 CVPR*, pp. 5686–5696, 2019.

# Results (cropped images)

| | Architecture | buildings | impervious surf. | low vegetation | trees | cars | OA | recall | prec | F1 |
|---|---|---|---|---|---|---|---|---|---|---|
| Full GT | FCN + PGM [1] | 0.84 | 0.81 | 0.68 | 0.92 | **0.86** | 0.81 | 0.82 | 0.72 | 0.77 |
| | U-Net [2] | **0.92** | 0.83 | 0.71 | 0.92 | 0.74 | 0.85 | **0.83** | 0.84 | 0.83 |
| | MFF method [3] | 0.91 | **0.97** | 0.61 | 0.88 | 0.64 | 0.85 | 0.80 | 0.82 | 0.81 |
| | HRNet [4] | 0.89 | 0.81 | 0.42 | 0.92 | 0.63 | 0.77 | 0.73 | 0.76 | 0.74 |
| | **Proposed method** | **0.92** | 0.85 | **0.73** | **0.93** | 0.73 | **0.86** | **0.83** | **0.85** | **0.84** |
| Scarce GT | FCN + PGM [1] | 0.94 | 0.68 | 0.49 | 0.86 | **0.74** | 0.76 | 0.74 | 0.75 | 0.75 |
| | U-Net [2] | **0.96** | 0.65 | 0.47 | **0.89** | 0.48 | 0.76 | 0.69 | **0.81** | 0.75 |
| | MFF method [3] | 0.91 | 0.75 | 0.44 | 0.87 | 0.51 | 0.76 | 0.70 | 0.74 | 0.72 |
| | HRNet [4] | 0.84 | 0.77 | 0.68 | 0.80 | 0.29 | 0.77 | 0.68 | 0.74 | 0.71 |
| | **Proposed method** | 0.90 | **0.79** | **0.70** | **0.89** | 0.68 | **0.82** | **0.79** | **0.81** | **0.80** |

# 04

# Conclusions and perspectives

# Conclusions and perspectives

- Novel semantic segmentation method based on FCN, fully connected NNs, and a spatial loss function.
- Addresses a major challenge of deep learning for semantic segmentation of VHR RS images in case of scarce GT
- The advantages of the proposed techniques are progressively more relevant as the training set is farther from the ideal densely-labeled case and closer to real-world annotations

## Future work

- extension of this methodology to the multisensor case, with optical and radar images acquired by different missions and therefore with different spatial resolutions, frequencies, and bands.
- study of the effect on classification of the incorporation of different amounts of long-range spatial information (adaptive kernel)
- integration of the proposed method with transfer learning to work with datasets related to other real world applications, such as natural disaster management

Thank you very much for your attention!

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