



Motivation

Objective: detect changes in image pairs

- Useful for measuring urban expansion, deforestation, natural disasters, water loss;
- We aim to detect changes at pixel level, i.e. dense prediction.

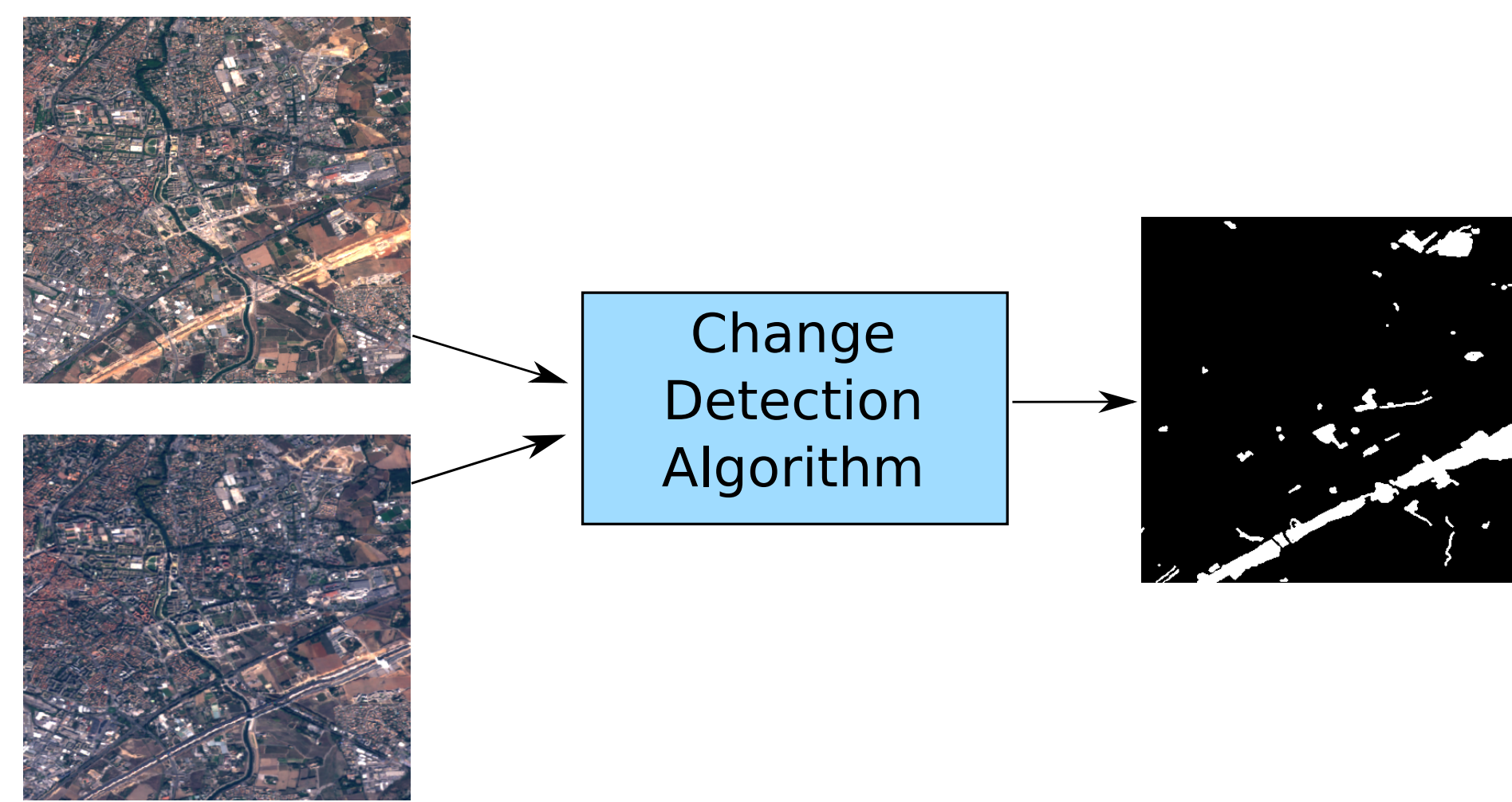


Fig. 1: Change detection flowchart.

Method: fully convolutional neural networks

- FCNNs are the state-of-the-art for dense classification problems due to their accuracy and speed;
- Change detection with CNNs through supervised learning has been shown to be feasible [1];

How to best extend traditional FCNNs for comparing two images?

Data

- OSCD dataset [1,5]: multispectral satellite images;

Data: <https://rcdaudt.github.io/oscd/>

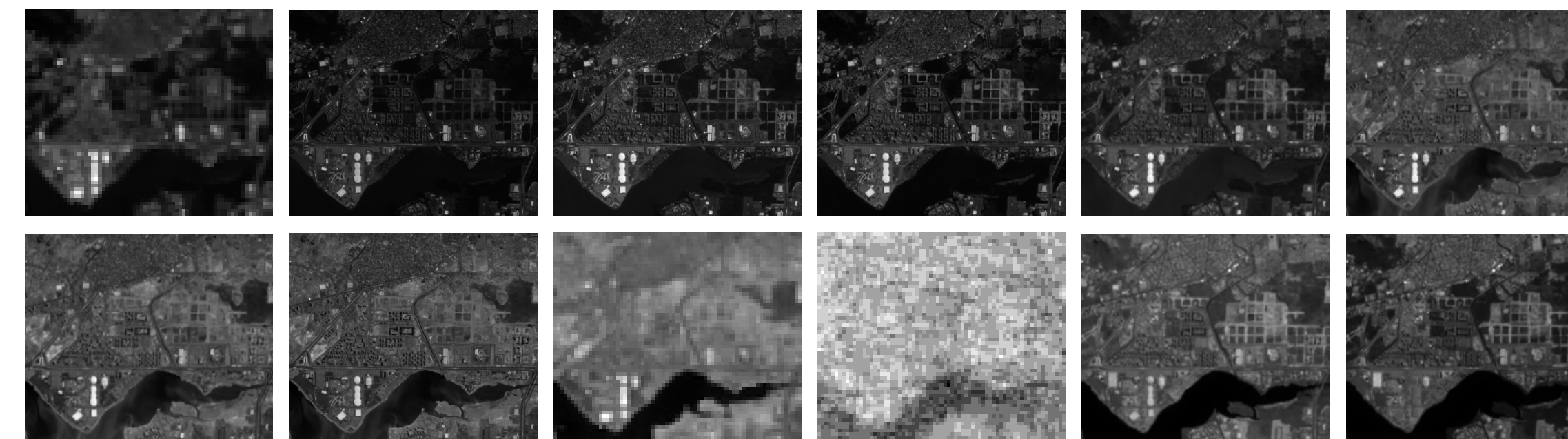


Fig. 2: Example of different bands of a Sentinel-2 multispectral image.



Fig. 3: True color image pair and associated change map from the OSCD dataset.

- Air Change dataset [2]: RGB aerial images.

Results

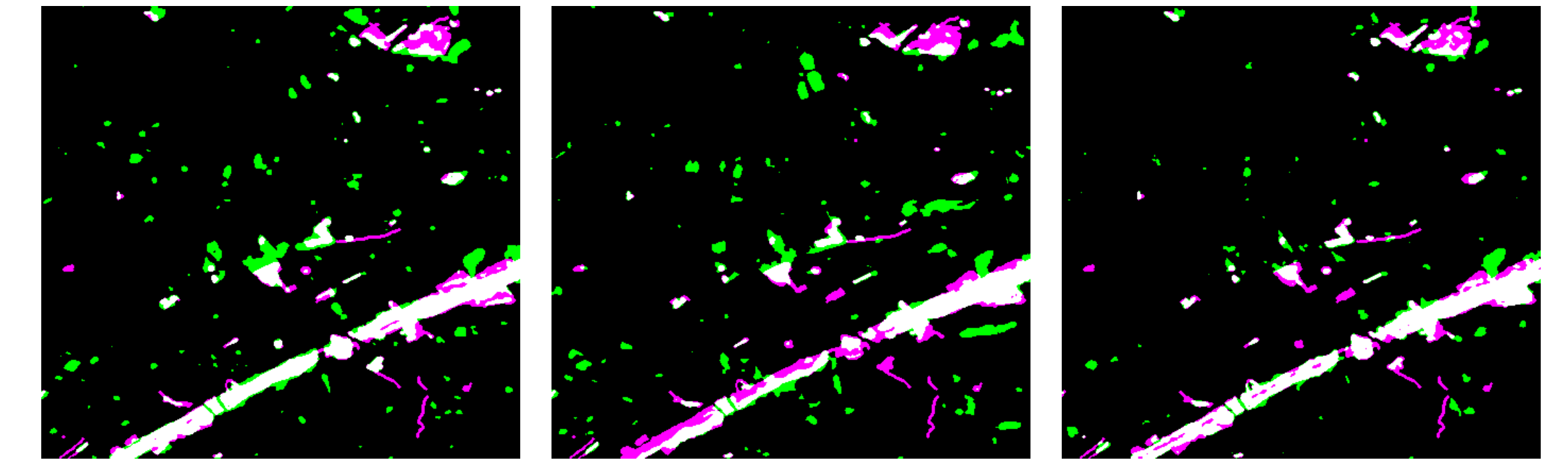


Fig. 8: From left to right: predictions by FC-EF, FC-Siam-conc, and FC-Siam-diff for the image pair in Fig. 3.

Data	Network	Prec	Recall	Global	F1
OSCD-3 ch.	Siam. [1]	21.57	79.40	76.76	33.85
	EF [1]	21.56	82.14	83.63	34.15
	FC-EF	44.72	53.92	94.23	48.89
	FC-Siam-conc	42.89	47.77	94.07	45.20
	FC-Siam-diff	49.81	47.94	94.86	48.86
OSCD-13 ch.	Siam. [1]	24.16	85.63	85.37	37.69
	EF [1]	28.35	84.69	88.15	42.48
	FC-EF	64.42	50.97	96.05	56.91
	FC-Siam-conc	42.39	65.15	93.68	51.36
	FC-Siam-diff	57.84	57.99	95.68	57.92
Szada/1 [2]	DSCN [4]	41.2	57.4	-	47.9
	CXM [2]	36.5	58.4	-	44.9
	SCCN [3]	24.4	34.7	-	28.7
	FC-EF	43.57	62.65	93.08	51.40
	FC-Siam-conc	40.93	65.61	92.46	50.41
	FC-Siam-diff	41.38	72.38	92.40	52.66
Tiszadob/3 [2]	DSCN [4]	88.3	85.1	-	86.7
	CXM [2]	61.7	93.4	-	74.3
	SCCN [3]	92.7	79.8	-	85.8
	FC-EF	90.28	96.74	97.66	93.40
	FC-Siam-conc	72.07	96.87	93.04	82.65
	FC-Siam-diff	69.51	88.29	91.37	77.78

Fig. 9: Quantitative comparison with other state-of-the-art methods.

Architectures

The nature of the problem can be used to build specialised change detection architectures.

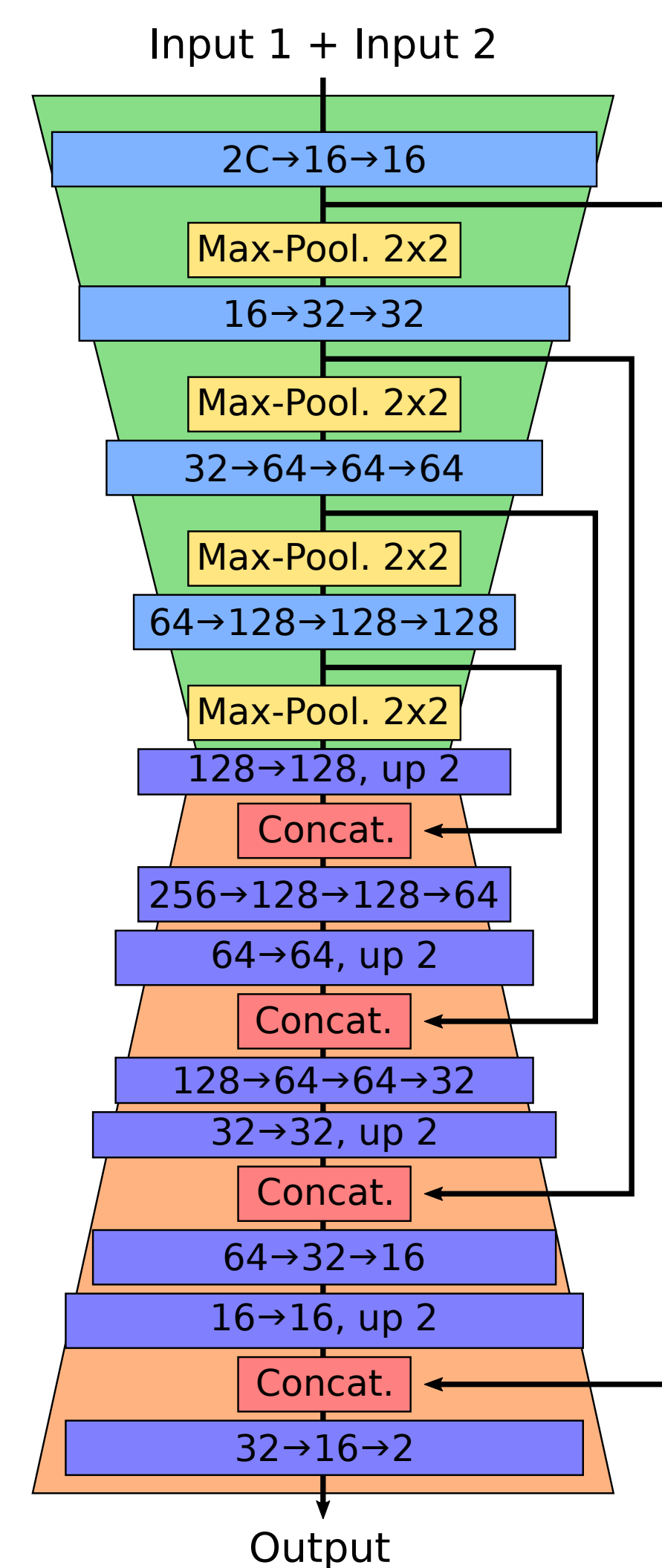


Fig. 5: No heuristics, U-Net based architecture: Early Fusion (FC-EF).

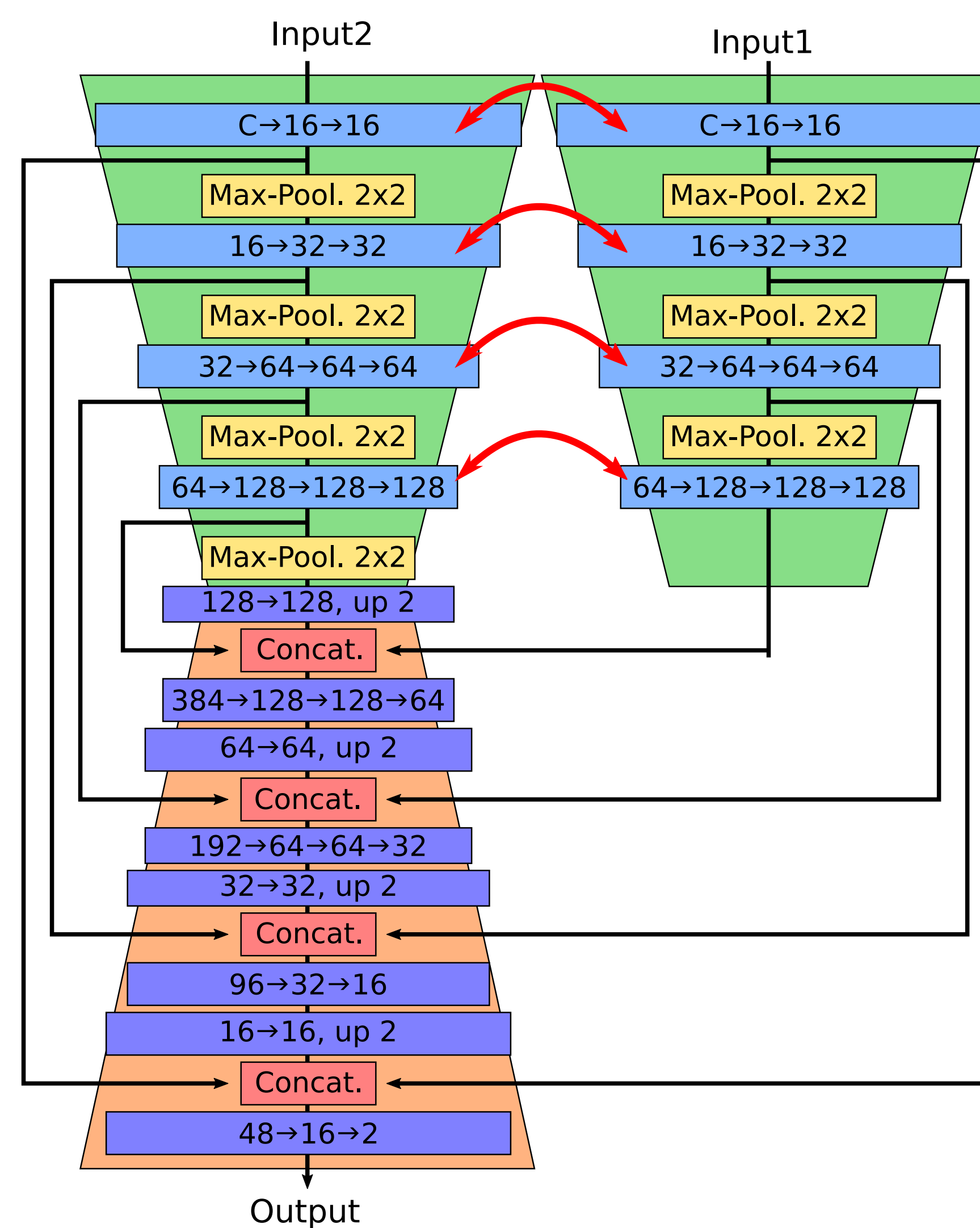


Fig. 6: Symmetric encoding of the images, fused decoding: Siamese - concatenation (FC-Siam-conc).

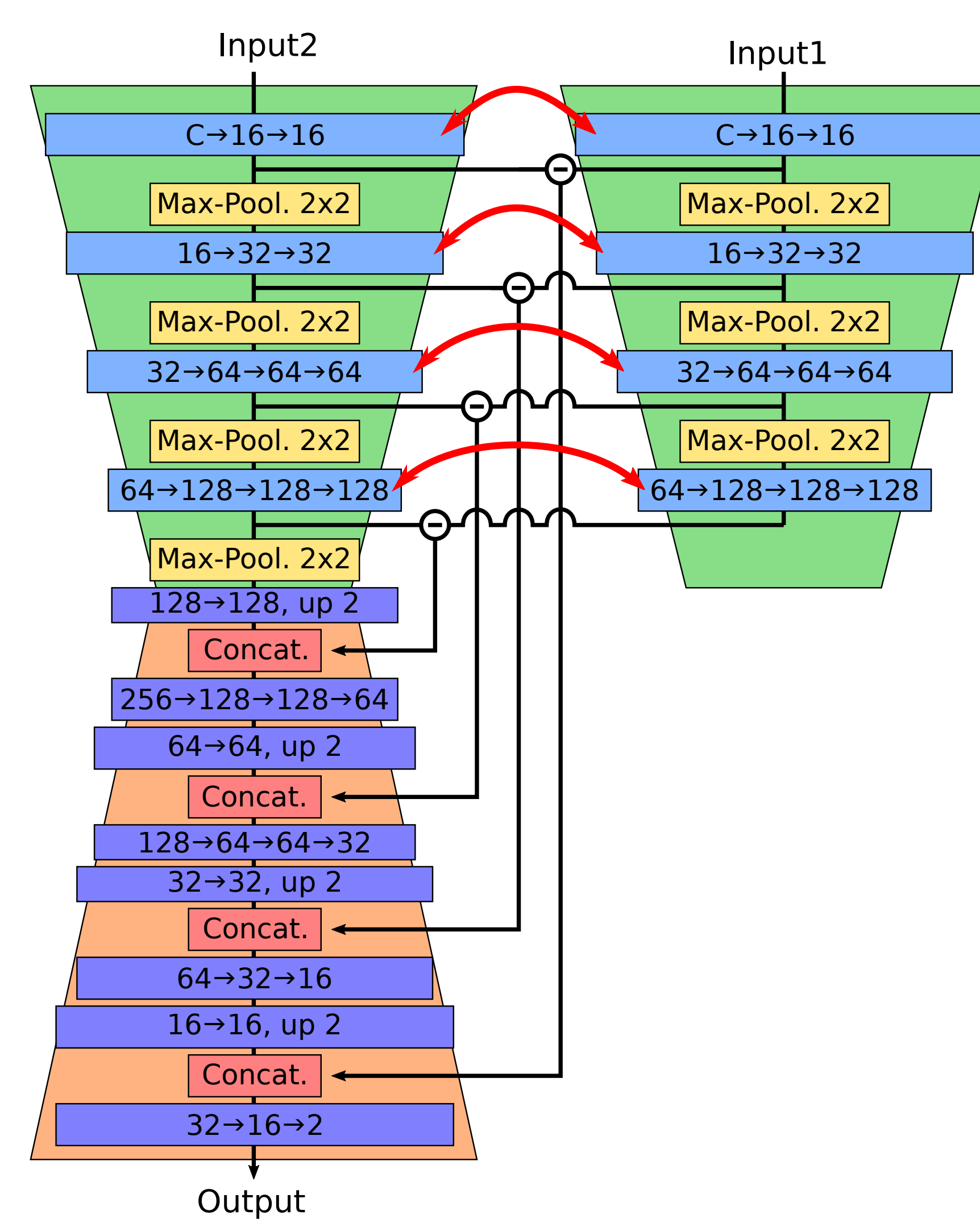


Fig. 7: Symmetric encoding, explicit comparison in skip connections: Siamese - difference (FC-Siam-diff).

Conclusion

- FCNNs trained for change detection for the first time;
- Outperformed previous methods in performance and speed without post-processing;
- Successful supervised learning despite size of datasets.

References

1. Rodrigo C. Daudt, Bertrand Le Saux, Alexandre Boulch, and Yann Gousseau. "Urban Change Detection for Multi-spectral Earth Observation Using Convolutional Neural Networks." IEEE International Geoscience and Remote Sensing Symposium. 2018.
2. Benedek, Csaba, and Tamás Szirányi. "Change detection in optical aerial images by a multilayer conditional mixed Markov model." IEEE Transactions on Geoscience and Remote Sensing. 2009.
3. Liu, J., Gong, M., Qin, K., and Zhang, P. (2016). A deep convolutional coupling network for change detection based on heterogeneous optical and radar images. IEEE transactions on neural networks and learning systems.
4. Zhan, Y., Fu, K., Yan, M., Sun, X., Wang, H., and Qiu, X. (2017). Change Detection Based on Deep Siamese Convolutional Network for Optical Aerial Images. IEEE Geoscience and Remote Sensing Letters, 14(10), 1845-1849.
5. OSCD Dataset: <https://rcdaudt.github.io/oscd/>