Deep learning based change detection in 3D point clouds

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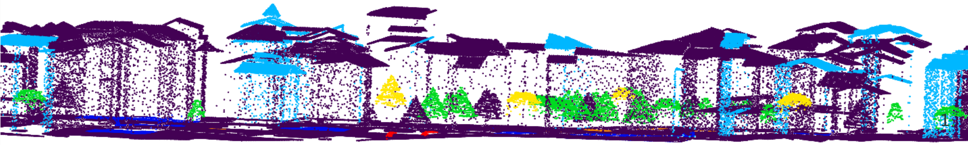
This work is part of a PhD funded by the CNES and Magellium



Change detection

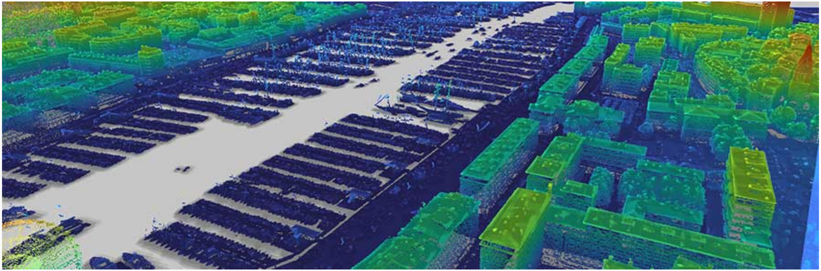
Google Earth Timelapse (Google, Landsat, Copernicus)

Wikipedia

More and more 3D data available...

Lebègue et al. 2020

https://www.intelligence-airbusds.com/



https://www.ign.fr/institut/lidar-hd-vers-une-nouvelle-cartographie-3d-du-territoire

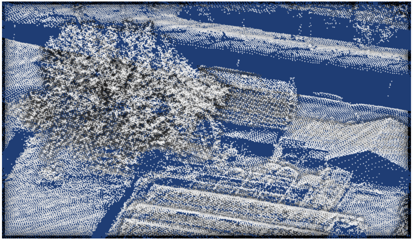
… and a need for methods dealing with these 3D data

- Consortium **AI4GEO**: AI at the service of 3D geospatial mapping
- **Post-disaster mapping** : Storm Alex (2020), Saint-Martin-Vésubie, France
- **Map updating**:
  - → **Monitoring** of **vegetation**, occupation of **public space**, **building** (shape of roofs)...
- **Fusion satellite 3D data/LiDAR-HD** :
  - → Updating the occasional ALS data with frequent satellite acquisition
  - → Denoising of 3D satellite data

⇒ **My PhD subject** : deep learning for 3D change detection

3D point clouds for change detection

Date 1



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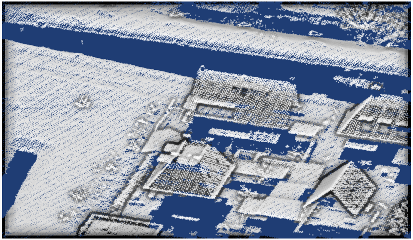

3D point clouds for change detection

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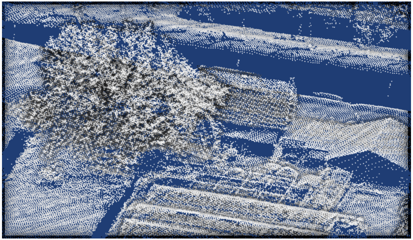

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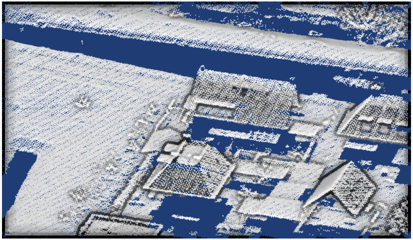

- Sparse
- Unordered

Unlike 2D images:

3D point clouds for change detection

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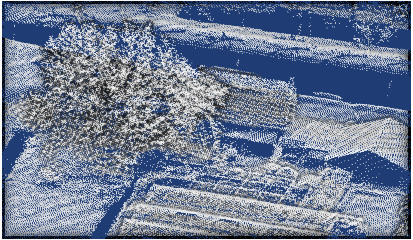

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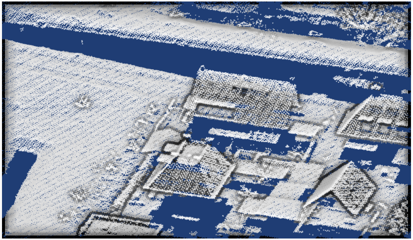

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$\Big\}$ Raw PCs $\neq$ matrices

Unlike 2D images:

3D point clouds for change detection

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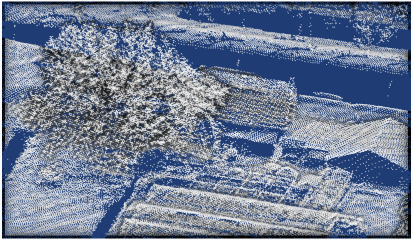

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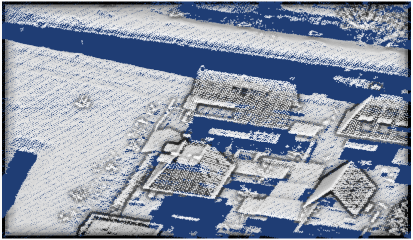

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$\Bigg\}$ Raw PCs $\neq$ matrices

Unlike 2D images:

- No direct comparison possible

3D point clouds for change detection

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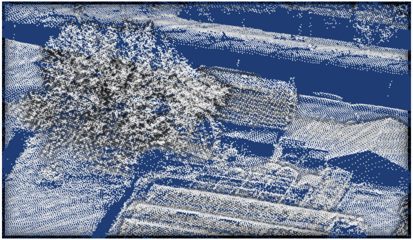

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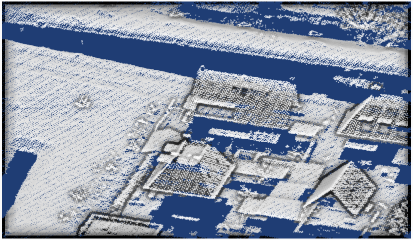

- Sparse
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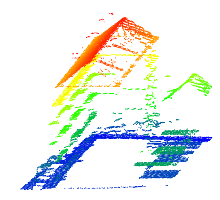
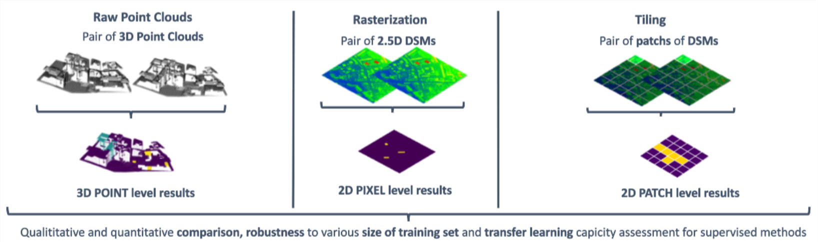
$\left.\begin{array}{l} \\ \\ \end{array}\right\}$ Raw PCs $\neq$ matrices



Unlike 2D images:

- No direct comparison possible
- Different hidden parts in each point cloud

Benchmark of methods for change detection



⇒ Majority of methods only focus on **DSMs** : loss of information

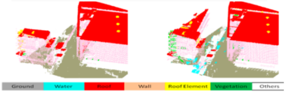
⇒ **Deep learning** method on produce a binary per 2D patch results

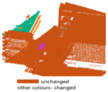
⇒ Existing **traditional methods** scores can be **largely improved**

Iris de Gélis, Sébastien Lefèvre, and Thomas Corpetti (2021b). "Change Detection in Urban Point Clouds: An Experimental Comparison with Simulated 3D Datasets". In: *Remote Sensing* 13.13, p. 2629

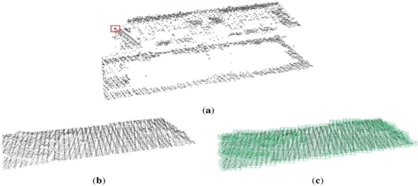
Related Works – Using raw 3D point clouds

Post-classification :
S. Xu, Vosselman, and Oude Elberink 2015

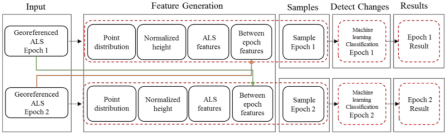




Pre-classification :
H. Xu et al. 2015

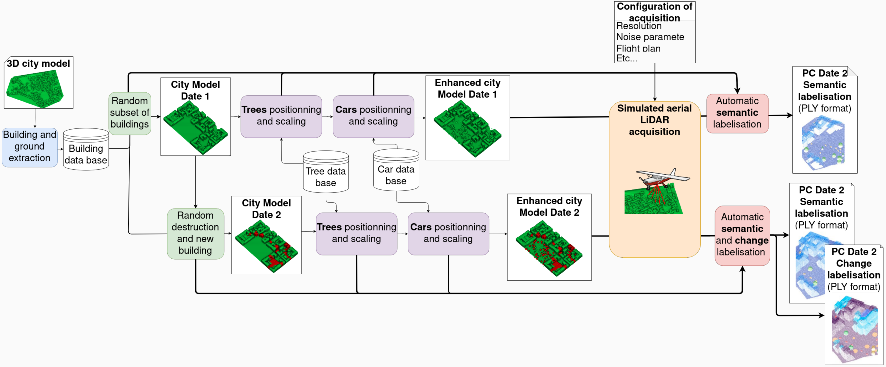


Single step methods
Tran, Ressl, and Pfeifer 2018



⇒ **No deep learning** based method for **3D point clouds change detection and categorization**

Urb3DCD - Simulator for 3D PCs in urban environment



→ **Automatic annotation** of PCs

→ Configuration of acquisition given by the user

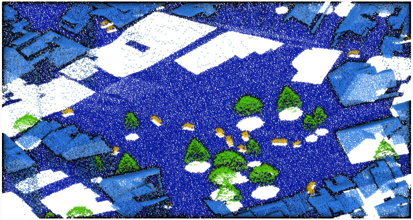
→ **8 different classes**: unchanged, new building, demolition, new vegetation, vegetation loss, vegetation growth, mobile objects

→ Mono-date semantic labels also available

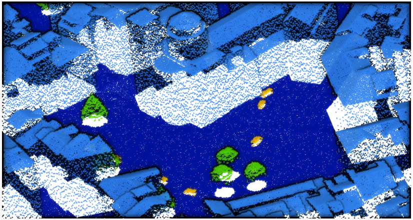
3D point clouds coming from our simulator V2

● Ground ● Building ● Vegetation ● Mobile Objects

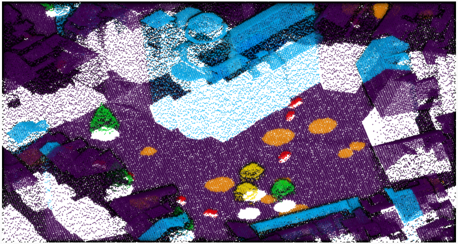
Date 1



Date 2

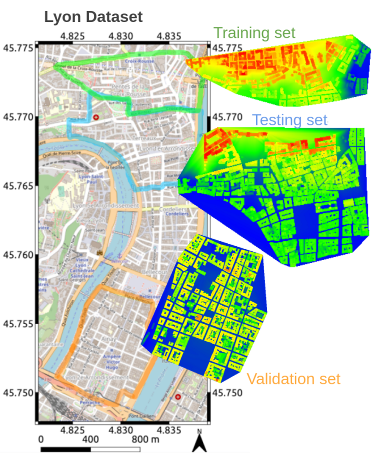


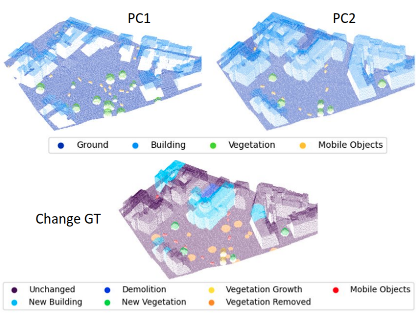
Labelling according to the change



● Unchanged ● New Building ● Demolition ● New Vegetation
● Vegetation Growth ● Vegetation Removed ● Mobile Objects

Urban 3D Point Clouds Changes Dataset



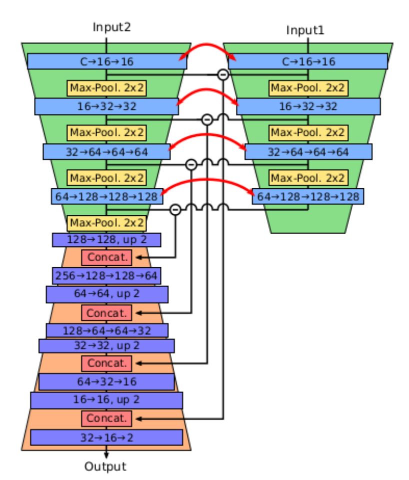


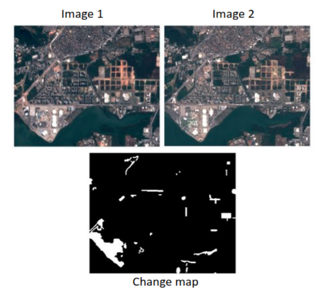
	Sub-datasets	
Parameters	LiDAR low res. Urb3DCD-1	MS Urb3DCD-2
Amount of training pairs	10	10
Density (points/m^2)	0.5	0.5 / 10
Noise range across track (°)	0.01	0.2 / 0.01
Noise range along track (°)	0	0.2 / 0
Noise scan direction (m)	0.05	1 / 0.05
Scan angle (°)	-20 to 20	-20 to 20
Overlapping (%)	10	10

⇒ This dataset is publicly available:

https://ieee-dataport.org/open-access/urb3dcd-urban-point-clouds-simulated-dataset-3d-change-detection

Fully Convolutional Siamese Network with difference

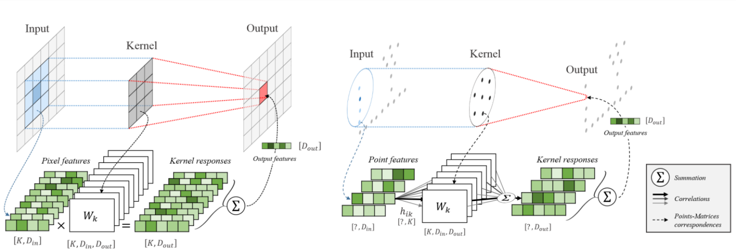




Daudt, Le Saux, and Boulch 2018

3D point clouds Semantic Segmentation : KPConv

2D Convolution **3D Kernel Point Convolution**



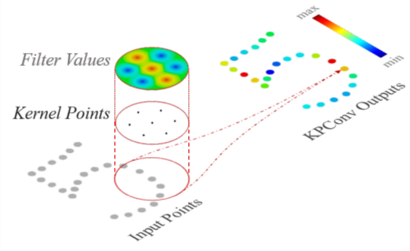
Thomas et al. 2019

Convolution by a kernel function g at a point $x \in \mathbb{R}^3$:

$$(\mathcal{F} * g)(x) = \sum_{x_i \in \mathcal{N}_i} g(\underbrace{x_i - x}_{y_i}) f_i$$

- x_i points from $\mathcal{P} \in \mathbb{R}^{N \times 3}$
- f_i corresponding features from $\mathcal{F} \in \mathbb{R}^{N \times D}$
- $\mathcal{N}_i = \{x_i \in \mathcal{P} | \|x_i - x\| \leq R\}$ with $R \in \mathbb{R}$
- g: kernel function defined inside $\mathcal{B}_R^3 = \{y \in \mathbb{R}^3 | \|y\| \leq R\}$

3D point clouds Semantic Segmentation : KPConv



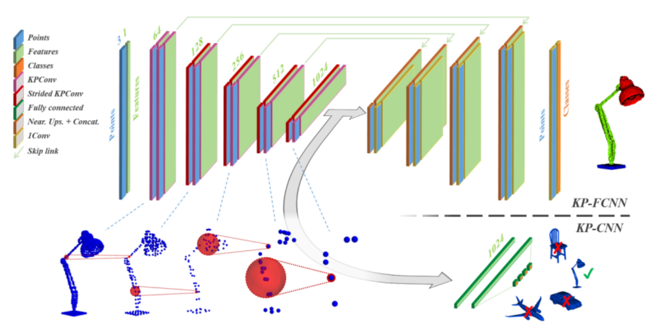
Thomas et al. 2019

Kernel function g applies weights to different areas :

$$g(y_i) = \sum_{k<K} h(y_i, \widetilde{x}_k) W_k$$

- $\widetilde{x}_k$: Kernel Point (k<K)
- W_k : Weight matrices $\{W_k | k < K\} \subset \mathbb{R}^{D_{in} \times D_{out}}$
- h : Correlation function: $h(y_i, \widetilde{x}_k) = max(0, 1 - \frac{\|y_i - \widetilde{x}_k\|}{\sigma})$
- σ : influence distance of kernel points

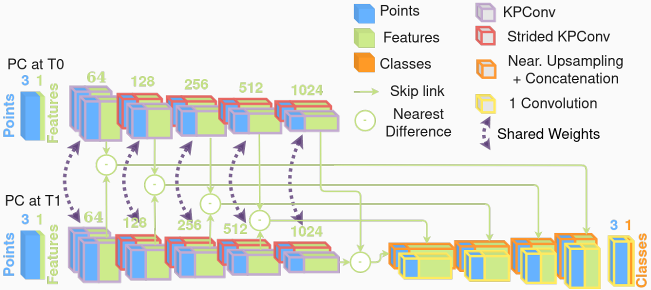
3D point clouds Semantic Segmentation : KPConv



Thomas et al. 2019

⇒ Network that looks like traditional 2D images CNN

Siamese Kernel Point Convolution Network



de Gélis, Lefèvre, and Corpetti 2021a

→ Nearest point feature difference: between the older PC $\mathcal{P}_0$ and its corresponding features in $\mathcal{F}_0$ and the newer PC $\mathcal{P}_1$ and its features $\mathcal{F}_1$

$$(\mathcal{P}_0, \mathcal{F}_0)(\mathcal{P}_1, \mathcal{F}_1) = f_{1i} - f_{0j|j=\arg\min(\|x_{\mathbf{1}i} - x_{\mathbf{0}j}\|)}$$

Learning strategies

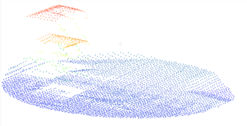
→ Cylindrical inputs for remote sensing large point clouds: $R = 25 \times dl_0$ (dl_0 input subsampling cell size)

→ Unbalanced classes: Input cylinders chosen thanks to a weighted random drawing

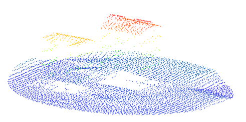
→ Loss: SGD with momentum (0.98) to minimize a point-wise weighted negative log likelihood loss

→ Data augmentation:

- Random rotation around vertical axis
- Point scale random Gaussian noise



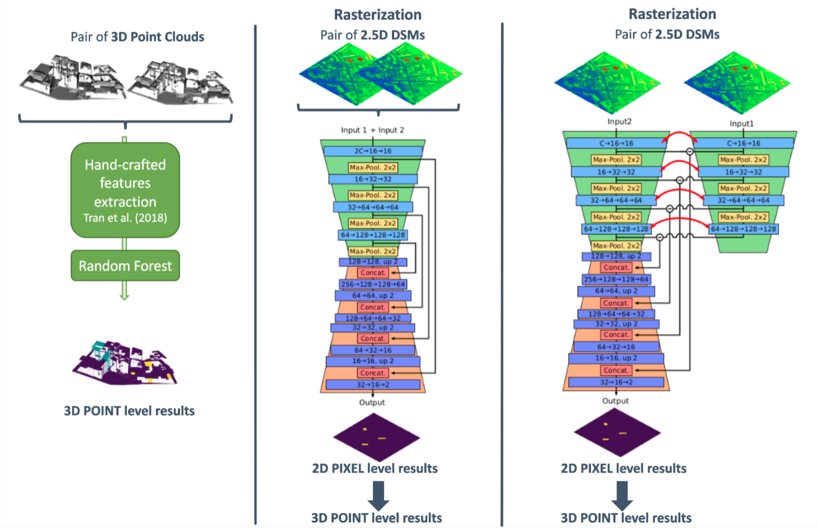
First cylinder



Second cylinder

Experimental Protocol

RF | DSM-FC-EF | DSM-Siamese



Tran, Ressl, and Pfeifer 2018

Daudt, Le Saux, and Boulch 2018
Zhang et al. 2019

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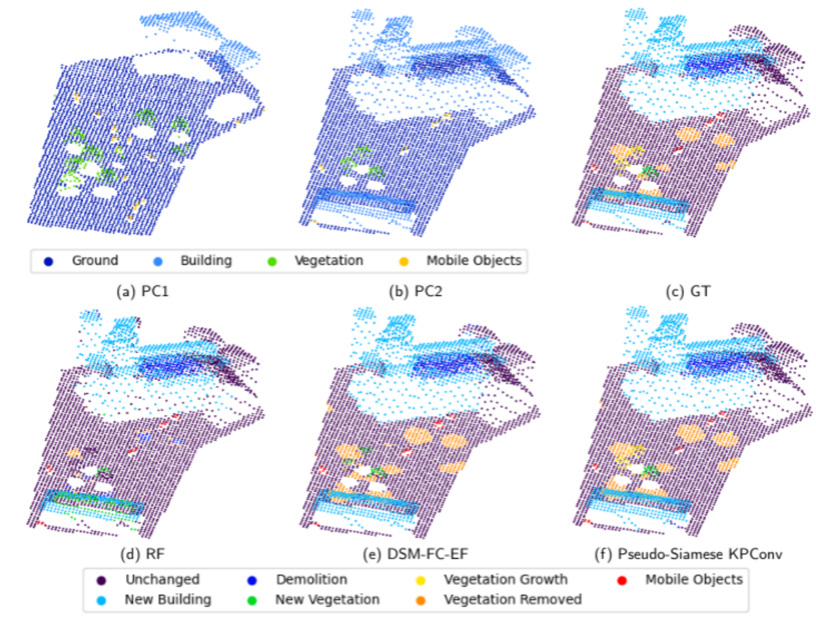
Zhang et al. 2019

Urb3DCD – LiDAR low density – Qualitative results



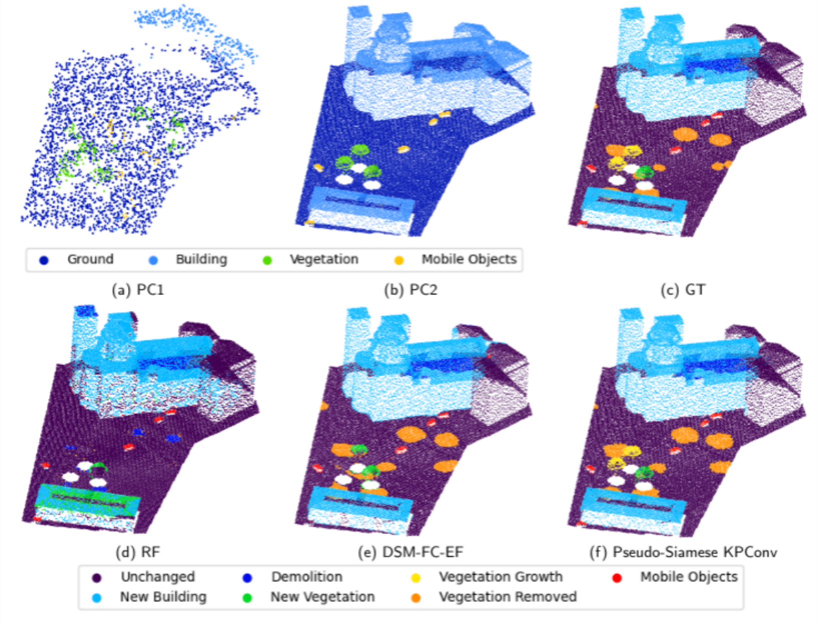
Urb3DCD – LiDAR low density – Quantitative results

Method	mAcc	mIoU$_{ch}$
Siamese KPConv	90.03 $\pm$ 0.69	81.54 $\pm$ 1.00
Pseudo-Siamese KPConv	**93.98** $\pm$ 1.26	**83.77** $\pm$ 1.20
DSM-Siamese	80.91 $\pm$ 5.29	57.41 $\pm$ 3.77
DSM-Pseudo-Siamese	75.17 $\pm$ 10.03	55.30 $\pm$ 8.17
DSM-FC-EF	81.47 $\pm$ 0.55	56.98 $\pm$ 0.79
RF	65.82 $\pm$ 0.05	52.37 $\pm$ 0.10

$\Rightarrow$ Large increase of performance with our (Pseudo-)Siamese KPConv

$\Rightarrow$ High results on harder classes (vegetation growth, mobile object)

Urb3DCD – Multi-Sensor – Qualitative results



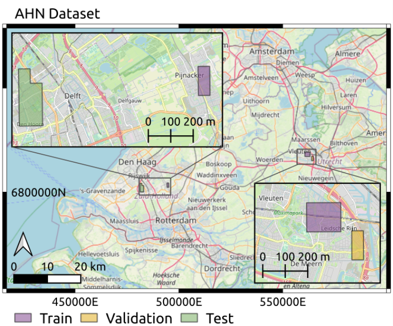
Urb3DCD – Multi-Sensor – Quantitative results

Method	mAcc	mIoU_{ch}
Siamese KPConv	58.19 $\pm$ 8.51	36.75 $\pm$ 5.46
Pseudo-Siamese KPConv	**89.74** $\pm$ 1.19	**75.59** $\pm$ 0.67
DSM-Siamese	69.91 $\pm$ 6.18	49.14 $\pm$ 4.92
DSM-Pseudo-Siamese	66.50 $\pm$ 10.82	46.60 $\pm$ 10.13
DSM-FC-EF	81.25 $\pm$ 1.86	55.59 $\pm$ 1.84
RF Tran, Ressl, and Pfeifer 2018	62.20 $\pm$ 0.02	46.81 $\pm$ 0.01

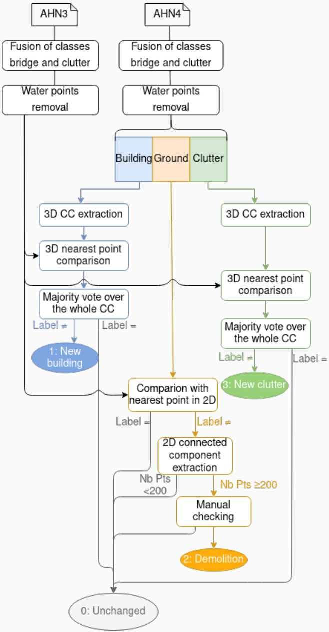
$\Rightarrow$ Unshared weights version of our network is better for multi-sensor dataset

What about results on real data?

- Actueel Hoogtebestand Nederland (**AHN**) : LiDAR data
- Classification for AHN3 and AHN4: ground, buildings, water, artwork, clutter

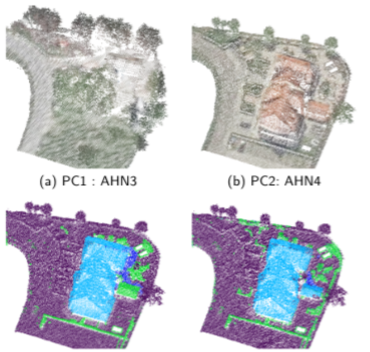


Test set annotation: manually corrected



Results on AHN Dataset

- Unchanged
- New Building
- Demolition
- New Clutter

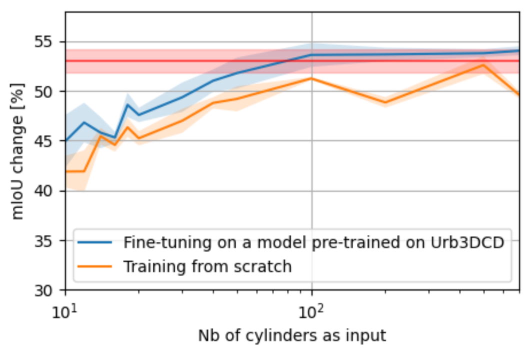


(a) PC1 : AHN3 (b) PC2: AHN4 (c) GT (d) Pseudo-Siamese KPConv

	mAcc	mIoU$_{ch}$
Siamese KPConv	87.84 $\pm$ 0.83	**72.73** $\pm$ 4.02
Pseudo Siamese KPConv	**89.20** $\pm$ 2.41	72.67 $\pm$ 1.06
DSM-Siamese	50.87 $\pm$ 1.15	30.96 $\pm$ 2.48
DSM-Pseudo-Siamese	70.71 $\pm$ 5.09	48.85 $\pm$ 7.03
DSM-FC-EF	71.47 $\pm$ 1.43	45.57 $\pm$ 0.98
RF	47.94 $\pm$ 0.02	29.45 $\pm$ 0.02

Transfer learning

Transferring from simulated to real datasets : can simulated data help when dealing with EO data?



$\Rightarrow$ **Reduction** of **85 %** of **input patches** from the target domain to reach the maximal mIoU_{ch}

Conclusions

- **Simulator** of **multi-temporal** urban **3D PCs** with **automatic annotation**
- End-to-end **deep learning** method for **change detection and categorization on raw 3D point clouds**
- IoU on classes of change: $\sim$ **+ 30 %** compared to RF with hand-crafted features
- **Pre-training** on dataset acquired thanks to our **simulator** : **reduction** by the **85%** of required **annotated data**
- **Future perspectives**:
  $\rightarrow$ Go to less supervision : self-supervised learning

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Thank you for your attention