Institut de Recherche en Informatique
et Systèmes Aléatoires

APPRENTISSAGE PROFOND POUR LA DÉTECTION DE CHANGEMENTS DANS DES NUAGES DE POINTS 3D

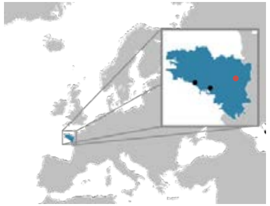
(WHEN DEEP LEARNING MEETS POINT CLOUDS AND CHANGE DETECTION)

Sébastien Lefèvre

ORASIS 2025, Le Croisic, 11 Juin 2025

IRISA, University of South Brittany, Vannes, France – sebastien.lefevre@irisa.fr

A BIT ABOUT ME



- Full Professor at University of South Brittany since 2010: www.univ-ubs.fr
  Adjunct Professor at UiT – The Arctic University of Norway since 2023
  Visiting Professor at ESA – Phi-lab since 2025
- Founder and former head of OBELIX group at IRISA:
  www.irisa.fr/obelix (25 researchers on AI4EO)
- Chair of the GeoData Science track
  EMJM Copernicus Master in Digital Earth: www.master-cde.eu

- Chair of the next AI4EO symposium (Rennes, September 2025): ai4eo2025.irisa.fr
- Looking for 2 new PhD students
  Explainable multimodal AI for assessing dynamic vulnerabilities from geospatial data
  Deep learning change detection from heterogeneous multitemporal remote sensing data

OBELIX GROUP

http://www-obelix.irisa.fr/

Focus on AI for EO

Founded 2013, ≈ 25 members (4 Prof, 7 Assoc.Prof, 5 Postdocs, 10 PhD, and regular visiting researchers… you're welcome!)

> 300 publications, 25 projects, 3 M€ contracts

OBELIX

Scientific challenges

Object detection

Land cover mapping

Lidar data

Earth and environment observations

- Multiple sensors (satellites, drones, etc.)
- Multiple nature of data (Multi or hyperspectral, LiDAR, SAR, temporal, etc.)
- Multiple settings of acquisition (ground or from above, atmospheric conditions)
- Tons of acquisition (large scale)
- Few labels, few annotations, sometimes available in multiple forms (vectorized, rasterized, point clouds)
- Uncertain, incomplete and noisy most of the time

→ Complex data that need dedicated learning and analysis methods for a variety of high-level tasks

OBELIX

A large playfield for many machine learning problems….

Handle the specific nature of data in the learning process

- domain adaptation, data imputation, robust learning with label noise, few-shot or multi-task learning (mostly in a deep learning context)

Exploit structure in the data

- Either by extracting specifically from the data or exploiting user-knowledge

Develop generative modeling for earth observation

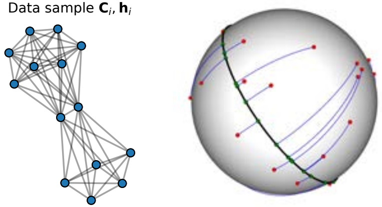
- transfer across modalities (e.g. multi-modal image fusion), super-resolution, or inverse reconstruction problem with deep priors

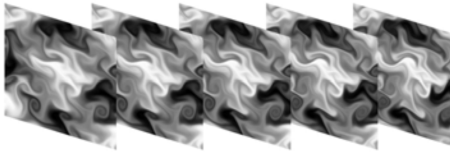
Physics-driven Machine learning

- Integrate physics priors in predictions and exploit physics in explaining dynamics in neural nets

High performance computing

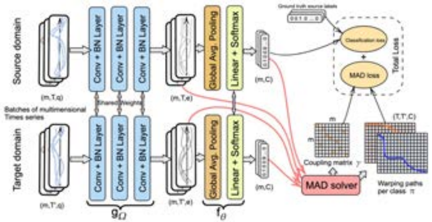
- Tackle large scale computing problems (energy efficiency) by e.g. quantization of neural nets.
- Quantum computing (prospective)

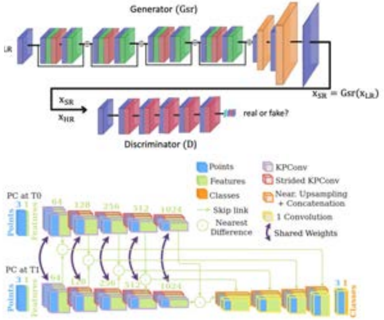




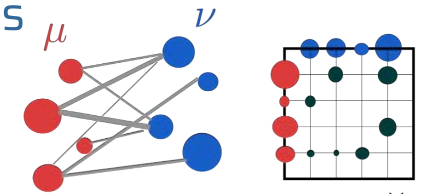
OBELIX

… that require many novel learning tools





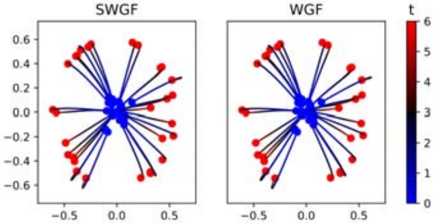
Deep Learning



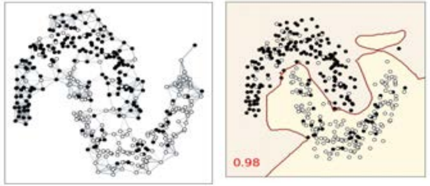
$\pi \in \mathbb{R}_{+}^{n\times m}$

$$\mathcal{T}_c(\mu,\nu) = \inf_{\pi\in\Pi(\mu,\nu)} \int_{\mathcal{X}\times\mathcal{Y}} c(x,y)\mathrm{d}\pi(x,y)$$

Optimal Transport

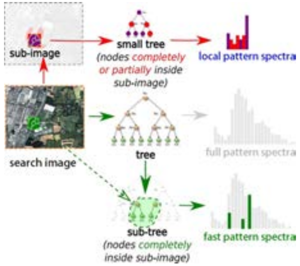


Gradient Flows



Structural regularization

…



Morphological hierarchies

Publication Communities

Machine Learning (Theoretical focus)

NeurIPS, ICML, ICLR, AISTATS, JMLR

Computer vision

ICCV, CVPR, ECCV, ACCV, TPAMI

Remote Sensing (Applied focus)

IEEE IGARSS, TGRS, Remote Sensing

APPRENTISSAGE PROFOND POUR LA DÉTECTION DE CHANGEMENTS DANS DES NUAGES DE POINTS 3D

WHEN DEEP LEARNING MEETS POINT CLOUDS AND CHANGE DETECTION

A BIT ABOUT YOU

Vers une approche multimodale basée sur l'apprentissage automatique et profon... pendant la chute

GLOBE: Localisation basée sur le recalage de modèles gaussien...

Comparaison de modèles d'apprentissage pour la dét...

Classification binaire des phases d'action...

Étude Comparative des CNNs...

Détection du Stre... Stochastique...

...processing in individ...

...dèles pré-entraînés da...

...tion

...per-résolution d'imag...

...par Rééchantillonnag... ...ection

Apprentissage en Contexte pour l...

InteractOR: Interacting with Images...

Segmentation multi-échelle des feux...

La hiérarchie en vision par ordinateur :...

Étude des méthodes de distillation de co...

Évaluation sans référence de la qualité de...

3DSES: an indoor Lidar point cloud segmen...

Calibration améliorée d'un capteur profileur l... ...la reconstruction 3D

Réseaux de neurones par graphes informés pa... ...que pour la reconstruction de champs de ... mécaniques

...uto-calibrée

...matique du domaine de convergence d'un asservissement visuel direct

...lants : Revue et évaluation d'approches génératives

...de représentations d'ima... ...idé par les relations spatiales

...iques de qualité pour... ...urs

...blématique de l'apprent... ...l'échelle de la méthode NeRF appliquée à l'imagerie satellitaire

Reconstru... ...Gaussiennes volumétriques

...dustrie

...eprésentations multi-modales d'images de

...pproche multimodale pour l'analyse

...e sous contraintes géom...

...ion

...e vers réel

...pour la Vidéo...

...rge-scale 3D D...

...hode de recon...

...k: 3D Talking ...

Apport de... de l...

...s-marines

...sation

...abels from a 3D...

...a Terre

...tions Visuelles à partir d'Images

...ssage de réseaux de neurones à impulsions

...r de rappel pour l'évaluation des modèles génératifs

...ales dans les modèles vision-langages

No Change Detection

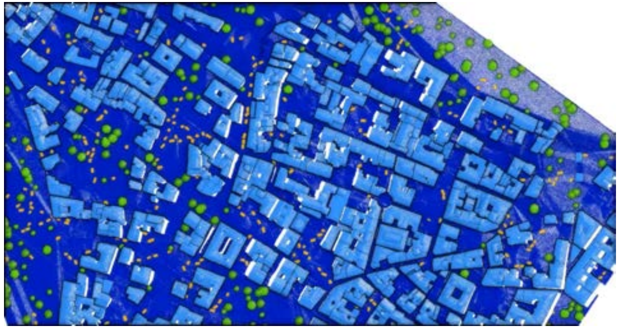
Not so much of Point Cloud / 3D data

But a lot of Deep Learning!

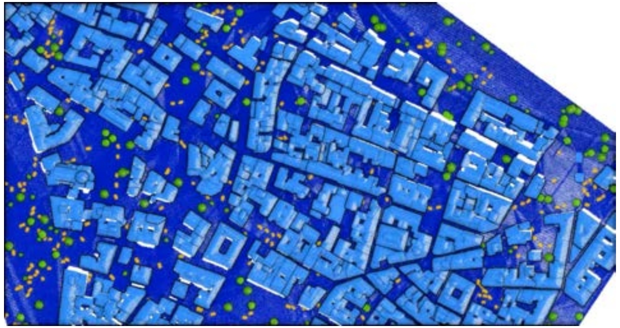
WHEN DEEP LEARNING MEETS POINT CLOUDS AND CHANGE DETECTION

When a new topic meets ORASIS’25 participants

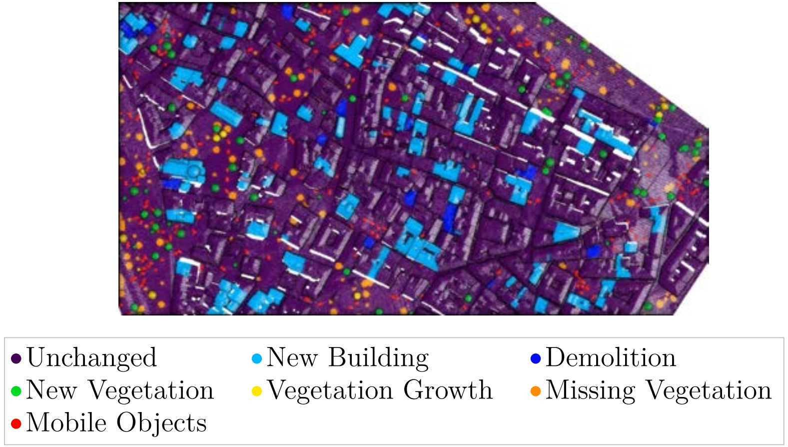
CHANGE DETECTION IN POINT CLOUDS: AN EO PERSPECTIVE



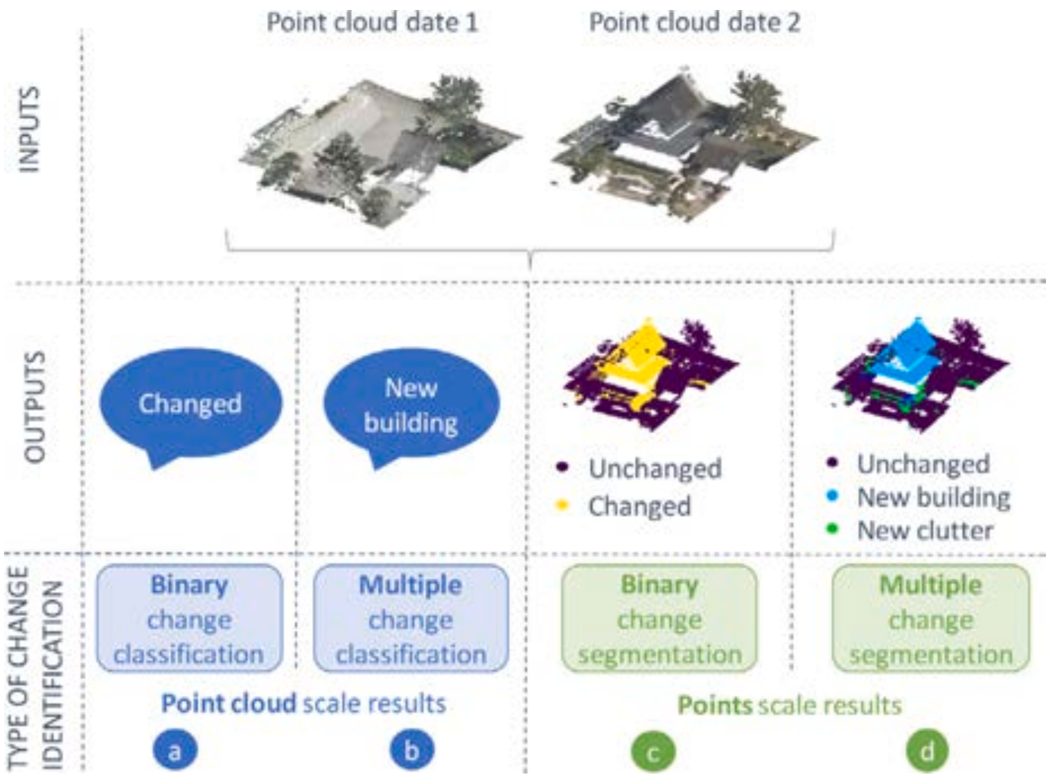
3D data at time 1



3D data at time 2



MULTIPLE TASKS IN CHANGE DETECTION



WHEN DEEP LEARNING MEETS POINT CLOUDS AND CHANGE DETECTION

When a new topic meets ORASIS'25 participants

But findings / good practices are not limited to Point Cloud Change Detection and can be used widely in Computer Vision

So let us start this keynote speech!

WHEN DEEP LEARNING MEETS POINT CLOUDS AND CHANGE DETECTION

Actually, they did only recently!

through the PhD thesis of Iris de Gélis (2020-2023)

awarded by AFRIF (special prize 2023) and GDR MAGIS (2024)

https://theses.hal.science/tel-04449411
https://scholar.google.com/citations?user=LH2QjwgAAAAJ
https://github.com/IdeGelis

1. Motivation

2. Data

3. Methods

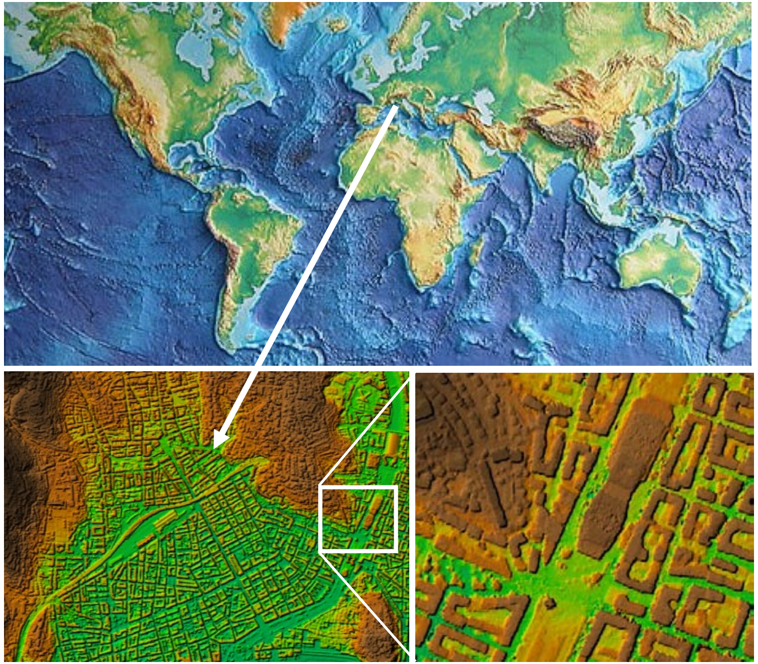
4. Supervision

5. Applications

CO3D EO MISSION

A constellation of 4 satellites to be launched in 2025

- CNES/AIRBUS (https://co3d.cnes.fr)
- 50cm RGB-NIR
- DSM 1m worldwide (land surface)



Figures from Laurent Lebègue (CNES)
https://doi.org/10.5194/isprs-archives-XLIII-B1-2020-299-2020

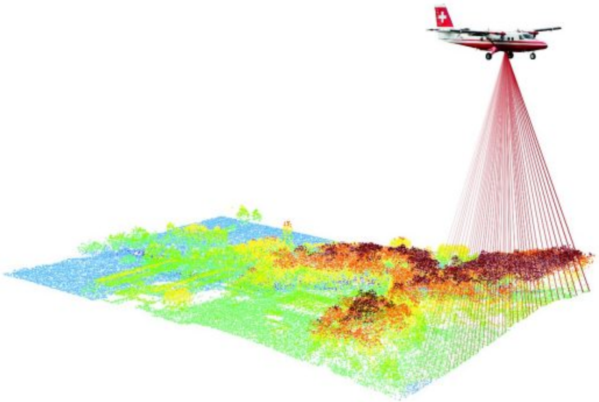
ACQUIRING POINT CLOUDS

Multiple LiDAR sensors
(ALS, TLS, MLS)

Photogrammetry
from sky or space

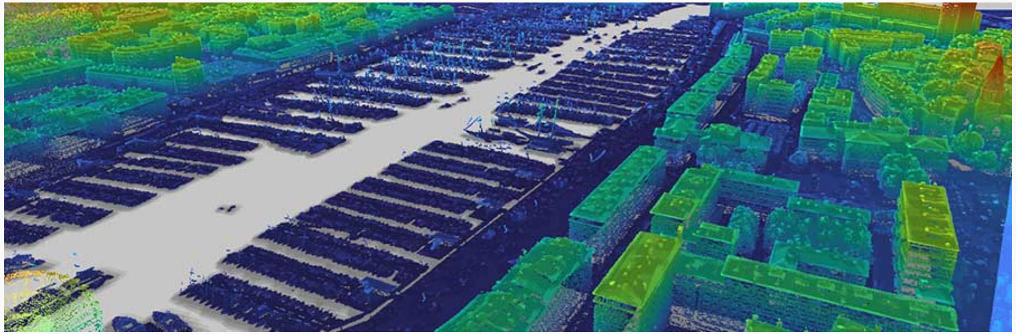
LiDAR HD: public data at
50cm / 1m / 5m resolution
(more than 10pts/m2)

Raw and classifier PC
+ DTM/DSM/DEM



(b) Aerial LiDAR
Source: swisstopo.admin.ch

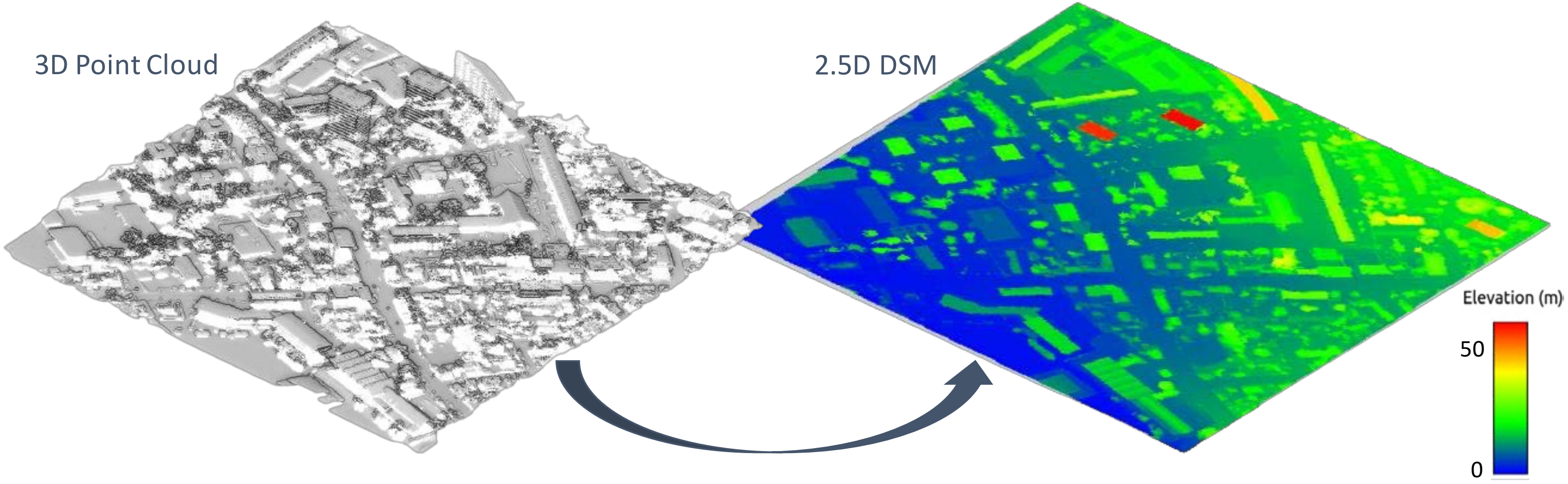
(a) Aerial photogrammetry
Source: J. Vallet



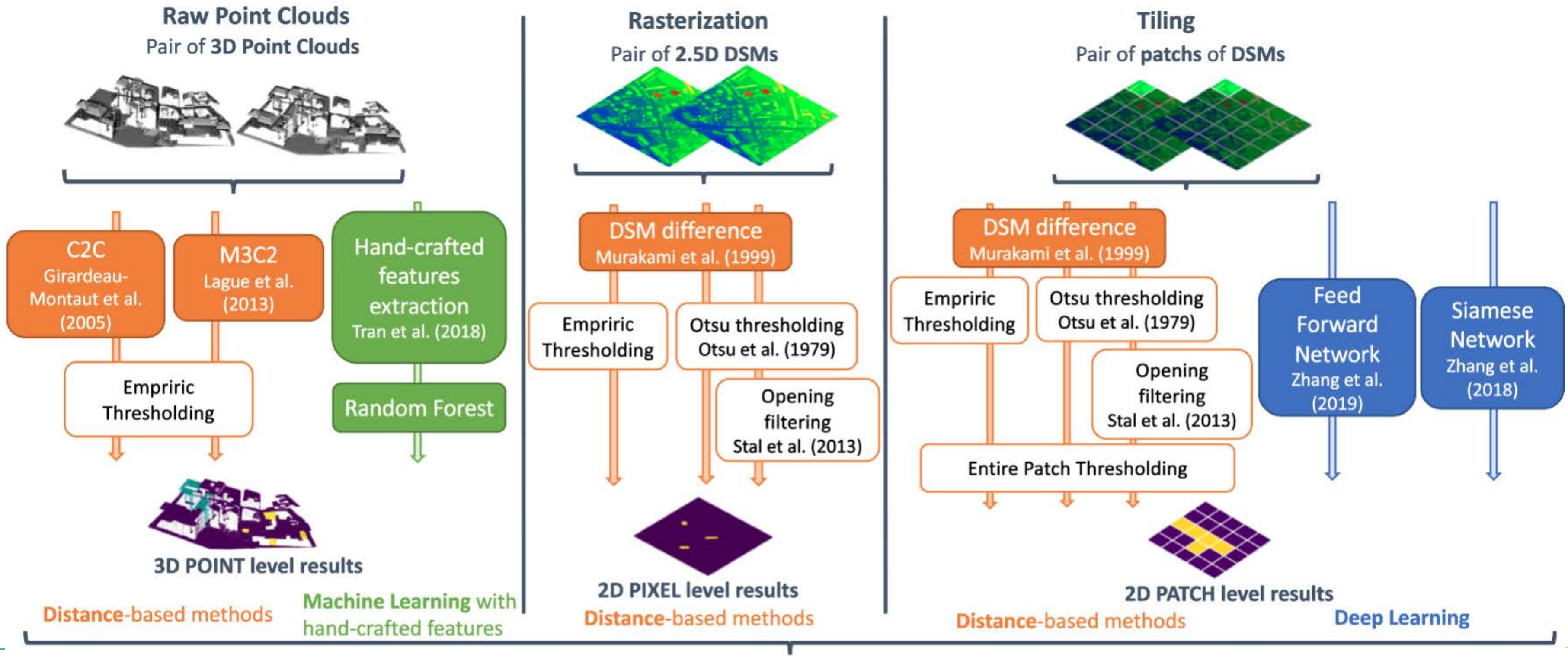
https://www.ign.fr/institut/lidar-hd-vers-une-nouvelle-cartographie-3d-du-territoire

3D = 2.5D?

In many (most) works, Point Clouds are rasterized in DEM/DSM/DTMs:
(+) allowing to easily use the many existing image processing/analysis tools
(-) but loosing some (key) information



3D CHANGE DETECTION IN THE EARLY YEARS



Qualititative and quantitative **comparison** on a common **public dataset** composed of **various qualities** of urban simulated **point clouds**

1. Motivation

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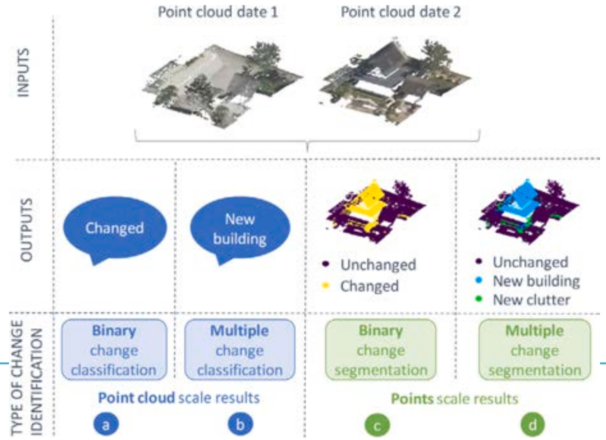
THERE ARE NO DATA LIKE MORE DATA

The role of datasets for DL/ML development in EO has already been demonstrated (similarly to other applications in CV)

TASK	PLATFORM	TIMESTAMPS	NAME	PUBLICATION DATE	POINT DENSITY (POINTS/M2)	NUMBER OF CLASSES	NUMBER OF POINTS	VOLUME (MB)
Change detection	ALS	Multiple	Abenberg ALS	2013	16	–	5,400,000	258
Classification	ALS	Single	NEWFOR	2015	Varies	Four	–	97
Classification	ALS	Single	DFC19	2019	–	Six	167,400,000	613
Classification	ALS	Single	ISPRS 3D Vaihingen	2014	8	Nine	780,879	–
Classification	Multiple	Single	ArCH	2020	Varies	10	136,138,423	–
Classification/semantic segmentation	ALS	Single	DublinCity	2019	240–348	13	260,000,000	3,000
Filtering	ALS	Single	OpenGF	2021	6 and 14	Three	542,100,000	2,280
Object detection/semantic segmentation	TLS	Single	LiSurveying	2021	Varies	54	2,450,000,000	–
Others	ALS	Single	RoofN3D	2018	4.72	Three	118,100	–
Semantic segmentation	ALS	Single	LASDU	2020	3–4	Six	3,120,000	–
Semantic segmentation	ALS	Single	DALES	2020	50	Eight	505,000,000	4,000
Semantic segmentation	ALS	Single	DALES Object	2021	50	Eight	492,000,000	5,000
Semantic segmentation	Drone	Single	Campus3D	2020	Varies	24	937,000,000	2,500
Semantic segmentation	Drone	Multiple	Hessigheim 3D	2021	800	11	73,909,354	5,950
Semantic segmentation	Drone	Single	WildForest3D	2022	60	Six	7,000,000	81
Semantic segmentation	MLS	Single	Toronto3D	2020	1,000	Eight	7,830,0000	1,100
Semantic segmentation	MLS	Multiple	HelixNet	2022	–	Nine	8,850,000,000	235,700
Semantic segmentation	Photogrammetry	Single	SensatUrban	2020	–	13	2,847,000,000	36,000
Semantic segmentation	Photogrammetry	Single	STPLS3D	2022	–	20	–	36,600 (images: 700,000)
Semantic segmentation	TLS	Single	Semantic 3D	2017	–	Eight	4000000000	23,940

Aerial/Space Point Cloud Change Detection:

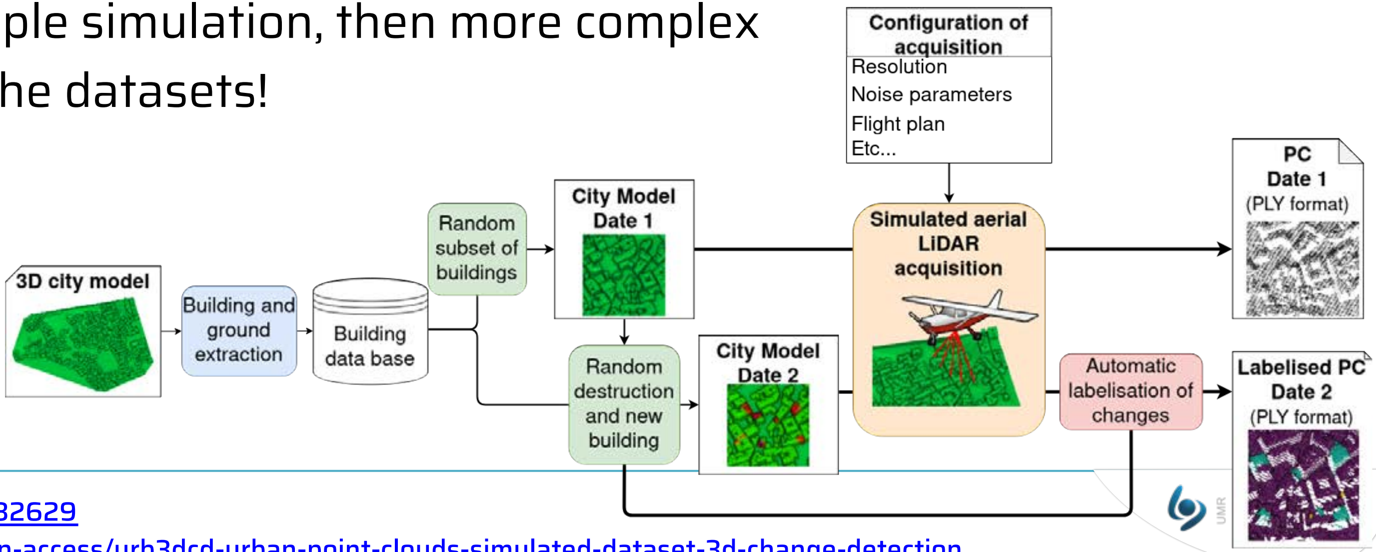
A new task that requires a new dataset



WHY SIMULATED DATA?

Parameters	Urb3DCD-V2-1 LiDAR low dens. Both PCs	Urb3DCD-V2-2 MS PC 1	PC 2	Urb3DCD-Cls Both PCs
Density (points/m^2)	0.5	0.5	10	10
Noise range across track (°)	0.01	0.2	0.01	0.01
Noise range along track (°)	0	0.2	0	0
Noise scan direction (m)	0.05	1	0.05	0.05
Scan angle (°)	−20 to 20	−20 to 20		−20 to 20
Overlapping (%)	10	10		10
Height of flight (m)	700	700		700
Annotation level	Point	Point		PC

- No need for tedious labeling!
  But we need a simulator…
- Customize the simulation leads to variants (e.g. point density) of the dataset to assess specific properties of the methods to be benchmarked
- Start with simple simulation, then more complex
- Disseminate the datasets!



https://doi.org/10.3390/rs13132629
https://ieee-dataport.org/open-access/urb3dcd-urban-point-clouds-simulated-dataset-3d-change-detection

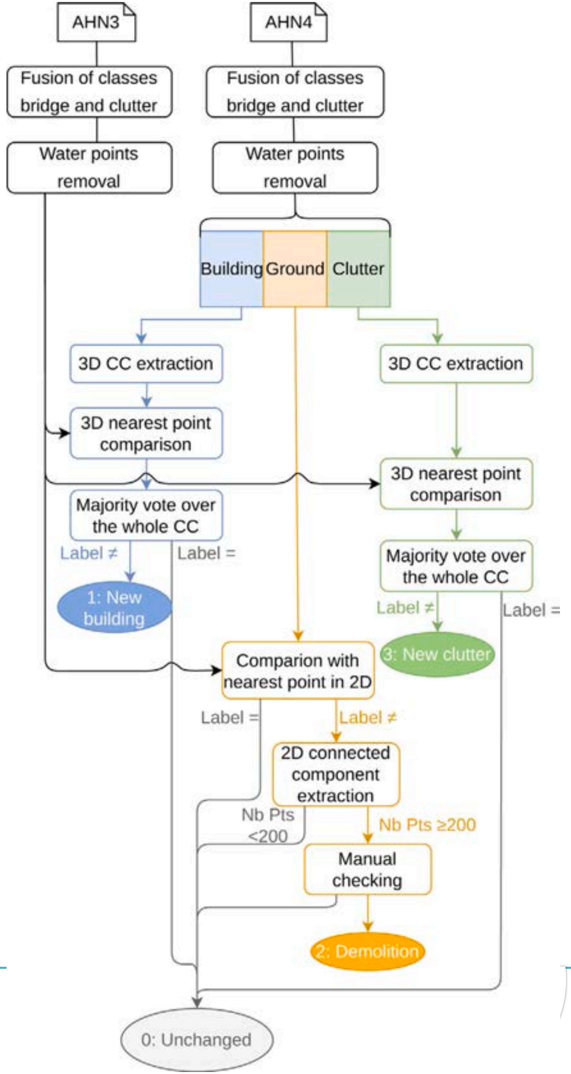
REAL DATA: A REALISTIC OBJECTIVE?

There are several multi-temporal PC datasets with point labels at each date

- AHN
- H3D

How to adapt them for change detection?

- Manual labeling is not realistic
- Automatic labeling is possible, but is not error-free



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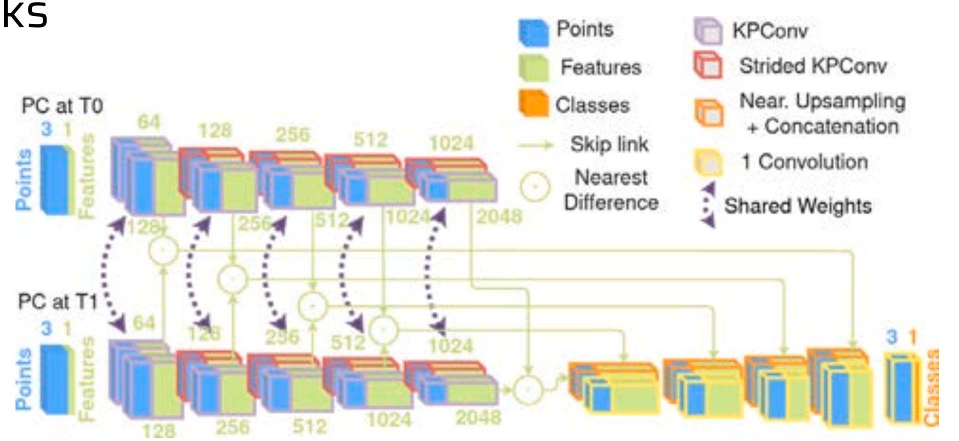
SIAMESE KPCONV

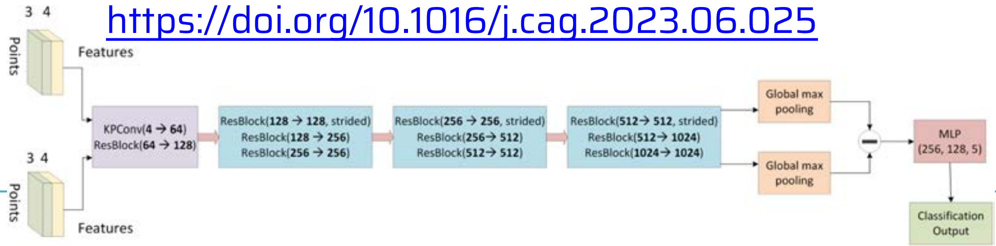
Reuse successful recipes!

- Change detection = Siamese networks
- Point cloud processing = KPConv
- Change detection over point clouds = Siamese KPConv (2021, 2023)
- Extended to classification



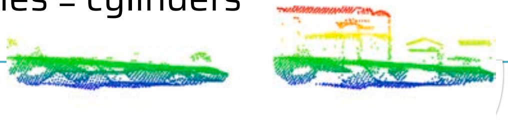
/!\ Plagiarism? SiamKPConv (2023)

https://doi.org/10.1016/j.cag.2023.06.025



https://doi.org/10.1016/j.isprsjprs.2023.02.001

Scalability?
Batches = cylinders



(a) First cylinder (b) Second cylinder

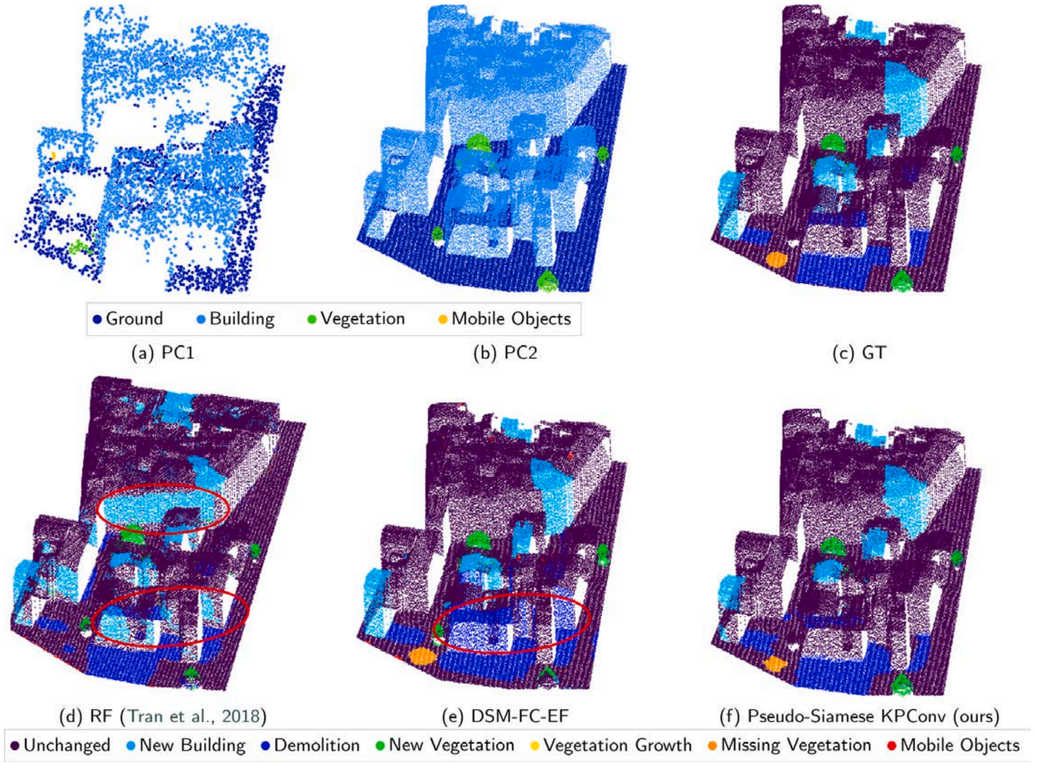
RESULTS ON SIMULATED DATA

Table 6
General results in % on Urb3DCD–V2 low density LiDAR dataset. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) works.

Method	mAcc	mIoU$_{ch}$
Siamese KPConv (ours)	91.21 ± 0.68	**80.12** ± 0.02
Pseudo-Siamese KPConv (ours)	**91.31** ± 2.34	77.80 ± 1.69
DSM-Siamese	80.91 ± 5.29	57.41 ± 3.77
DSM-Pseudo-Siamese	75.17 ± 10.03	55.30 ± 8.17
DSM-FC-EF	81.47 ± 0.55	56.98 ± 0.79
RF (Tran et al., 2018)	65.82 ± 0.05	52.37 ± 0.10

Table 7
General results in % on Urb3DCD–V2 MS dataset. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) works.

Method	mAcc	mIoU$_{ch}$
Siamese KPConv (ours)	73.24 ± 5.7	58.55 ± 4.86
Pseudo-Siamese KPConv (ours)	**87.86** ± 0.94	**74.48** ± 0.59
DSM-Siamese	69.91 ± 6.18	49.14 ± 4.92
DSM-Pseudo-Siamese	66.50 ± 10.82	46.60 ± 10.13
DSM-FC-EF	81.25 ± 1.86	55.59 ± 1.84
RF (Tran et al., 2018)	62.20 ± 0.02	46.81 ± 0.01



(a) PC1 (b) PC2 (c) GT
(d) RF (Tran et al., 2018) (e) DSM-FC-EF (f) Pseudo-Siamese KPConv (ours)

IRISA

RESULTS ON REAL DATA

Fig. 7. Example of a scene from the Change3D dataset with the points of interests an their corresponding labels.

Caution with existing scientific material

- Methodological flaws in reported results

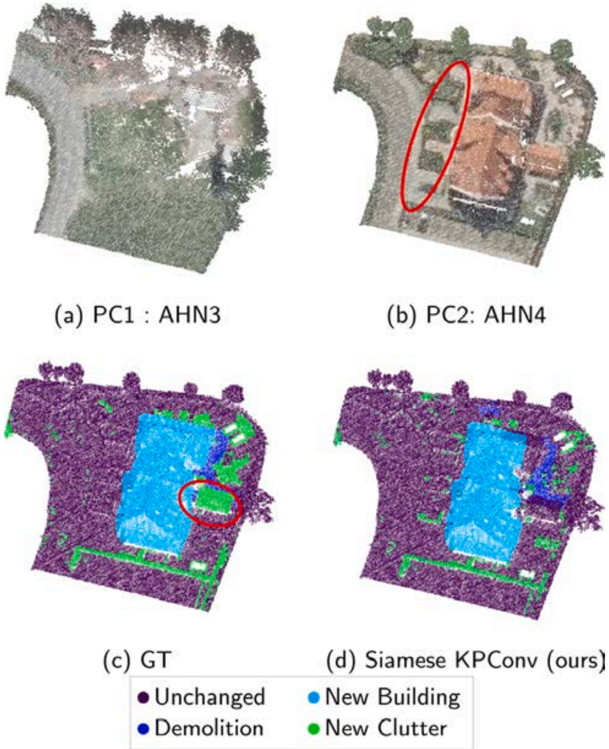
Table 12
Change classification results on Change3D real dataset. PoChaDeHH, HGI-CD, and SiamGCN have been introduced in Ku et al. (2021). For PoChaDeHH and HGI-CD, results are directly taken from the original publication. For SiamGCN, the public code has been used to retrain the model on a valid train/val/test split. Results are given in %.

Method	mAcc	mIoU	Per class IoU				
			No change	New building	Demolition	New veg.	Missing veg.
Siamese KPconv Cls (ours)	**49.64** ± 1.35	**34.64** ± 1.18	55.35 ± 2.80	**43.41** ± 3.71	**47.93** ± 4.74	**19.85** ± 9.25	6.67 ± 11.55
PoChaDeHH (Ku et al., 2021)	45.18	30.22	**61.06**	31.58	40.00	4.17	**14.29**
HGI-CD (Ku et al., 2021)	25.82	17.17	55.30	16.28	14.29	0.00	0.00
SiamGCN (Ku et al., 2021)	32.04 ± 6.49	19.18 ± 1.03	42.56 ± 1.78	24.33 ± 0.83	11.27 ± 3.07	14.00 ± 2.19	3.70 ± 4.94

- GT errors in datasets (corrected with our method?)

Table 10
Results on AHN-CD dataset given in %. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) works.

Method	mAcc	$mIoU_{ch}$	Per class IoU			
			Unchanged	New building	Demolition	New clutter
Siamese KPConv (ours)	81.86 ± 0.72	**59.93** ± 0.14	**95.94** ± 0.06	**83.19** ± 1.54	**56.05** ± 1.74	**40.53** ± 0.56
Pseudo-Siamese KPConv (ours)	**84.44** ± 1.24	52.32 ± 4.31	92.96 ± 1.34	76.54 ± 11.39	43.67 ± 1.88	36.76 ± 2.95
DSM-Siamese	62.85 ± 1.13	33.18 ± 3.56	88.58 ± 2.53	60.95 ± 5.54	18.04 ± 1.59	20.54 ± 3.59
DSM-Pseudo-Siamese	67.04 ± 0.77	41.40 ± 0.62	92.25 ± 0.11	73.26 ± 0.68	22.91 ± 1.82	28.02 ± 0.73
DSM-FC-EF	74.98 ± 0.80	44.73 ± 2.16	92.95 ± 1.49	74.21 ± 0.37	33.68 ± 6.84	26.32 ± 0.04
RF (Tran et al., 2018)	50.11 ± 0.01	28.56 ± 0.02	93.13 ± 0.00	70.5 ± 0.21	2.04 ± 0.04	13.27 ± 0.02



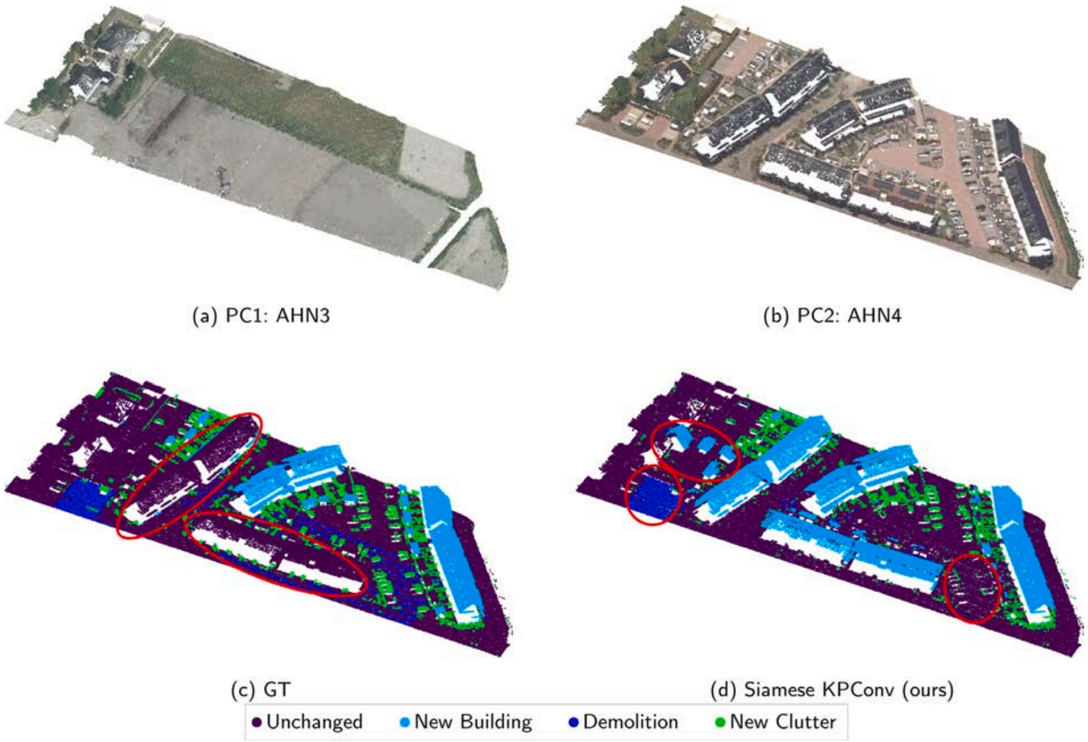


Table 13
Results (given in %) on the AHN-CD dataset sub-part that has been manually annotated. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) works.

Method	mAcc	mIoU$_{ch}$	Per class IoU			
			Unchanged	New building	Demolition	New clutter
Siamese KPConv (ours)	85.65 ± 1.55	**72.95** ± 2.05	**89.75** ± 2.18	82.77 ± 5.38	**86.44** ± 0.88	**46.65** ± 0.16
Pseudo-Siamese KPConv (ours)	**87.87** ± 1.89	69.33 ± 1.99	88.90 ± 1.89	**86.93** ± 5.32	84.01 ± 0.87	37.08 ± 2.85
DSM-Siamese	50.87 ± 1.15	30.96 ± 2.48	77.10 ± 1.51	76.77 ± 0.79	4.91 ± 8.33	11.20 ± 1.71
DSM-Pseudo-Siamese	70.71 ± 5.09	48.85 ± 7.03	78.00 ± 5.09	75.32 ± 8.59	47.46 ± 11.92	23.76 ± 0.56
DSM-FC-EF	71.47 ± 1.43	45.57 ± 0.98	70.77 ± 1.13	90.32 ± 0.61	30.58 ± 1.76	15.81 ± 0.81
RF (Tran et al., 2018)	47.94 ± 0.02	29.45 ± 0.02	78.24 ± 0.00	74.64 ± 0.03	0.00 ± 0.00	13.72 ± 0.06

WHEN CHANGE DETECTION NEEDS CHANGE INFORMATION

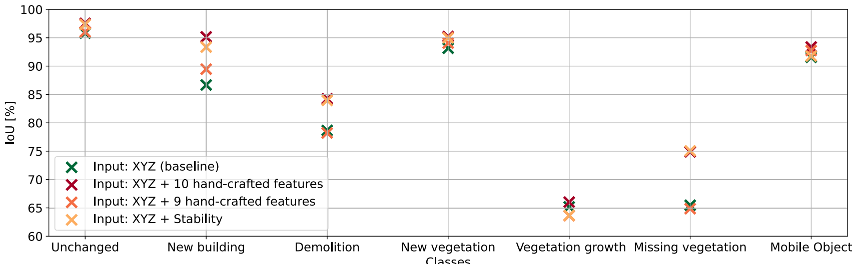
Siamese KPConv achieves good performance…

but does it really pay attention to changes?

if not, how can we force it to do so?

Providing handcraft features as input: point distribution, point normals, height information, and change information (stability feature = ratio between number of points in the spherical vs cylindrical neighborhood)

# of input features		mAcc	mIoU_{ch}
0		91.21 ± 0.68	80.12 ± 0.02
10		$\mathbf{93.65} \pm 0.16$	$\mathbf{84.82} \pm 0.58$
9	w/o *Stability*	91.44 ± 0.47	80.49 ± 0.64
1	*Stability* only	92.92 ± 0.47	83.80 ± 0.89



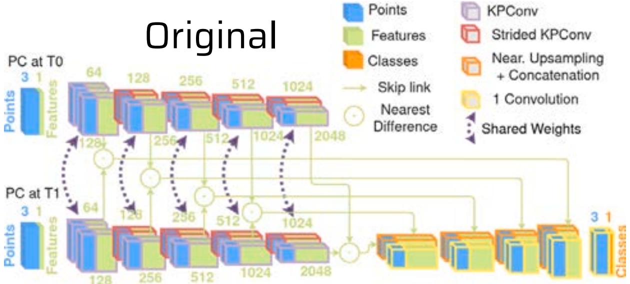
https://doi.org/10.1109/TGRS.2024.3359484

WHEN CHANGE DETECTION NEEDS LEARNING CHANGE INFORMATION

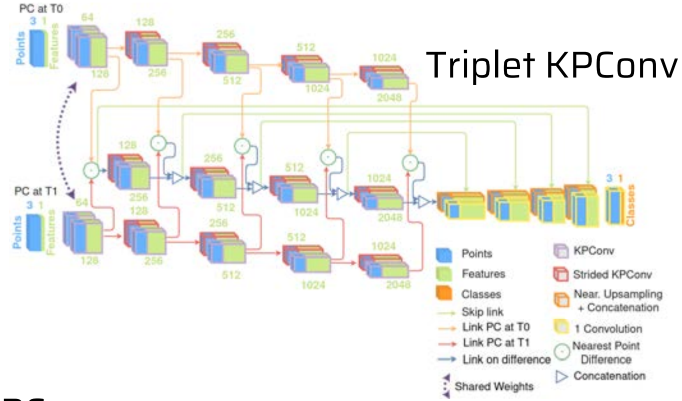
We have seen that change information is useful, but can we learn it?

We explore 3 different variants of the original Siamese KPConv

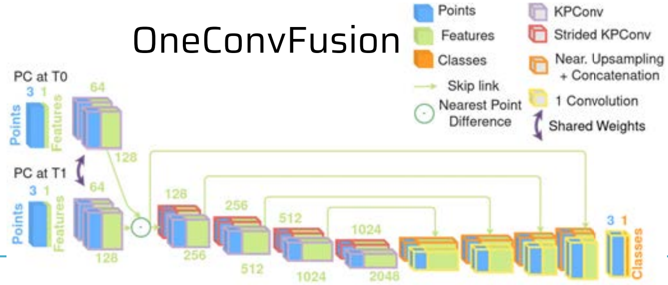
Original



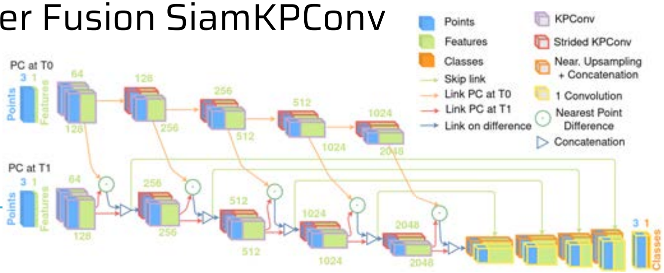
Triplet KPConv



OneConvFusion



Encoder Fusion SiamKPConv



https://doi.org/10.1109/TGRS.2024.3359484

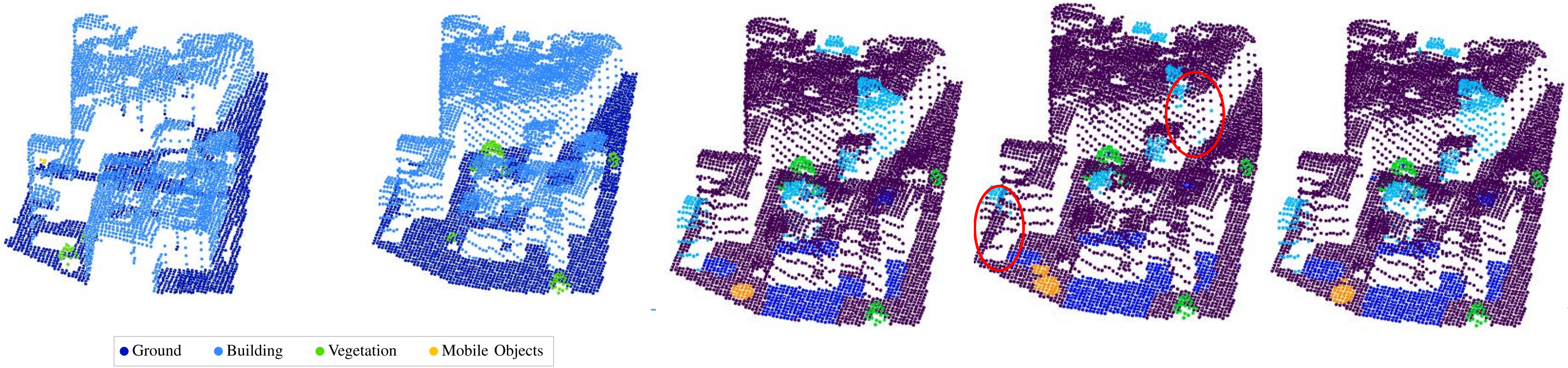
WHEN CHANGE DETECTION NEEDS LEARNING CHANGE INFORMATION

RESULTS IN % OF THE THREE SIAMESE KPCONV EVOLUTIONS ON THE URB3DCD-V2 LOW-DENSITY LIDAR DATASET

Method	mAcc (%)	$mIoU_{ch}$ (%)
Siamese KPConv [19]	91.21 ± 0.68	80.12 ± 0.02
Siamese KPConv (+10 input features)	93.65 ± 0.16	84.82 ± 0.58
OneConvFusion	92.62 ± 1.10	81.74 ± 1.45
Triplet KPConv	92.94 ± 0.53	84.08 ± 1.20
Encoder Fusion SiamKPConv	**94.23** ± 0.88	**85.19** ± 0.24

RESULTS IN % OF THE THREE SIAMESE KPCONV EVOLUTIONS ON THE MANUALLY CLEANED AHN-CD DATASET

Method	mAcc (%)	$mIoU_{ch}$ (%)
Siamese KPConv [19]	85.65 ± 1.55	70.65 ± 2.05
Siamese KPConv (+10 input features)	88.47 ± 1.09	73.29 ± 1.32
OneConvFusion	90.03 ± 0.38	**75.62** ± 1.04
Triplet KPConv	88.25 ± 0.23	72.37 ± 0.55
Encoder Fusion SiamKPConv	**90.26** ± 0.22	75.00 ± 0.74



(a) PC 1 (b) PC 2 (c) GT (d) Siamese KPConv [19] (g) Encoder Fusion SiamKPConv

1. Motivation

2. Data

3. Methods

4. Supervision

5. Applications

FINE-TUNING

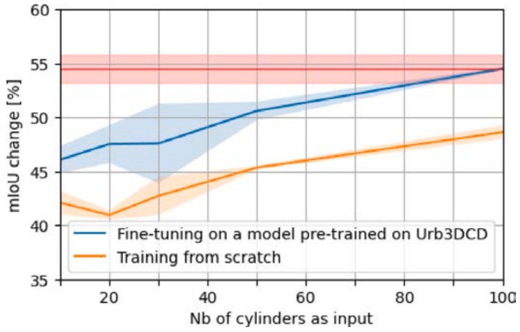


Fig. 15. Comparison between training from scratch and using pre-trained weights learned on a simulated dataset of Siamese KPConv. The mean of IoU over classes of change is given as a function of the number of cylinders of 50 m in diameter given as input. In red, the best results obtained with Siamese KPConv trained from scratch over 6000 cylinders with random drawing. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

- Transfer learning between two different datasets (even simulated ones) is challenging
- **Pre-training with simulated data** reduces from 3000x the need for target labels

Table 8
Per-class IoU scores on Urb3DCD–V2 low density LiDAR dataset. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) works. Results are given in %. Veg. stands for vegetation.

Method	Unchanged	New building	Demolition	New veg.	Veg. growth	Missing veg.	Mobile object
Siamese KPConv (ours)	**95.82** ± 0.48	**86.68** ± 0.47	**78.66** ± 0.47	**93.16** ± 0.27	**65.17** ± 1.37	**65.46** ± 0.93	**91.55** ± 0.60
Pseudo-Siamese KPConv (ours)	95.20 ± 0.18	86.23 ± 1.37	76.08 ± 0.54	92.98 ± 0.95	55.96 ± 9.41	63.50 ± 1.41	91.88 ± 0.71
DSM-Siamese	93.21 ± 0.11	86.14 ± 0.65	69.85 ± 1.46	70.69 ± 1.35	8.92 ± 15.46	60.71 ± 0.74	8.14 ± 5.42
DSM-Pseudo-Siamese	93.44 ± 0.23	84.65 ± 2.05	68.41 ± 1.77	70.38 ± 4.98	15.42 ± 13.81	59.77 ± 3.32	33.15 ± 29.12
DSM-FC-EF	94.39 ± 0.12	91.23 ± 0.31	71.15 ± 0.99	68.56 ± 3.92	1.89 ± 2.82	62.34 ± 1.23	46.70 ± 3.49
RF (Tran et al., 2018)	92.72 ± 0.01	73.16 ± 0.02	64.60 ± 0.06	75.17 ± 0.06	19.78 ± 0.30	7.78 ± 0.02	73.71 ± 0.63

Table 14
Transfer learning tests with training on the Urb3DCD–V2 MS sub-dataset and testing on the Urb3DCD–V2 low-density LiDAR dataset. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) works. Results are given in %. Build., demol., veg. and M.O. stand for building, demolition, vegetation and mobile object respectively.

Method	$mIoU_{ch}$	Per class IoU						
		Unchanged	New build.	Demol.	New veg.	Veg. growth	Missing veg.	M.O.
Pseudo-Siamese KPConv (ours)	**59.10**	**92.91**	69.73	**63.71**	**40.88**	**35.80**	**65.69**	**78.79**
DSM-Siamese	37.07	92.08	**74.61**	54.67	39.41	0.43	38.05	15.25
DSM-Pseudo-Siamese	35.77	91.55	69.36	56.02	36.3	4.76	30.11	17.94
DSM-FC-EF	42.01	92.87	67.11	55.63	33.41	1.14	39.1	29.72
RF (Tran et al., 2018)	14.48	87.74	54.03	21.91	8.24	0.47	0.02	2.19

SELF-SUPERVISED LEARNING…

- **An example of student mobility at TUM!**
- Adapt an SSL CD method to PC
- Hypothesis: changes are rare

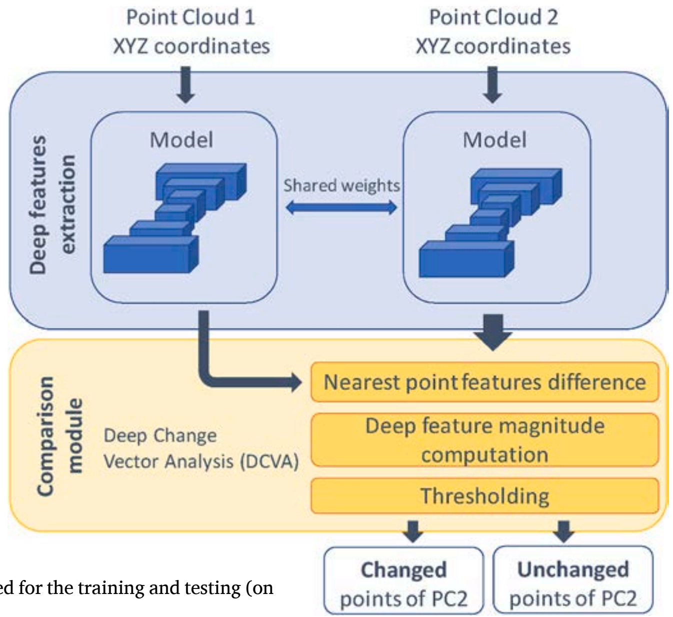


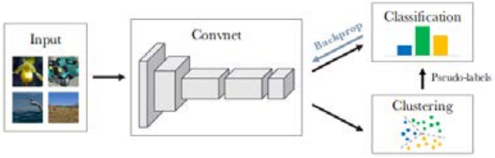
Table 1
Quantitative results on AHN-CD dataset with both unsupervised and supervised methods. Approximate computation times are provided for the training and testing (on the manually annotated part) step.

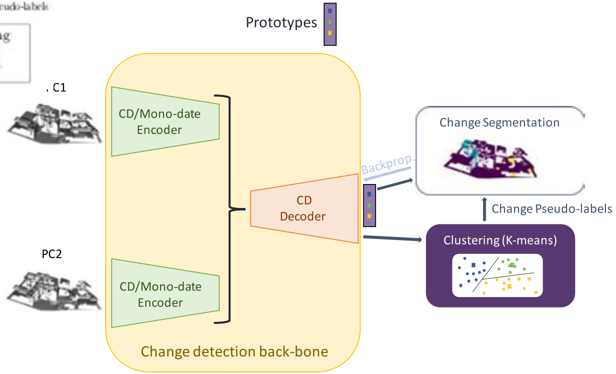
		mAcc	mIoU	IoU (%)		Computation time	
		(%)	(%)	Unchanged	Changed	Training	Testing
Unsupervised	SSL-DCVA (ours)	**85.20**	**74.14**	**78.91**	**69.38**	9 min	40 s
	SSST-DCVA (ours)	81.88	66.93	70.02	63.85	17 h	40 s
	Siamese KPConv transfer (de Gélis et al., 2023)	81.83	69.76	75.80	63.73	28 h	25 s
	k-means (features from Tran et al. (2018))	81.00	66.81	71.11	62.51	40 min	3 min
	M3C2 (Lague et al., 2013)	51.77	43.56	3.66	39.90	–	5 s
	C2C (Girardeau-Montaut et al., 2005)	76.67	65.16	76.98	53.34	–	5 s
Supervised	Siamese KPConv (de Gélis et al., 2023)	**94.23**	**89.96**	**92.27**	**87.65**	15 h	25 s

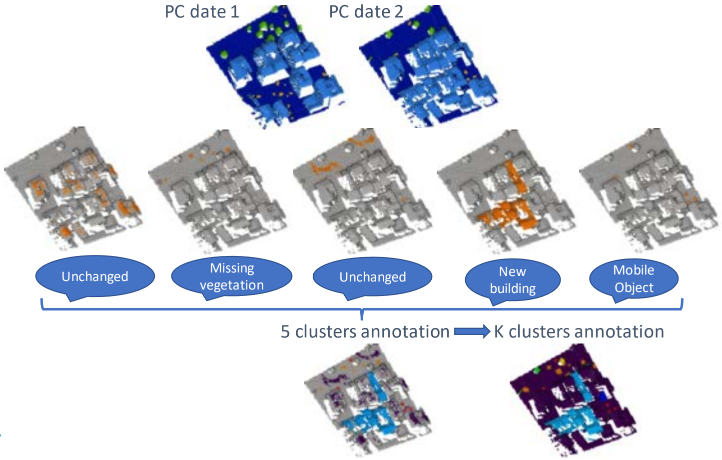
https://doi.org/10.1016/j.ophoto.2023.100044

UNSUPERVISED LEARNING

- Another recipe: DeepCluster
- Adaptation to our settings
- Unsupervised method that can be used in a weakly supervised/ interactive mode







https://doi.org/10.1016/j.isprsjprs.2023.10.022

Table 3

Qualitative assessment of DC3DCD on the manually annotated sub-part of AHN-CD dataset. *Top*: supervised methods. DSM-based methods are adaptation of Daudt et al. (2018) networks to DSM inspired by Zhang et al. (2019) and RF refers to Random Forests. In supervised settings, the training is performed on the semi-automatically annotated AHN-CD dataset containing some errors (see de Gélis et al. (2023b)). *Bottom*: Weakly supervised methods with *k*-means and our proposed DC3DCD with *Encoder Fusion SiamKPConv* architecture and with the addition of 10 hand-crafted features as input to the network.

	Method	mAcc (%)	mIoU$_{ch}$ (%)
Supervised	Siamese KPConv (de Gélis et al., 2023b)	85.65 ± 1.55	72.95 ± 2.05
	Encoder Fusion SiamKPConv (de Gélis et al., 2023a)	**90.26** ± 0.22	**75.00** ± 0.74
	DSM-Siamese	50.87 ± 1.15	30.96 ± 2.48
	DSM-FC-EF	71.47 ± 1.43	45.57 ± 0.98
	RF (Tran et al., 2018)	47.94 ± 0.02	29.45 ± 0.02
Weakly Sup.	*k*-means	70.07 ± 0.56	53.12 ± 0.79
	DC3DCD *Encoder Fusion SiamKPConv* (with input features)	**83.18** ± 1.10	**66.69** ± 2.19

Table 5

Quantitative comparison on a binary change segmentation task on the manually annotated sub-part of AHN-CD dataset..

	Method	mAcc	IoU (%)	
		(%)	Unchanged	Changed
Supervised	Siamese KPConv (de Gélis et al., 2023b)	**97.08**	**95.39**	**92.95**
	Encoder Fusion SiamKPConv (de Gélis et al., 2023a)	96.75	94.79	92.10
Unsupervised	SSL-DCVA (de Gélis et al., 2023c)	**85.20**	**78.91**	**69.38**
	SSST-DCVA (de Gélis et al., 2023c)	81.88	70.02	63.85
Weakly Supervised	DC3DCD *Encoder Fusion SiamKPConv* (with input features)	**94.43**	**91.24**	**86.96**

1. Motivation
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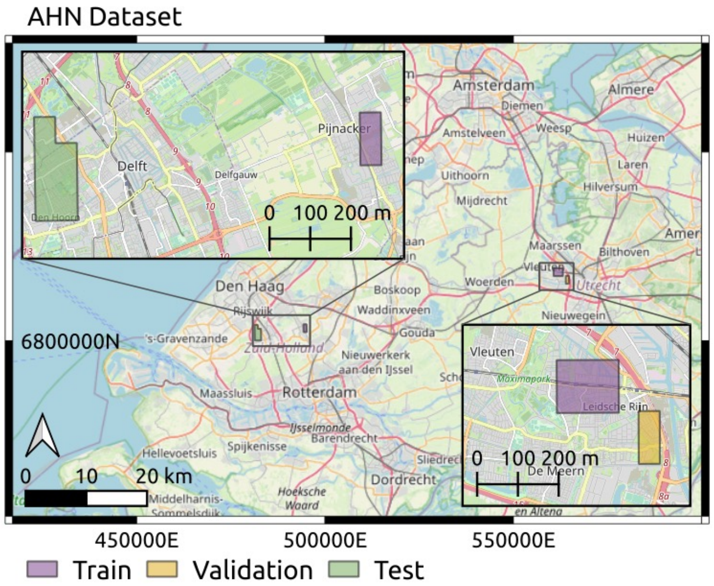
AHN dataset for real data



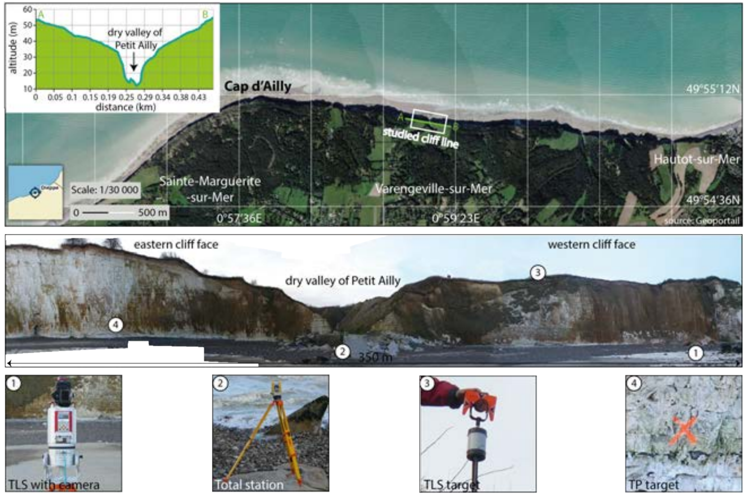
Method	mAcc (%)	mIoU_{ch} (%)
Siamese KPConv [19]	85.65 ± 1.55	70.65 ± 2.05
Siamese KPConv (+10 input features)	88.47 ± 1.09	73.29 ± 1.32
OneConvFusion	90.03 ± 0.38	**75.62** ± 1.04
Triplet KPConv	88.25 ± 0.23	72.37 ± 0.55
Encoder Fusion SiamKPConv	**90.26** ± 0.22	75.00 ± 0.74
DSM-Siamese	50.87 ± 1.15	30.96 ± 2.48
DSM-Pseudo-Siamese	70.71 ± 5.09	48.85 ± 7.03
DSM-FC-EF	71.47 ± 1.43	45.57 ± 0.98
RF	47.94 ± 0.02	29.45 ± 0.02

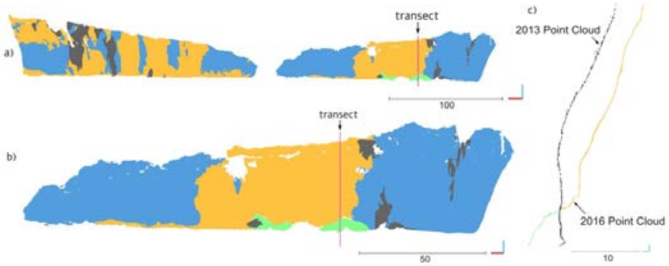
(**a**) PC 1: AHN3 (**b**) PC 2: AHN4 (**c**) GT

• Unchanged • New Building • Demolition • New Clutter

CLIFFS

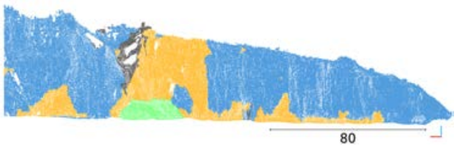
Collaboration with coastal geographers/geomorphologists (Brest)



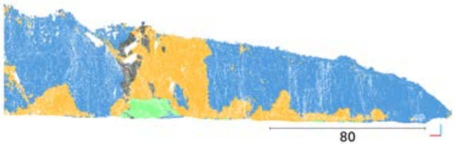


● Unchanged ● Erosion ● Accumulation ● No data to compare

PC pairs	Type	Class distribution (%) Unchanged	Erosion	Accumulation	"No data to compare"
2013-09-25 – 2016-01-28	TLS – TP	51.77	40.57	1.32	6.33
2016-01-28 – 2017-11-02	TP – TLS	66.07	22.43	0.47	11.02
2017-11-02 – 2018-01-16	TLS – TLS	79.65	16.20	3.19	0.96
2018-01-16 – 2020-04-14	TLS – TLS	69.67	29.92	0.00	0.41



(a)



(b)

● Unchanged ● Erosion
● Accumulation ● No data to compare

	Per class IoU(%) Unchanged	Erosion	Acc.	$\mathbf{mIoU}_{int}$
Siam. KPConv	91.94	83.86	**70.28**	**82.03**
M3C2 + threshold	**95.06**	**87.23**	48.20	68.12

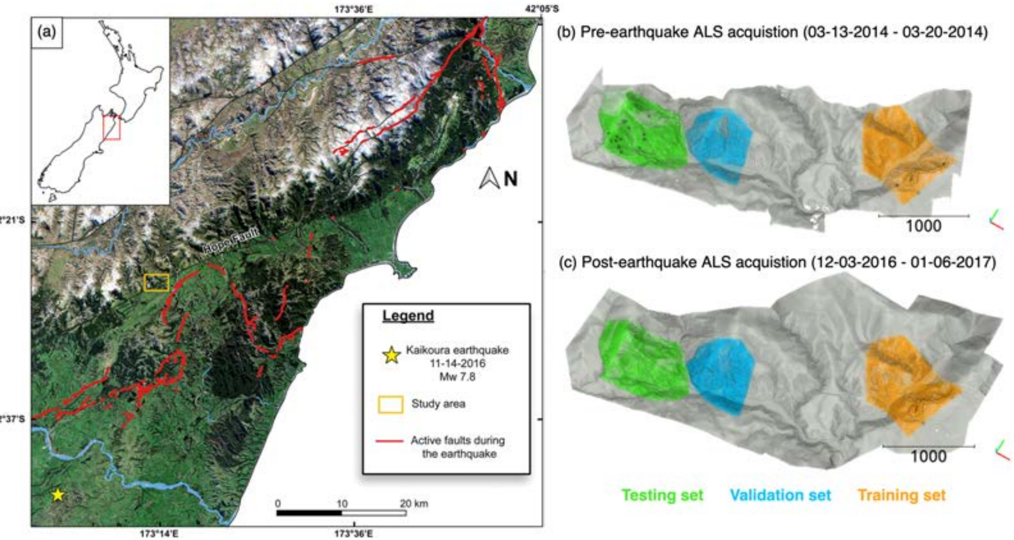
https://doi.org/10.5194/isprs-annals-V-3-2022-649-2022

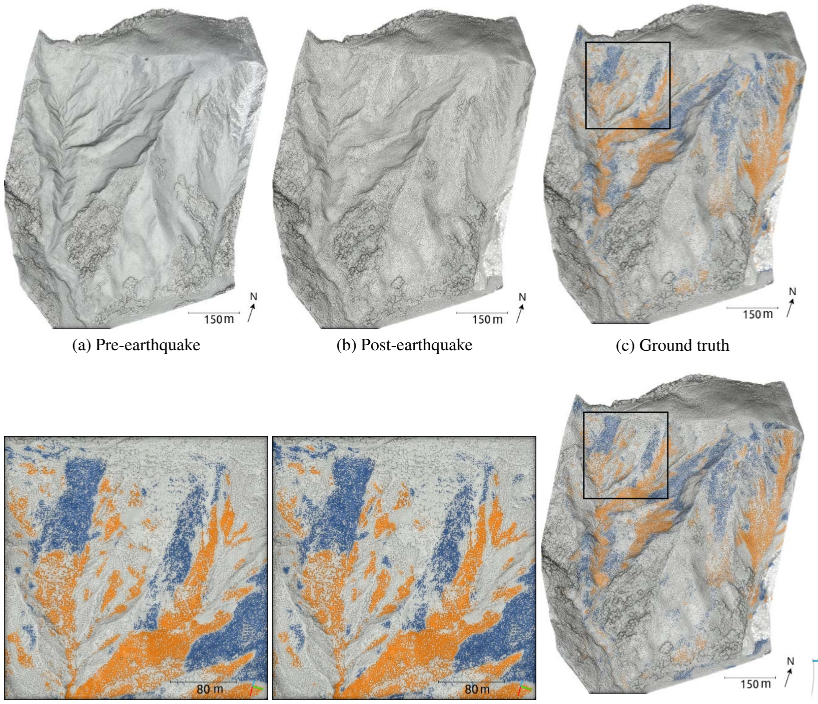
LANDSLIDES

Method	mAcc (%)	mIoU (%)	Per class IoU (%)		
			Unchanged	Source	Deposit
Encoder Fusion SiamKPConv	93.87	83.84	93.58	74.38	83.57

Collaboration with geomorphologists in Rennes

No need for prior vegetation masking





(a) Pre-earthquake (b) Post-earthquake (c) Ground truth
(d) Zoom in the ground truth (e) Zoom in the prediction (f) Siamese KPConv prediction

https://doi.org/10.1109/IGARSS53475.2024.10641348

WHEN DEEP LEARNING MEETS POINT CLOUDS AND CHANGE DETECTION

Lessons learnt from the PhD thesis of Iris de Gélis

CONTRIBUTIONS

An example of a prolific thesis, awarded by French Pattern Recognition Society

1. State-of-the-art (comparative review) + synthetic/real datasets (IGARSS21+RS21)
2. Siamese KPConv, first deep method for PC change detection (ISPRS21+P&RS23)
3. Strategies to better embed/learn the change information (TGRS24)
4. Countering supervision through SSL (mobility at TUM) (OJPRS23)
5. Countering supervision through unsupervised learning with DC3DCD (P&RS23)
6. Applications on cliffs (ISPRS22) and landslides (IGARSS24) through collaboration with other researchers

PERSPECTIVES

The initial PhD topic was deep learning on PC time series

If the study was to be restarted today:

- Less supervision: foundation models?
- Efficiency (green AI)
- XAI

LESSONS LEARNT

1. No dataset: build your own! (possibly by adapting some existing ones)
2. Keep an eye on the literature (the field is evolving fast)
3. Don't reinvent the wheel (numerous methods with codes are available, but their use can be time-consuming)
4. Publish your code for impactful research (and helping not reinventing the wheel)
5. Consider a doctoral mobility!

Thanks for listening… and thanks to Iris!