3DMASC : Objective Evaluation on Benchmarked Urban Environment LiDAR Data

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Oral Defense

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Context of the project

1. 3DMASC and Feature Optimization routine : main subject of Mathilde Letard's thesis.

Objective 1:

Training and testing 3DMASC on CloudCompare and Python

Objective 2:

Objective Evaluation of 3DMASC on Urban Environment

Understanding 3DMASC

3DMASC : 3D Point Cloud Classification framework, Multiple Attributes, Multiple Scales and Multiple Clouds (Letard et al. 2023, sub).

1. Supervised machine learning model using a random forest classifier.
2. Achieved significant scores on topo-bathymetric LiDAR data (>0.95 OA).
3. Stands out for its compactness and explainability.

Remark

3DMASC is available with a GUI on CloudCompare (Giradeau-Montault, 2011) and in command line in Python.

3DMASC Clouds and Features

Uses classical features used in 3D point cloud classification (point-based features, contextual features) + new dual-cloud features.

1. PC1 and PC2, both characterizing the scene of interest at two different times.
2. PCX : core points (subset of PC1). Classified cloud.
3. CTX : context cloud, spatial and contextual information. Lower resolution than PC1.

Eg. Point-based features

- Intensity : the return strength of a laser beam (insight on the nature of the surface)
- Echo Ratio : measure for local transparency and roughness (Return Number / Number of Returns)

Eg. Context-based features

- DZ to KNN : Mean vertical distance to k nearest neighbor
- DH to KNN : Mean horizontal distance to k nearest neighbor

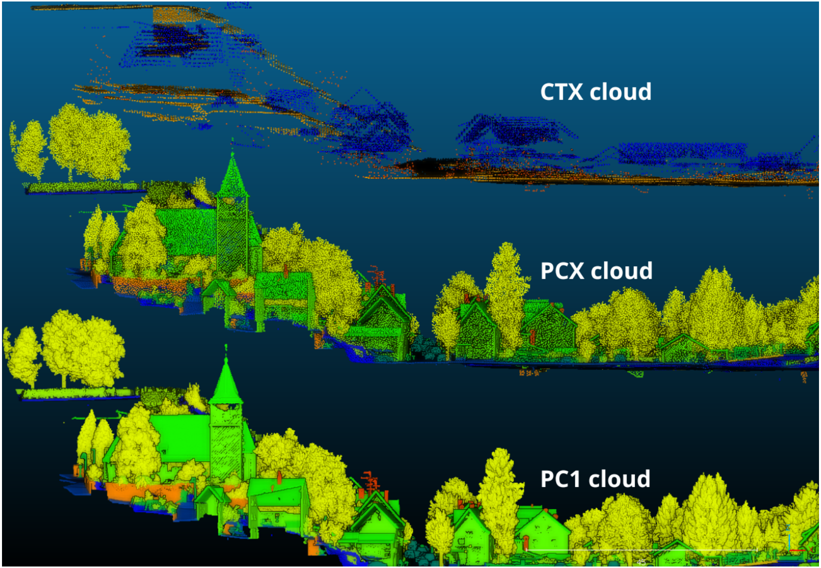

Figure 1: Hessigheim 3D Dataset : PC1, PCX (subset of PC1) and CTX clouds

The Hessigheim 3D Dataset

Figure 2: Partition of the H3D(PC) dataset (epoch March 2018) into training (colored by class colors), validation (colored by class colors and marked by yellow box) and test set (grey).

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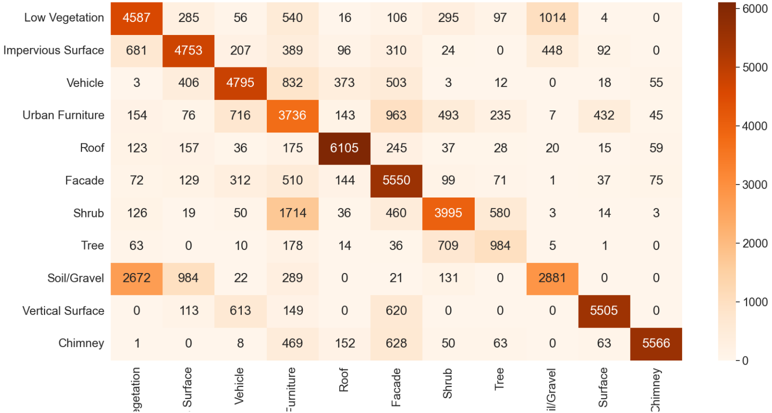
First Approach : no context cloud and optimization



	egetation	Surface	Vehicle	urniture	Roof	Facade	Shrub	Tree	il/Gravel	Surface	chimney
Low Vegetation	4587	285	56	540	16	106	295	97	1014	4	0
Impervious Surface	681	4753	207	389	96	310	24	0	448	92	0
Vehicle	3	406	4795	832	373	503	3	12	0	18	55
Urban Furniture	154	76	716	3736	143	963	493	235	7	432	45
Roof	123	157	36	175	6105	245	37	28	20	15	59
Facade	72	129	312	510	144	5550	99	71	1	37	75
Shrub	126	19	50	1714	36	460	3995	580	3	14	3
Tree	63	0	10	178	14	36	709	984	5	1	0
Soil/Gravel	2672	984	22	289	0	21	131	0	2881	0	0
Vertical Surface	0	113	613	149	0	620	0	0	0	5505	0
Chimney	1	0	8	469	152	628	50	63	0	63	5566

Figure 3: First Approach : Confusion Matrix. Predictor composed of classic 3D point cloud classification features.

Conclusion on First Approach

1. Miss-classification of ground related classes and under-represented classes.
2. Model cannot contextualize objects and surroundings.
3. The model is penalized by some features or scales.

Hence the use of a CTX cloud with 3DMASC

Second Approach : building a context cloud

The CTX cloud is composed of labelled 3 classes Roof (class 4), Ground (class 0, 1, 8) and Others. The classifier is trained on:

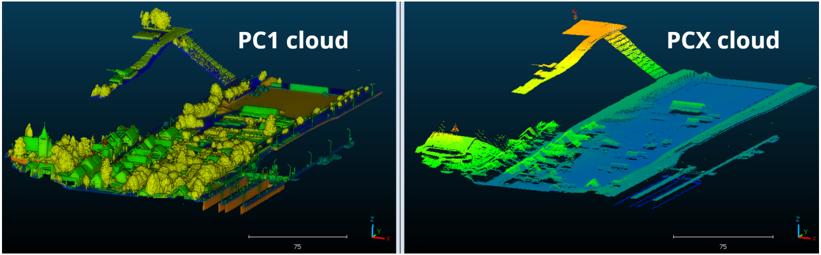
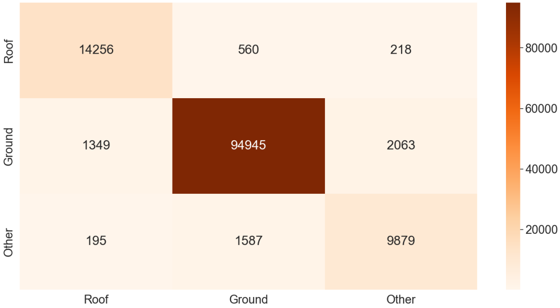


Figure 4: On the left, PC1. On the right, PCX, mapping of the roofs and ground via rasterization.

Making the CTX cloud "reliable"



	Roof	Ground	Other
Roof	14256	560	218
Ground	1349	94945	2063
Other	195	1587	9879

Figure 5: Confusion matrix of the CTX classifier. OA : 0.95

Remark

It is important to build the final CTX out of the best predictions of our model i.e. the most "confident" ones.

Thresholding the CTX will allow us to keep the most "confident" predictions.

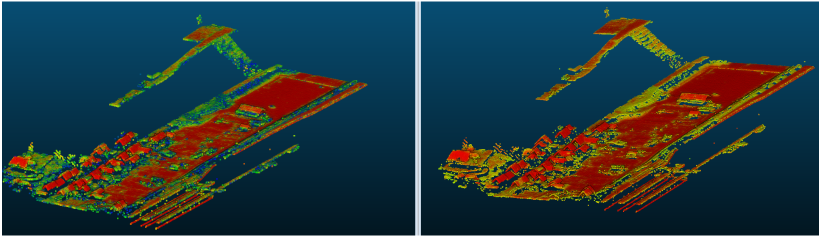


Figure 6: On the left : CTX cloud with no threshold. On the right : CTX cloud with 70% confidence threshold.

Remark

Balance between confidence and amount of data discarded. Here, each point has at least 70% of classification confidence and still 85% of the data is available.

Third Approach : context cloud and feature/scales optimization

Important to select the features that are positively contributing to the model. Features selected according to their :

- Information Gain and Pearson Coefficient -> Correlation selection. (automatic in Python)
- Feature Importance (manual in CloudCompare)

Lightweight optimized model

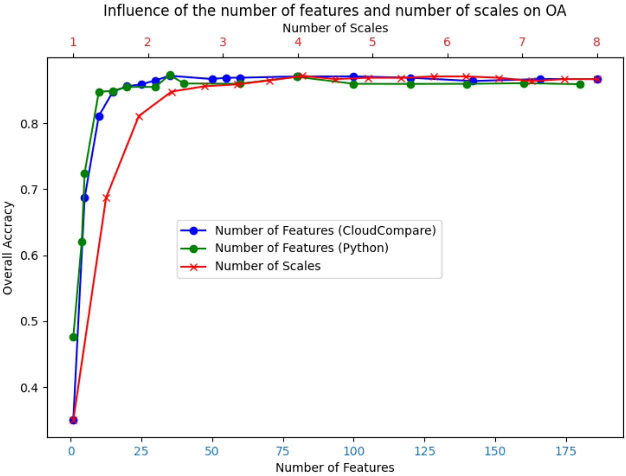
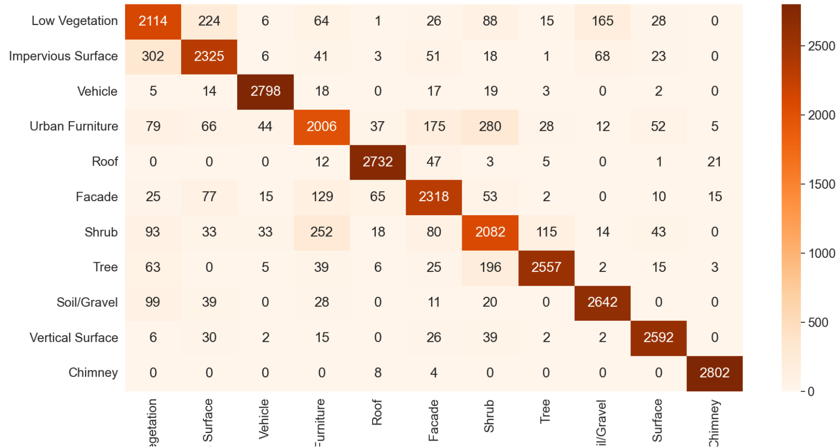


Figure 7: OA vs Number of Features / Number of Scales. Nb Features : 35, Nb Scales : 6

Optimized Model



	egetation	Surface	Vehicle	urniture	Roof	Facade	Shrub	Tree	il/Gravel	Surface	Chimney
Low Vegetation	2114	224	6	64	1	26	88	15	165	28	0
Impervious Surface	302	2325	6	41	3	51	18	1	68	23	0
Vehicle	5	14	2798	18	0	17	19	3	0	2	0
Urban Furniture	79	66	44	2006	37	175	280	28	12	52	5
Roof	0	0	0	12	2732	47	3	5	0	1	21
Facade	25	77	15	129	65	2318	53	2	0	10	15
Shrub	93	33	33	252	18	80	2082	115	14	43	0
Tree	63	0	5	39	6	25	196	2557	2	15	3
Soil/Gravel	99	39	0	28	0	11	20	0	2642	0	0
Vertical Surface	6	30	2	15	0	26	39	2	2	2592	0
Chimney	0	0	0	0	8	4	0	0	0	0	2802

Figure 8: Optimized Model : confusion matrix

1. Most Important features stand out as being contextual (most important), multi-echo and geometry-based (minority) features.

Contextual Features, mean IG ≈ 0.0562

$DZ\_PCX\_CTX\_11@KNN = 3$, $DZ\_PCX\_CTX\_11@KNN = 1$, ...

Multi-Echo Features, mean IG ≈ 0.0452

$EchoRat\_PC1\_MEAN@4$, $Number\_Of\_Returns\_PC1\_MEAN@4$, $EchoRat\_PC1\_MEAN@2$, $Number\_Of\_Returns\_PC1\_MEAN@2$

Geometric Features, mean IG ≈ 0.0314

$PCA3\_PC1@1.5$, $Dip\_PC1@4$

Conclusion on third approach

1. The model is able to achieve decent scores with few features and few data.
2. The ground-related classes and under-represented classes are still miss-classified.
3. The contextual features and feature selection routine highly improves the model.

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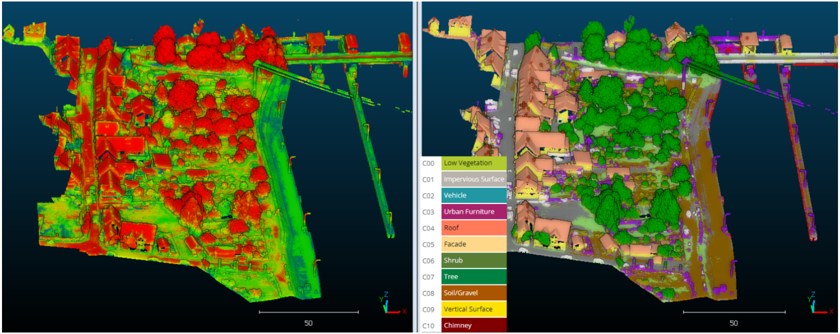
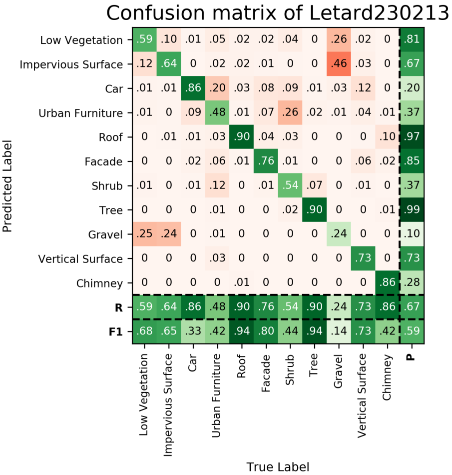


Figure 9: Classification of the Benchmarked Dataset. On the right : classified point cloud. On the left : classification confidence

- Confidence shows that the model has difficulties classifying ground-related classes.
- Important structures (houses, trees) are well classified thanks to contextual features.



	Low Vegetation	Impervious Surface	Car	Urban Furniture	Roof	Facade	Shrub	Tree	Gravel	Vertical Surface	Chimney	**P**
Low Vegetation	.59	.10	.01	.05	.02	.02	.04	0	.26	.02	0	.81
Impervious Surface	.12	.64	0	.02	.02	.01	0	0	.46	.03	0	.67
Car	.01	.01	.86	.20	.03	.08	.09	.01	.03	.12	0	.20
Urban Furniture	.01	0	.09	.48	.01	.07	.26	.02	.01	.04	.01	.37
Roof	0	.01	.01	.03	.90	.04	.03	0	0	0	.10	.97
Facade	0	0	.02	.06	.01	.76	.01	0	0	.06	.02	.85
Shrub	.01	0	.01	.12	0	.01	.54	.07	0	.01	0	.37
Tree	0	0	0	.01	0	0	.02	.90	0	0	.01	.99
Gravel	.25	.24	0	.01	0	0	0	0	.24	0	0	.10
Vertical Surface	0	0	0	.03	0	0	0	0	0	.73	0	.73
Chimney	0	0	0	0	.01	0	0	0	0	0	.86	.28
R	.59	.64	.86	.48	.90	.76	.54	.90	.24	.73	.86	.67
F1	.68	.65	.33	.42	.94	.80	.44	.94	.14	.73	.42	.59

Figure 10: Confusion matrix of the inference. The matrix was computed by the IFP institute. OA : 66%

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Number of Samples and Intensity Feature

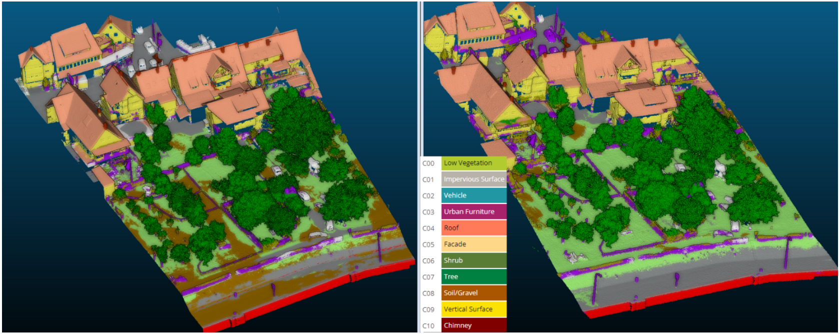

Figure 11: Classification on an extract of the benchmark dataset. Left : model trained on 7 000 samples per class. Right : model trained on 30 000 samples per class with Intensity feature.

Labelling

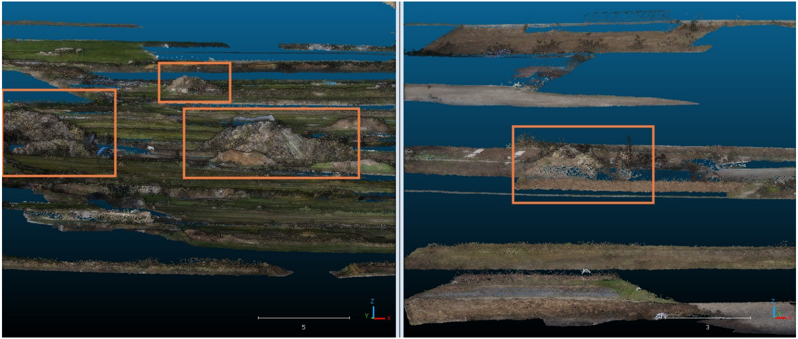

Figure 12: Label inconsistencies in the dataset may have biased the model. Left is class "Low Vegetation". Right is class "Soil/Gravel"

Comparison to Benchmark Competition

- Our model did not perform well in terms of OA (13th out of 15), but still more compact and explainable than DL methods.
- IFPs RF algorithm is the best model on the benchmark but very poorly documented. (features, context cloud, number of samples).
- Previous discussion shows that Intensity feature and number of samples can improve the model (up to 92% OA for the training phase)

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Conclusion of the Study

1. Newly introduced model 3DMASC stands out for its explainability and compactness.

I

The number of samples for the model is important when training on complex environments.

II

Feature Selection protocol doesn't take into consideration inherent usefulness of a feature in a given environment (eg. Intensity)

III

Contextual features -> spatially contextualize objects. Neighbourhood-based features -> grasp the nature of surfaces/shapes. Both contributing to making the model more discriminant.

Thank you for your time