Automatic detection of waterbeds in shallow and muddy water bodies in the Netherlands using green LiDAR

Vasileios Alexandridis 2020



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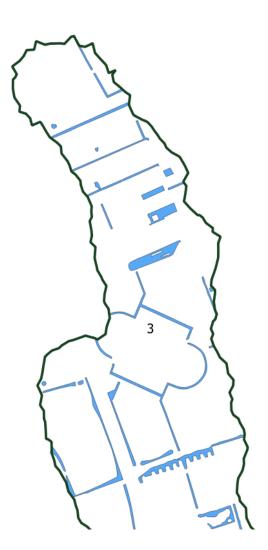
Maarten Pronk (Deltares)

Co-reader: Balázs Dukai Delegate: Angeliki Sioli



Introduction











Introduction



Source : "Pilotproject: Meten ondiepe sloten in de polder groot wilnis vinkeveen met laser bathymetry" [Aerodata, 2015]





Motivation

- Previous studies tried to detect waterbeds in water bodies using bathymetric LIDAR data in case of the Netherlands
- However, developed methods have not succeeded in detecting bottom points with high certainty and accuracy.
- ❖ Other methods (e.g. pulse, neighbourhood-based) could improve the detection process and deal particularly with shallow and muddy water bodies.





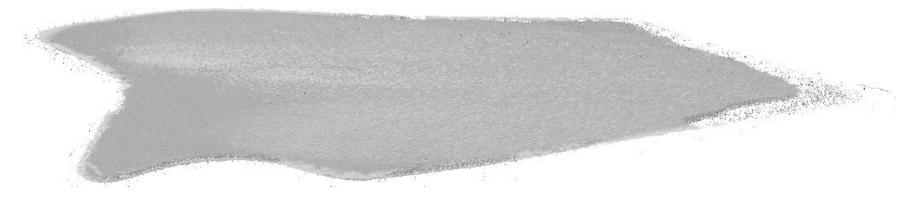
Source: Shallow and muddy water areas, Wadden Sea 2019 (Deltares)





Main goal of study

From: an unclassified green airborne LiDAR

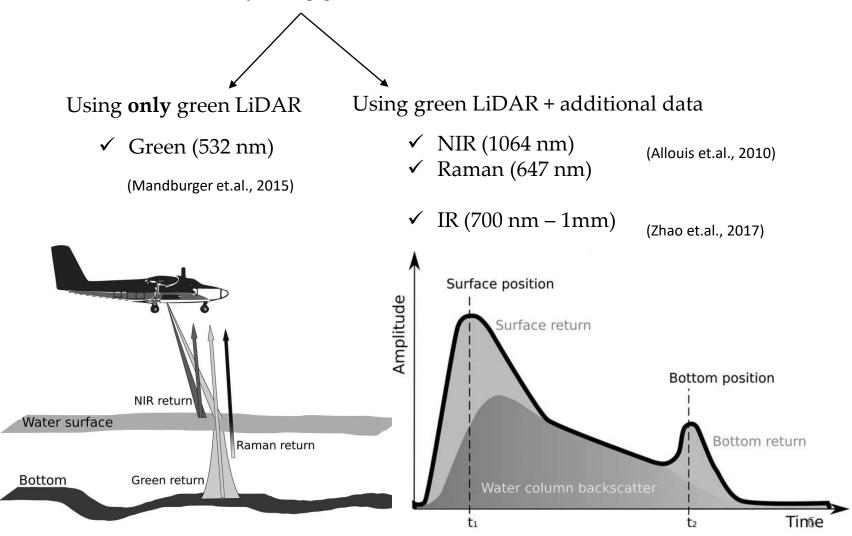


To: a classified green airborne LiDAR





Several studies have been done in the field of mapping river and shallow water body using green LiDAR.

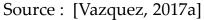


Dutch waterboards collected ALB dataset using NIR and green LiDAR (Aerodata., 2015)
Water depth measurements were collected

❖ Laboratory study tested the use of yellow wavelength (590nm)

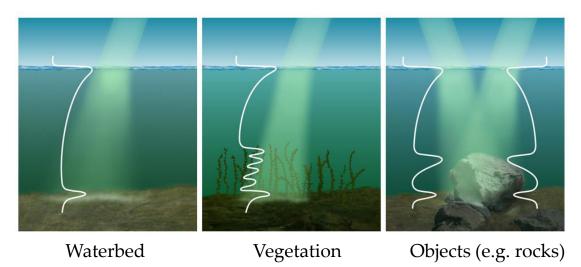
(Vazquez., 2017a)







- Many environmental factors can negatively influence the direction, strength and shape of the laser pulse.
 - ✓ Water clarity
 - ✓ Organic particles & Suspended sediments
 - ✓ Water turbidity (waves)
 - ✓ Vegetation





Direction of waveform into the water (Deltares)



Pulse and **Neighbourhood** – based methods:



✓ Points' characteristics

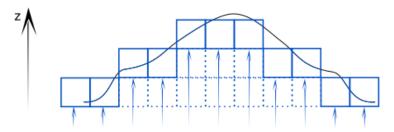
(Meng et. al., 2010)



✓ Local neighbourhood of points

(Boerner et. al., 2017)

✓ Voxelization for ground segmentation







Research Questions

Q1: Can the bottom points of shallow and muddy water bodies in the Netherlands be automatically detected using ALB?

q2: Can pulse and/or neighbourhood - based methods in a green ALB be used to classify and detect the bottom points?

q3: What is the influence of different voxel resolutions for classification, in terms of accuracy and computation load?

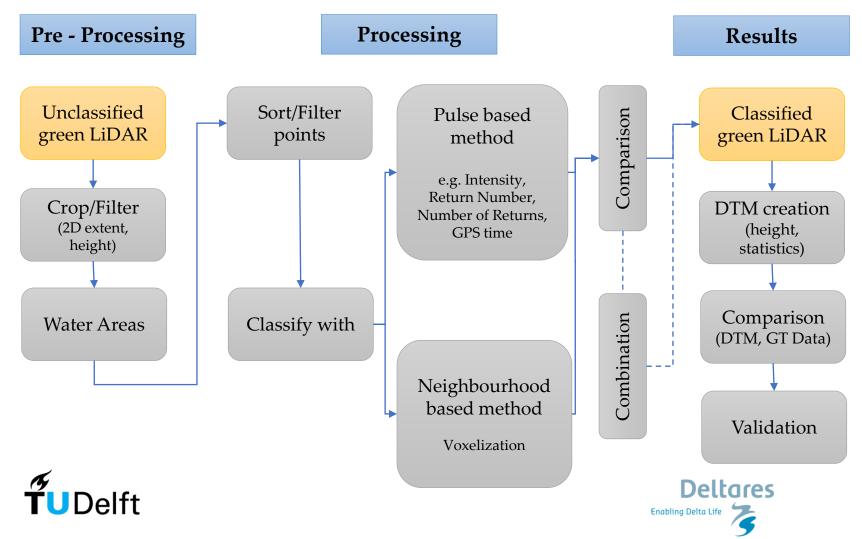
q4: How does the various point cloud quality (i.e. density, outliers) affect the classification process?

q5: Can a confidence value of water bodies be calculated? If it is possible, how?

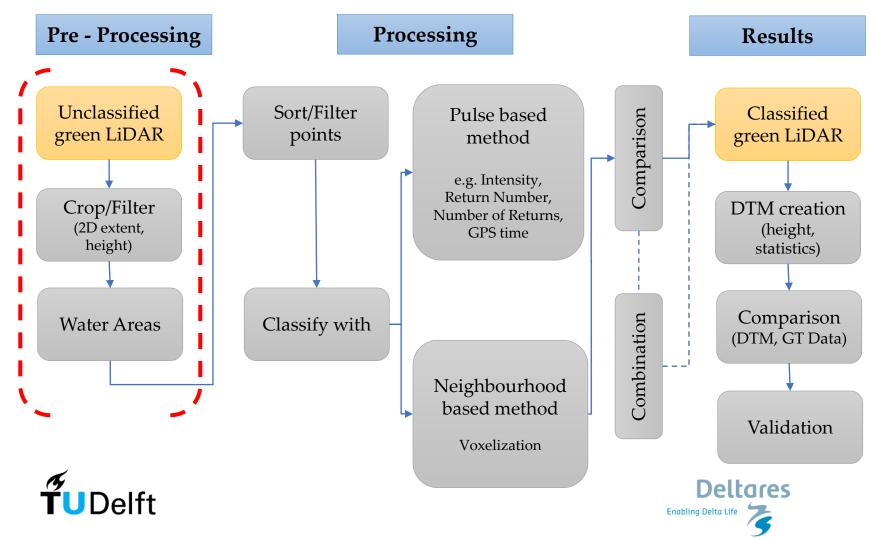




Flowchart

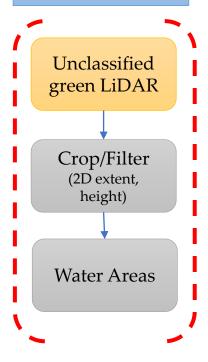


Steps



Steps

Pre - Processing

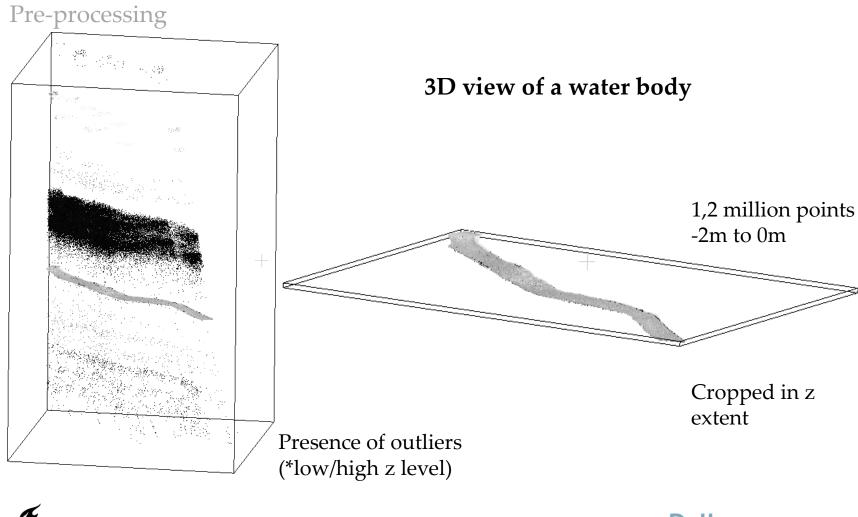


Unclassified point cloud

- Green LiDAR data from 6 different regions
- For each region:
 - Crop water bodies using *TOP10NL* water polygons
 - Filter them in z dimension (height thresholds)
 - Store them into separate LAZ files (LAStools)
 - Process only 5 water bodies from 6 regions



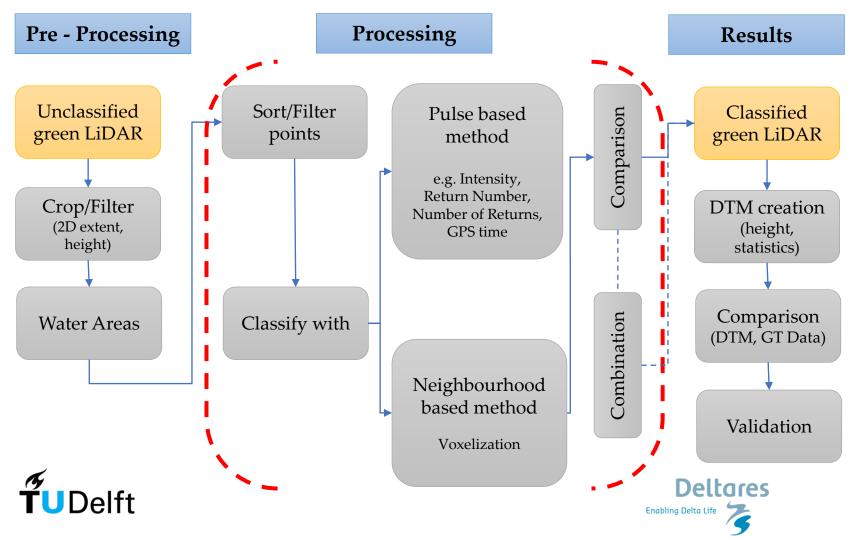






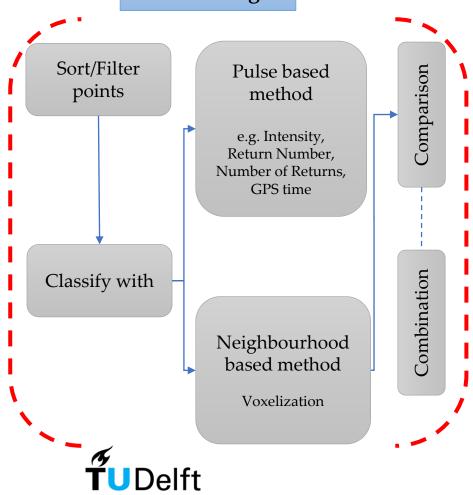


Steps



Steps

Processing



Sort per GPS time

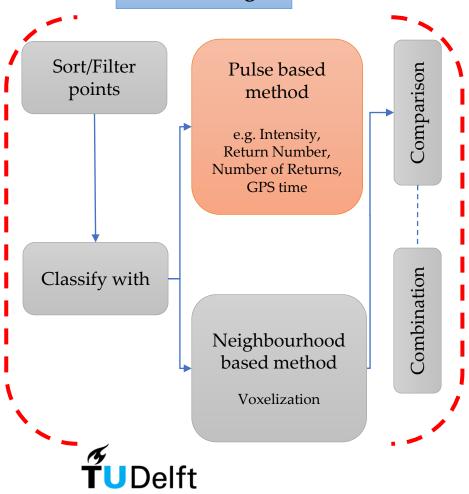
To assure data contains right info

- Quality check of Discrete LiDAR (LAStools)
 - Completeness (all returns in the file)
 - Correctness (correct return numbers)



Steps

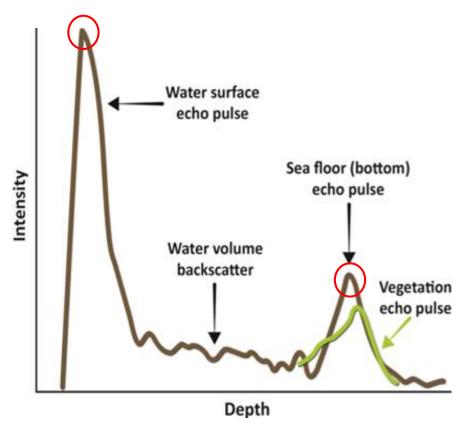
Processing



- Pulse approximation
 - recontruct waveform with discrete returns
- Group points per pulse
 - use points' characteristics
 - 1. return number (rn)
 - 2. number of returns (nr)
 - 3. GPS time
 - 4. intensity
- Classes: water-surface (1st point)
 water/bottom (2nd/2nd point)
 bottom (3rd point)

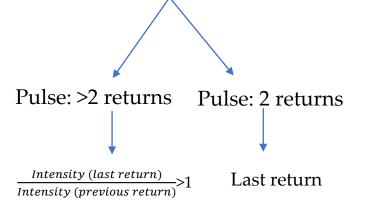


Theory – How?



Source: [Iqmulus,2019]

- Laser pulse- Depth (1)- Intensity (1)
- Small peak (intensity)
- Potential bottom point

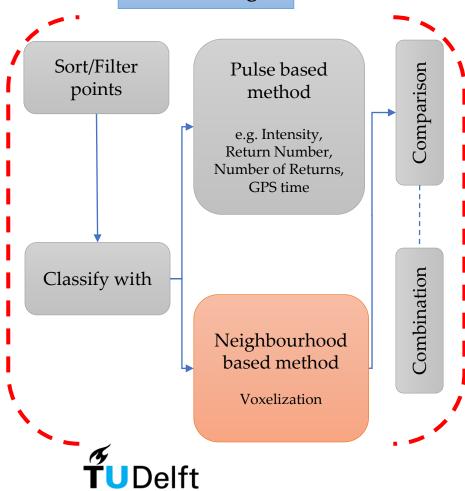




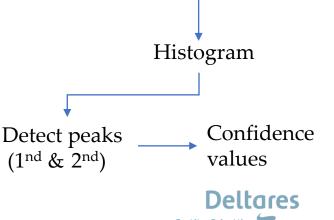


Steps

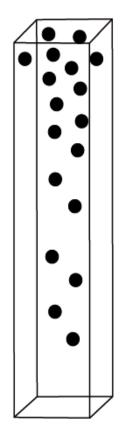
Processing



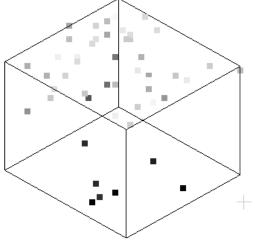
- 3D Voxel structure
- Voxel size selection:
 - Density
 - Area
 - Processing time
- Points per Voxel/Water column



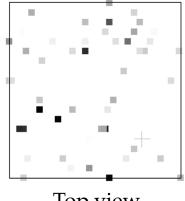
Theory - 3D Voxel structure



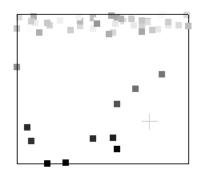
3D Voxel - Water column



Voxel – 3D view; distributed points



Top view

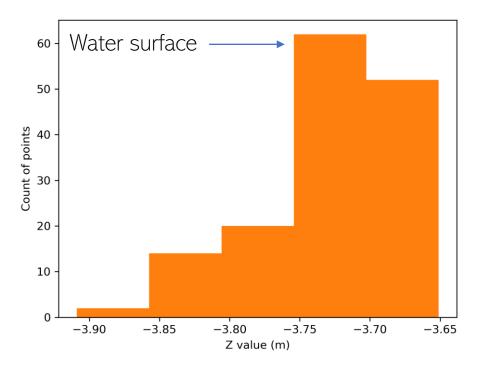


Section view





Theory – Histogram and Peaks' Detection



70 Water surface 60 Count of points Waterbed 20 10 -3.65-3.60 -3.55-3.45-3.40-3.35-3.30-3.50Z value (m)

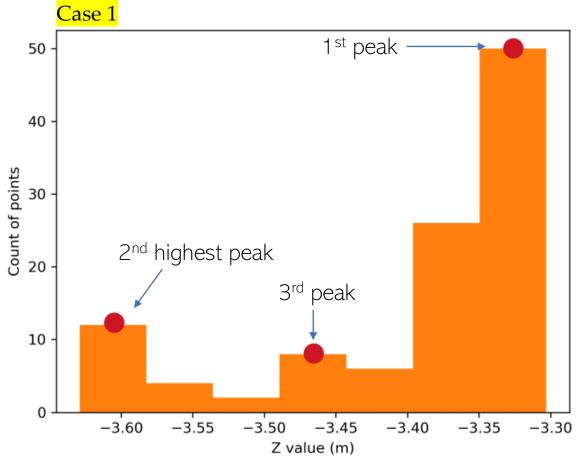
Example 1: Voxel with **one** peak

Example 2: Voxel with **two** peaks





Theory – Peaks' Detection



- Histogram; constant bin size
- 3 peaks in histogram
- 1st peak: highest point of its bin

water surface

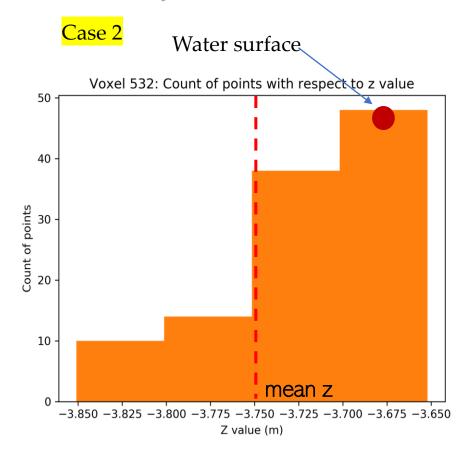
• 2nd peak: lowest point of its bin

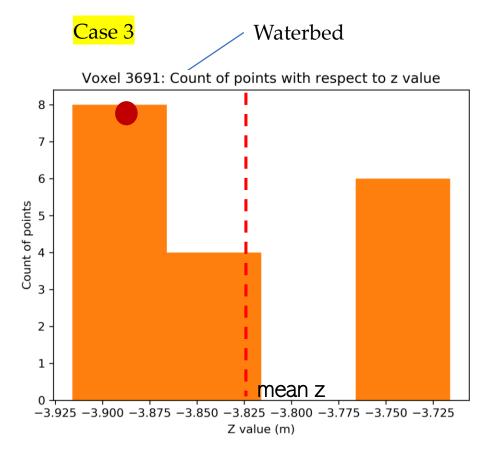
potential bottom point (how confident?)

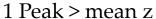




Theory – Peaks' Detection









1 Peak < mean z



Theory – Confidence values

How certain is a point to be **bottom**?

Define condifence values based on:

Density

(Number of points in bin)

Distance

(Z level: 1st - 2nd peak)

Intensity

(Lowest point)

Density (τ _{den})	Distance (τ _{dis})	Intensity (τ _{int})	Conf. value
> \tau_{den}	$>$ $\tau_{\rm dis}$	$> \tau_{\rm inten}$	1
> \tau_{den}	<= τ _{dis}	$> \tau_{inten}$	2
> \tau_{den}	$>$ $\tau_{ m dis}$	<= τ _{inten}	3
<= τ _{den}	$>$ $\tau_{ m dis}$	$> \tau_{inten}$	4
<= τ _{den}	$>$ $\tau_{ m dis}$	<= τ _{inten}	5
> \tau_{den}	<= τ _{dis}	<= τ _{inten}	6
<= τ _{den}	<= τ _{dis}	$> \tau_{inten}$	7
<= τ _{den}	<= τ _{dis}	<= τ _{inten}	8

• 8 values:

- high confident: (1)

- low confident: (8)

8 combinations based on **order**:

1. Density/Intensity

2. Distance

• (τ_{int}) , (τ_{den}) : median

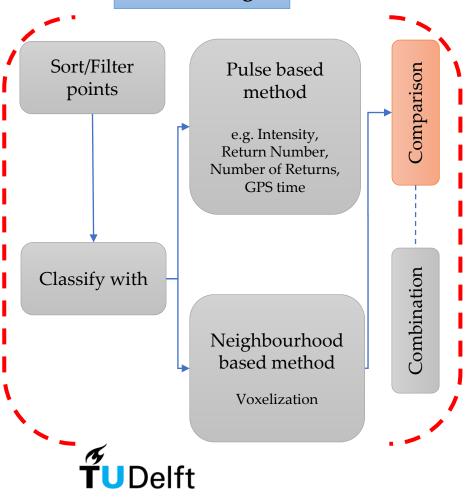
• (τ_{dis}) : mean





Steps

Processing



Pulse – based method

- Points' attributes (NR, RN, GPS, Intensity)
- Easy-going process

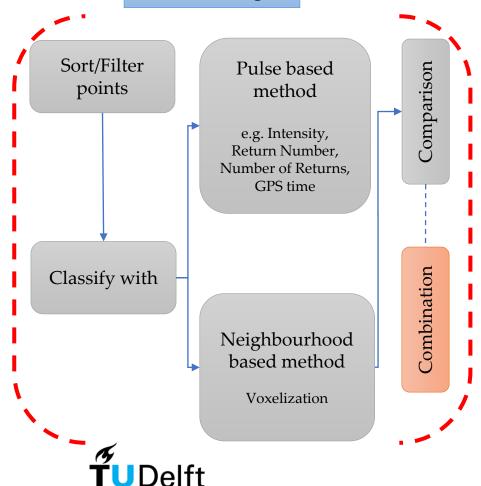
Voxel – based method

- 2D regular grid
- Voxel size selection
- Spatial distribution of points
- Computationally demanding due to density of the data



Steps

Processing



Pulse & Voxel – based method

Not all the points of a pulse always fall in a voxel due to the voxel size

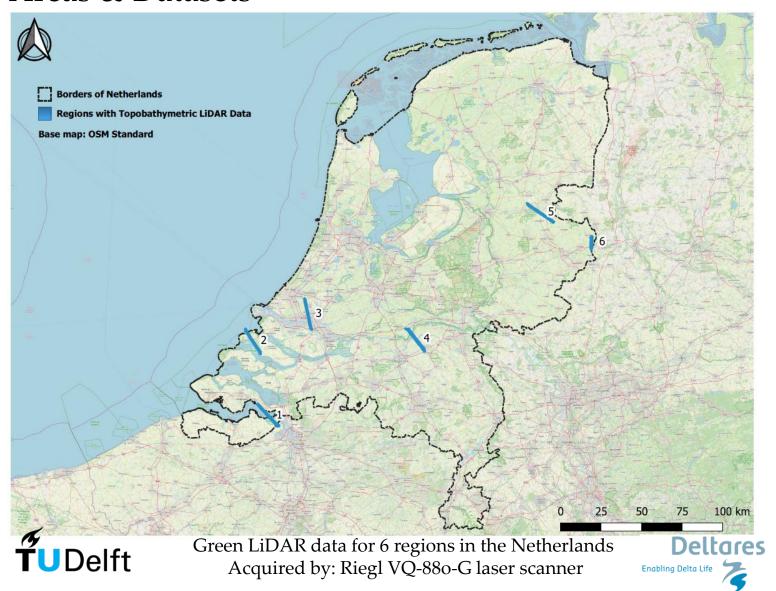
E.g. 3 returns in a pulse Only the last return in the voxel

 Small voxel size to get more bottom points → then, combine with pulse bottom ones

High computation time



Areas & Datasets



Areas & Datasets



Ground truth data

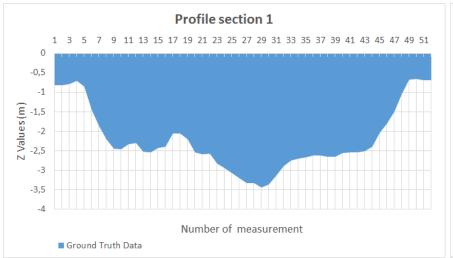
- GPS measurements of 4 profile sections
- Difficulties:
 - Presence of a sludge layer
 - Quality is affected by other factors:
 - ✓ water turbidity
 - ✓ vegetation (e.g. algae)
- Only for water body 51, Region NL1

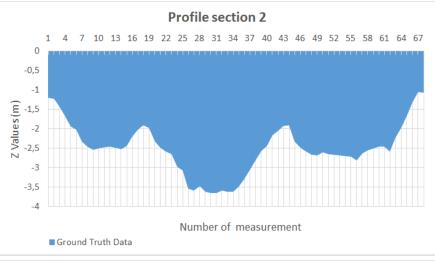
Water body 51 Region NL1

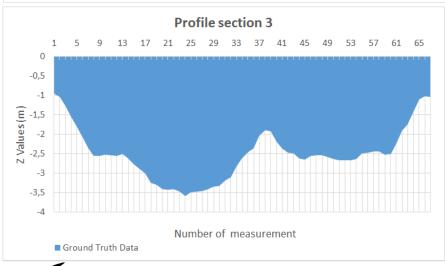


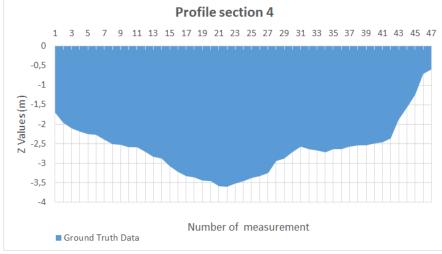


Areas & Datasets







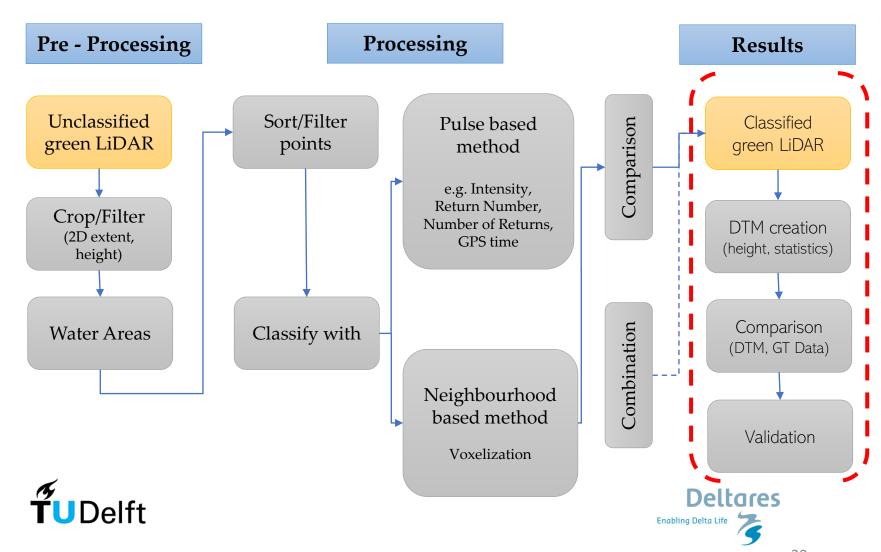




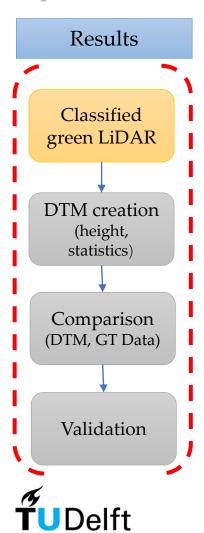
Ground truth data



Steps



Steps

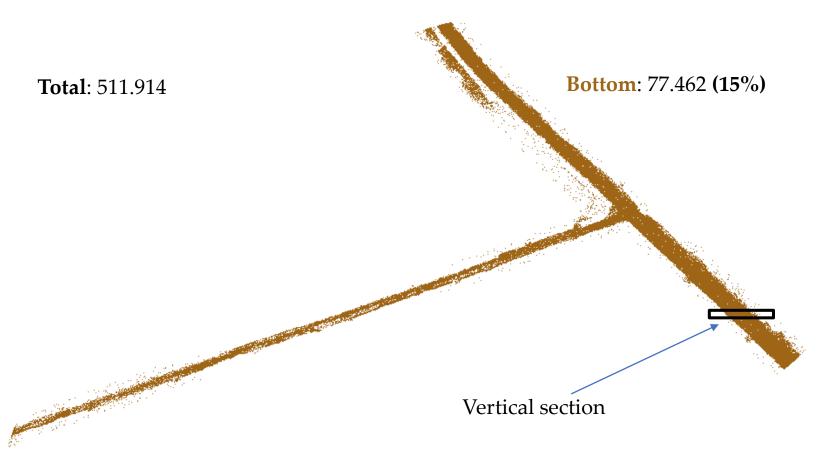


Classification

- **5 datasets**: 51NL1, 130NL2, 376NL3, 378Nl3, 199NL4
- Raster outputs (DTM) for both methods
- Comparison of rasterized GT Data and DTM rasters for datasets: 51NL1 & 199NL4



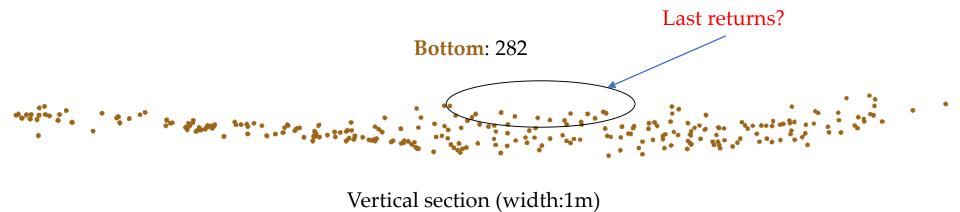
51NL1 Dataset







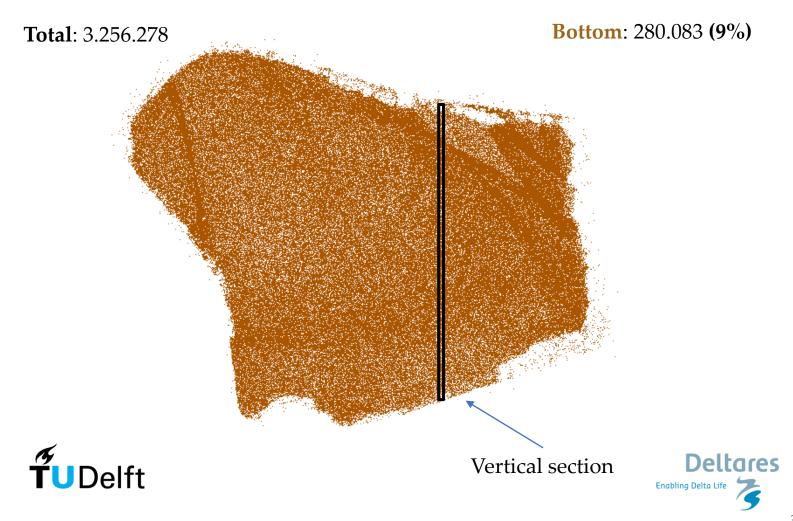
51NL1 Dataset







199NL4 Dataset



199NL4 Dataset

Bottom: 1.976

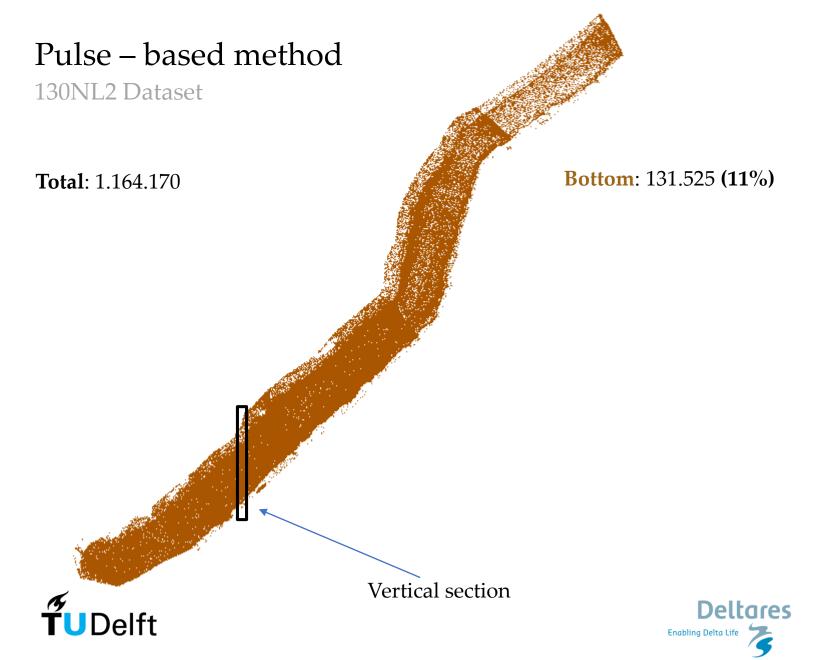




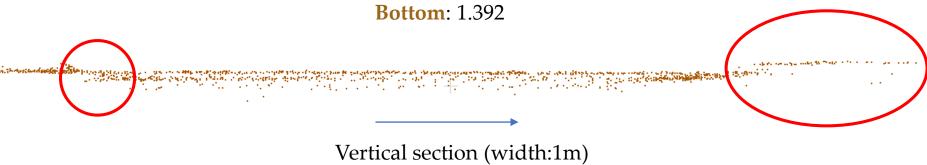
Vertical section (width:1m)







130NL2 Dataset

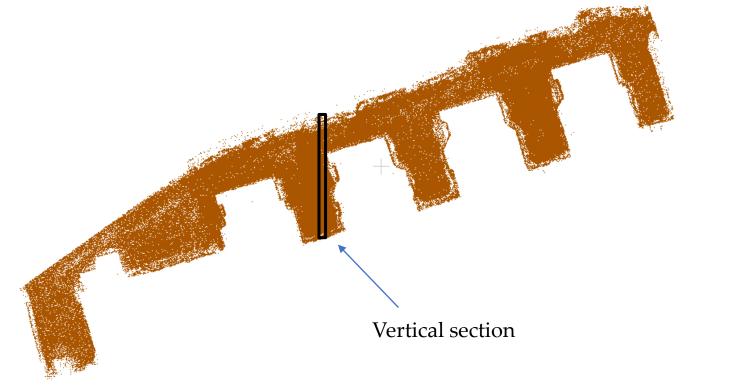






376NL3 Dataset

Total: 2.033.586 **Bottom**: 322.381 (16%)





376NL3 Dataset

Bottom: 7.112

运动性原则的现代形式通过电影的

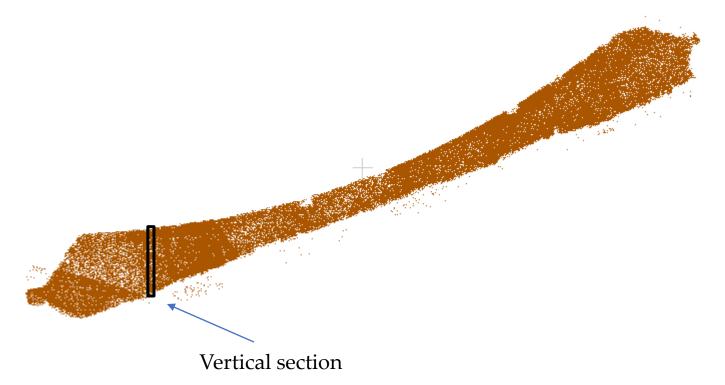
Vertical section (width:1m)





378NL3 Dataset

Total: 607.216 **Bottom**: 123.020 **(20%)**

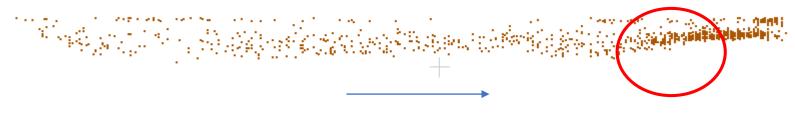






378NL3 Dataset

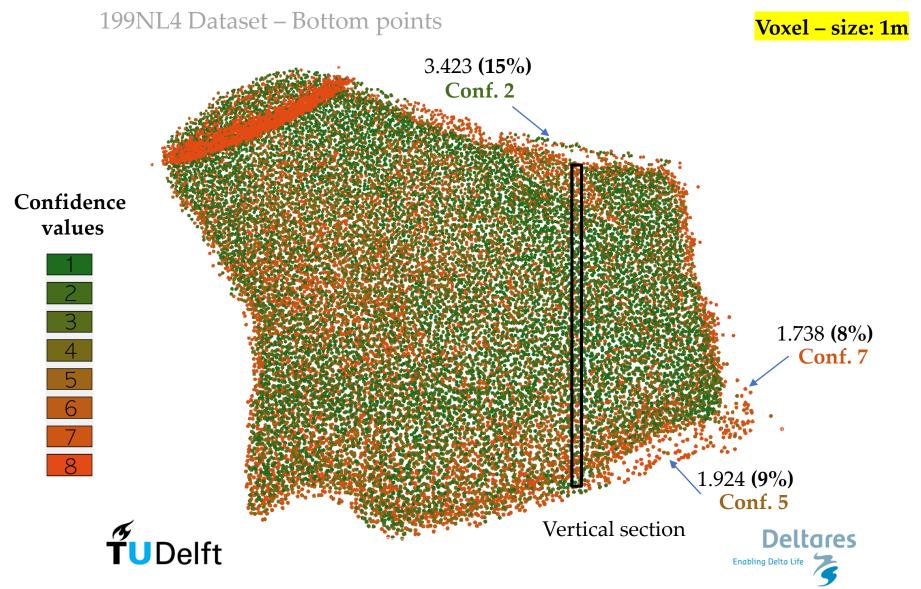
Bottom: 1.443



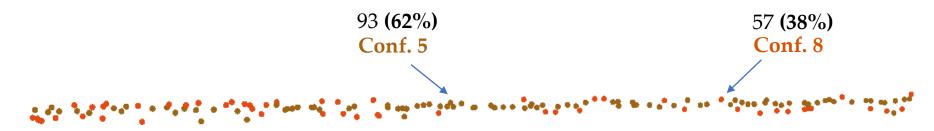
Vertical section (width:1m)







199NL4 Dataset – Bottom points (section)



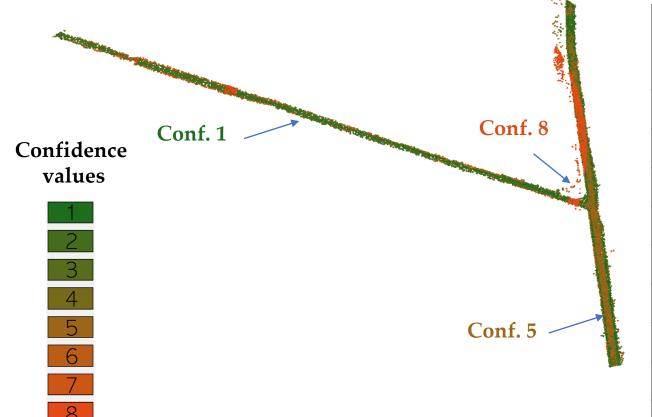
Vertical section

Parameters	Mean	Median
NormDensity	0,001	0,004
NormDistance	0,25	0
NormIntensity	0,194	0,194





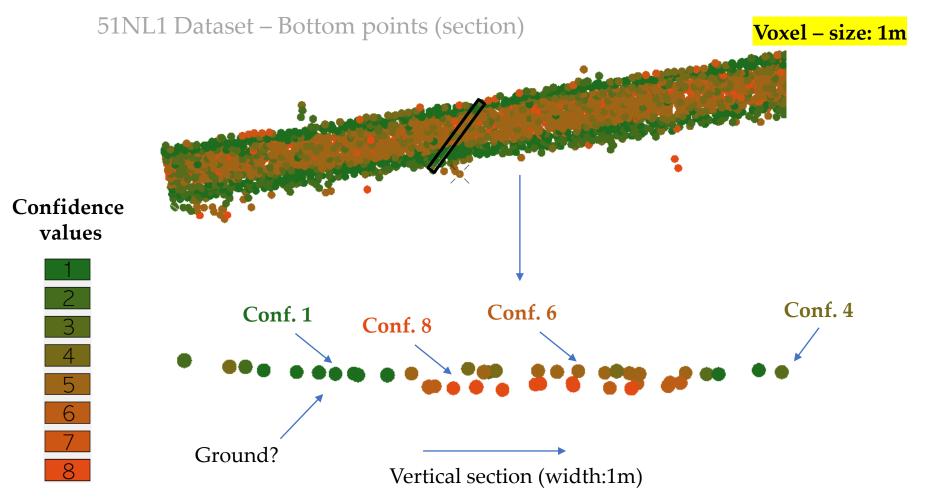
51NL1 Dataset - Bottom points



Conf. Values	Bottom Points	%
Conf.1	1.396	15
Conf.2	1.950	20
Conf.3	293	3
Conf.4	1.070	11
Conf.5	1.256	13
Conf.6	984	10
Conf.7	391	4
Conf.8	2.307	24
	9.647	



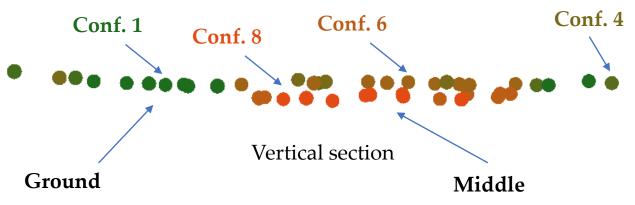








51NL1 Dataset – Bottom points (section)



Parameters	Mean	Median
NormDensity	7,81	6
NormDistance	0,13	0
NormIntensity	0,52	0,6

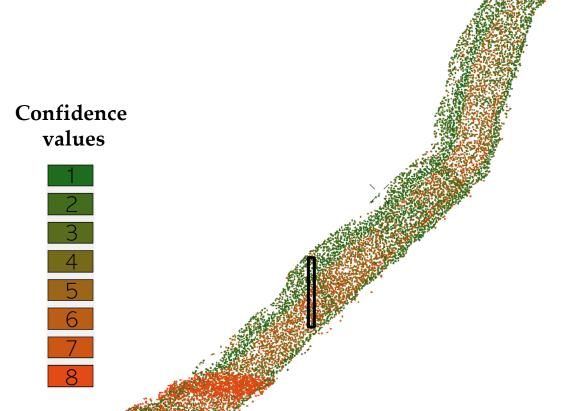


Conf. Values	Bottom Points	%
Conf.1	1.396	15,5
Conf.2	1.950	20
Conf.3	293	0,03
Conf.4	1.070	11
Conf.5	1.256	13
Conf.6	984	10
Conf.7	391	0,04
Conf.8	2.307	24
	9.647	

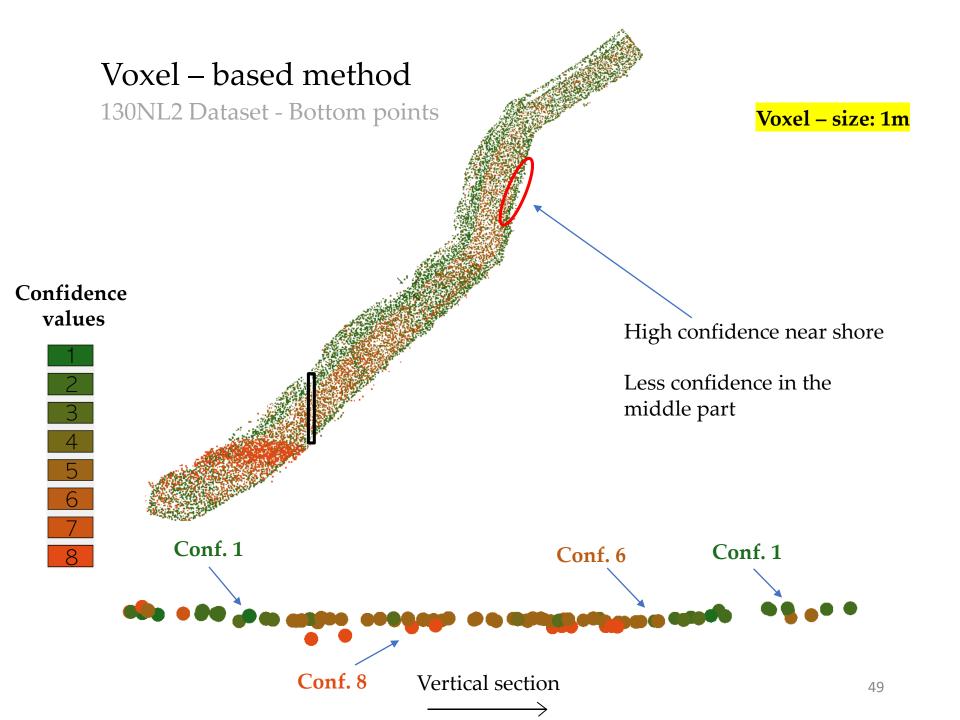


130NL2 Dataset - Bottom points

<mark>Voxel – size: 1m</mark>



Conf. Values	Bottom Points	%
Conf.1	1.059	9
Conf.2	3.502	30
Conf.3	987	8,5
Conf.4	1.061	9
Conf.5	2.808	24
Conf.6	51	0,4
Conf.7	189	1,6
Conf.8	1.979	17
	11.636	48

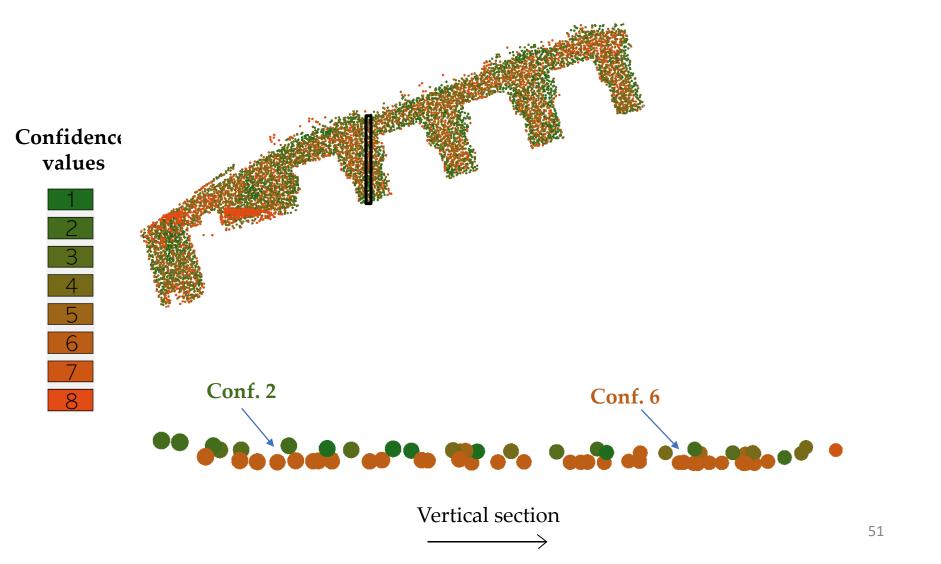


376NL3 Dataset - Bottom points

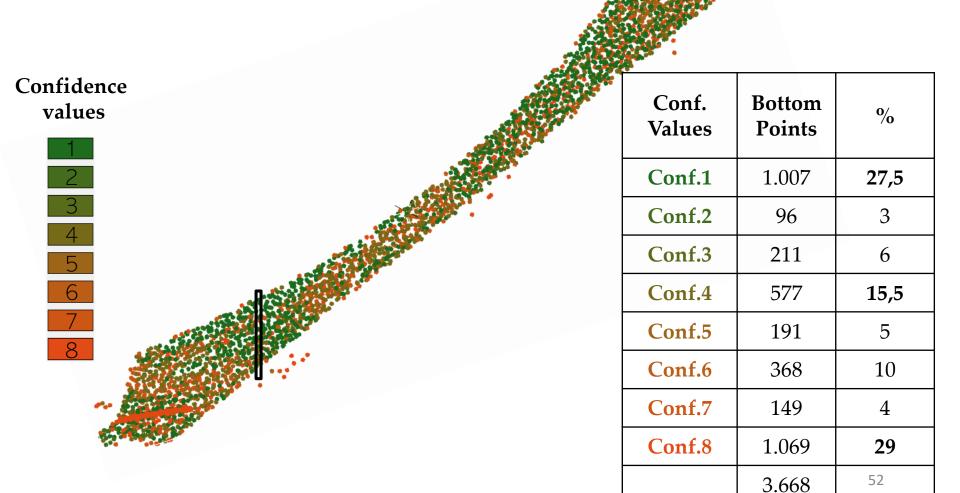


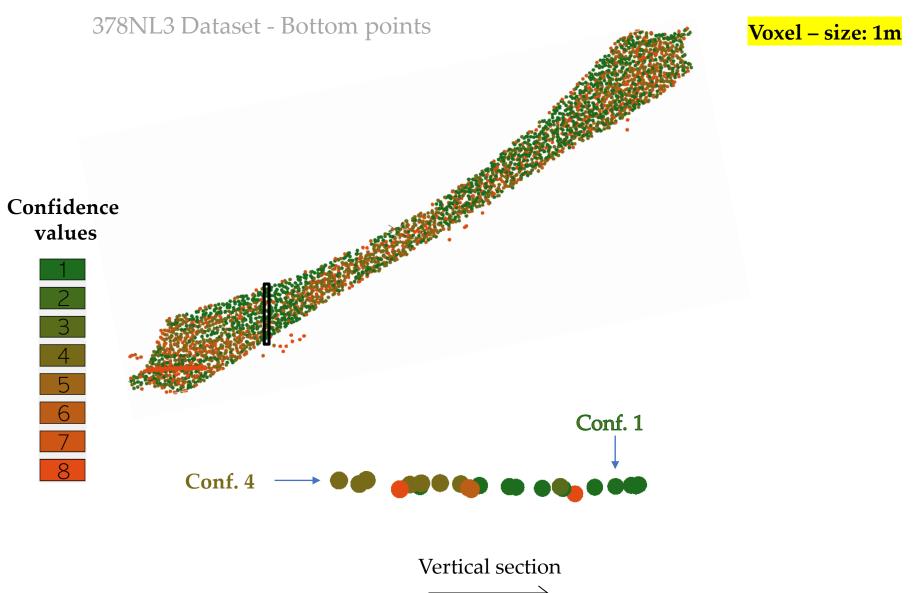
Conf. Values	Bottom Points	%
Conf.1	338	4
Conf.2	1.636	20
Conf.3	96	1,1
Conf.4	1.685	20
Conf.5	618	7,4
Conf.6	2.103	25
Conf.7	523	6,2
Conf.8	1.369	16,3
	8.368	50

376NL3 Dataset - Bottom points



378NL3 Dataset - Bottom points





To sum up

Voxel – size: 1m

Based on the density of the point cloud → more detected bottom points

Near the borders of waterbody \rightarrow ground points (Conf. 1-2)

In the middle part of waterbody \rightarrow less confident to be bottom (Conf. 6-8)

Name	Total	Z_Range	Voxel size	Voxels	Bottom points	Point Density (points/m2)
199NL4	2.851.512	1 to 4	1m x 1m	28.504	22.264	~215 -~250
51NL1	391.309	-3,6 to -2,6	1m x 1m	13.048	9.647	~25 - ~100
130NL2	1.023.501	-2 to 0	1m x 1m	57.124	37.393	~35 - ~130
376NL3	1.872.542	-4,2 to -3	1m x 1m	10.163	8.368	~325 - ~660
378NL3	548.919	-4,5 to -3,3	1m x 1m	4.402	3.668	~250 - ~430





Comparison

51NL1 dataset

Voxel – size: 1m

Section points: 42 Section width: 1m

Voxel - based method







Pulse - based method

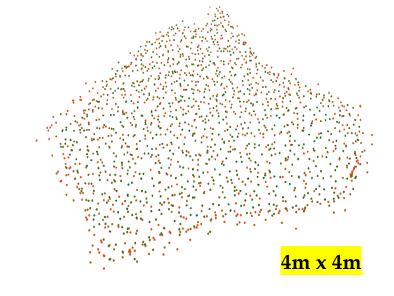
Section points: 282 Section width: 1m





199NL4 Dataset - Different voxel sizes

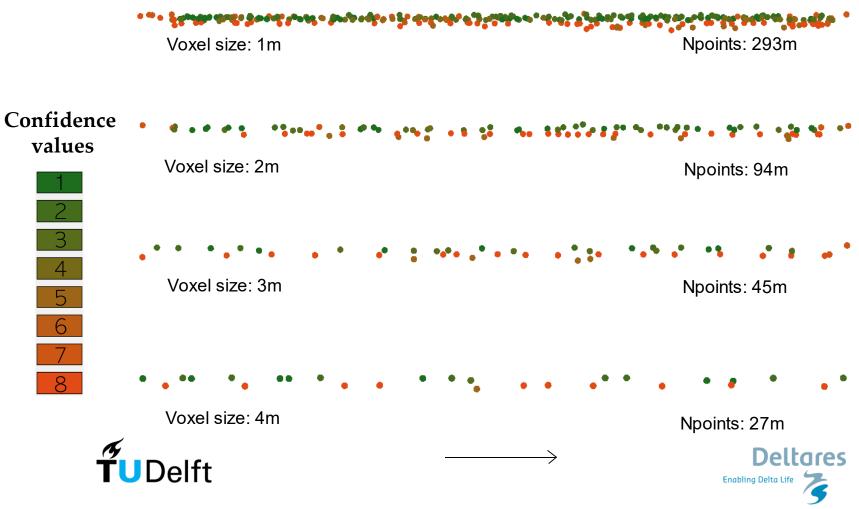
Name	Total	Voxel size	Voxels	Bottom points	Time (sec)
199NL4	2.851.512	2m x 2m	7.458	6.152	525
199NL4	2.851.512	3m x 3m	3.417	2.902	300
199NL4	2.851.512	4m x 4m	1.916	1.705	187







199NL4 Dataset – Bottom points



51NL1 Dataset - Different voxel sizes

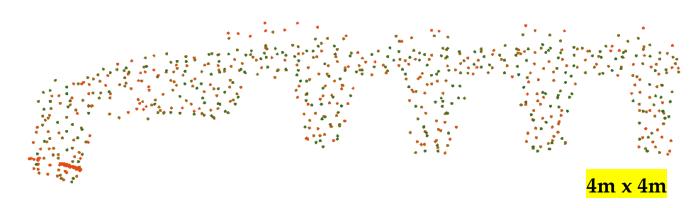






376NL3 Dataset - Different voxel sizes

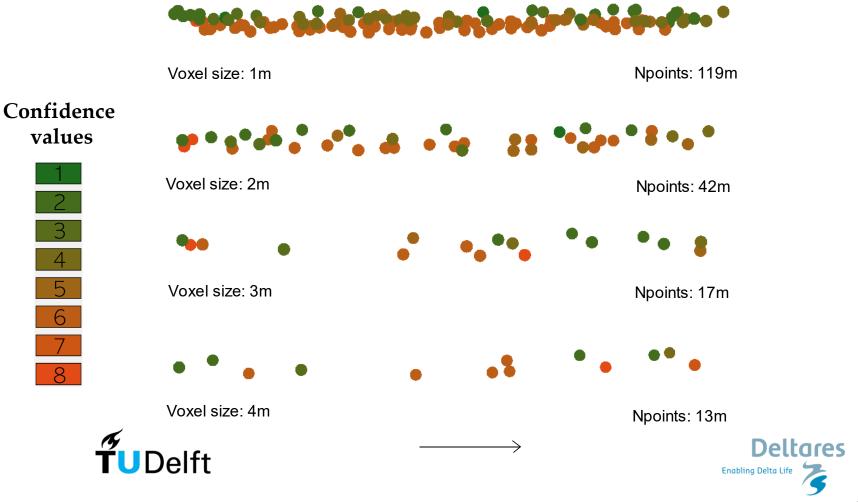
Name	Total	Voxel size	Voxels	Bottom points	Time (sec)
376NL3	2.033.586	2m x 2m	2.868	2.419	107
376NL3	2.033.586	3m x 3m	1.416	1.232	49
376NL3	2.033.586	4m x 4m	862	766	30





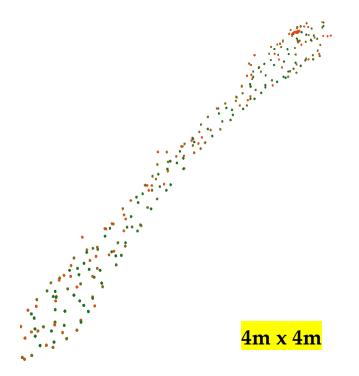


376NL3 Dataset - Different voxel sizes - Sections



378NL3 Dataset - Different voxel sizes

Name	Total	Voxel size	Voxels	Bottom points	Time (sec)
378NL3	607.216	2m x 2m	1.272	929	44
378NL3	607.216	3m x 3m	637	439	25
378NL3	607.216	4m x 4m	397	292	12







378NL3 Dataset - Different voxel sizes - Sections

Various voxel sizes



Confidence values

1

5

6

_____/

<u>ර</u>



Voxel size: 2m Npoints: 13m



Voxel size: 3m Npoints: 8m

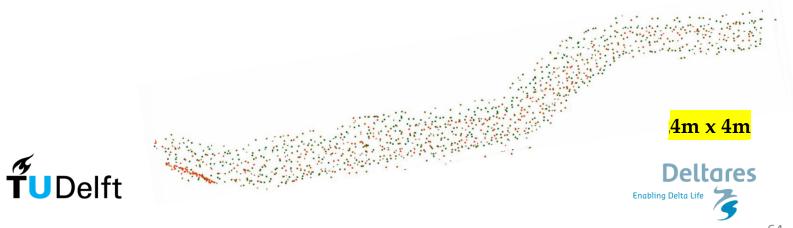
Voxel size: 4m Npoints: 1m



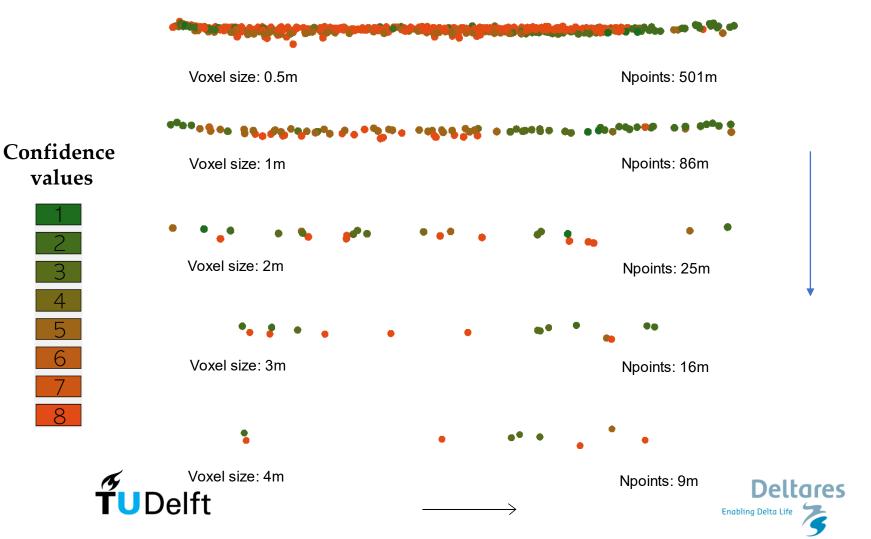


130NL2 Dataset - Different voxel sizes

Name	Total	Voxel size	Voxels	Bottom points	Time (sec)
130NL2	1.164.170	0.5m x 0.5m	57.124	37.393	1.326
130NL2	1.164.170	2m x 2m	5.320	3.836	150
130NL2	1.164.170	3m x 3m	2.665	1.960	85
130NL2	1.164.170	4m x 4m	1.620	1.272	62



130NL2 Dataset - Different voxel sizes - Sections



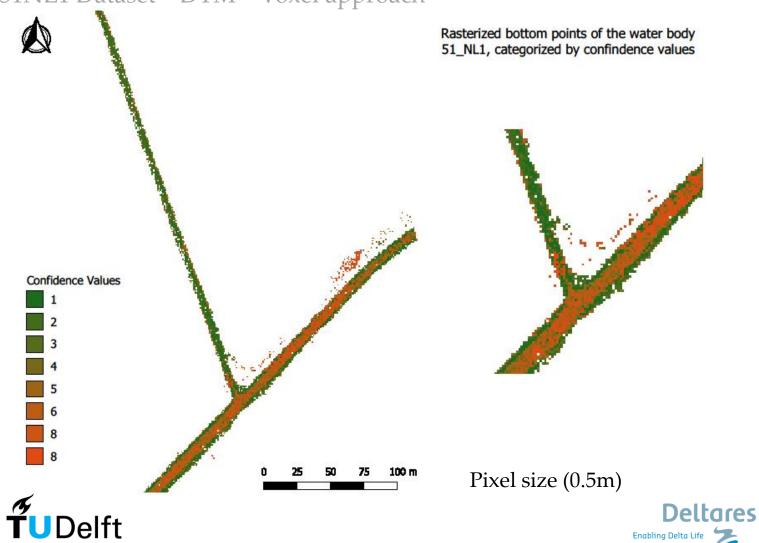
To sum up

- As the voxel size increases, less bottom points are detected
- Voxel size $(0.5m) \rightarrow$ too many points \rightarrow unnecessary (!?)
- Voxel size >2m (most cases) → Sparse distribution of points
 - → Bottom surface reconstruction becomes difficult
- In 378NL3 with voxel size $4m \rightarrow \text{just one}$ bottom point
- The computation time increases rapidly, as the voxel size increases

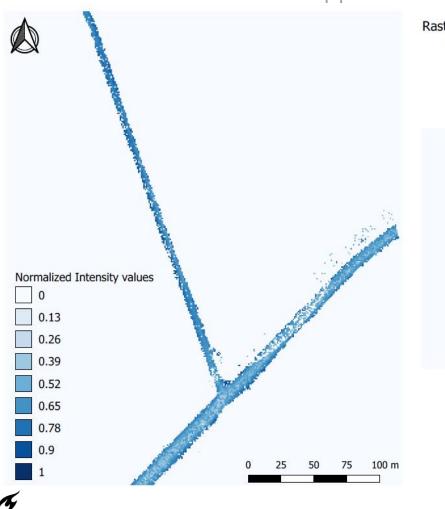




51NL1 Dataset – DTM – Voxel approach



51NL1 Dataset – DTM – Voxel approach



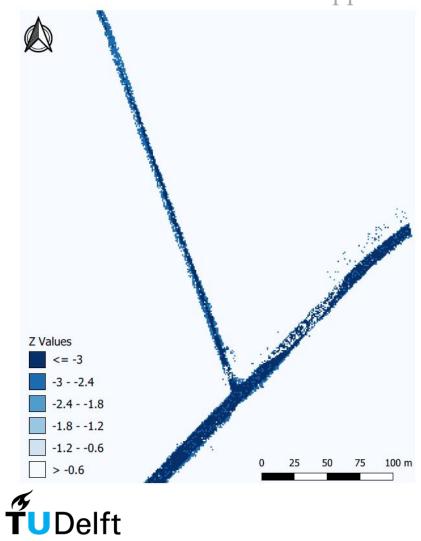
Rasterized bottom points of the water body 51_NL1, categorized by normalized intensity values







51NL1 Dataset – DTM - Voxel approach



Rasterized bottom points of the water body 51_NL1, categorized by z values



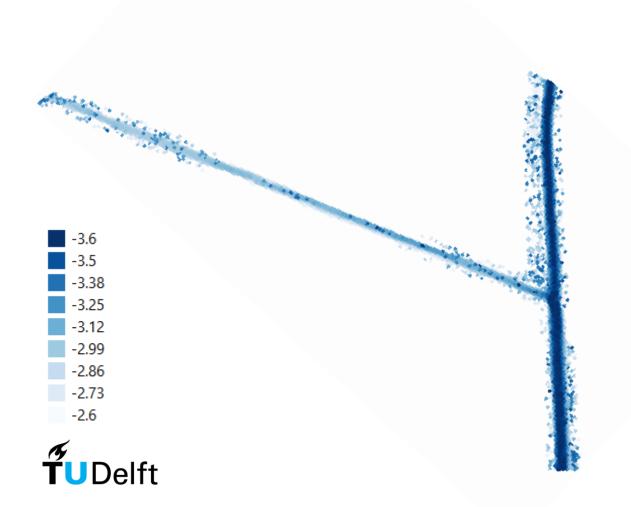
Voxel – based method:

- Rasterized z values
- Pixel size (0.5m)





51NL1 Dataset – DTM - Pulse approach

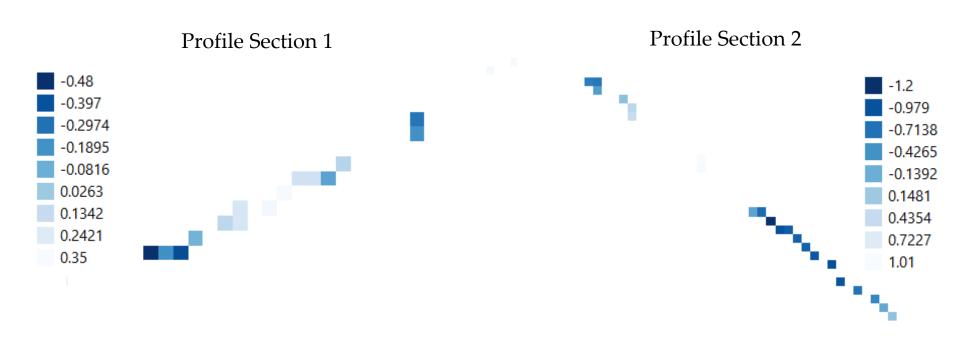


Pulse – based method:

- Rasterized z values
 - Pixel size (0.5m)



51NL1 Dataset: Pulse – based method VS GtD

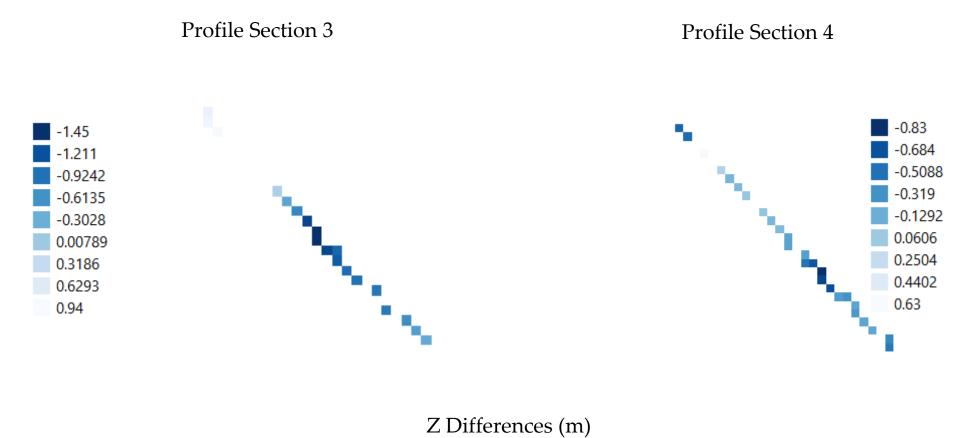


Z Differences (m)





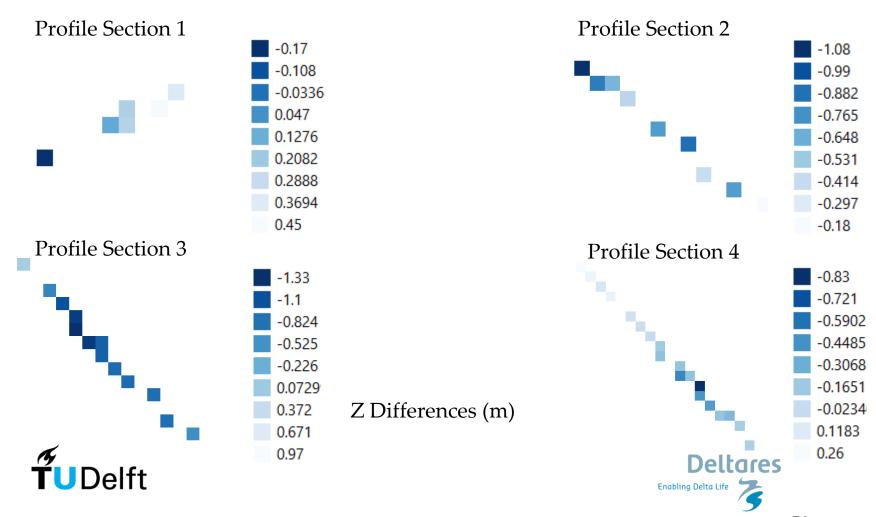
51NL1 Dataset: Pulse – based method VS GtD







51NL1 Dataset: Voxel – based method VS GtD



51NL1 Dataset

Prof. Section 1	Z Differences (m)		
Points	р3	p5	
Actual Z (m)	-3,33	-2,60	
Pulse-based	0,21	0,19	
Voxel-based	0,24	0,17	

Range: 21cm - 49 cm

Range: 11cm - 44 cm

	Prof. Section 2	Z Differences (m)				
	Points	р4	p5			
	Actual Z (m)	-1,90	-1,90			
	Pulse-based	-1,20	-1,20			
ĺ	Voxel-based	1,07	-1,07			

Range: 7 cm - 1,2 m

Range: 40cm -1,07m



51NL1 Dataset

Range:

84cm - 1,4m

14cm - 1,22m

Prof. Section3	Z Differences (m)								
Points	p1	p2	p8	р9	p11	p14	p16	p18	p21
Actual Z (m)	-3,58	-2,83	- 2,54	-2,46	-2,55	-2,47	-2,48	-2,03	-1,93
Pulse-based	0,94	0,13	0,65	0,72	0,87	1,0	1,11	1,29	1,50
Voxel-based	0,97	0,14	0,55	0,64	0,84	0,96	0,96	1,09	1,23

Range:

20cm - 73cm

20cm - 83cm

Prof. Section	n4	Z Differences (m)								
Points		p2	рЗ	p4	p6	р7	p8	p11	p12	p15
Actual Z (m)	-3,6	3,47	- 3,45	-2,54	-3,34	-2,73	-2,95	-2,88	-2,68
Pulse-bas	ed	0,05	0,06	0,08	0,19	0,2	0,25	0,5	0,5	0,69
Voxel-bas	ed	0,2	0,08	0,21	0,11	0,2	0,19	0,5	0,5	0,39

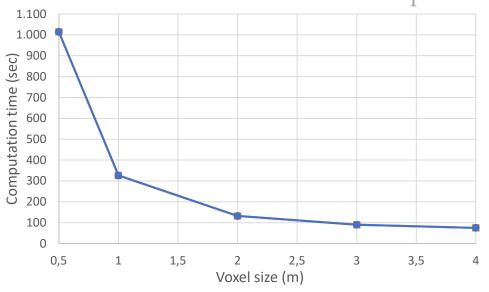


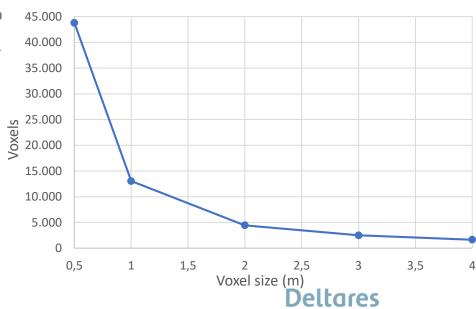
Using Point Sampling Tool



Computation time

51NL1 Dataset – half million points





Enabling Delta Life



To sum up

- Bottom points can be partially detected using both methods
- **Less** bottom points in the voxel approach due to the voxel size, but **more accurate** compared to the ground truth data (GtD)
- The z differences (**GtD vs Voxel**) vary from few centimeters (11cm) to more than a meter (1,3m) in the four profile sections
- More points detected as bottom in the pulse based method, but less accurate
- The z differences (**GtD vs Pulse**) vary from (20cm) to (1,4m).
- Refraction correction has not been applied and can influence the accuracy
- Different voxel sizes might affect the classification result





Research Questions & Conclusions

- **q2**: Can pulse and/or neighbourhood based methods in a green ALB be used to classify and detect the bottom points?
- Both methods managed to classify the water bodies; especially their bottom points.
- **q3**: What is the influence of different voxel resolutions for classification, in terms of accuracy and computation load?
- Smaller than 0,5m voxel size results to unpractical computation time, but bigger number of voxels. Various point density in a voxel influences the running time.
- **q4**: How does the various point cloud quality (i.e. density, outliers) affect the classification process?
- Outliers affect the pulse-based approach as many points do not correspond to a pulse.
- Density affects the computation time.
- **q5**: Can a confidence value of water bodies be calculated? If it is possible, how?
- Yes, based on density, distance and intensity parameters.





Research Questions & Conclusions

Q1: Can the bottom points of shallow and muddy water-bodies in the Netherlands be automatically detected using ALB?

Yes, using both methods. The result depends on:

- the **density** of a water body
- the presence of **outliers** during the pre-processing steps
- the right trade off between **voxel size** and **running time**

Except the pre-processing steps, the procedure is **automated**.





Recommendations for future work

- Deep learning algorithms on point cloud (e.g. PointNet++)
- Pre-processing automation
- Ground filtering
- Test more datasets with extreme cases





Thank you for your attention!



