Enhancing 3D Model for Urban Area with Neural Representations

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1. Introduction

3D Models For Urban Area

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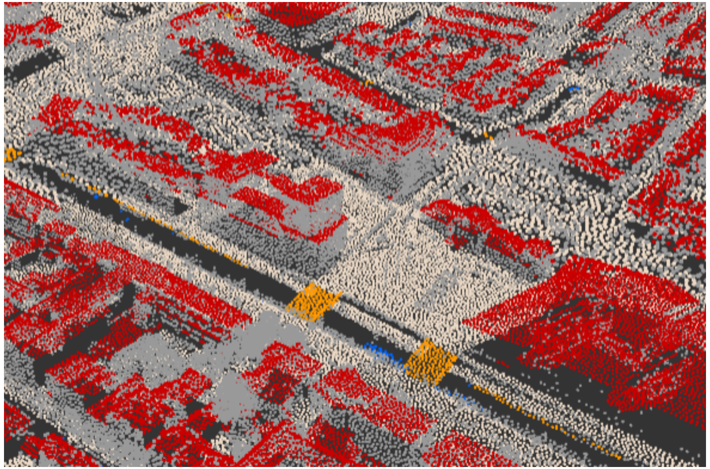
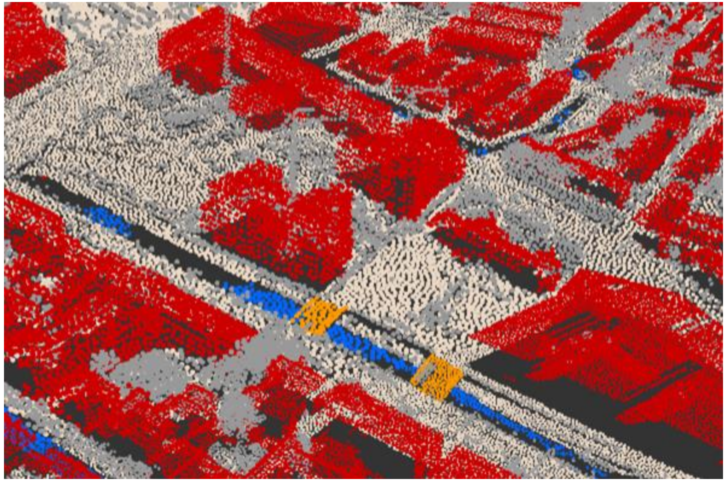
- Construction monitoring





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3D Models For Urban Area

- Irradiation analysis

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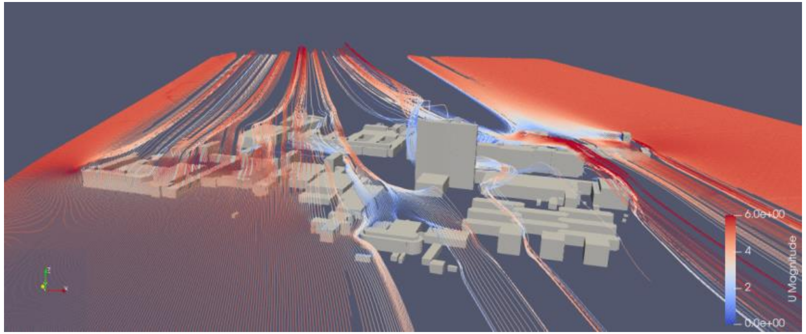
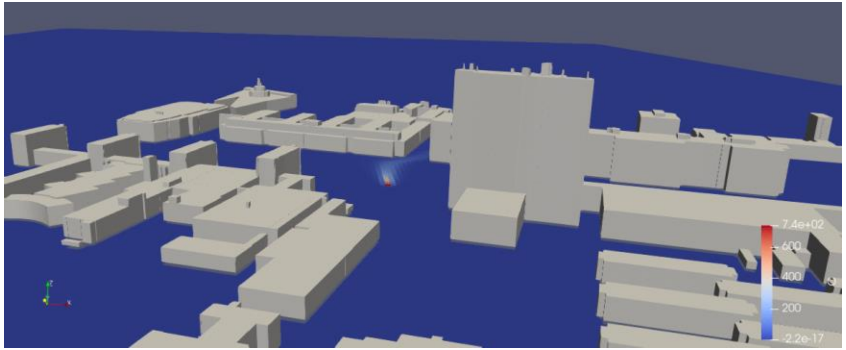
3D Models For Urban Area

- Wind simulation





Limited Quality

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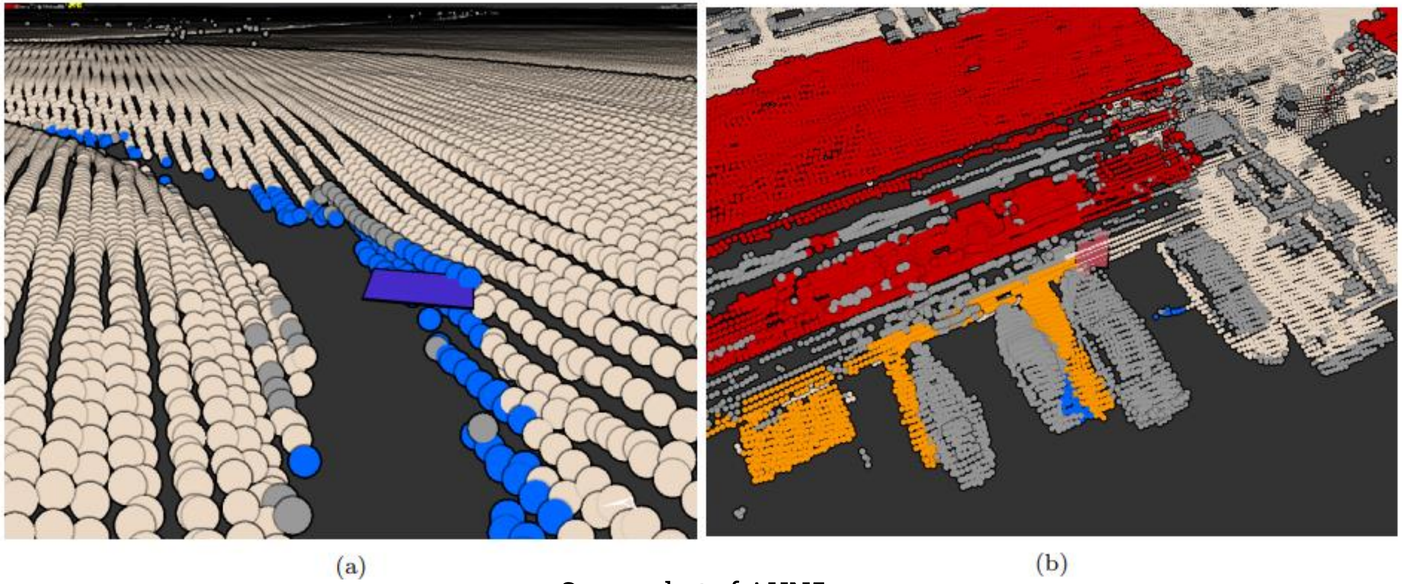

Screenshot of AHN5

- Discretized representation
- Limited resolution

Missing data

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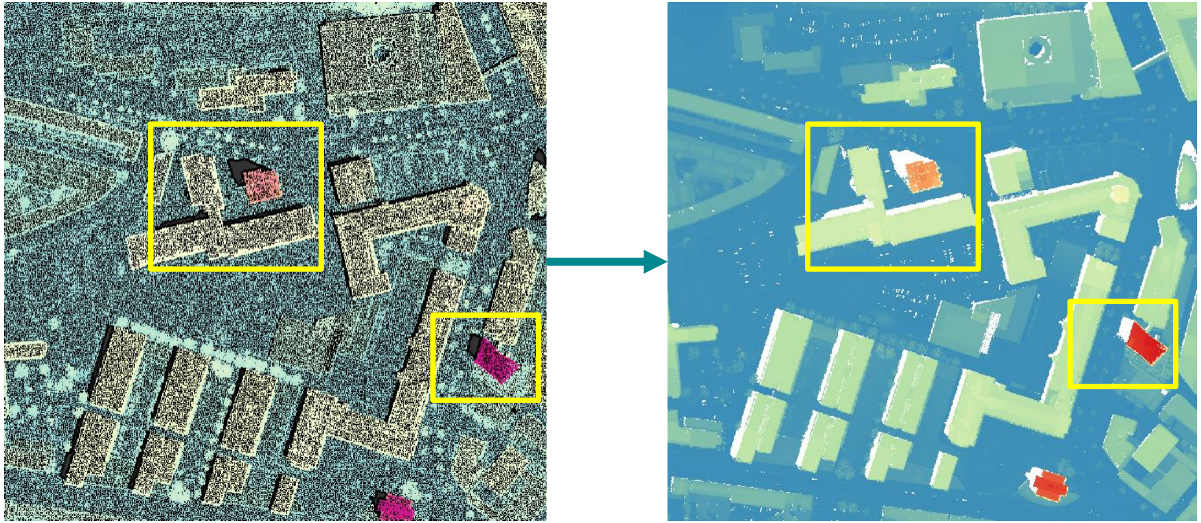

- low reflectance surfaces
- Occlusion

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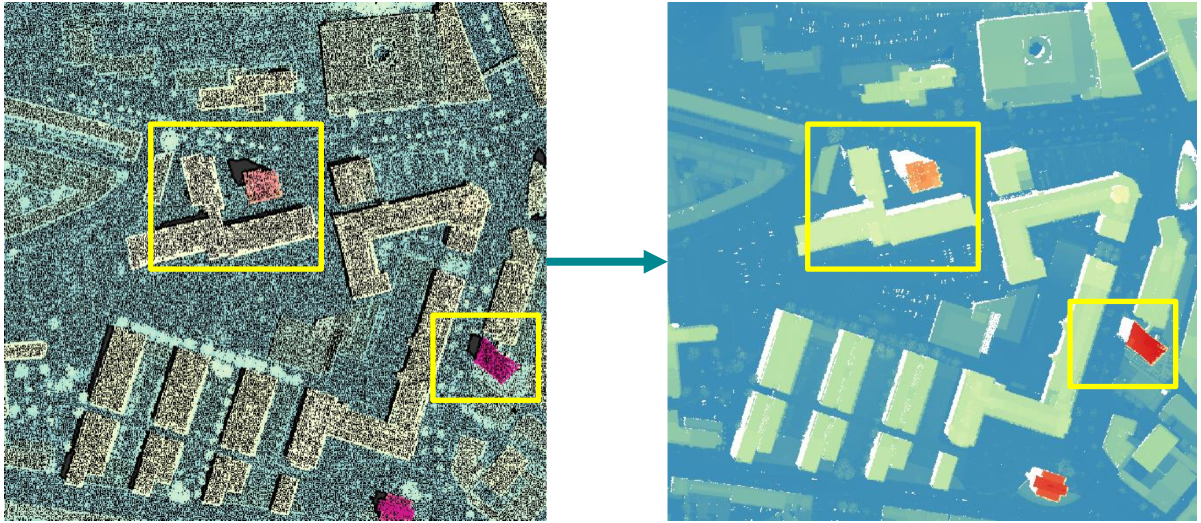
Missing data



- Better sensors or more flight lines
- Interpolation
- Fill with reference data

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Missing data

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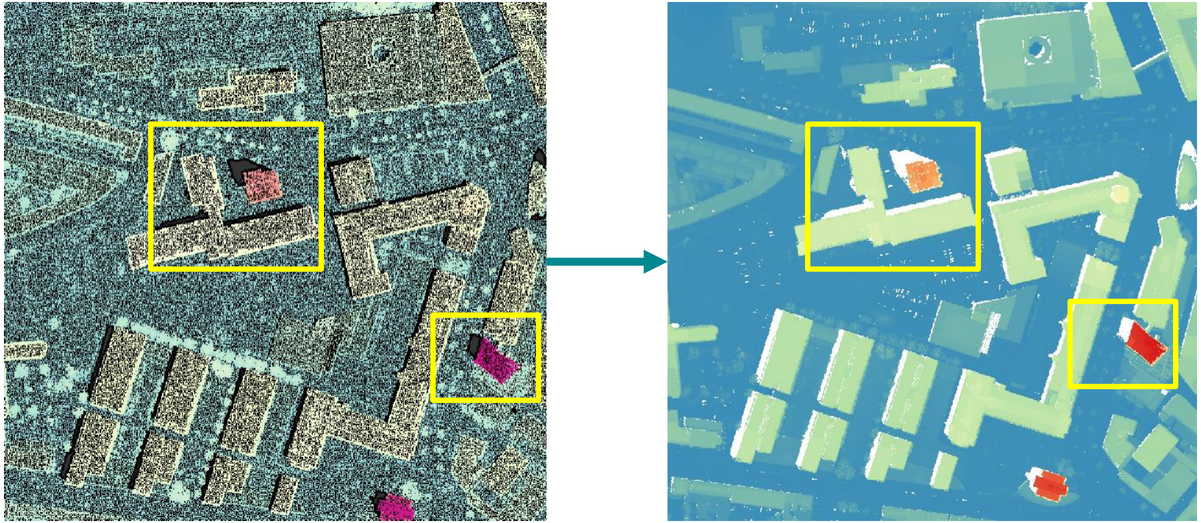
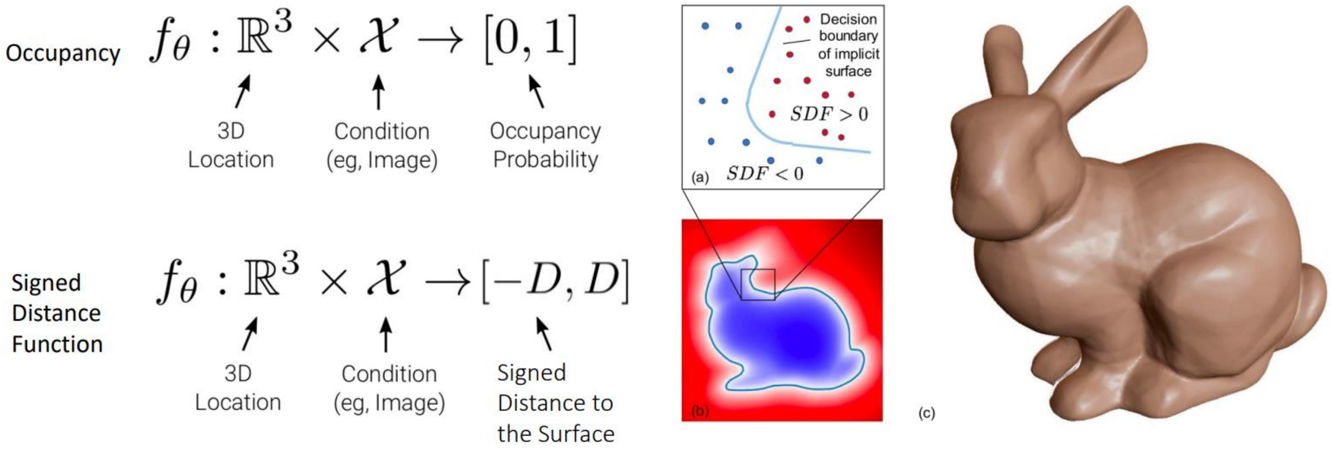


High cost
Frequent manual adjustment
Limited reference data sources

Implicit neural representation

- Utilize neural networks to implicitly encode complex, high-dimensional data into a continuous functional field.
- Return result at any designated point.



Picture from: Mescheder, L., et al. (2018). Occupancy networks: Learning 3d reconstruction in function space.

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Implicit neural representation

- Multi-modal inputs have the potential to significantly improve the quality of 3D models and can enrich it with more detailed information.
- The generalizable nature of this approach enable the generation of parts that is not directly captured during data acquisition.
- The continuous nature ensures that the final products, such as DSMs, are complete without any no-data parts.

Picture from: Chou, et al. (2022) . Diffusion-SDF: Conditional Generative Modeling of Signed Distance Functions

Research question

What are the characteristics of implicit neural representation when it's used for 3D real-scene urban area reconstruction

- What process steps are needed to adapt current geospatial data to the network?
- What is the geometric performance of implicit neural representation when applied to real-scene urban data reconstruction?
- How effective is the generalizability of the implicit representation functions on AHN3 urban data?
- Compared to traditional methods, what are the advantages and disadvantages of using the implicit neural representation for urban scene reconstruction with open-source datasets in the Netherlands?

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2. Related work

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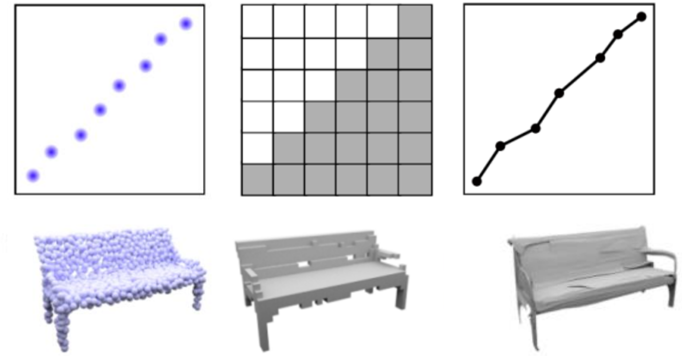
Explicit Representations

- Point cloud
  - ✗ No connectivity and topological structures
  - ✗ No global shape
  - ✓ Multi-modal inputs
  - ✓ Generation of various products



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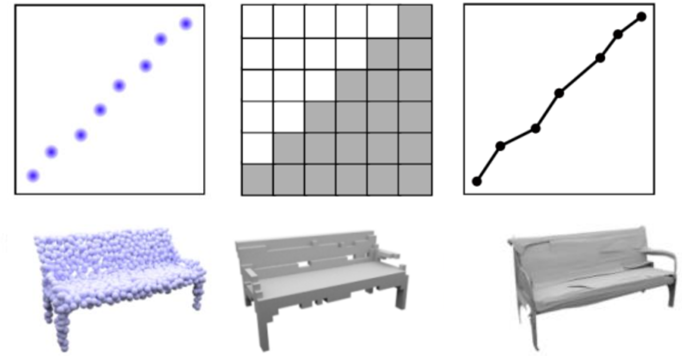
Explicit Representations

- Point cloud
  - ✘ No connectivity and topological structures
  - ✘ No global shape
  - ✓ Multi-modal inputs
  - ✓ Generation of various products
- Voxel
  - ✘ Manhattan World bias
  - ✘ Limited resolution (256^3)
  - ✓ Aligned with world coordinate
  - ✓ Continuous



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Explicit Representations

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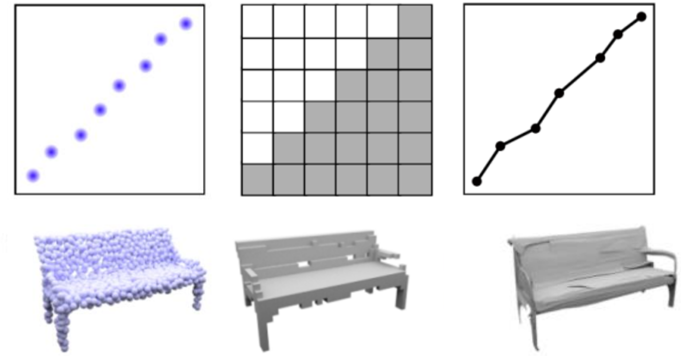
- Point cloud
  - ✗ No connectivity and topological structures
  - ✗ No global shape
  - ✓ Multi-modal inputs
  - ✓ Generation of various products
- Voxel
  - ✗ Manhattan World bias
  - ✗ Limited resolution (256^3)
  - ✓ Aligned with world coordinate
  - ✓ Continuous
- Mesh
  - ✗ Require class-specific templates
  - ✗ Topology problems (self-intersection)
  - ✓ Represent shape as functions
  - ✓ Continuous and intersection-free



Picture from: Mescheder, L., et al. (2018). Occupancy networks: Learning 3d reconstruction in function space.

Implicit representation in 3D reconstruction

DeepSDF (2019)

- Learn continuous signed distance functions for complex geometries
- ✘ High computational demands

Convolutional Occupancy Network (2020)

- Translation equivariance

ImpliCITY (2022)

- Apply to real scene data in Zurich
- Use orthophotos as second latent encoding to add topology information
- ✘ Closed-sourced datasets
- ✘ No analysis on the characteristics

3. Methodology

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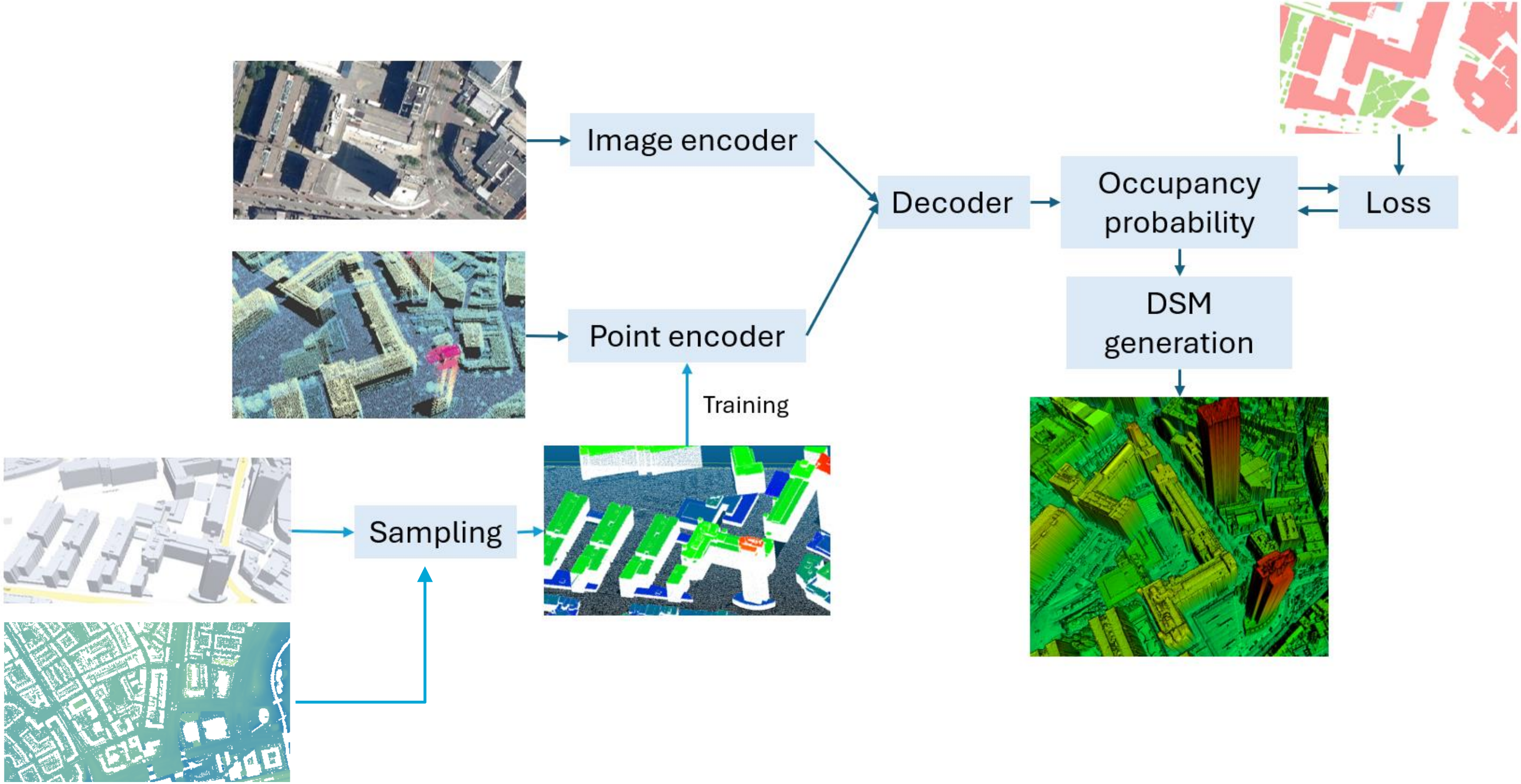
Pipeline Overview



Data Pre-Processing

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Open-sourced datasets in the Netherlands

Fully reproducible

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Data Pre-Processing

AHN3

- Raw point cloud

  Clipped and merged by PDAL command

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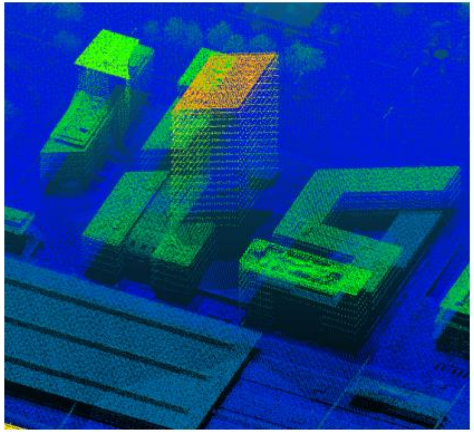
Data Pre-Processing

AHN3

- Raw point cloud
  - Clipped and merged by PDAL command
  - Generate reference DSM



(a) Area 1 in point cloud

(b) Area 1 in DSM

Data Pre-Processing

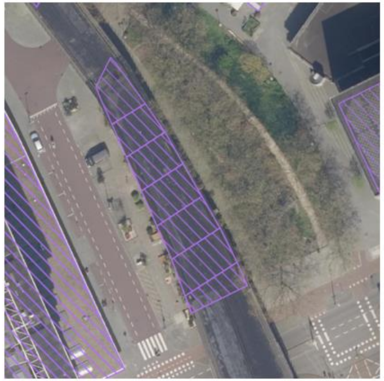
AHN3

- Raw point cloud
  - Clipped and merged by PDAL command
  - Generate reference DSM
  - Building class points used to generate building mask

(a) Accuracy for some building polygon is low

Feature	Value
pand [3]	
identificatie	0599100000617974
(Derived)	
(Actions)	
gid	1716638
bouwjaar	1935
identificatie	0599100000617974
pandstatus	Pand in gebruik
geconstateerd	false
documentdatum	1/1/1975
documentnummer	01/3744/72
voorkomenidentificatie	1
begindatumtijdvakgeldigheid	1/1/1975 00:00:00 (UTC)
einddatumtijdvakgeldigheid	10/16/2015 00:00:00 (UTC)
tijdstipregistratie	8/27/2010 18:39:30 (UTC)
eindregistratie	10/16/2015 17:33:29 (UTC)
tijdstipinactief	NULL
tijdstipregistratielv	8/27/2010 19:01:23 (UTC)
tijdstipeindregistratielv	10/16/2015 18:00:02 (UTC)
tijdstipinactieflv	NULL
tijdstipnietbaglv	NULL
aanduidingrecordinactief	false
geom_valid	true

(b) Registration time is not complete and hard to understand



(c) Underground part is also included in the BAG

Data Pre-Processing

AHN3

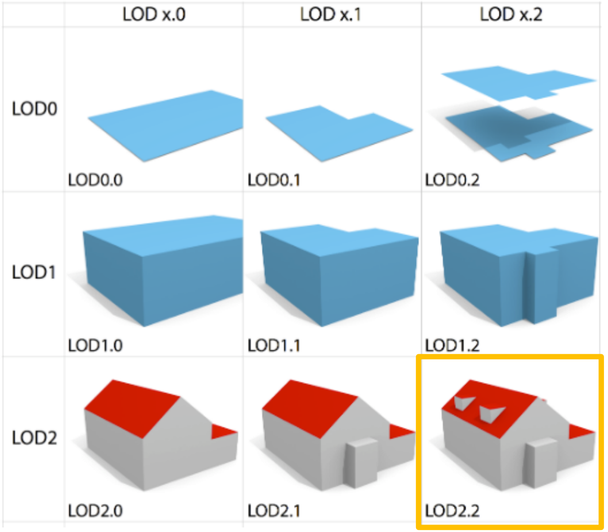
- Raw point cloud
  - Clipped and merged by PDAL command
  - Generate reference DSM
  - Building class points used to generate building mask
- Reference terrain points
  - Sampled from DTM in AHN3
  - No terrain surface in 3DBAG

Data Pre-Processing

3DBAG

- Reference point cloud

LOD 2.2 model which includes detailed roof



Picture from: Biljecki, F., Ledoux, H., and Stoter, J. (2016). An improved LOD specification for 3d building models.

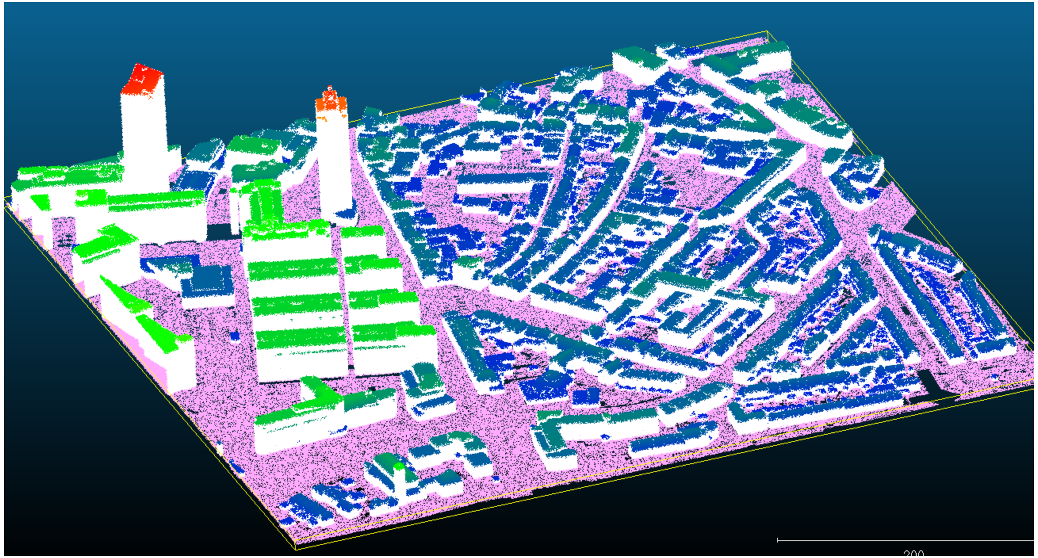
Data Pre-Processing

3DBAG

- Reference point cloud

  LOD 2.2 model which includes detailed roof

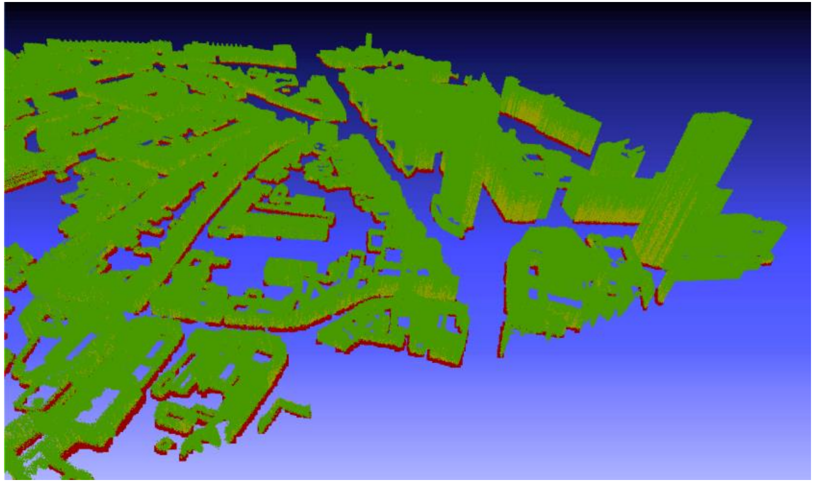
  Sampled with different density on roof, wall and ground



Data Pre-Processing

3DBAG

- Reference point cloud
    - LOD 2.2 model which includes detailed roof
    - Sampled with different density on roof, wall and ground
    - Divided into three categories with regard to DSM and DTM



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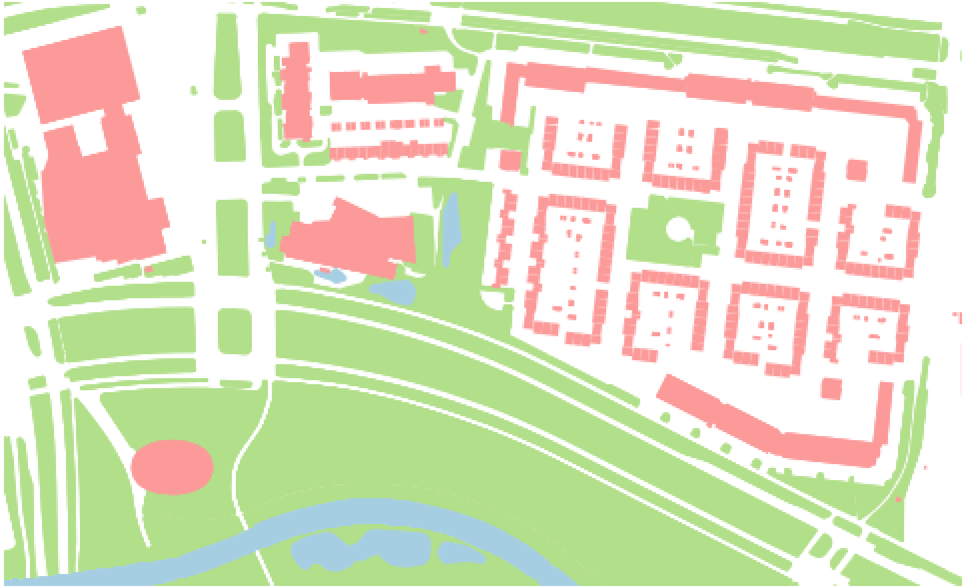
Data Pre-Processing

BGT

- Water and vegetation layers as masks

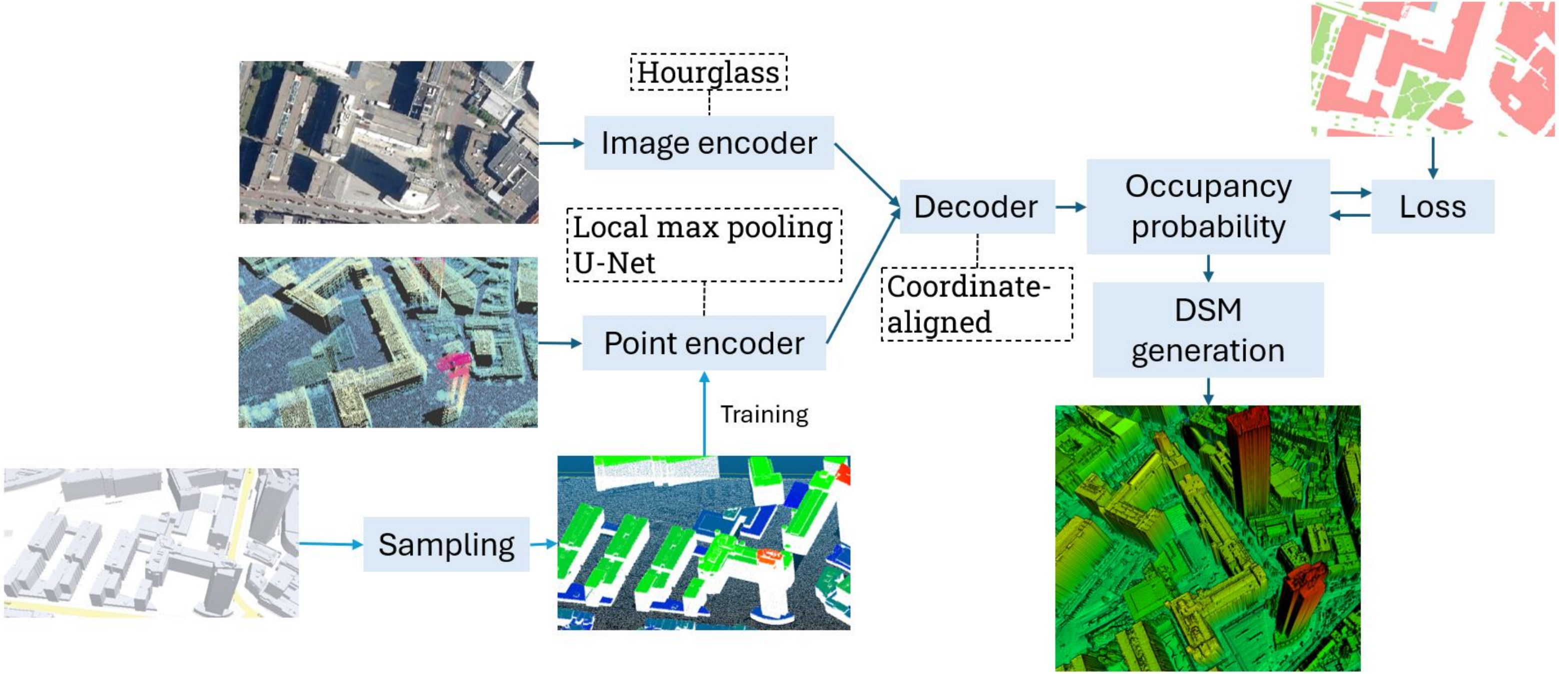


Data Pre-Processing

Luchtfoto Beeldmateriaal

- 25 cm resolution
- Converted to black and white

Network Overview



Network Architecture—Point encoder

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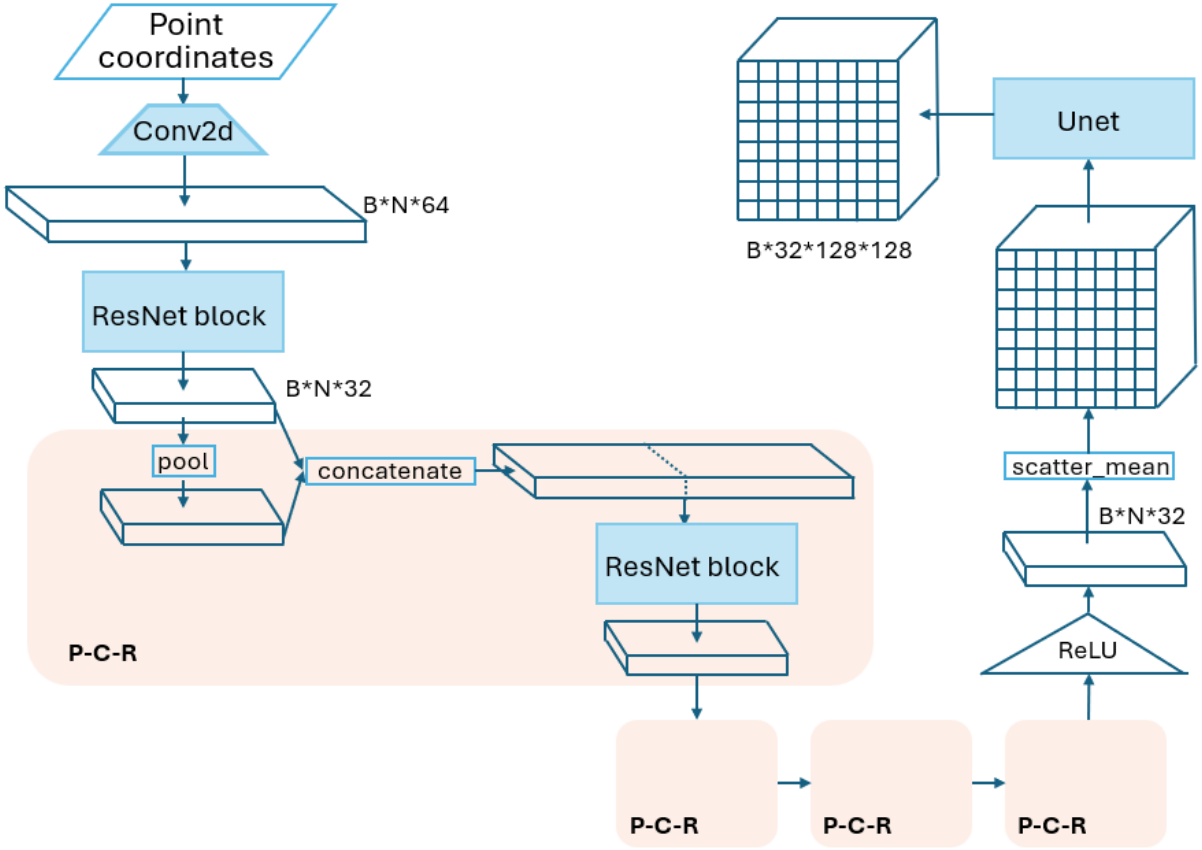
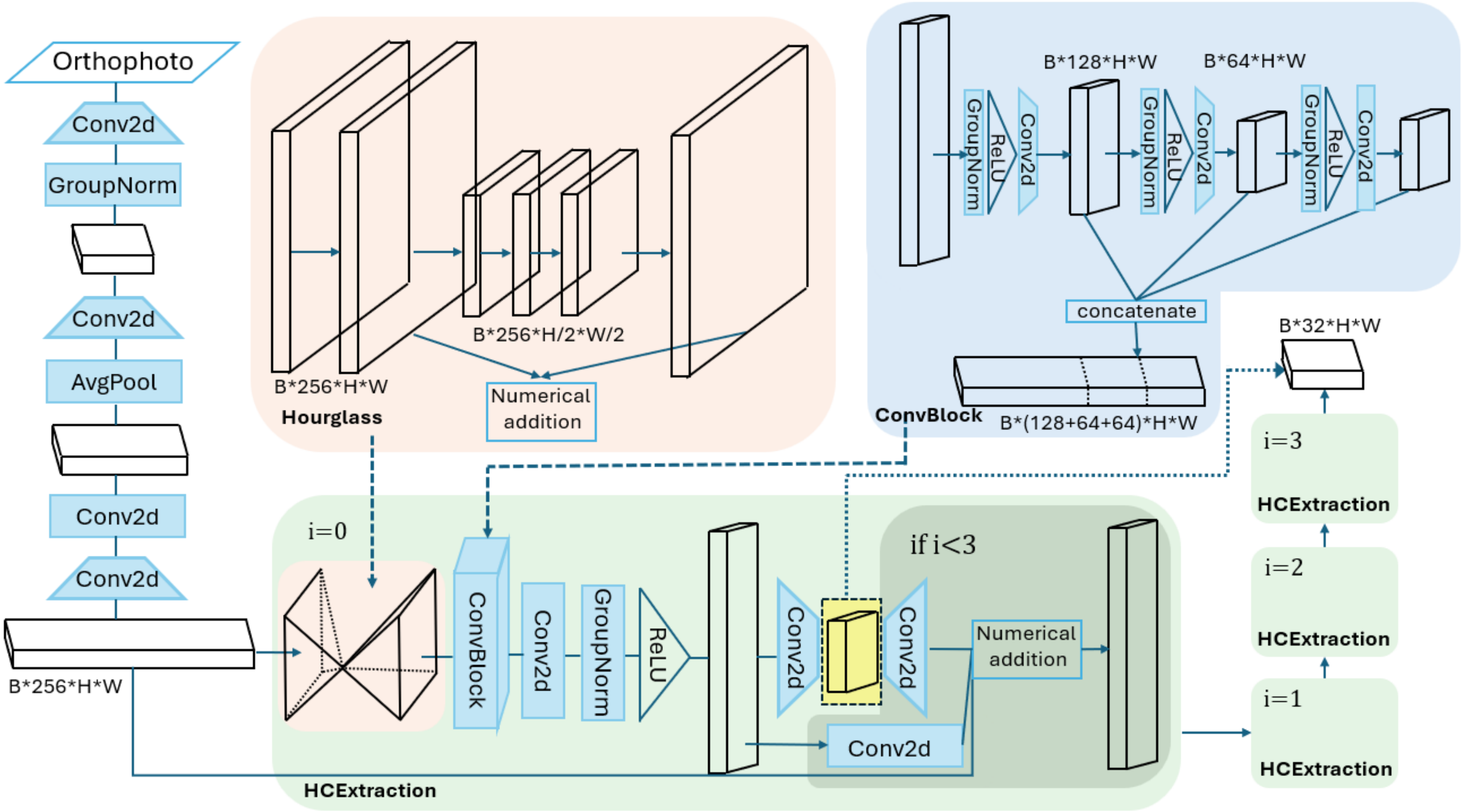


Network Architecture—Image encoder



Network Architecture—Occupancy probability decoder

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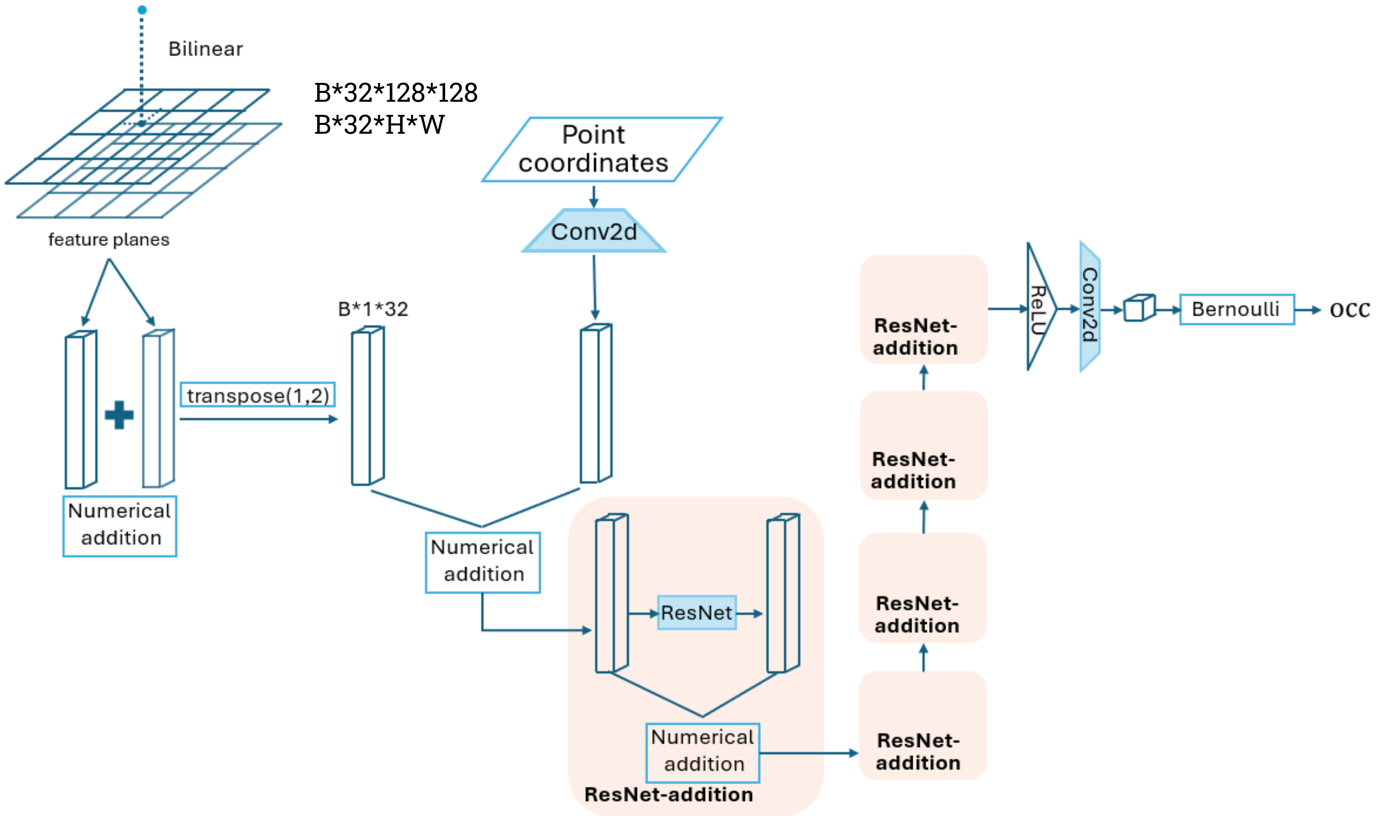

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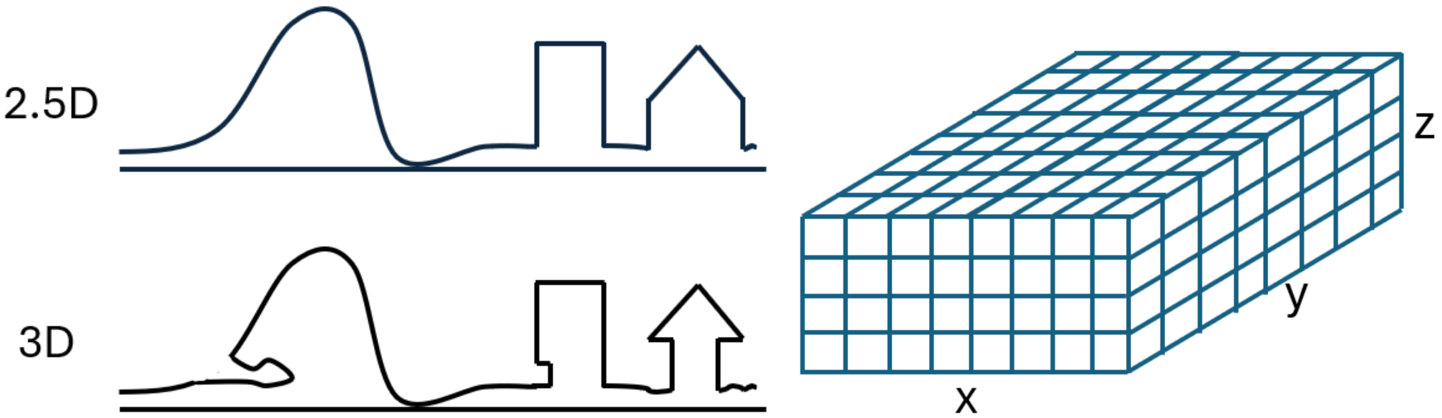
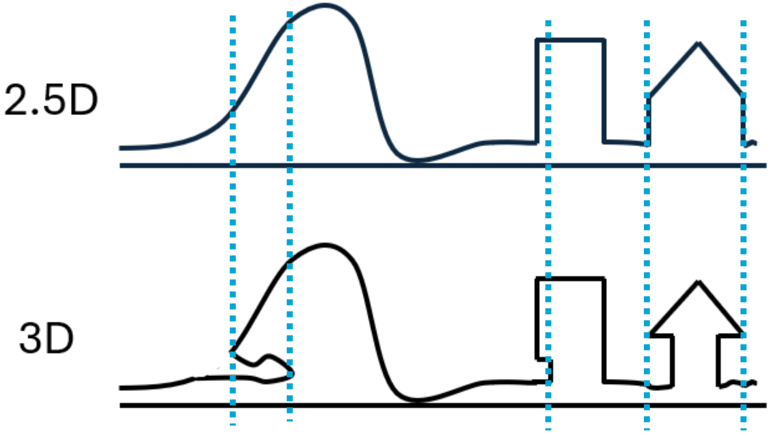
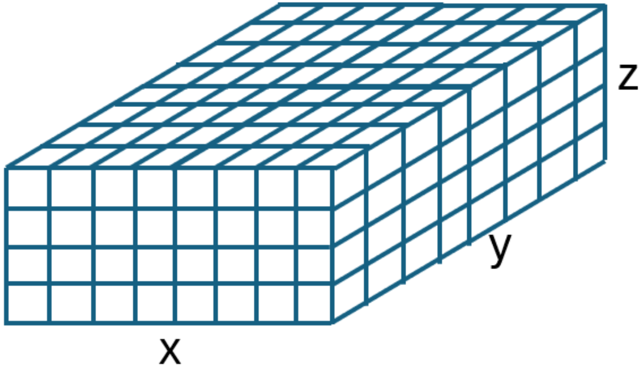
DSM Generation



Create a grid at the desired horizontal resolution but considerably low vertical resolution.

DSM Generation





Create a grid at the desired horizontal resolution but considerably low vertical resolution.

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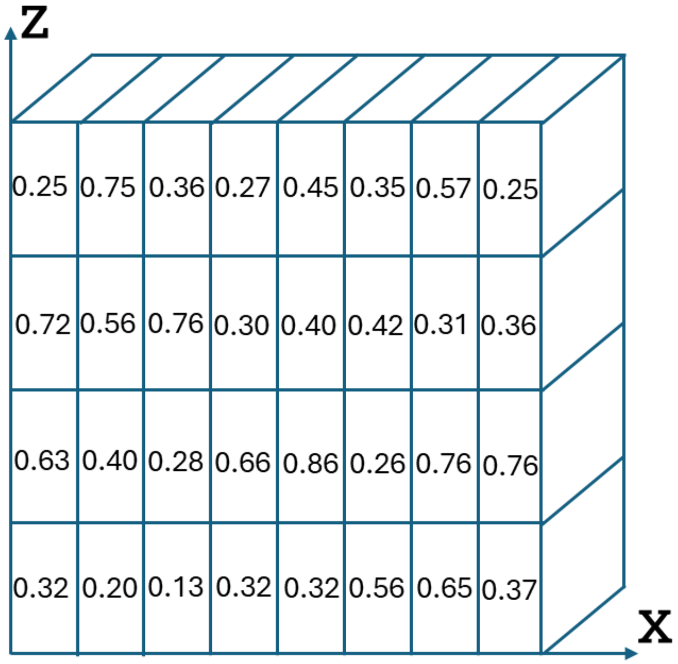
DSM Generation—Highest cell method

Only the cell is predicted to be occupied and is the highest in the column, will it be divided into four smaller voxels for further iteration.



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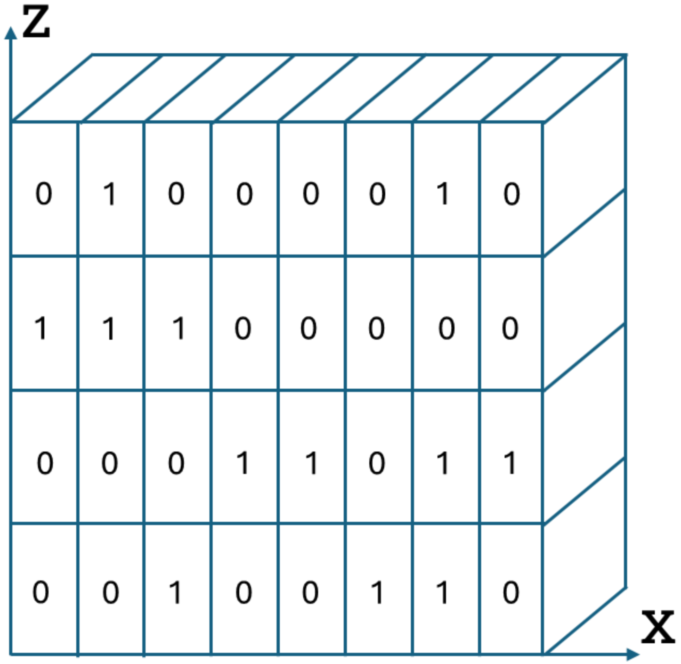

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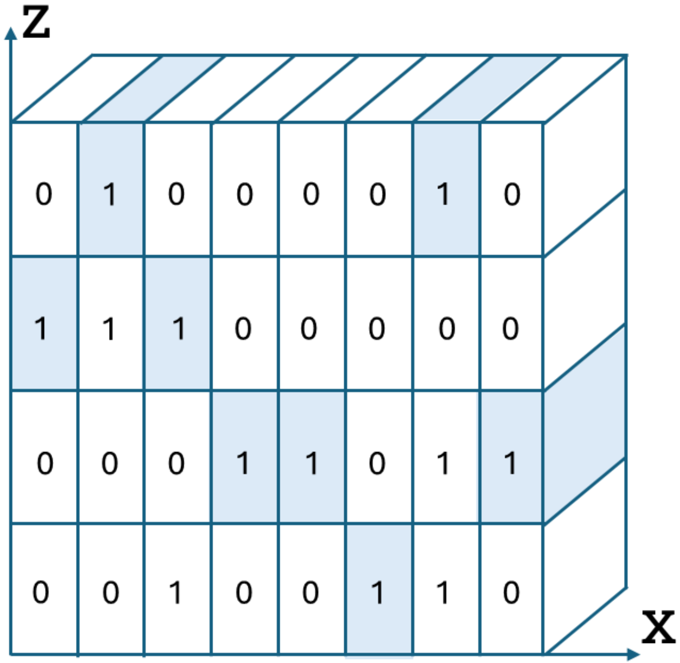

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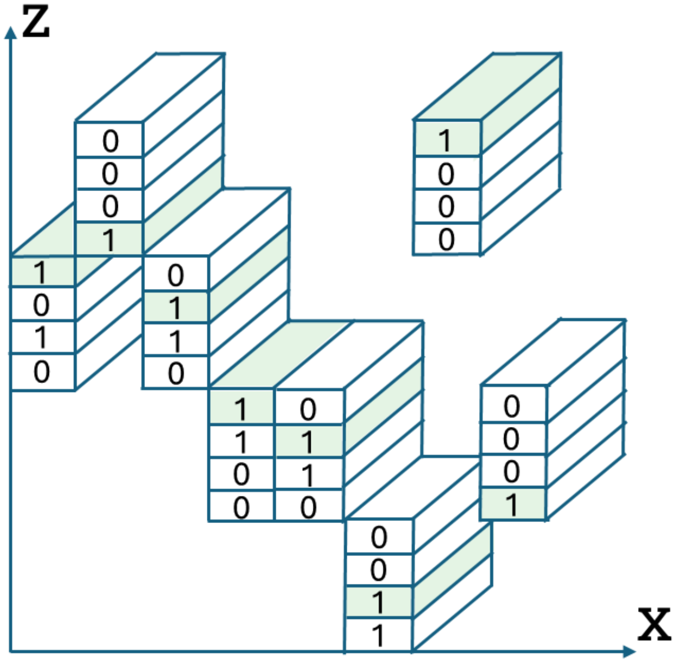

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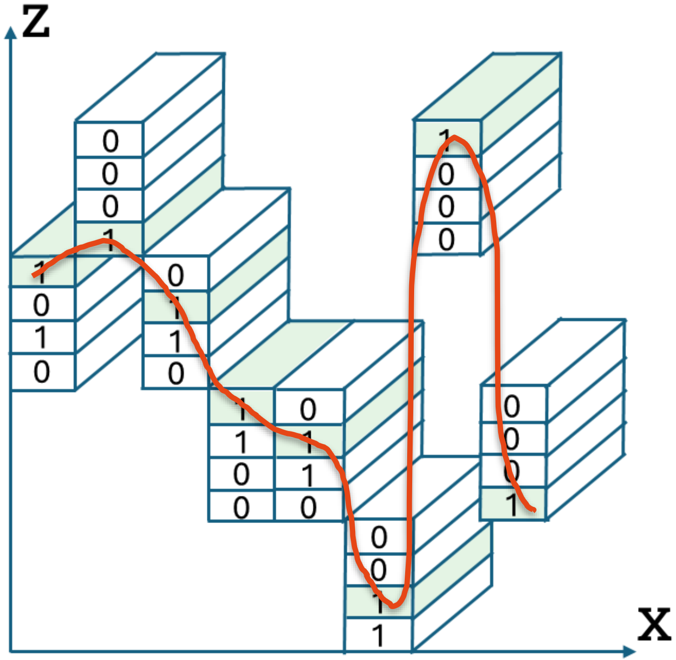
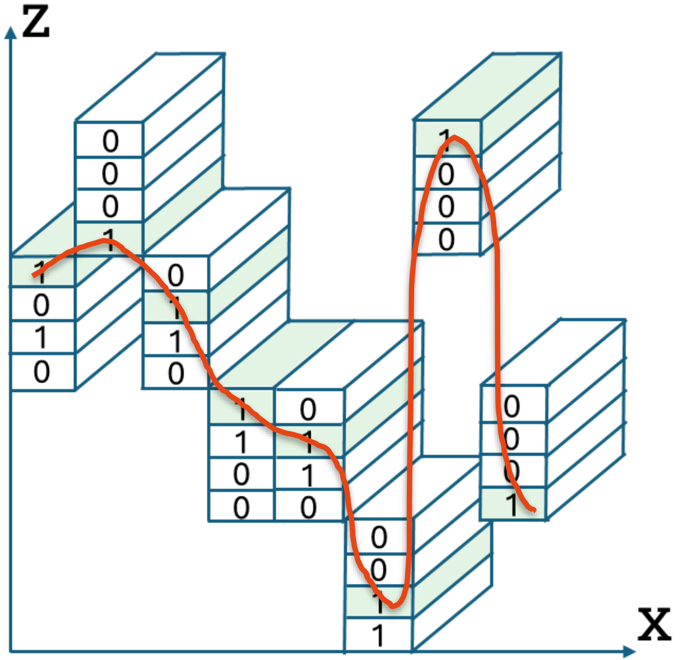
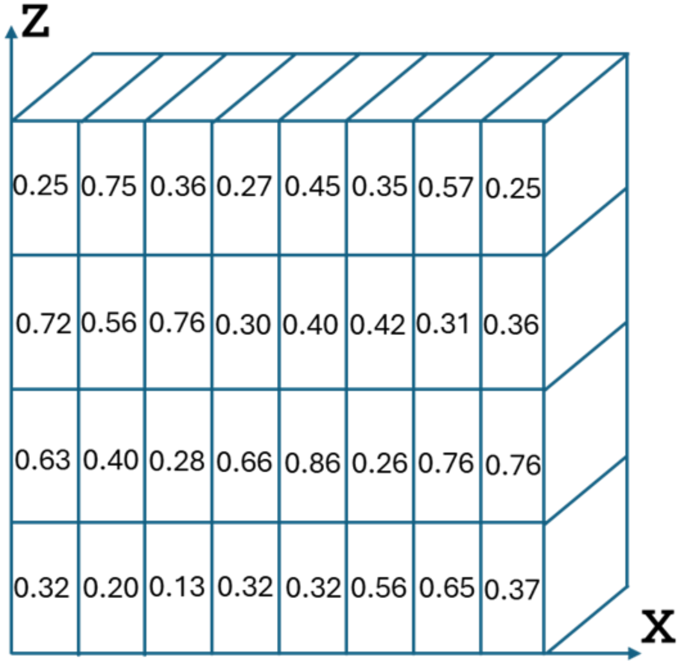


DSM Generation—Top-n probability method

- Probability larger than the threshold
- Ranking among the top-n
- The highest in the z-direction





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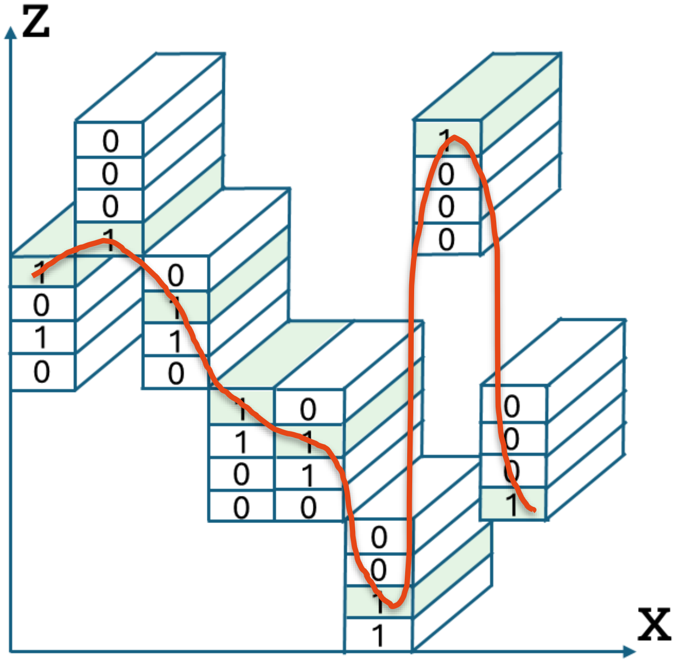

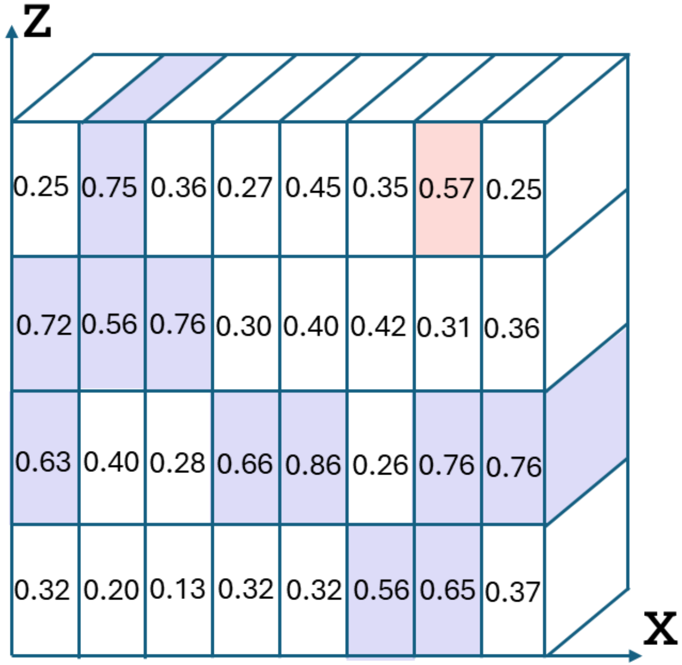

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DSM Generation—Top-n probability method

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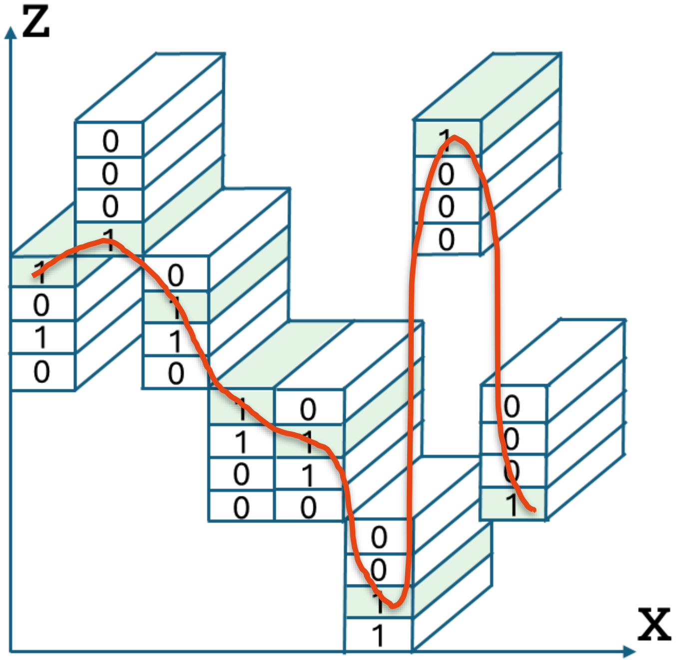

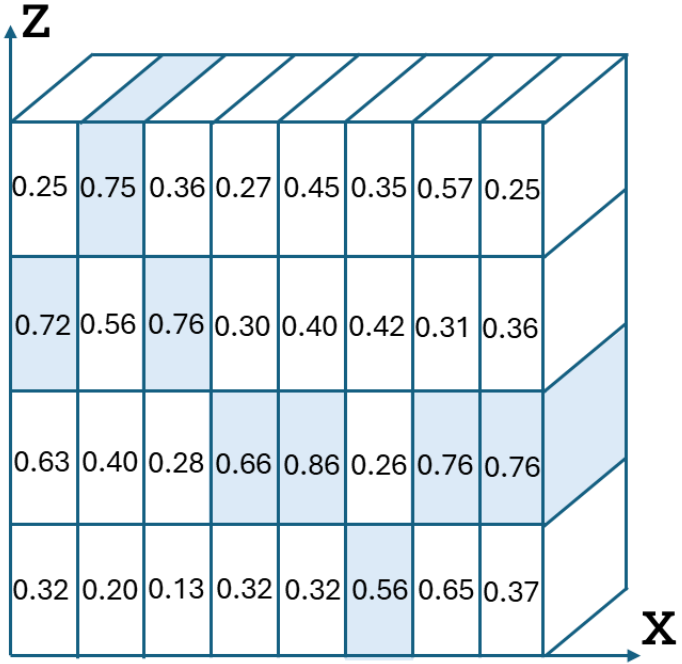

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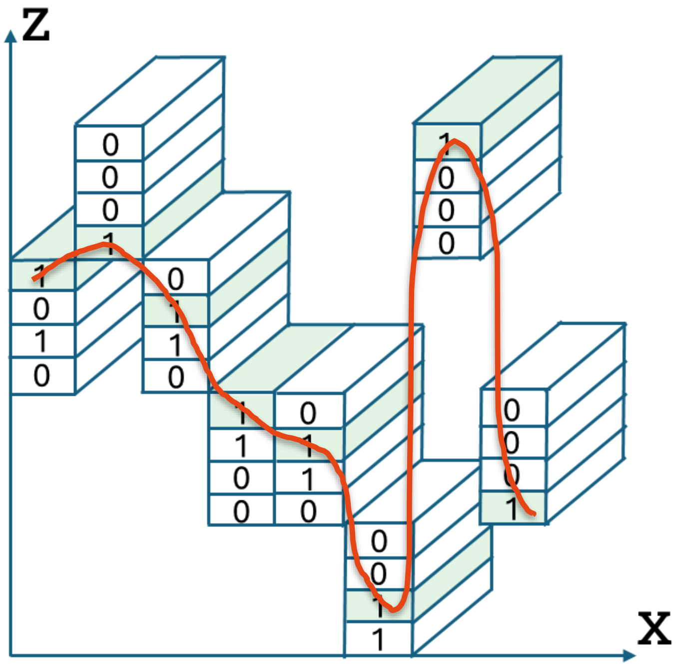

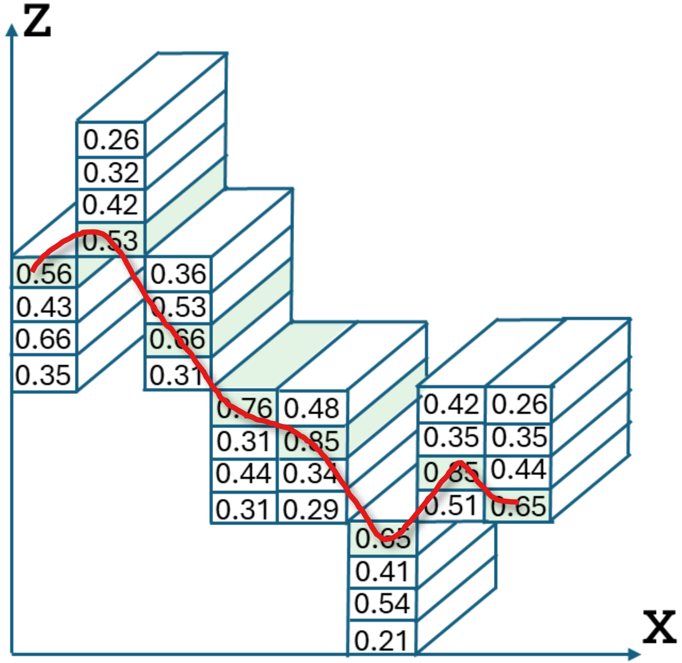

DSM Generation—Top-n probability method

- Probability larger than the threshold
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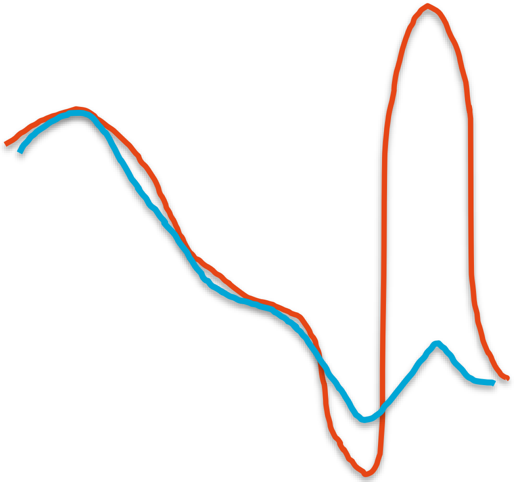
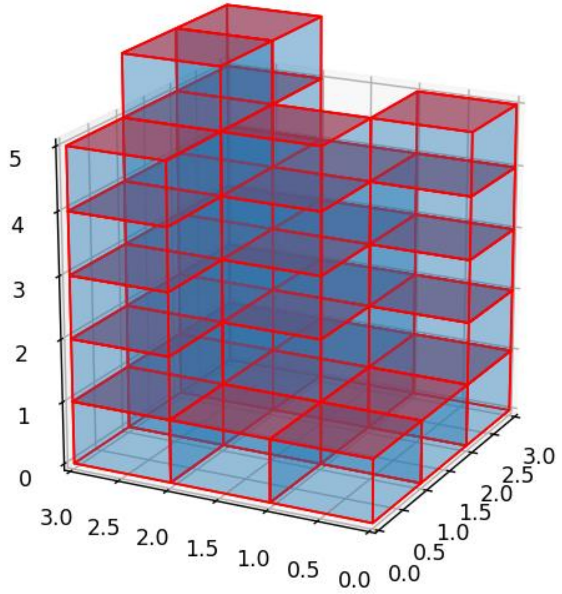


DSM Generation—Top-n probability method

- Elevation > 80%×max_height
- 3×3 neighborhood
- Height differences

1	1	5
1	5	6
5	4	6



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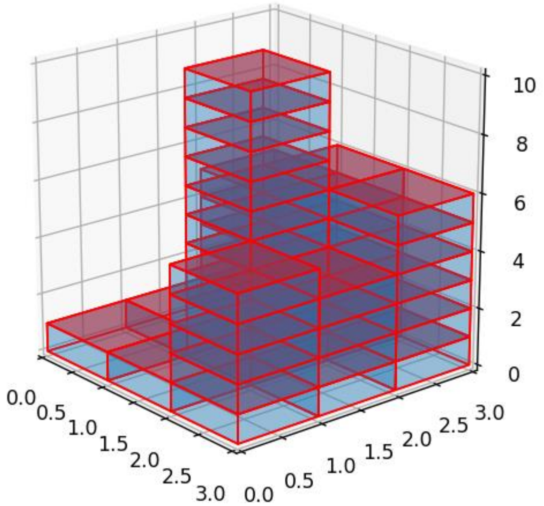
DSM Generation—Top-n probability method

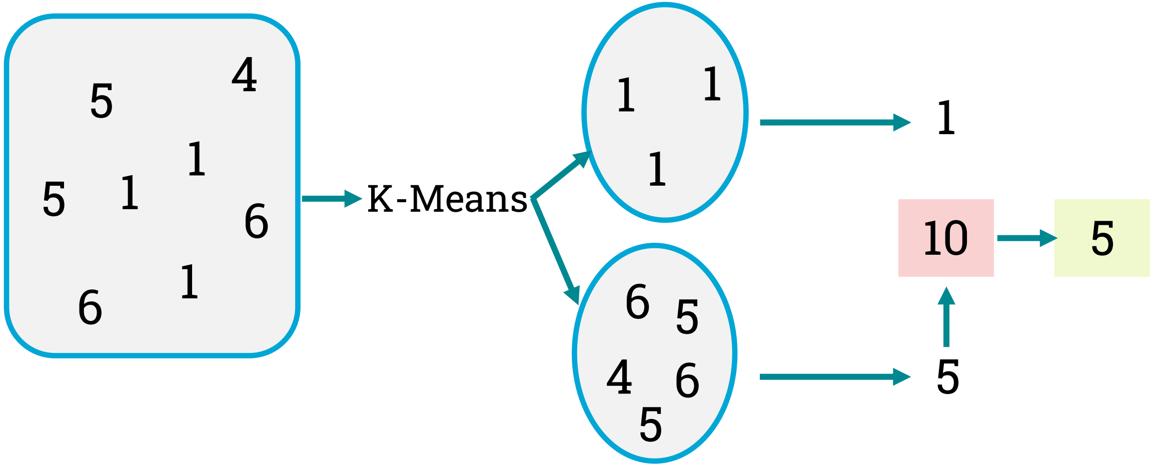
- Elevation > 80%×max_height
- 3×3 neighborhood
- No neighbor have the same height, or all differences exceed 2×current_height_resolution.

1	1	5
1	10	6
5	4	6



DSM Generation—Top-n probability method

- K-Means to separate into two, representing roof and ground elevations.
- Depending on the center value, it selects the appropriate cluster
- Mean value of the cluster is assigned to the center position



4. Result

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Study area

1. Eindhoven
   2.043km*1.103km
   Train and test data

2. Rotterdam
   0.665km*1.139km
   Test data

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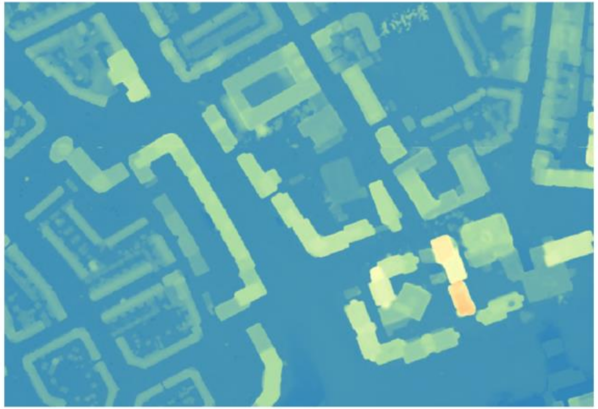
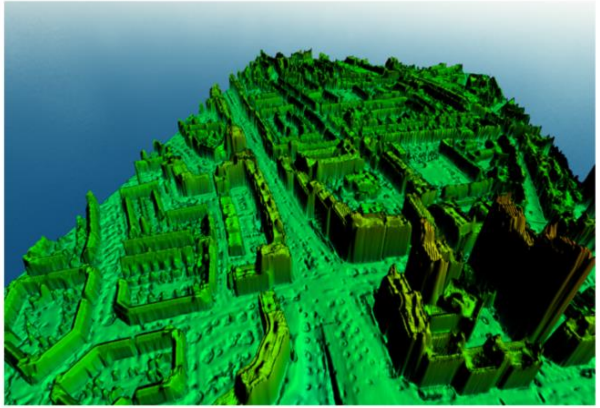
DSM Generation result on training area

Highest cell method



(a)

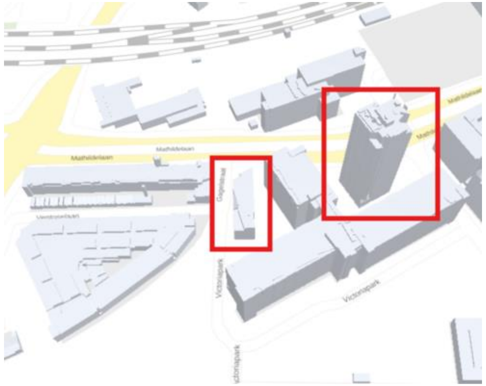


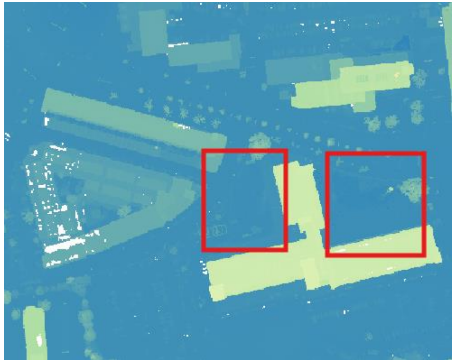
(b)

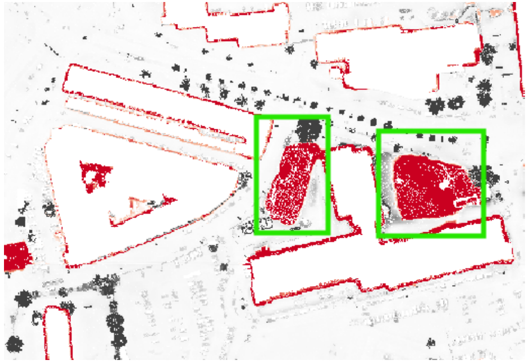
Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	1.2828	0.2093	2.7408	6.6293	2.1450	17209506
Building	2.1471	-1.9780	3.6042	6.4280	6.2400	3529615
Vegetation	0.5515	0.4728	3.5183	8.6550	0.5023	718374
Terrain	0.3573	0.3118	2.0316	5.3886	0.2266	6862569
Terrain_no_Vegetation	0.3497	0.2985	1.8928	5.2770	0.2114	4937153

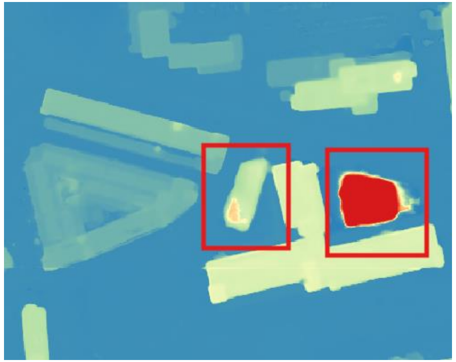
DSM Generation result on training area

Differences in AHN and 3DBAG



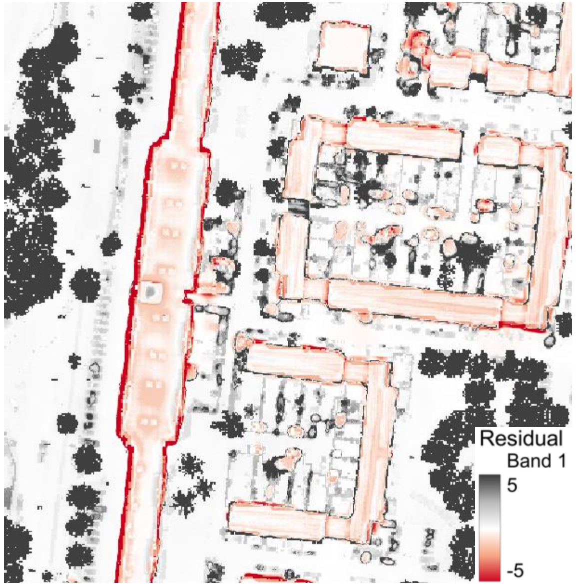






DSM Generation result on training area

Vegetation and other small object are removed



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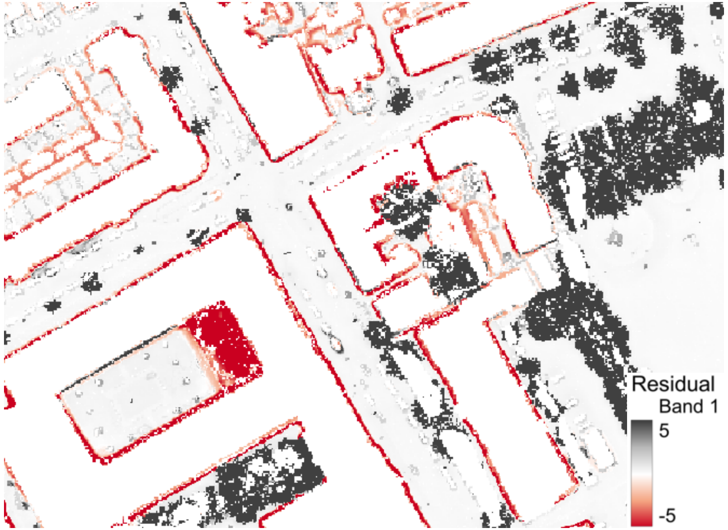
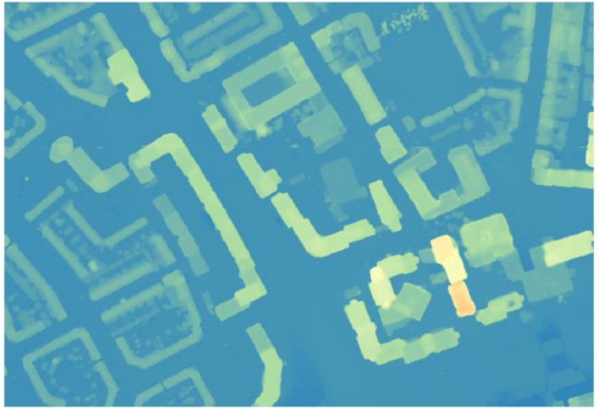
DSM Generation result on training area

Model not used to sudden height change

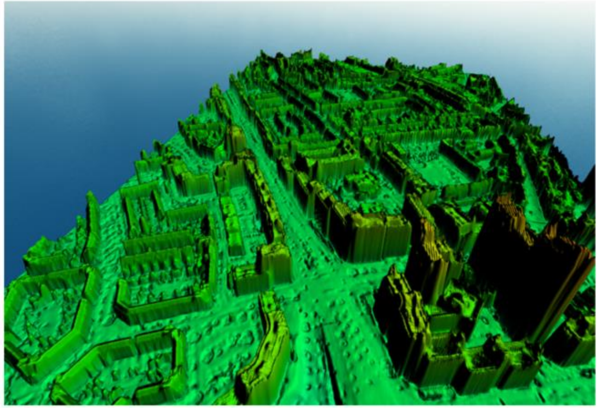


DSM Generation result on training area

Highest cell method



(a)



(b)

Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	1.2828	0.2093	2.7408	6.6293	2.1450	17209506
Building	2.1471	-1.9780	3.6042	6.4280	6.2400	3529615
Vegetation	0.5515	0.4728	3.5183	8.6550	0.5023	718374
Terrain	0.3573	0.3118	2.0316	5.3886	0.2266	6862569
Terrain_no_Vegetation	0.3497	0.2985	1.8928	5.2770	0.2114	4937153

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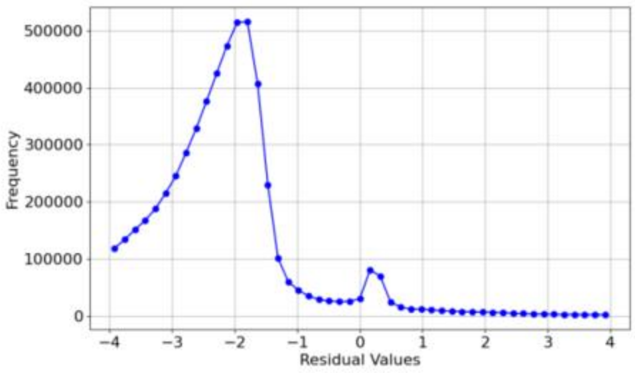
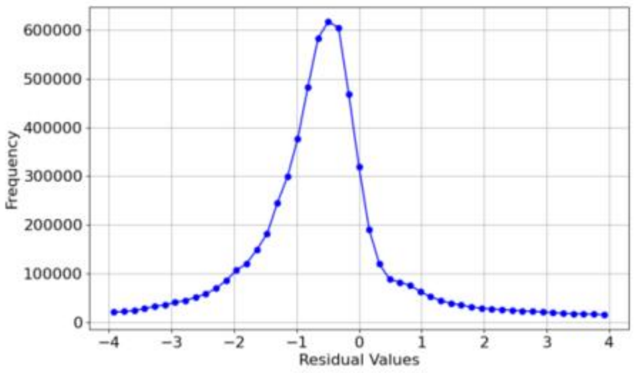
DSM Generation result on training area

Top-2 probability method



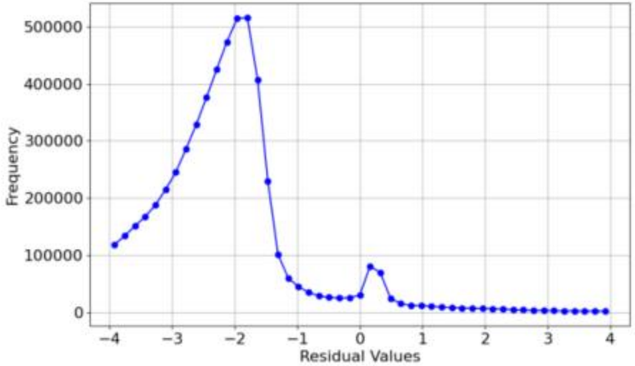
(a) Distribution of building residual of the highest cell method



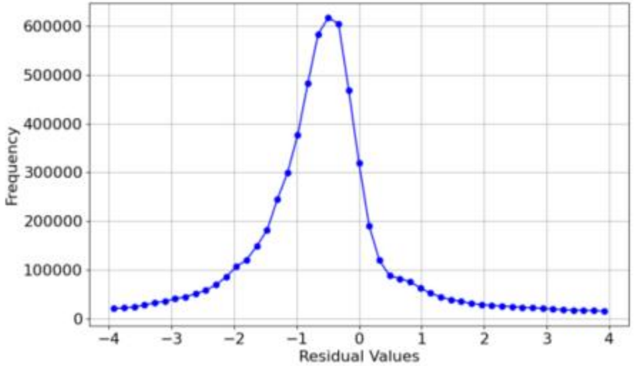
(b) Distribution of building residual of the top-2 probability method

DSM Generation result on training area

Top-2 probability method



(a) Distribution of building residual of the highest cell method



(b) Distribution of building residual of the top-2 probability method

Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	1.5199	1.0424	3.5156	6.9758	2.8159	17209506
Building	0.7912	-0.5777	2.5448	7.3884	2.2274	3529615
Forest	3.5613	3.3565	6.1072	9.4555	3.5732	718374
Terrain	2.1896	2.0857	4.2174	6.6949	1.9181	6862569
Terrain_no_vegetation	2.0066	1.8859	3.8383	6.3075	1.7083	4937153

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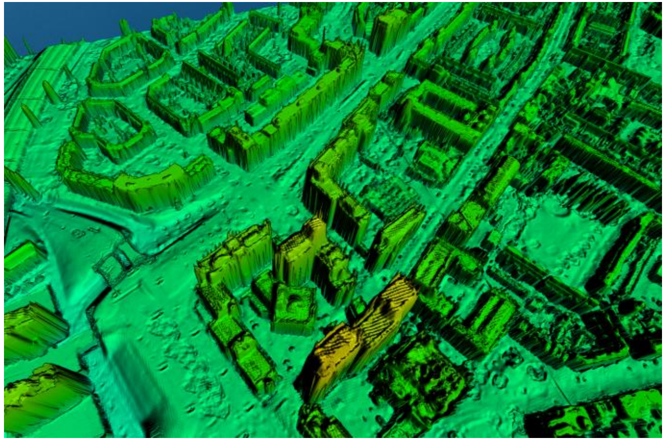
Combined DSM



Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	0.4843	0.1882	2.2267	6.2917	1.0183	17209506
Building	0.7983	-0.4930	1.9334	4.0296	2.1755	4535085
Vegetation	0.4801	0.4085	3.3444	8.5057	0.4615	718374
Terrain	0.3016	0.2636	2.7728	8.6806	0.2045	6230403
Terrain_no_vegetation	0.2900	0.2543	2.6568	8.1074	0.1816	4328152

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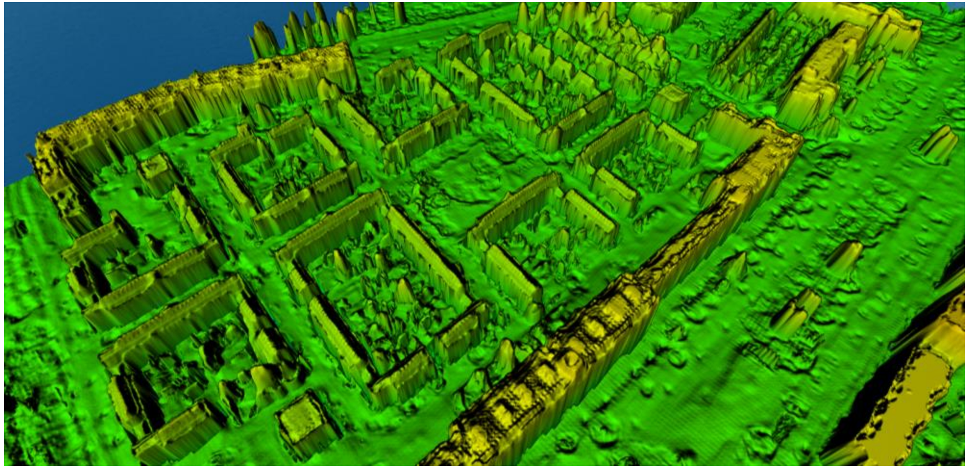
Generalization ability

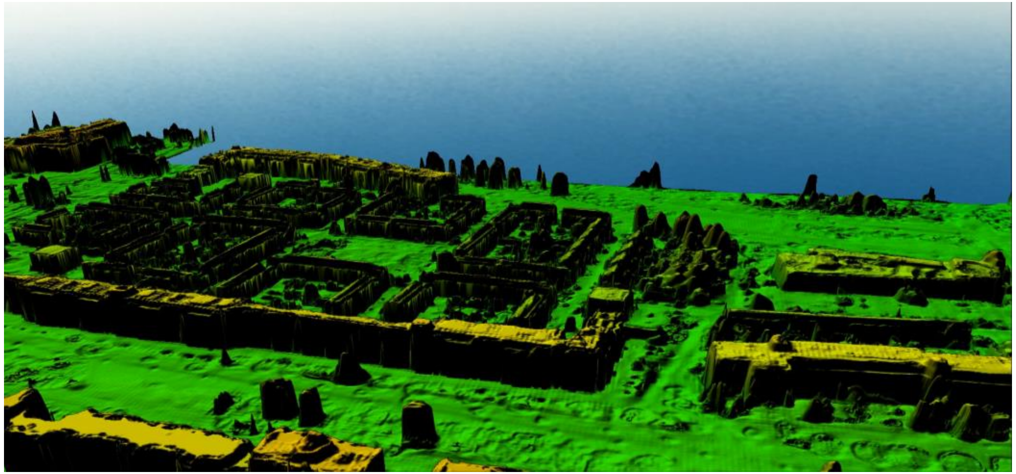
Eindhoven



Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	0.3364	0.2281	2.4177	5.2011	0.4988	6066614
Building	0.7137	-0.4039	1.9222	4.1182	1.9224	822627
Vegetation	0.2777	0.2609	3.9082	7.3576	0.4117	915725
Terrain	0.2747	0.2663	2.7092	5.7631	0.4073	3697489
Terrain_no_vegetation	0.2999	0.2885	2.0520	4.5059	0.2693	1702021

Generalization ability

Eindhoven



Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	0.3364	0.2281	2.4177	5.2011	0.4988	6066614
Building	0.7137	-0.4039	1.9222	4.1182	1.9224	822627
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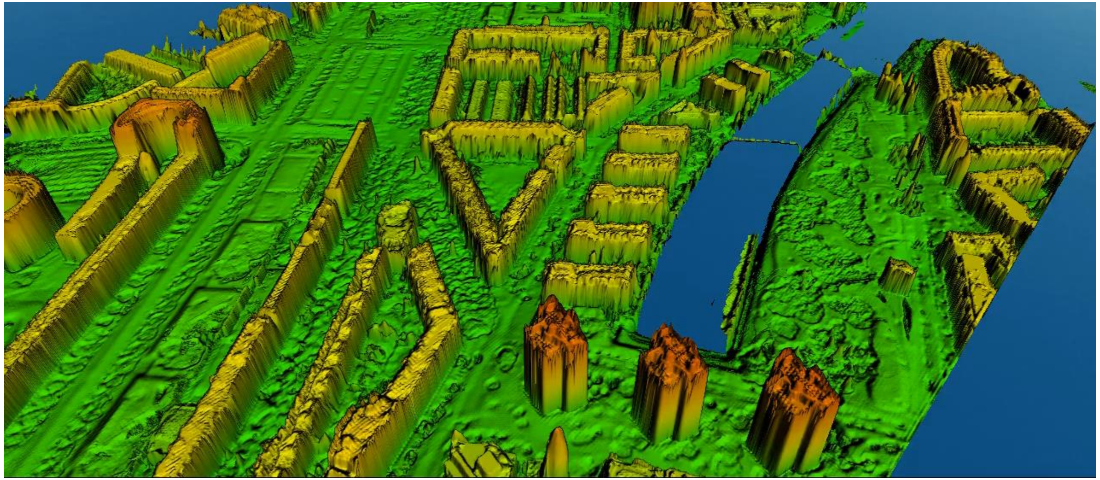
Terrain	0.2747	0.2663	2.7092	5.7631	0.4073	3697489
Terrain_no_vegetation	0.2999	0.2885	2.0520	4.5059	0.2693	1702021

Generalization ability

Rotterdam



Type	MedAE[m]	Median[m]	MAE[m]	RMSE[m]	NMAD[m]	Pixels
Overall	0.2304	0.0000	1.4960	3.9871	0.3416	11942849
Building	0.8582	-0.6525	1.6034	3.3675	2.4043	1123399
Vegetation	0.4043	0.3548	3.1362	6.3861	0.3088	940520
Terrain	0.0000	0.0000	1.3113	3.8818	0.0000	8617636
Terrain_no_vegetation	0.0000	0.0000	0.8120	2.8603	0.0000	6730096

Generalization ability--No-value data filling

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Visual inspection

Generalization ability--No-value data filling

Quantitative evaluation

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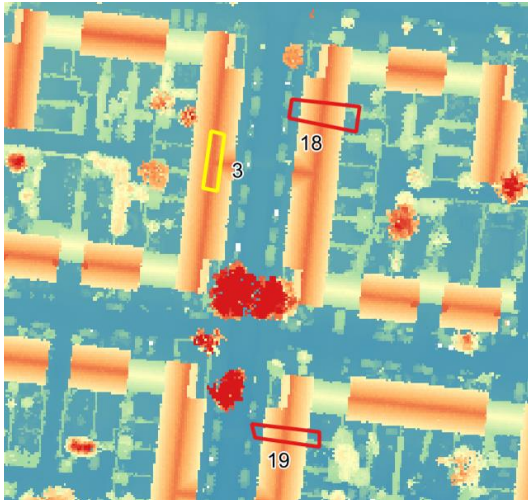
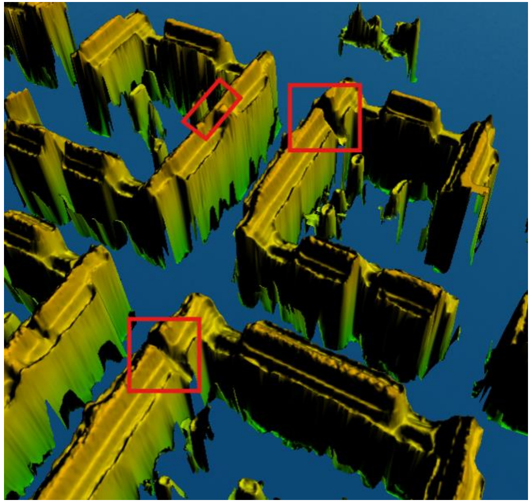
Generalization ability--No-value data filling

Quantitative evaluation





ID	Area [m²]	MAE [m]	RMSE [m]	MedAE [m]	Median [m]	NMAD [m]	Pixels
3	40.386	0.146	0.228	0.061	0.000	0.091	1100
18	76.187	1.295	2.119	0.416	0.000	0.617	1950
19	46.613	0.906	1.940	0.112	0.000	0.167	1302

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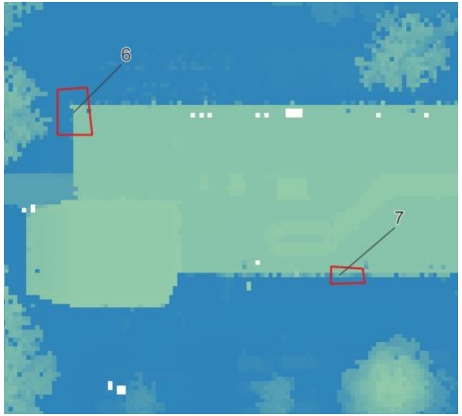
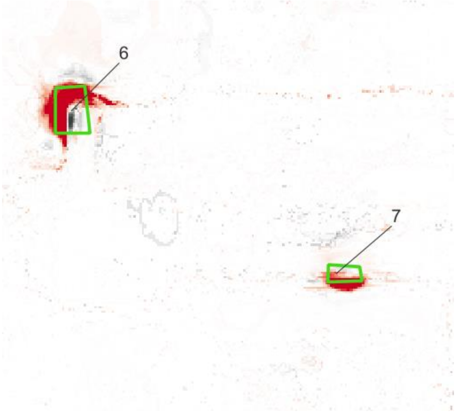
Generalization ability--No-value data filling

Quantitative evaluation





- The model struggles to generate clear features in areas with missing points along the edges.

DSM Generation—Iteration number

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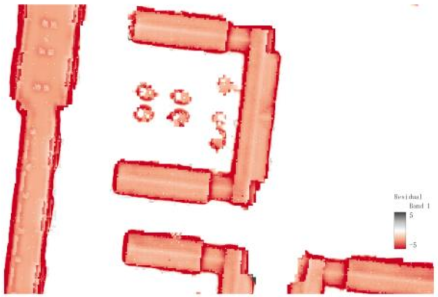
Iteration number


5500

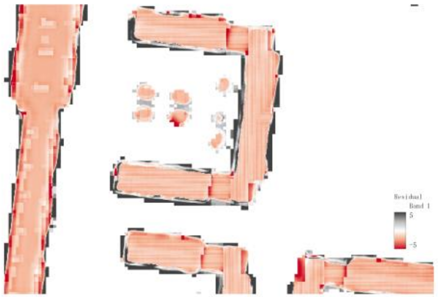

8000


13500

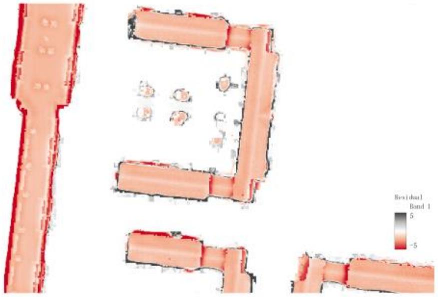
DSM Generation—Threshold



0.2



0.5



0.7

5. Conclusion

Contribution

- Data preprocessing algorithms
- New DSM generation method
- Generalization ability exploration
- Effect of training iteration and threshold

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Research question

Sub-question: What process steps are needed to adapt current geospatial data to the network?

Data	Source	Processing method
Raw point cloud	AHN3	Clipped and merged by PDAL command
Reference point cloud	3D BAG AHN3	Download in .obj format, with varying sample densities on the roof, wall, and ground Terrain points from AHN3 DTM
Orthophoto	Luchtfoto Beeldmateriaal	Convert the image to black and white
Masks	BGT, AHN3	Plant and water mask can be extracted from BGT using API Building mask is made with building type points in AHN3

Research question

Sub-question: What is the geometric performance of implicit neural representation when applied to real-scene urban data reconstruction?

The best result is a merged DSM, with buildings generated using the top-2 probability method and other areas using the highest cell method.

This DSM shows clear edges and corners, with most roof parts accurately generated.

The residual map shows accuracy reaching 0.8 m of MedAE for buildings and 0.3 m for terrain.

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Research question

Sub-question: How effective is the generalizability of the implicit representation functions on AHN3 urban data?

The model is tested in area with totally different landscape and height distribution. The evaluation shows nearly the same accuracy as in the trained area.

The filling of void parts shows good results in both visual and quantitative checks.

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Research question

Sub-question: Compared to traditional methods, what are the advantages and disadvantages of using the implicit neural representation for urban scene reconstruction with open-source datasets in the Netherlands?

Traditional DSM generation methods often requires frequent manual adjustments and limited data sources.

- ✓ Use only open-source datasets
- ✓ Deep learning network can automatically calculate suitable hyperparameters for DSM generation and void filling.
- ✓ Implicit neural representation allows for unlimited resolution and generates a continuous field, solving the problem of losing information due to discrete explicit representation.

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Research question

Sub-question: Compared to traditional methods, what are the advantages and disadvantages of using the implicit neural representation for urban scene reconstruction with open-source datasets in the Netherlands?

Traditional DSM generation methods often requires frequent manual adjustments and limited data sources.

- ✗ Requires a variety of data for training whereas traditional methods only need DSM covering the same area.
- ✗ The model is also prone to overfitting, with increased iterations potentially leading to artifacts on flat roofs rather than improved accuracy.
- ✗ The entire learning process is a black box, unlike traditional methods where all the hyperparameters can be fully understood and adjusted as needed.

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Research question

Main question: What are the characteristics of implicit neural representation when it's used for 3D real-scene urban area reconstruction?

Implicit neural representations demonstrate strong performance when used for 3D real-scene urban area reconstruction with geospatial data.

They can effectively generate **continuous** and **high-resolution** DSM with high accuracy. The model exhibits notable **generalization** capabilities, allowing them to generate accurate data for areas with entirely different landscapes. Additionally, its ability to **fill voids** in the data has been validated, further supporting their efficacy in real-world applications.

These characteristics underscore the potential of implicit neural representations in advancing geospatial data processing and urban area reconstruction.

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Future work

Network input optimization

- RGB and Infrared information of the point cloud

  Eliminate the issues of geological alignment and feature differences caused by varying data acquisition times.

- Synthetic maps to be used as input data.

  Much clearer topological guidance

Future work

Generation of other formats of 3D models

- Point cloud. Current methods use only threshold as constrain for extraction and can create redundant points at various height. Further work need to be done to find out how to extract desired clean surface when applied to geospatial data.
- 3D city model. Current method was only applied on single building reconstruction and it's not an end-to-end network architecture. Still, this show the potential of using implicit neural representation as indicator for city model reconstruction on larger scale.

Future work

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Rotation-invariance in the representation of point cloud

- Rotation invariance can enhance the robustness of the model by seeing more data in different rotational poses and ensures the consistency in the output.
- Random flipping and rotating data patch does not guarantee covering all possible orientations and there always exists unseen angle for the model.
- The possible solution is to generate transformation-invariant features of the point cloud by methods like local canonicalization and use it as an additional input for each point.

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Future work

Extended application on vegetation classification

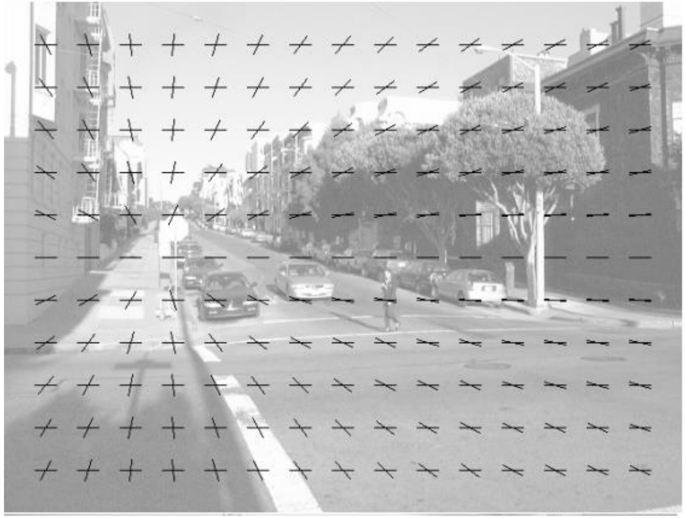
- An excessive removal of vegetation details.
- Consequently, vegetation can be identified from the residual map where the height is lower than expected.
- By utilizing point cloud spectral information, detailed insights into vegetation and water content can be obtained by calculating NDVI and NDWI for each point.
- Incorporating these indices in the training process improves the model's capability to accurately identify and classify vegetation, making it an effective tool for environmental monitoring and landscape management.

Thanks for hearing!

Question

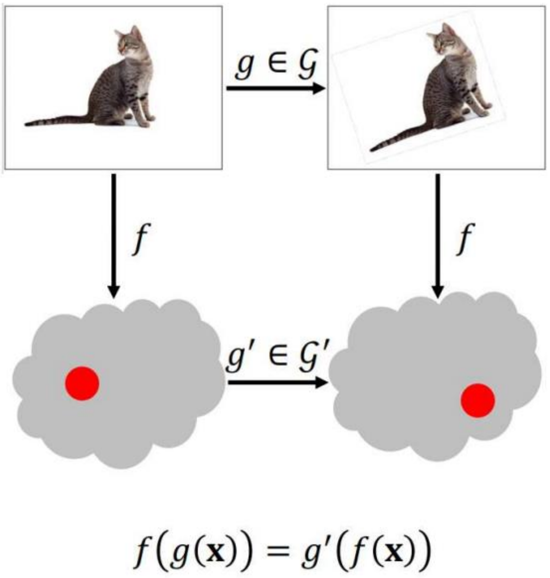
Manhattan World bias

- many visual scenes are based on a ”Manhattan” three-dimensional grid which imposes regularities on the image statistics.
- grid-based structure force the axis to be straight and orthogonal
- do not naturally accommodate the spherical shape of the Earth



Translation Equivariance

- If the input (e.g., an image or 3D shape) is translated, the features extracted by the convolutional layers are translated in the same way.
- This property ensures that the network's understanding of the features is consistent regardless of their position.
- When a network learns to identify a feature (like an edge in an image or a specific pattern in a 3D shape), it can recognize that feature whether it's small or large, as long as the relative proportions remain consistent.



PointNet

1. **Processing of Point Clouds**
2. **Feature Extraction**: PointNet uses a series of neural network layers (such as multi-layer perceptrons) to extract features from each point independently. This means it learns to understand the characteristics of each point, considering its position (in this case, on the x-y plane) and potentially other features like color or intensity if available.
3. **Symmetric Function for Unordered Data**: A key aspect of PointNet is its use of a symmetric function (like max pooling) to ensure that the output is invariant to the order of the points in the input. This is crucial since point clouds are inherently unordered.

U-Net

1. **Efficient Use of Data**: U-Net is designed to work well with a limited amount of training data.
2. **Symmetric Expanding Path**: U-Net's architecture consists of a contracting path (encoder) to capture context and an expanding path (decoder) that enables precise localization. This symmetric structure helps in learning representations that are effective for segmentation tasks.
3. **Feature Concatenation**: In the expanding path, U-Net concatenates features from the contracting path. This skip-connection feature concatenation helps the network to use information gathered at various resolutions, improving the accuracy of the segmentation.

Too early heuristic reduction

- **Heuristic Reduction**: This refers to the process of simplifying or reducing the complexity of the original point cloud data. Heuristics are rules or methods applied to make this process more manageable or efficient. However, these rules are based on general assumptions or estimations rather than specific, detailed analysis of each point.
- **Loss of Detail**: The original point cloud contains a wealth of detail. Early reduction to a height field or mesh can **oversimplify** these details, especially if the heuristics used do not adequately capture the nuances of the data.

Data Generation

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Data combination
Water removal

Generalization ability--No-value data filling

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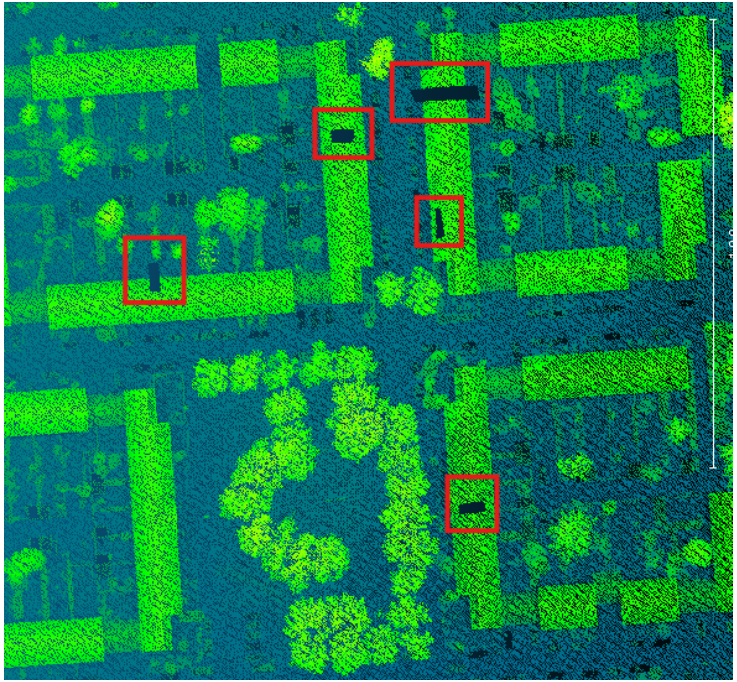
Quantitative evaluation



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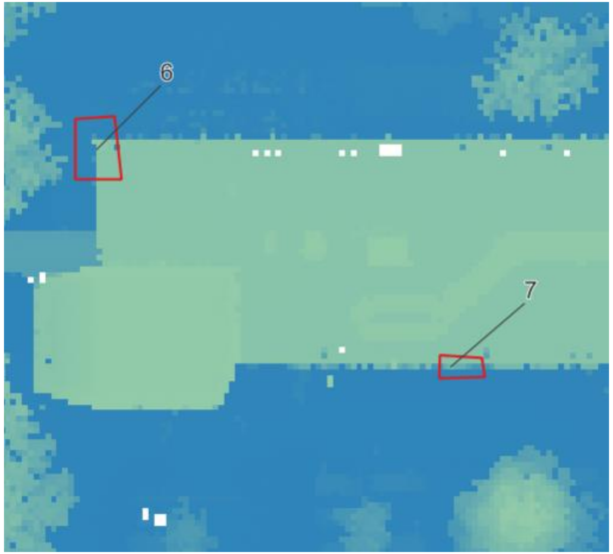
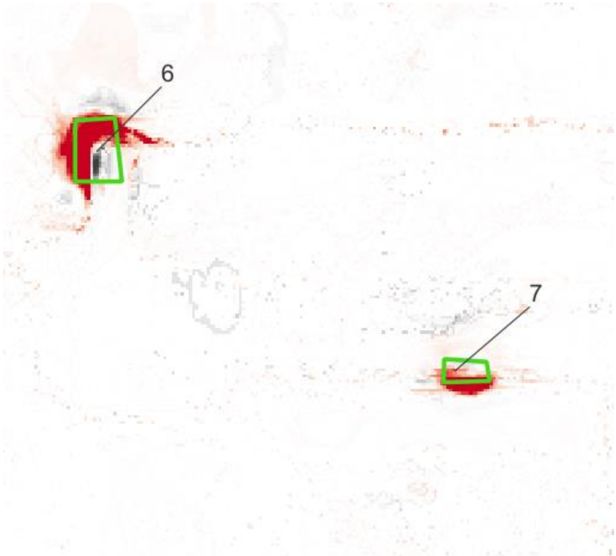
Quantitative evaluation

The performance of edge regeneration is not ideal.

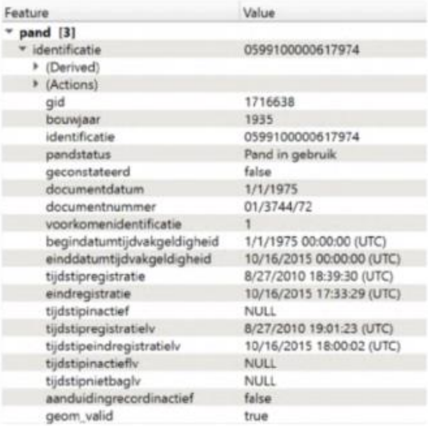




Data preparation

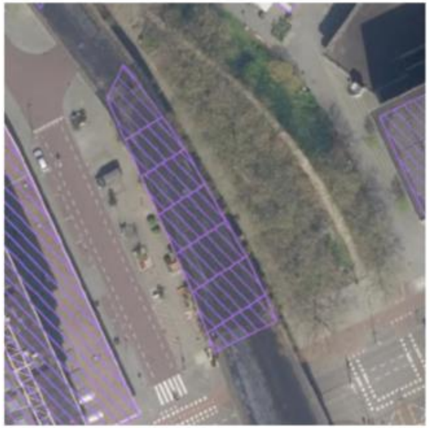
Building mask is generated from classified point cloud instead of using the “pand” layer from BGT or BAG.

(a) Accuracy for some building polygon is low



Feature	Value
pand [3]	
identificatie	0599100000617974
(Derived)	
(Actions)	
gid	1716638
bouwjaar	1935
identificatie	0599100000617974
pandstatus	Pand in gebruik
geconstateerd	false
documentdatum	1/1/1975
documentnummer	01/3744/72
voorkomenidentificatie	1
begindatumtijdvakgeldigheid	1/1/1975 00:00:00 (UTC)
einddatumtijdvakgeldigheid	10/16/2015 00:00:00 (UTC)
tijdstipregistratie	8/27/2010 18:39:30 (UTC)
eindregistratie	10/16/2015 17:33:29 (UTC)
tijdstipinactief	NULL
tijdstipregistratielv	8/27/2010 19:01:23 (UTC)
tijdstipeindregistratielv	10/16/2015 18:00:02 (UTC)
tijdstipinactieflv	NULL
tijdstipnietbaglv	NULL
aanduidingrecordinactief	false
geom_valid	true

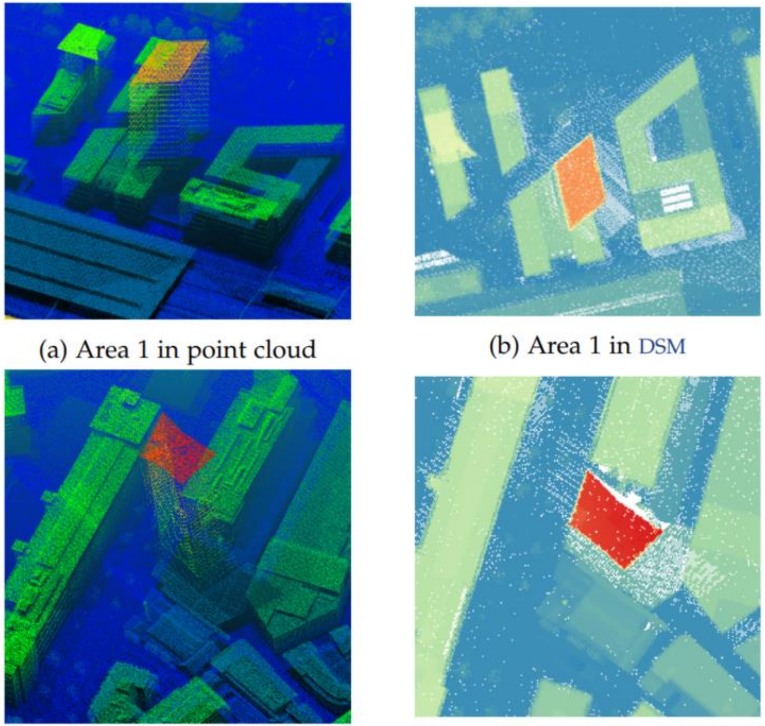
(b) Registration time is not complete and hard to understand



(c) Underground part is also included in the BAG

Data preparation

A reference DSM is created using the AHN point cloud due to the presence of abnormal data gaps in the AHN3 version.



(a) Area 1 in point cloud
(b) Area 1 in DSM
(c) Area 2 in Point cloud
(d) Area 2 in DSM

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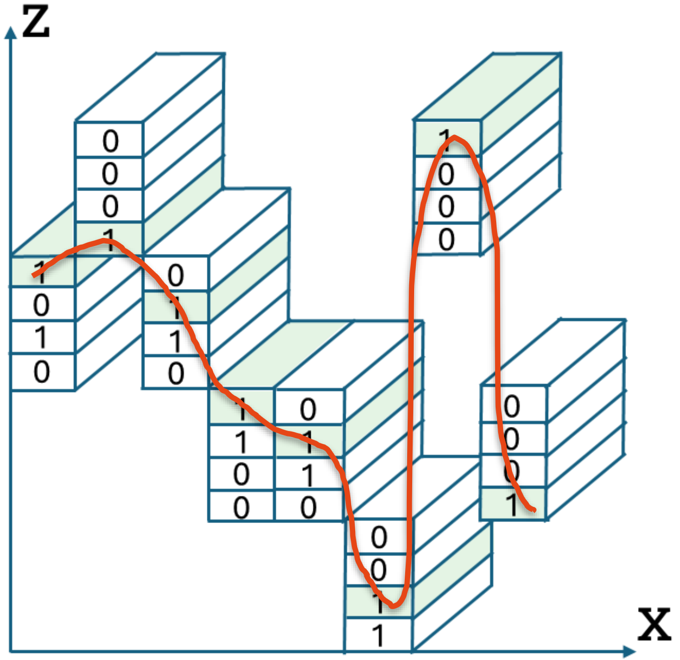
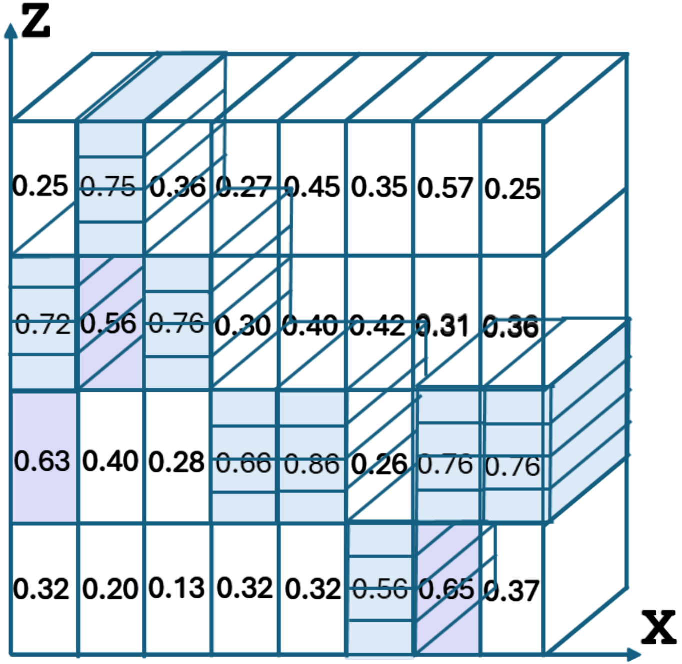
DSM Generation—Top-n probability method

- Probability larger than the threshold
- Ranking among the top-n
- The highest in the z-direction





Data Pre-Processing

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Data	Source	Processing method
Raw point cloud	AHN3	Clipped and merged by PDAL command
Sampled point cloud	3D BAG	Download in .obj format, with varying sample densities on the roof, wall, and ground
Orthophoto	Luchtfoto 25cm database	Convert the image to black and white
Masks	BGT, AHN3	Plant and water mask can be extracted from BGT using API Building mask is made with building type points in AHN3

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3D Models For Urban Area

- Accuracy and completeness