3D City Models in the Context of Urban Mining

A case study based on the CityGML model of Rotterdam

Final Presentation

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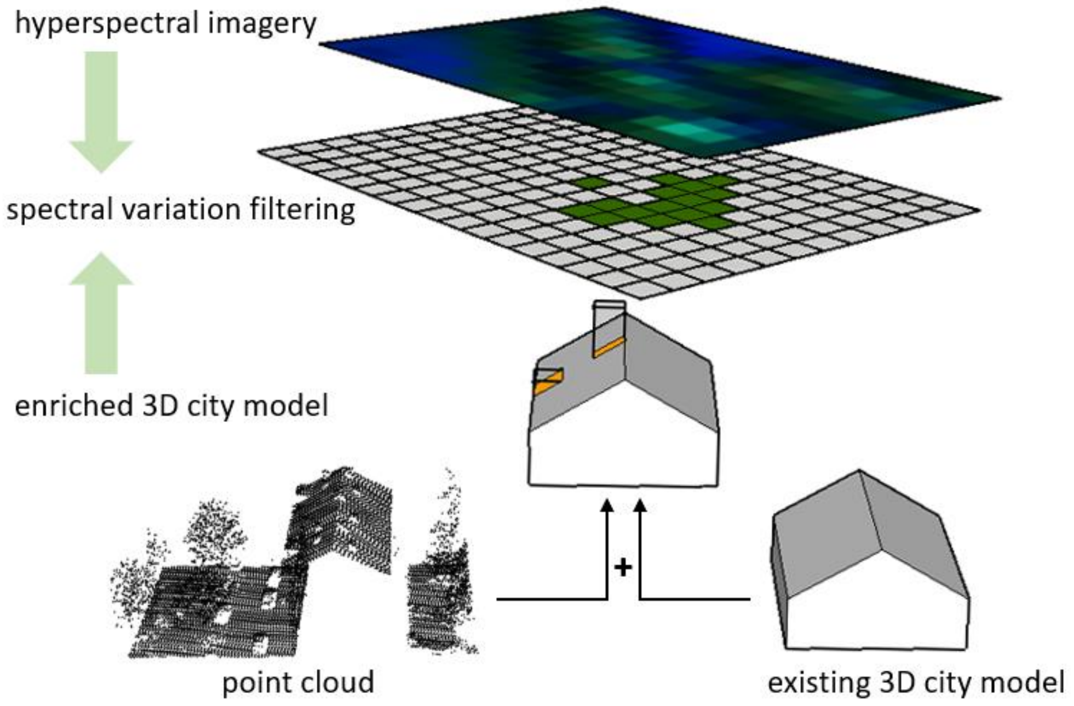
Co-reader: Kaixuan Zhou – Delegate: Regina Bokel



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I. Context

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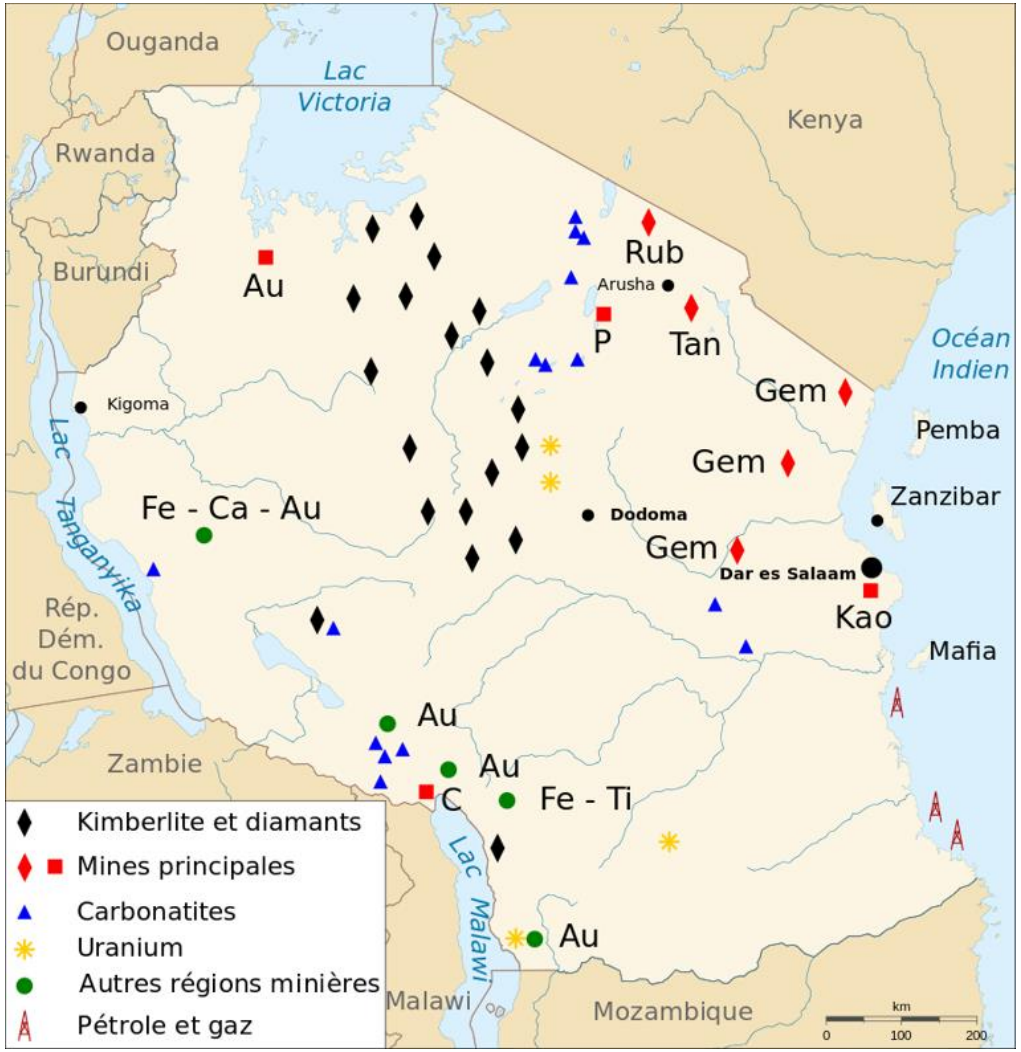
I. Context

Input for circularity strategies

Mapping



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Case of roofs

"In general, the lifetime of an asphalt shingle roof ranges between approximately 12 to 25 years"
(Townsend et al., 2007)

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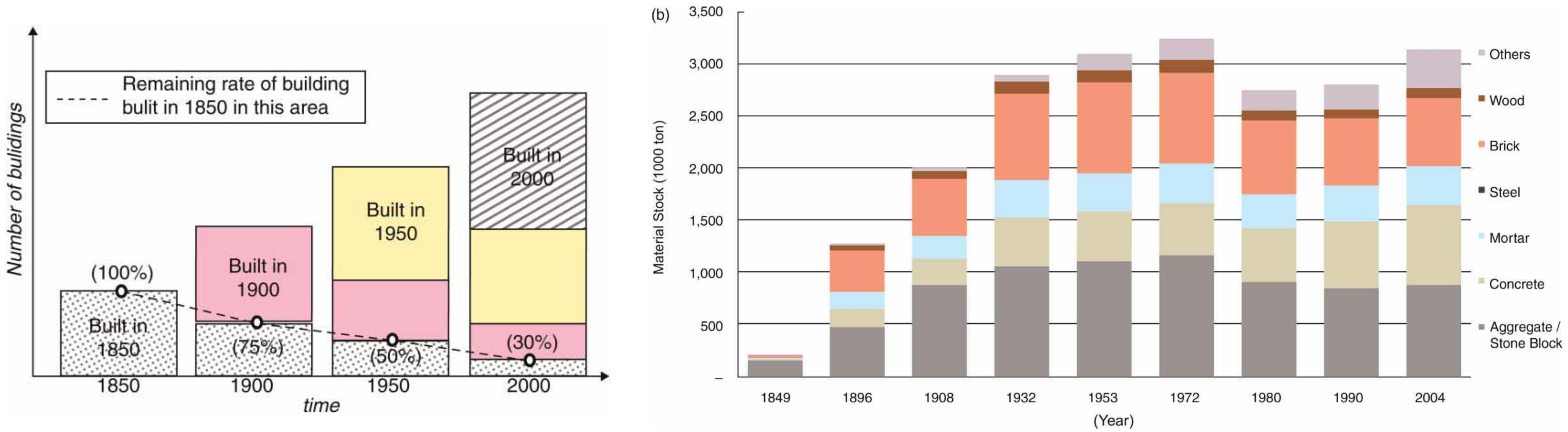
Statistical estimation approach



Accumulation and remaining rate of buildings (left) and material stock over time.

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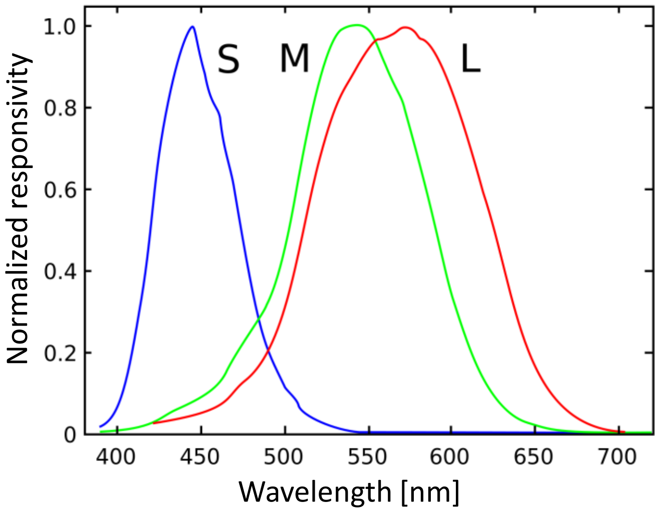
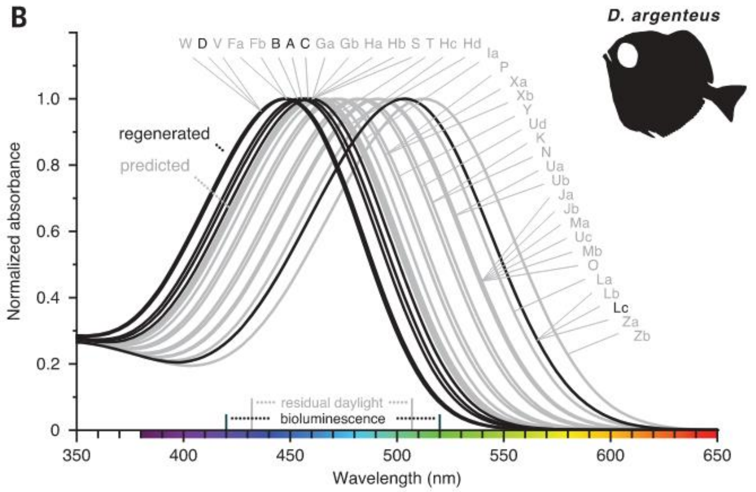
Hyperspectral imagery

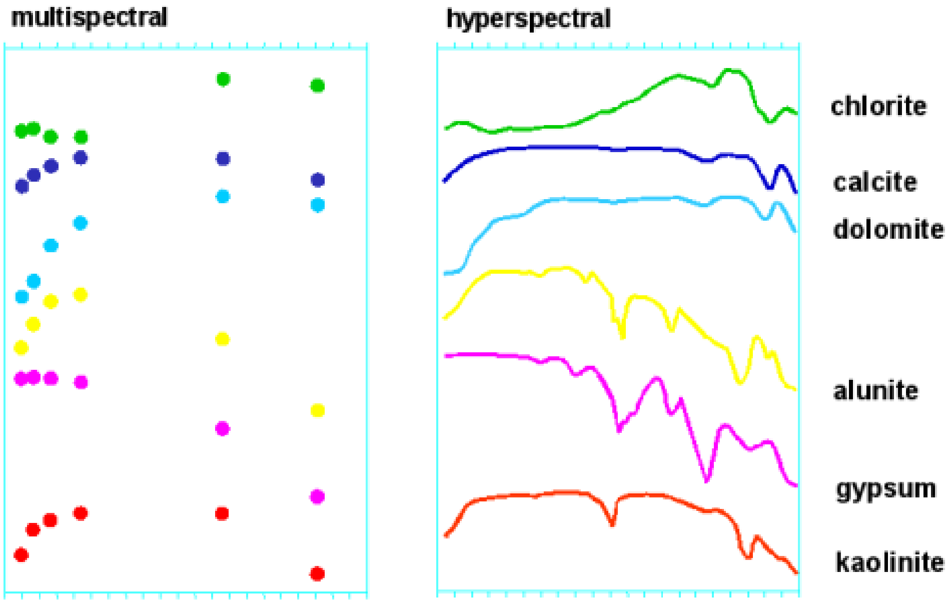
Human: 3 molecules

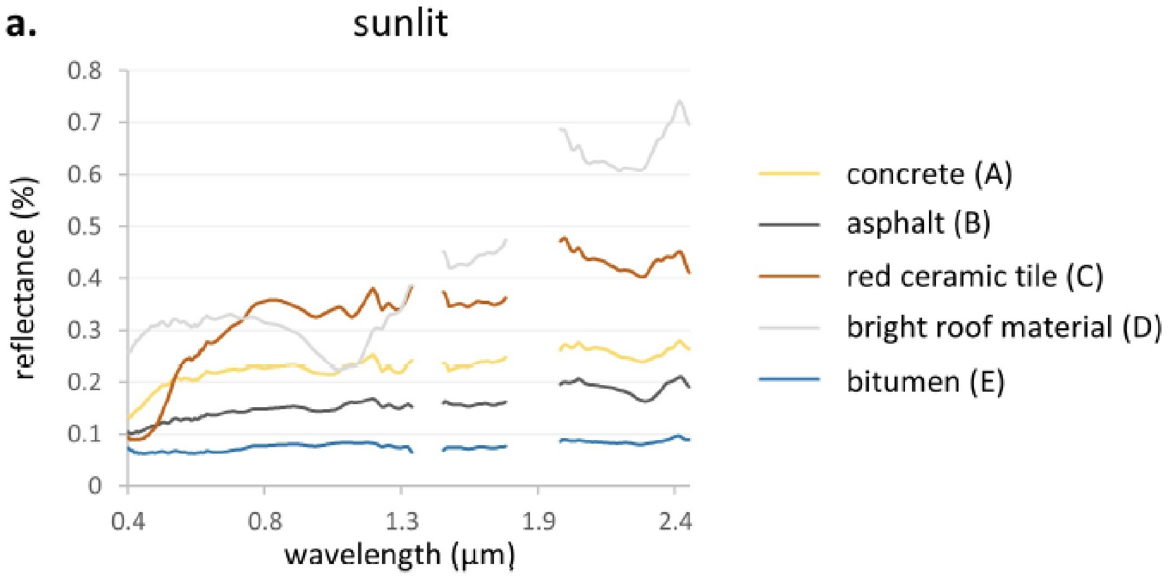


Silver Spinyfin: 38 molecules



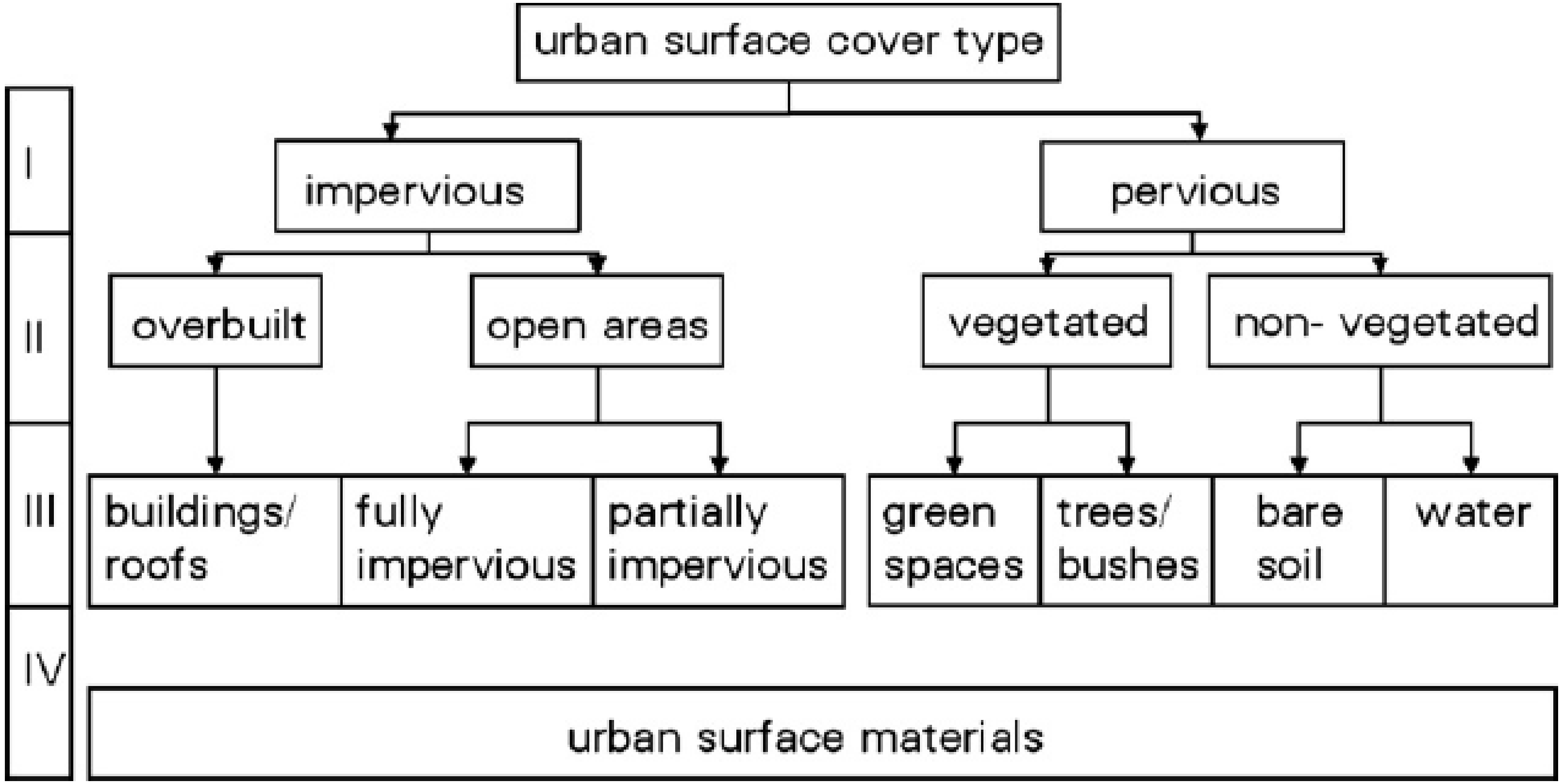
Hyperspectral imagery



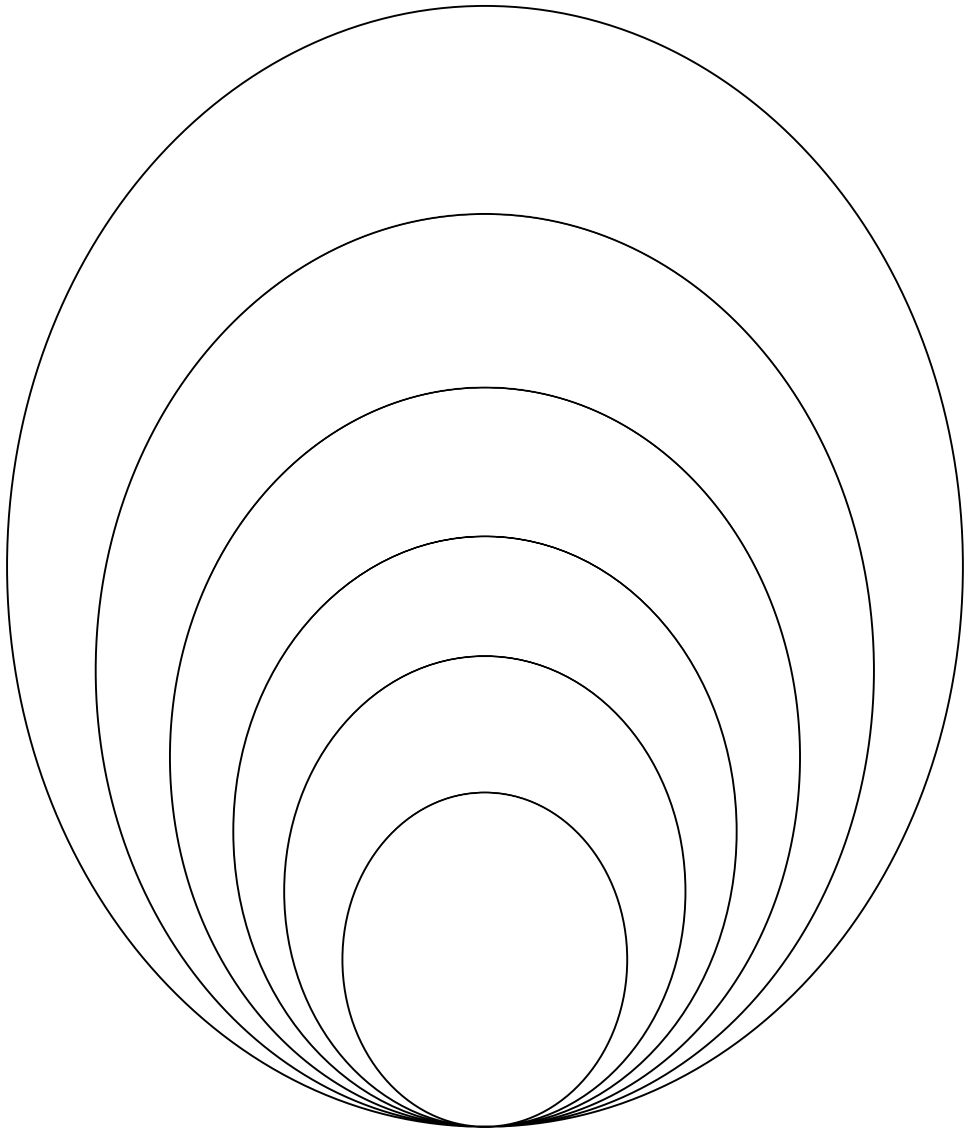


Priem, Canters, 2016

Hyperspectral imagery



II. Problem & research questions



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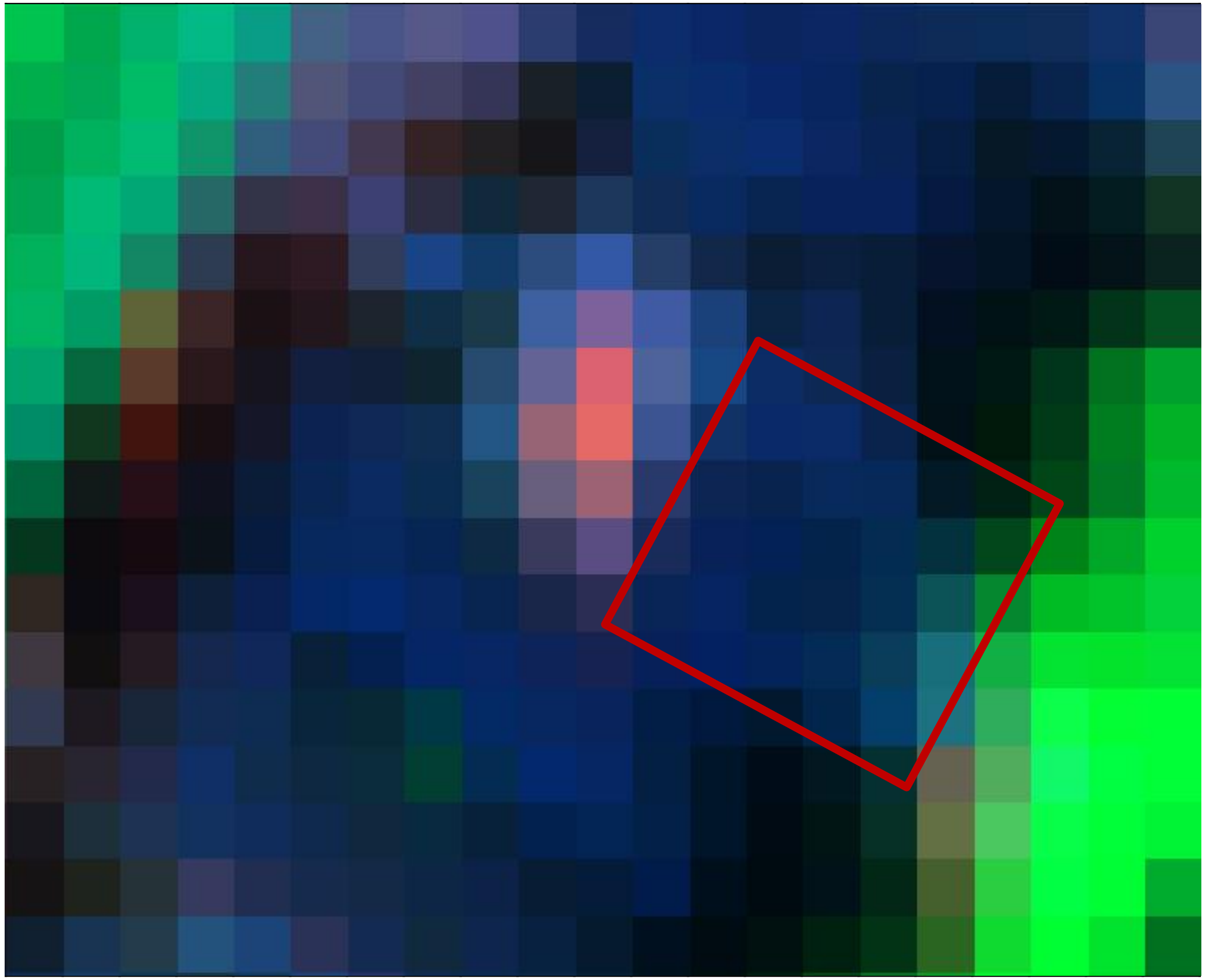
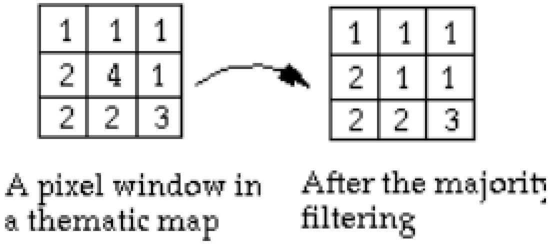
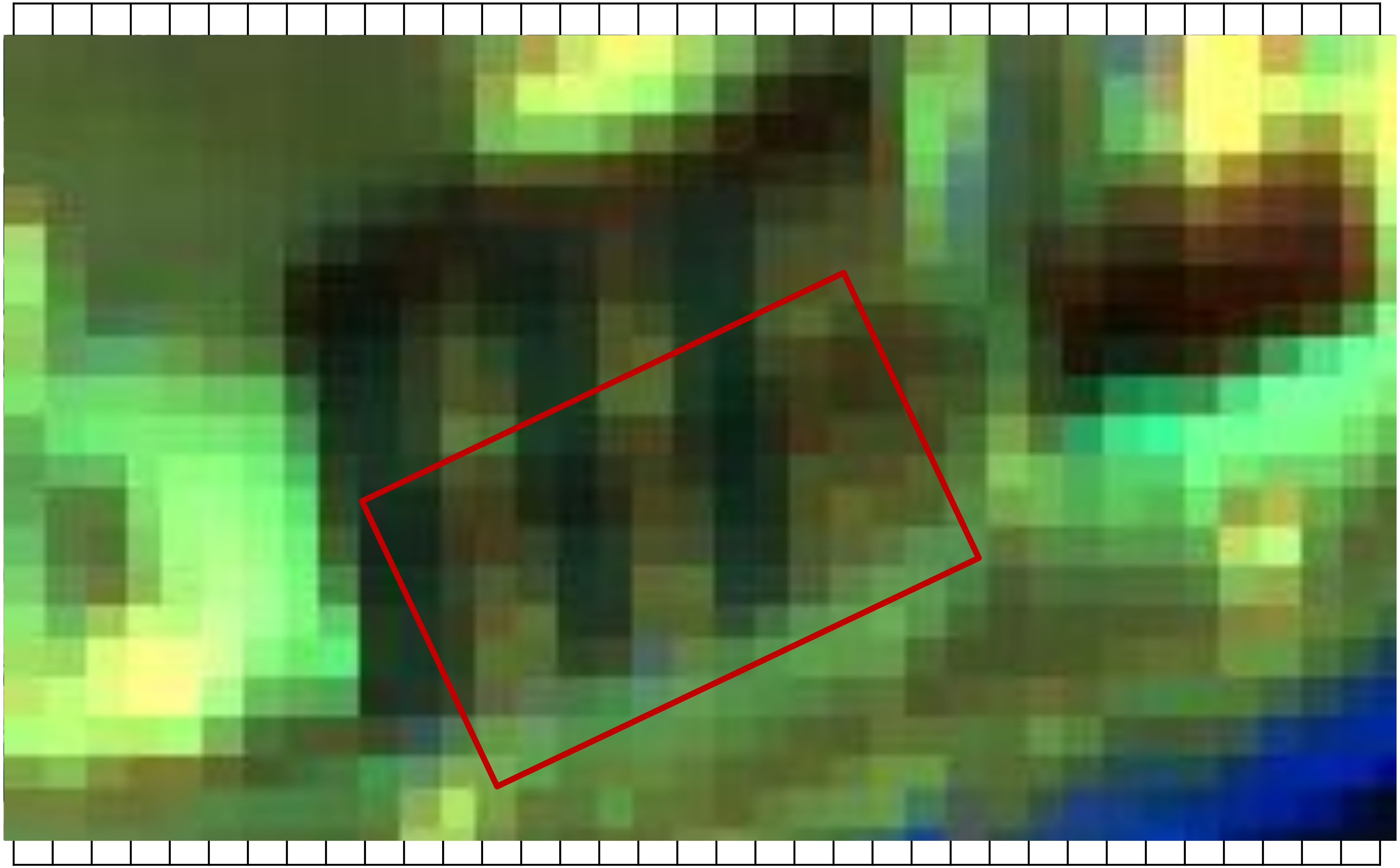
Salt and pepper effect



Pixel size = 4x4m

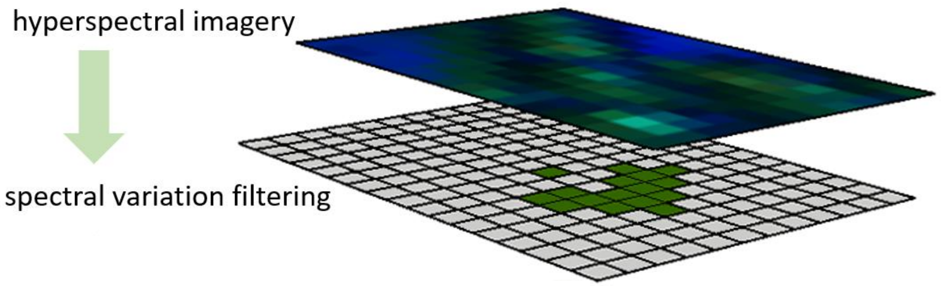




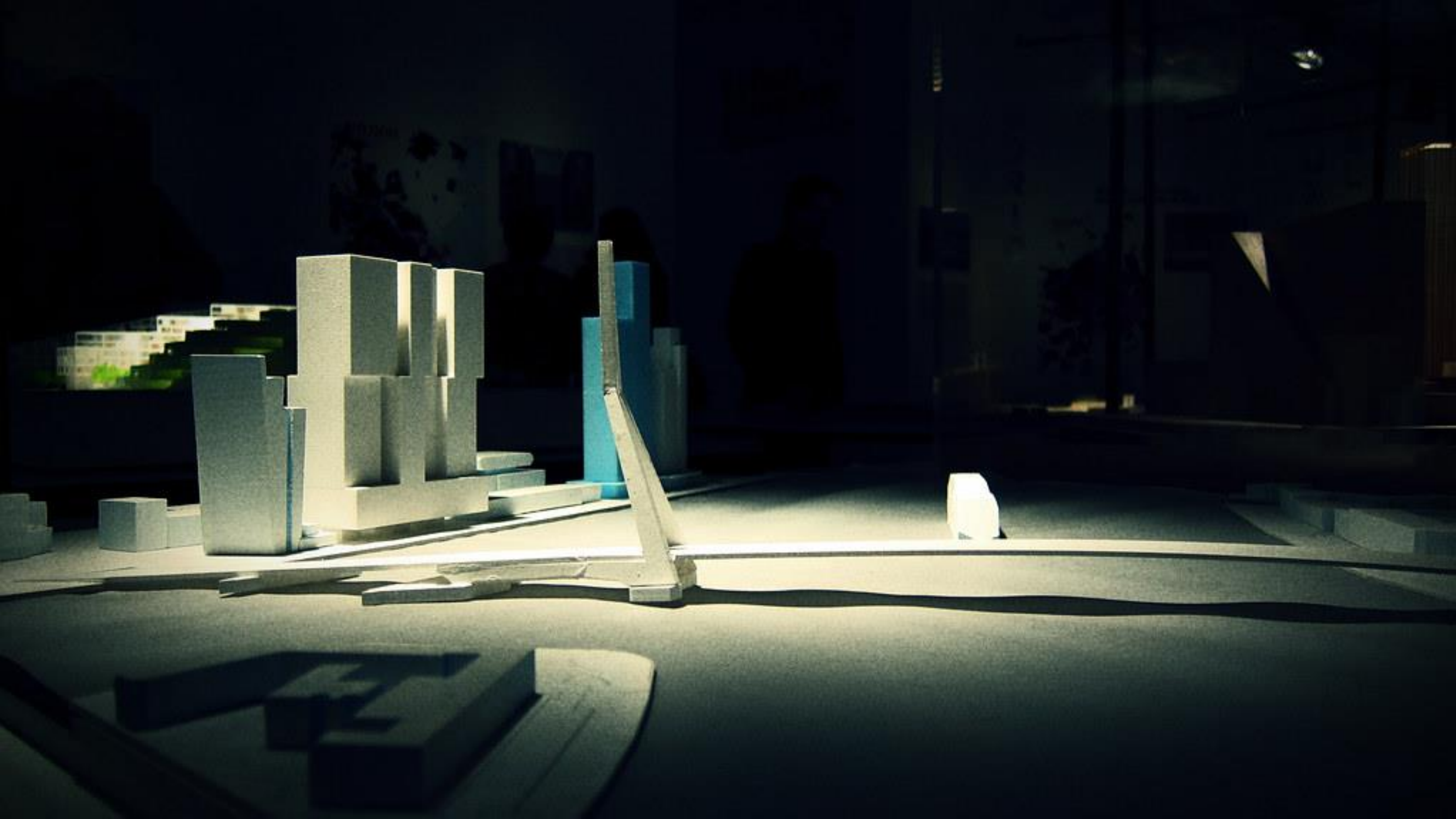
Pixel size = 4x4m

Problem statement

- 1) Need for identifying pixels containing spectral variations.

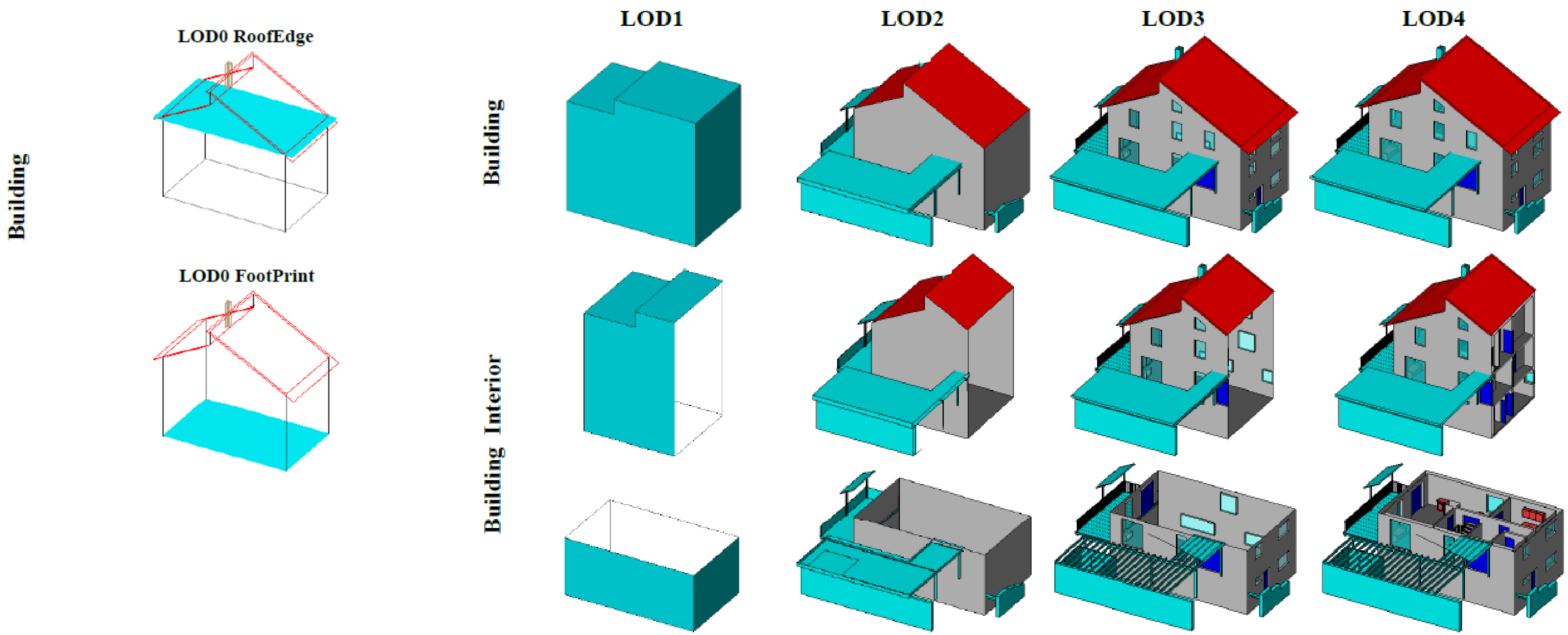



kpn
M



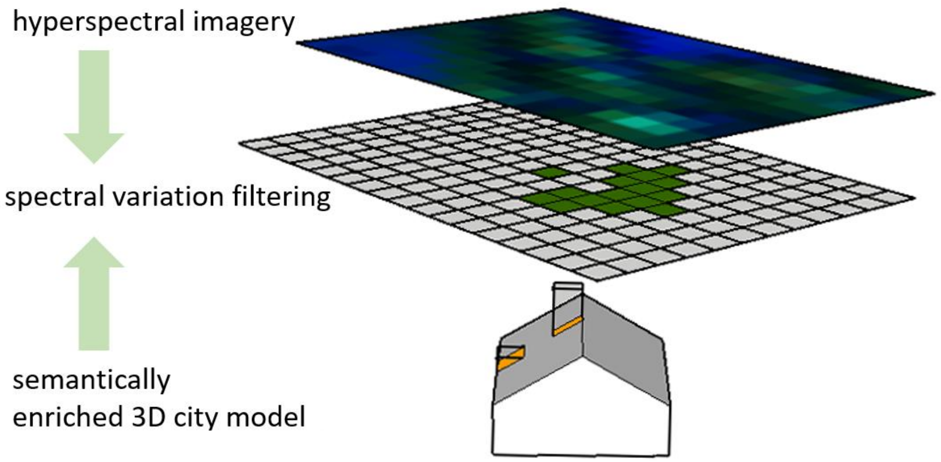

CESIUM
Gerealiseerd voor de Gemeente Rotterdam | Contact Gemeente Rotterdam
Mogelijk gemaakt door FutureInsight BV in samenwerking met virtualci SYSTEMS G bH
Privacy verklaring

CityGML – Levels of detail (LOD)

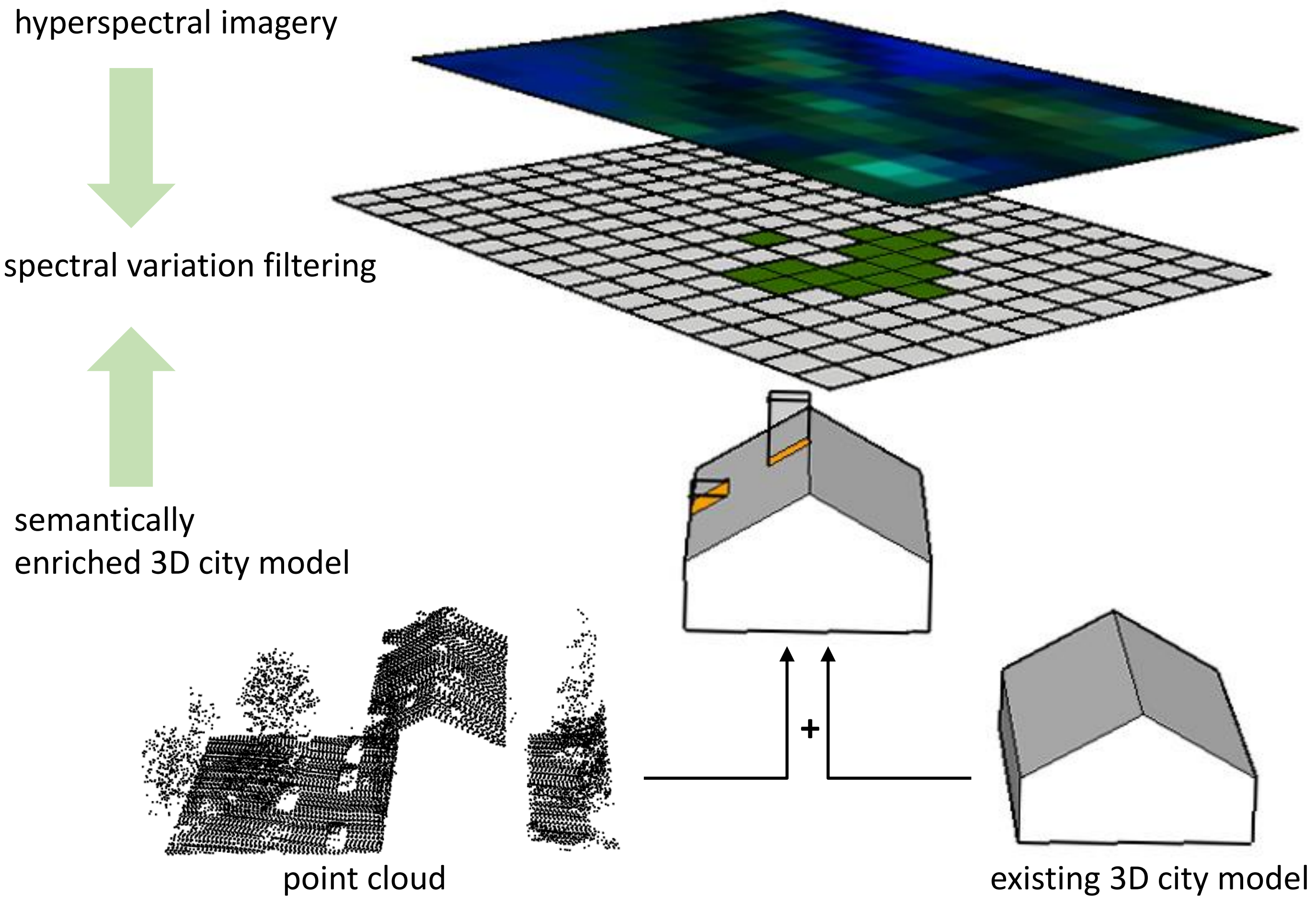


Problem statement

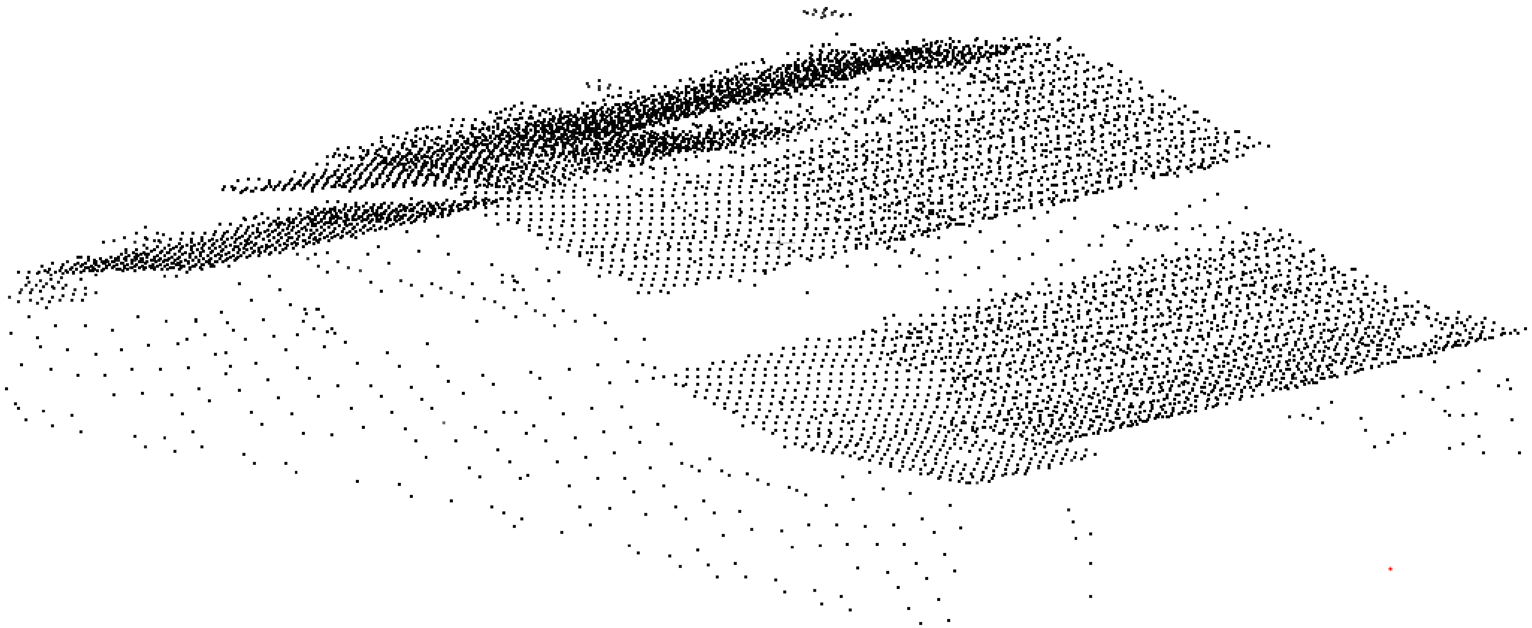
- 1) Need for identifying pixels containing roof material deviations.
- 2) A highly detailed 3D city model (LOD >2) would fulfil such criterion, it is often unavailable.



Proposed approach

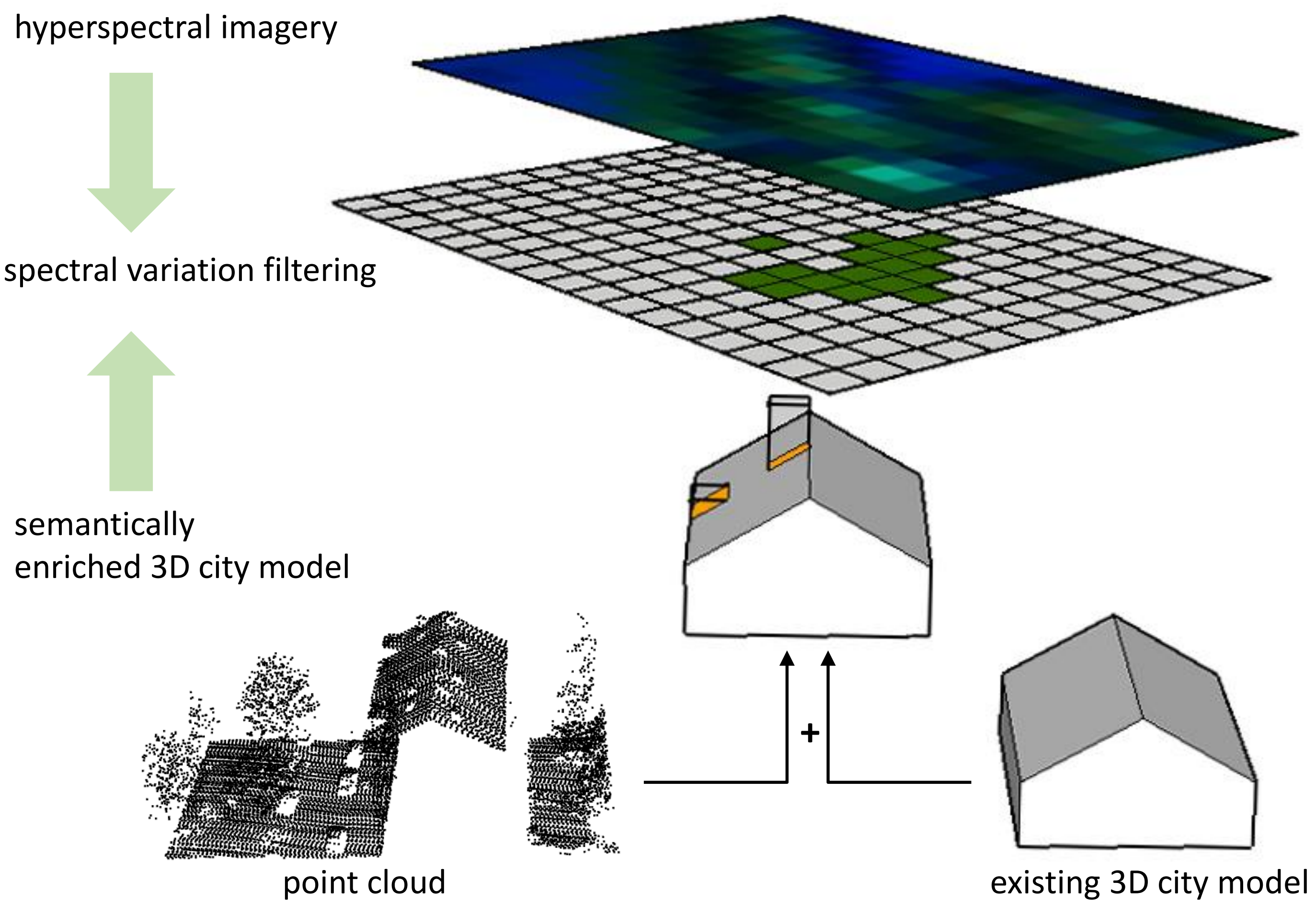


Point clouds



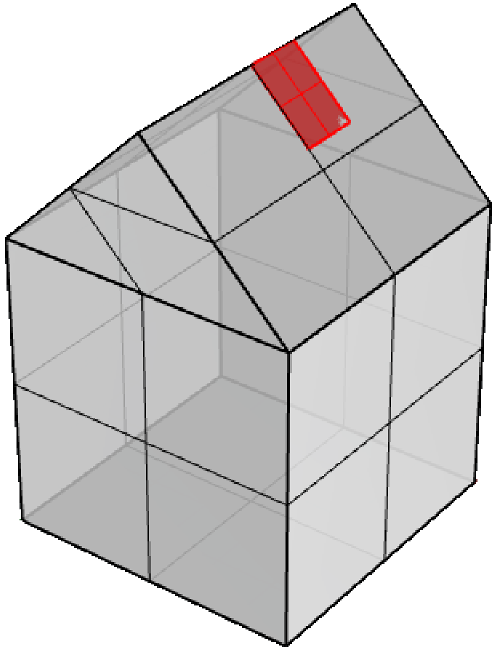
Light Detection and Ranging (LiDAR)

Proposed approach



Semantical enrichment

=



Research questions

How can a CityGML LOD2 model be semantically enriched in order to improve material classification performed on roof surfaces?

- 1. Which method is suitable to identify ‘deviations’ of LiDAR point clouds compared to LOD2?
- 2. What are the requirements with regard to CityGML LOD2, LiDAR point clouds and hyperspectral imagery data?
- 3. To which extent does such a method support the identification of clean pixels?

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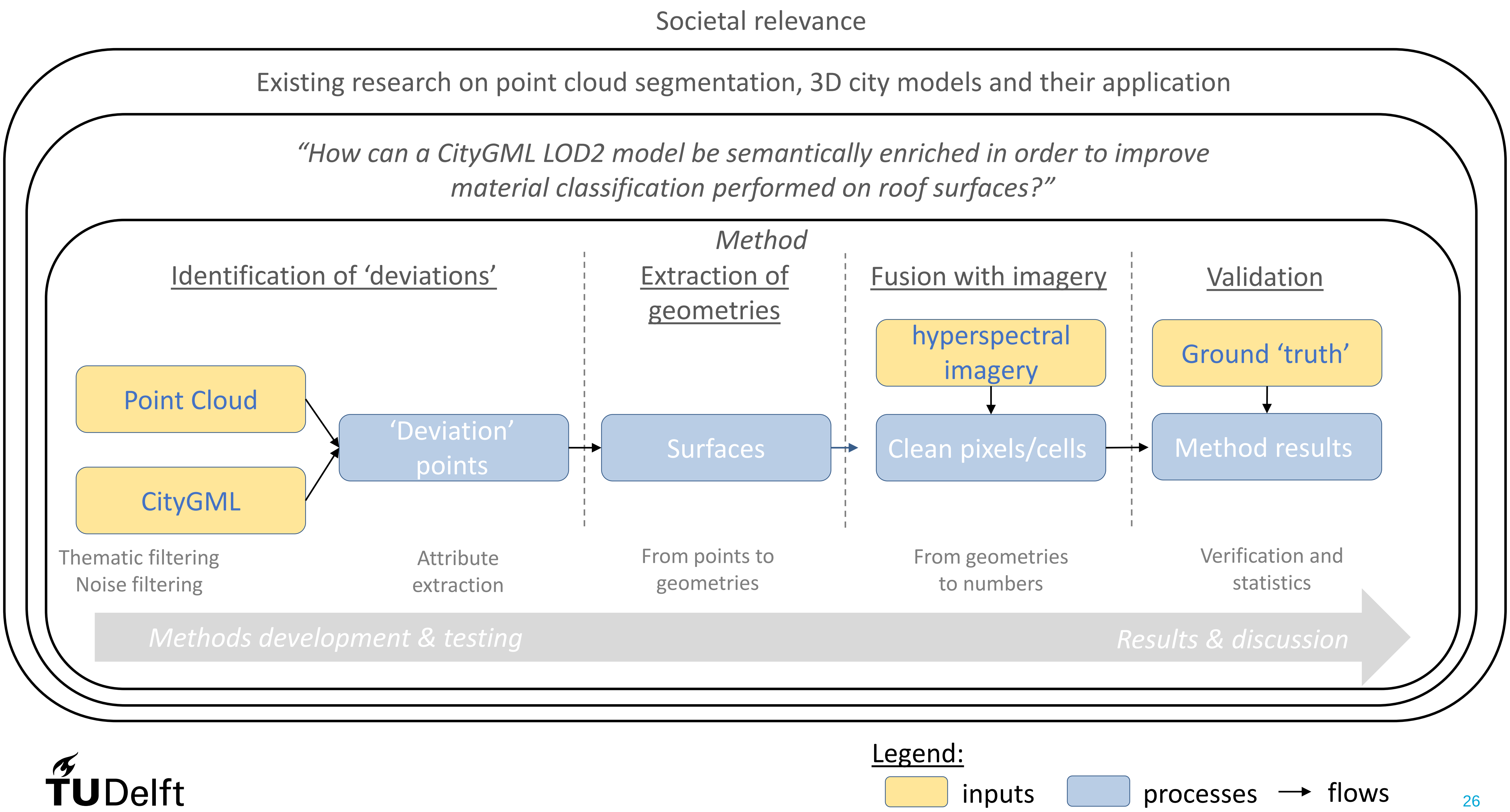
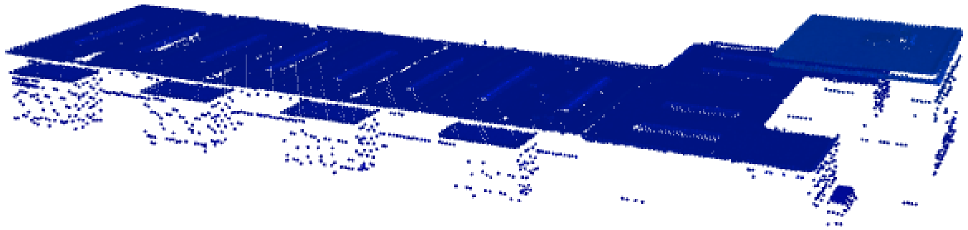
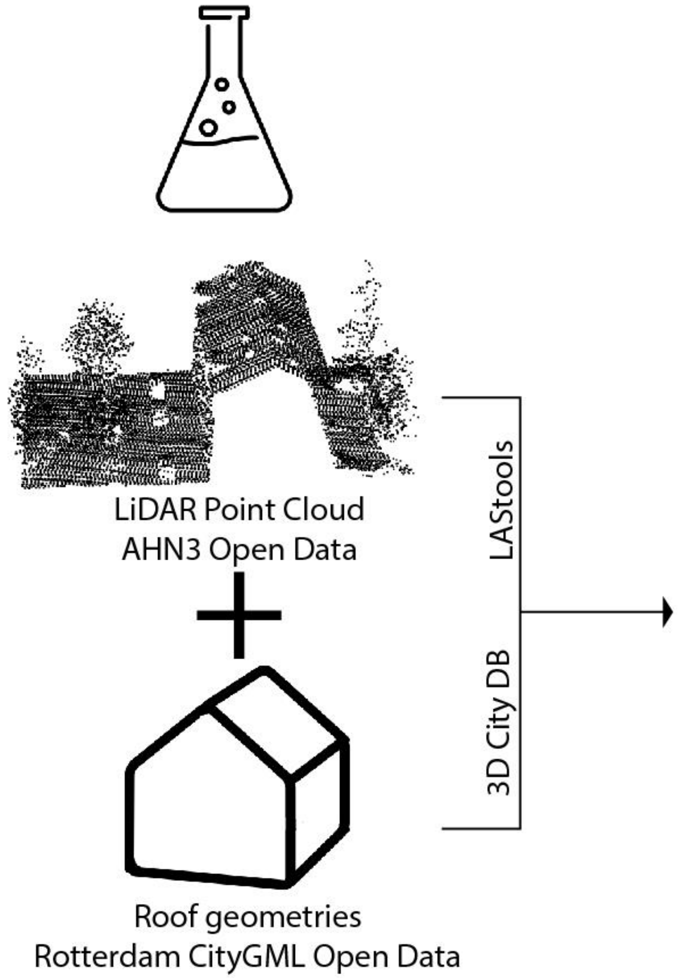

Societal relevance
Existing research on point cloud segmentation, 3D city models and their application
"How can a CityGML LOD2 model be semantically enriched in order to improve material classification performed on roof surfaces?"
Method
Identification of 'deviations'
Extraction of geometries
Fusion with imagery
Validation
Point Cloud
CityGML
'Deviation' points
Surfaces
hyperspectral imagery
Clean pixels/cells
Ground 'truth'
Method results
Thematic filtering
Noise filtering
Attribute extraction
From points to geometries
From geometries to numbers
Verification and statistics
Methods development & testing
Results & discussion
Legend:
inputs
processes
flows

III. Development of the methods

III.1 Deviation identification



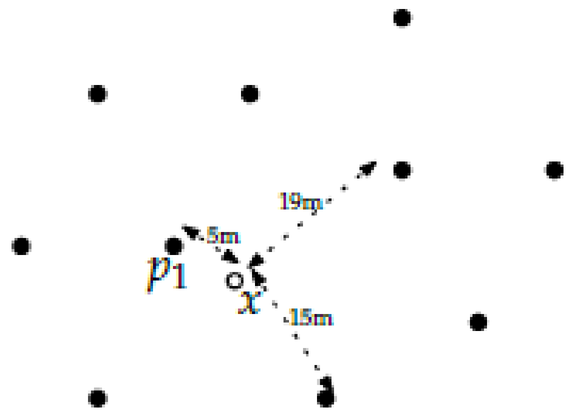
Data inputs



- AHN 3 open point cloud data (2016)
  - 8 points/m^2
  - Only class ‘building’ (filtered)
- Open CityGML model of Rotterdam (2016)
  - LOD2 semantic model including roof surfaces
  - Position, orientation of roofs

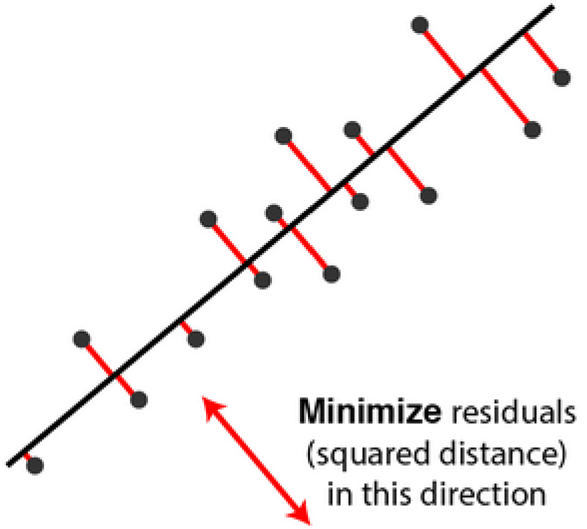
Mathematical tools

k-nearest neighbours

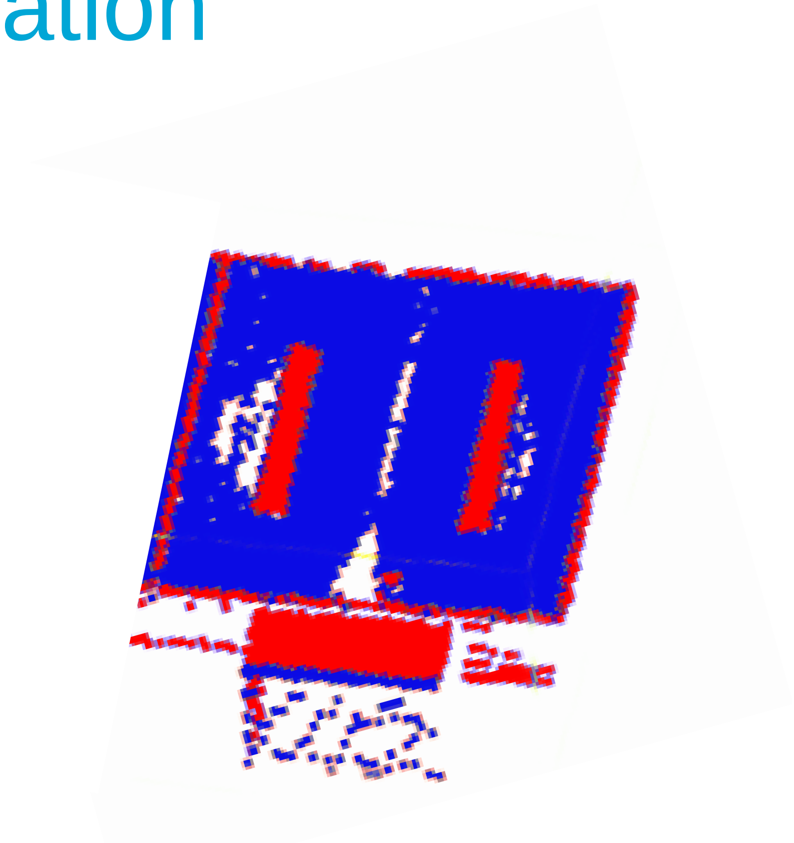


(a)

Principal components analysis (PCA)

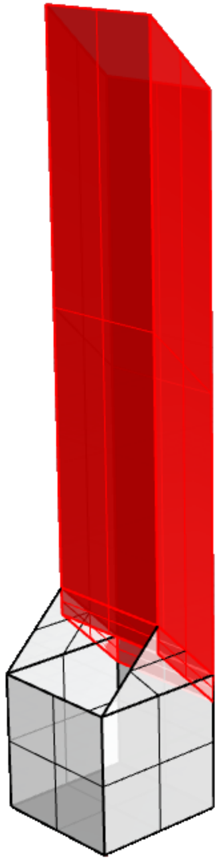


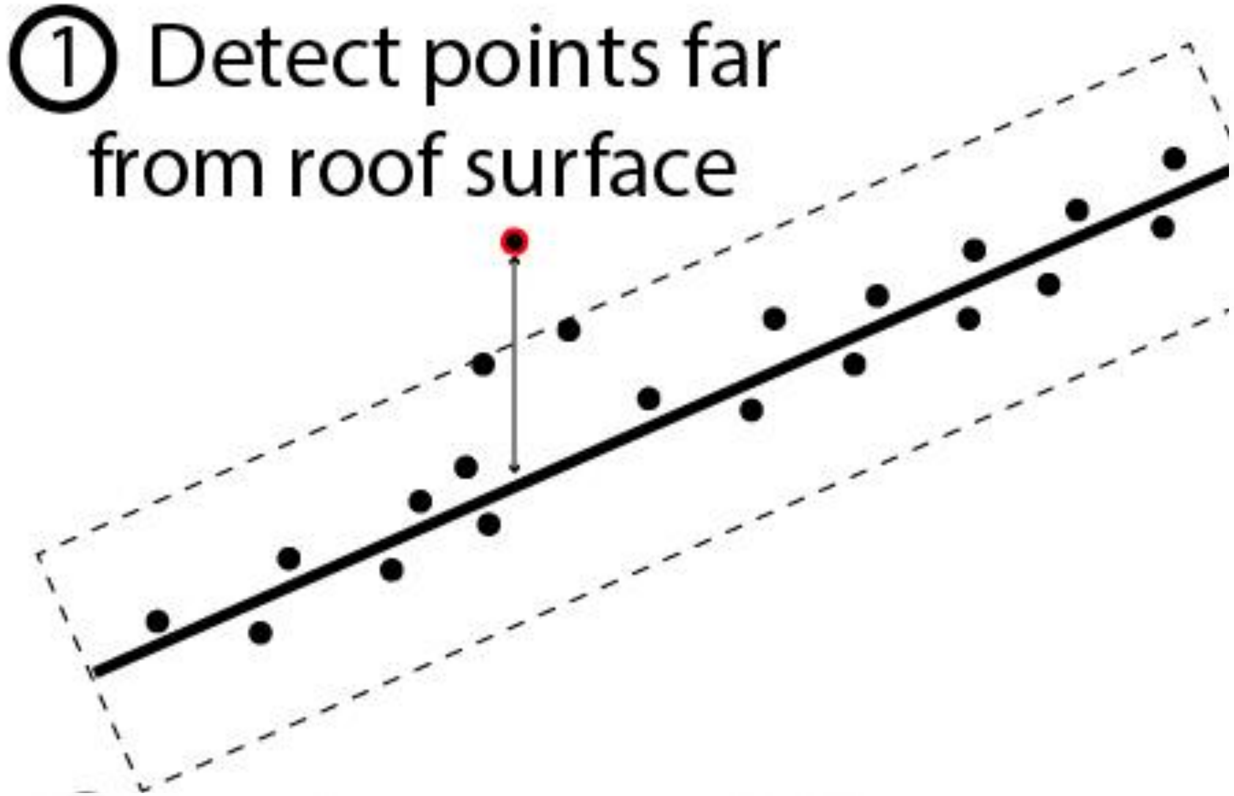
Exploration



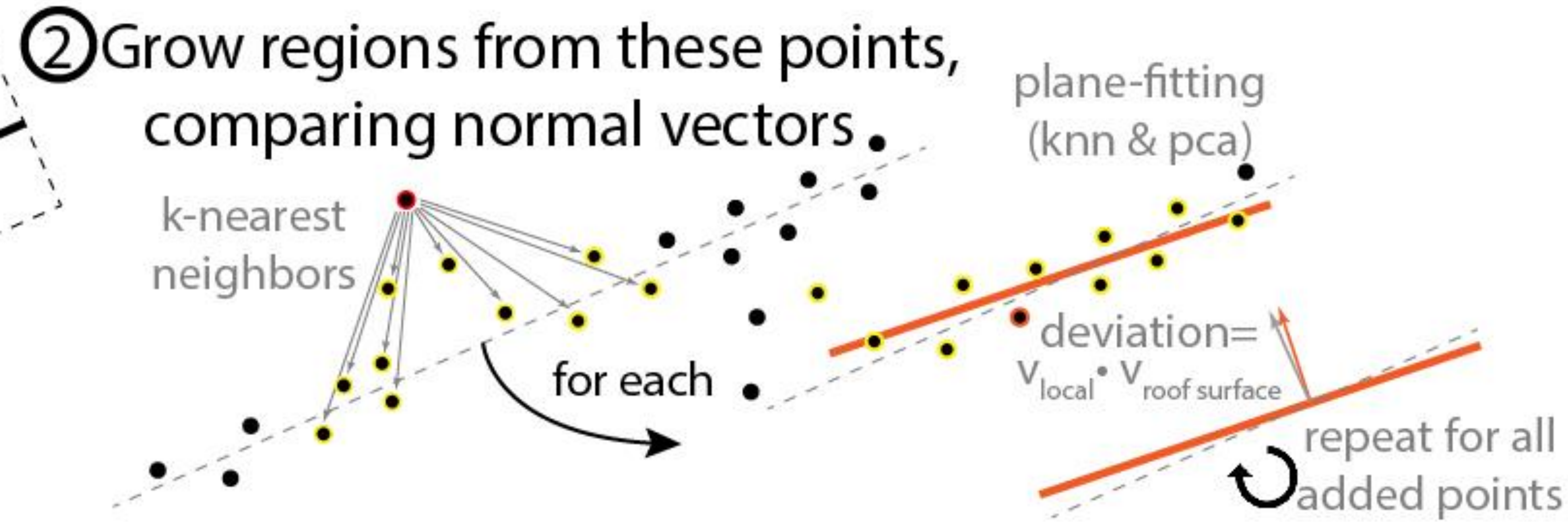
Points located at more than 30cm from the main roof surface

Normal vectors, with deviation >8° using PCA on KNN=10

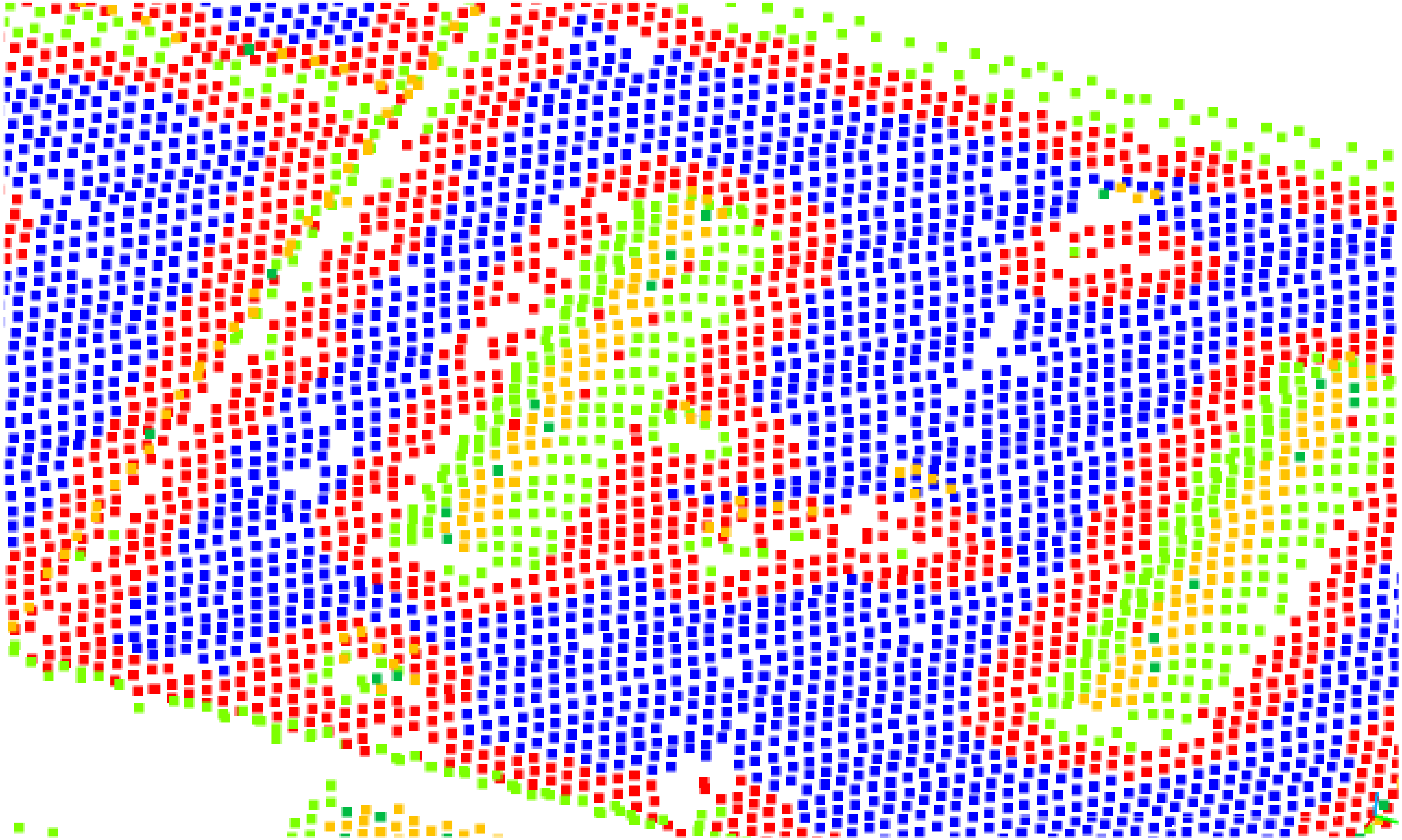




- Reduce point cloud to roof surface (2D)
- All points from -1m until +20m are taken into account (region of interest)
- The points with a distance >$\mathrm{threshold}$ (in m) are labelled as deviation seeds



- Region growing from the seeds:
  - For each seed, find the 10-nearest neighbours
  - Else: calculate the local normal using PCA on vicinity (10-nearest neighbours)
    - If the normal vector is >$\mathrm{threshold}$° different: add point and restart process from that point.
  - Stop once no points can be added and no seeds are left



Legend: distance

Identified as distance deviation

Region growing

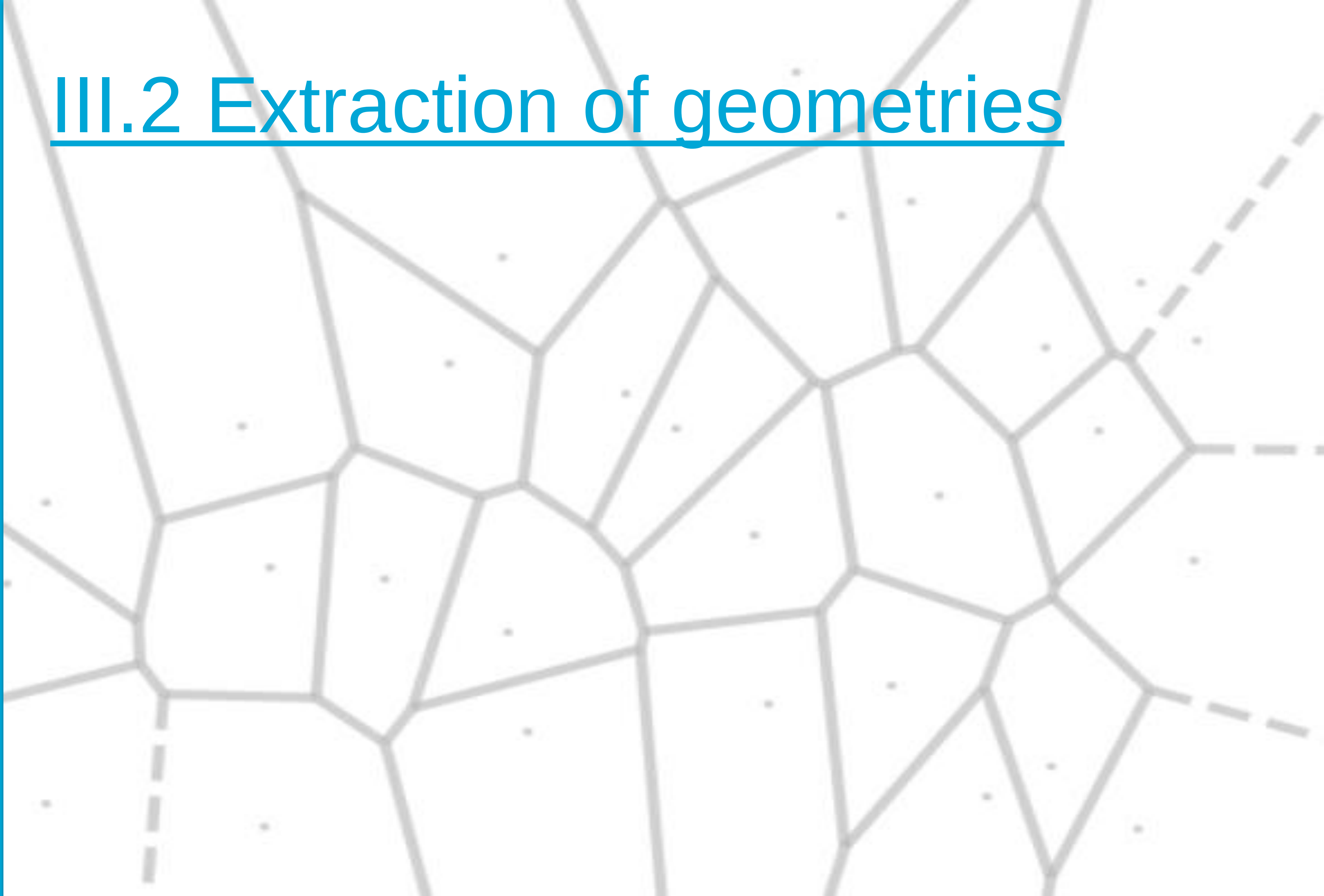
Used as seeds

Not visited

Added by region growing

Rejected during region growing

III.2 Extraction of geometries



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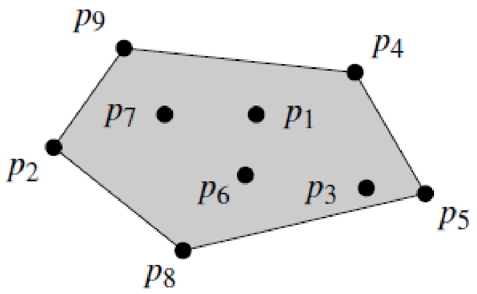
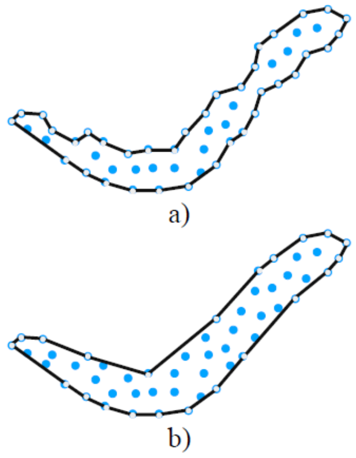
Options



+ no settings
- overestimation
- no holes

De Berg et al. 1997

Convex



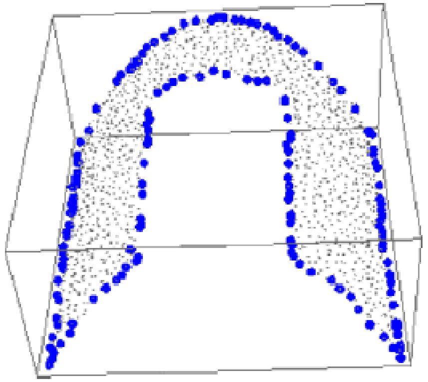
Concave

Moreira, Santos 2007

+ minimal surface
- no holes/settings

+ allows holes
- settings

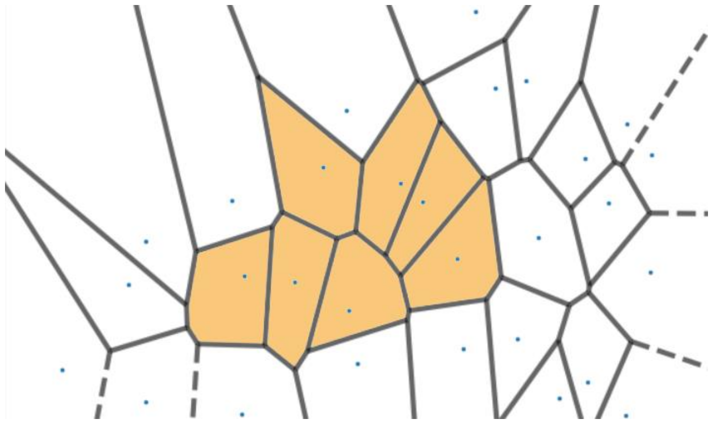
Border extraction



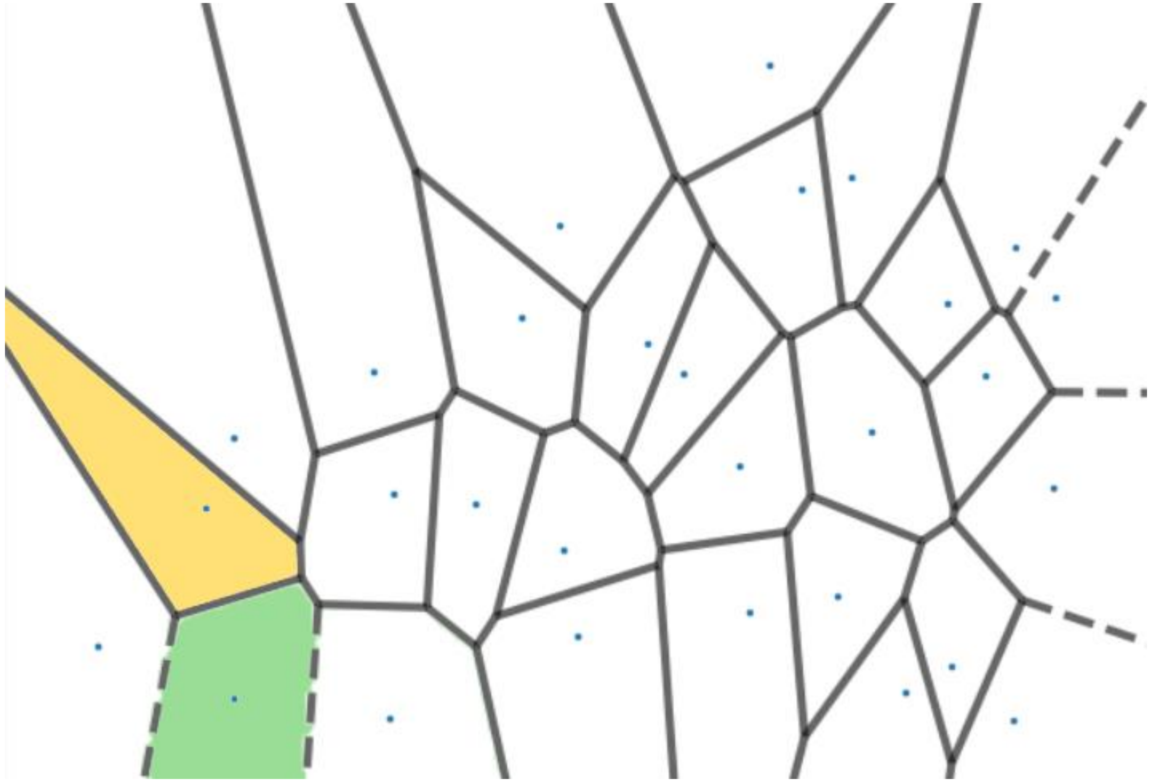
Wang, Shan 2009

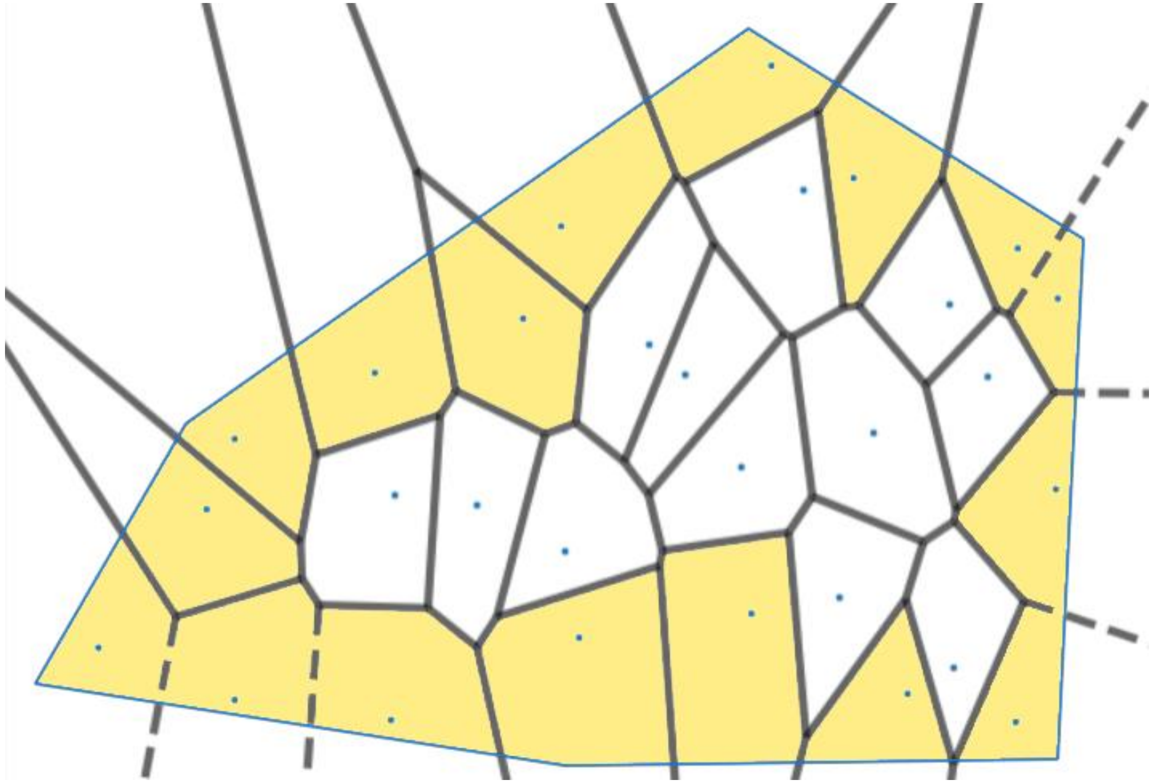
Voronoi

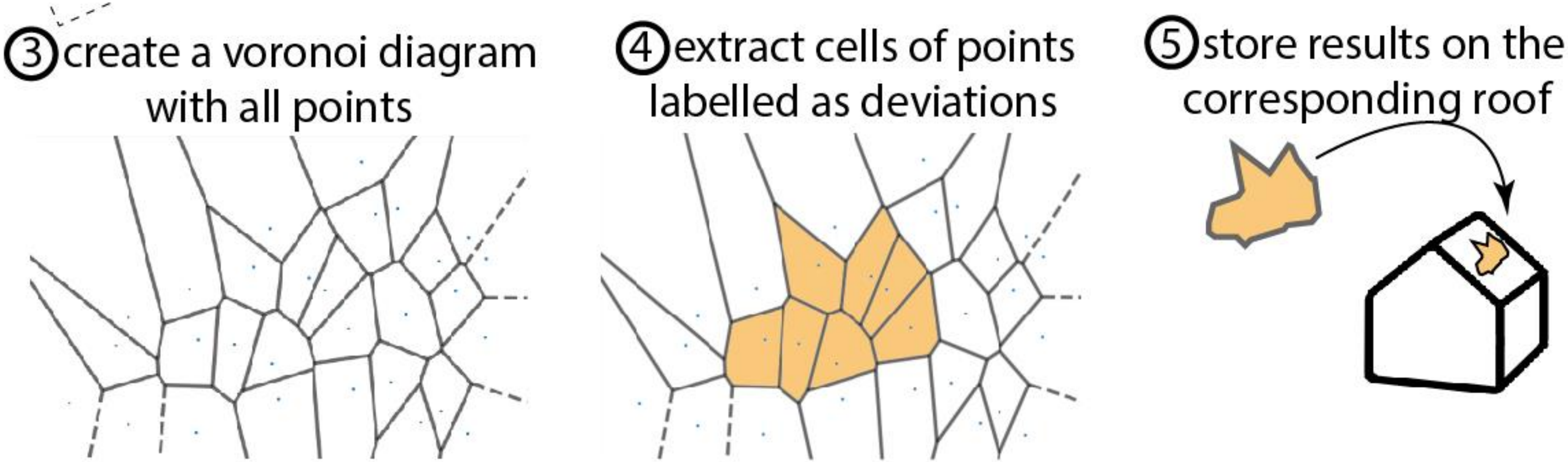
+ holes & [1:n]points
+ no settings
- requires all points



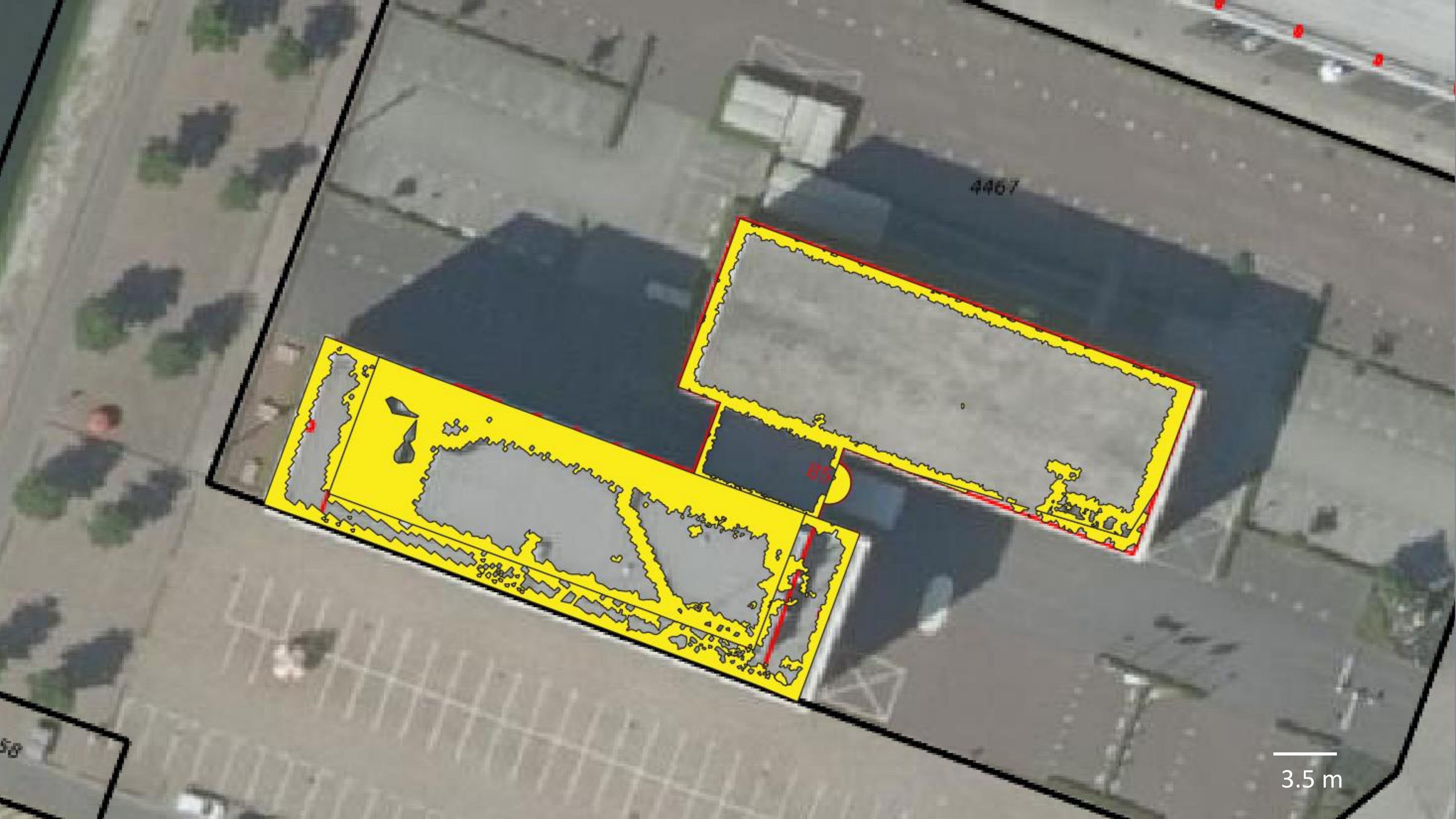
Voronoi diagram: infinite lines






3 create a voronoi diagram with all points
4 extract cells of points labelled as deviations
5 store results on the corresponding roof


4467
85
3.5 m


4467
85
58
3.5 m

deviations_0.2_0.9962_extend_validations :: Features Total: 1108, Filtered: 1108, Selected: 0

	roof surface gmlid	mean distance to roof	90th percentile distance to roof	building gmlid
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5	RCID_0675094a-3a61...	0.17233333333033826	0.9554999999970752	ID_0599100000634532
6	RCID_0675094a-3a61...	0.008499999999761783	0.08789999999972976	ID_0599100000634532
7	RCID_0675094a-3a61...	0.07050000000021966	0.21950000000019063	ID_0599100000634532
8	RCID_0675094a-3a61...	1.0023163265277715	2.1425999999975454	ID_0599100000634532
9	RCID_0675094a-3a61...	0.7101901408437957	2.1372999999985334	ID_0599100000634532
10	RCID_074a3be4-b54f...	-0.19182035826440114	-0.22802035826440062	ID_0599100010056978
11	RCID_074a3be4-b54f...	0.18812835968431704	0.24077964173560246	ID_0599100010056978
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13	RCID_074a3be4-b54f...	-0.1982489296929728	-0.2522203582644025	ID_0599100010056978
14	RCID_078a3a40-0676...	-0.24699067797208507	0.06306607130546837	ID_0599100010056978
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18	RCID_0c98a539-652c...	-0.4489519774378633	0.06361311228410764	ID_0599100010056978
19	RCID_0d765dde-3294...	5.588548826005052	19.571884974338342	ID_0599100000359215

Show All Features

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III.3 Fusion with imagery

APEX imagery of Rotterdam (2014)
Red = 399-413 nm, Green = 1145-1155 nm, Blue = 2423-2432 nm

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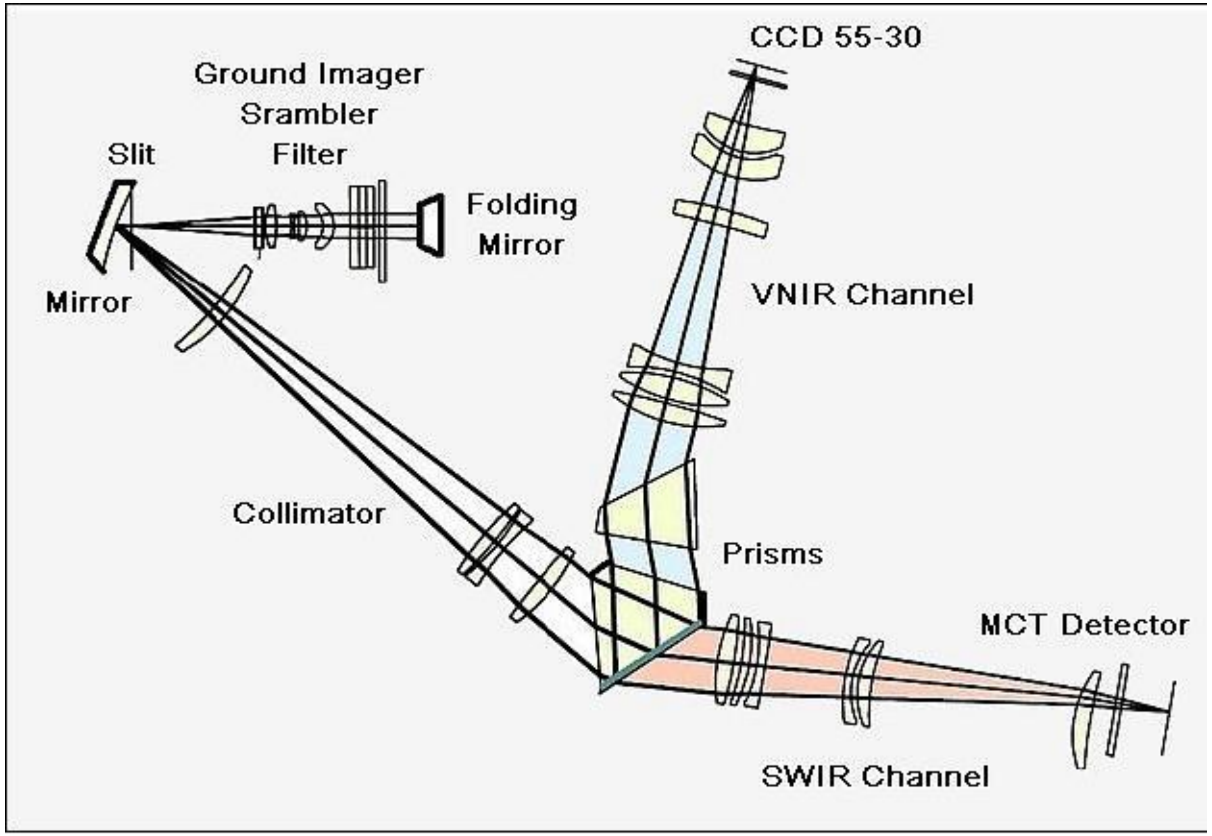
Aerial/Hyperspectral imagery acquisition

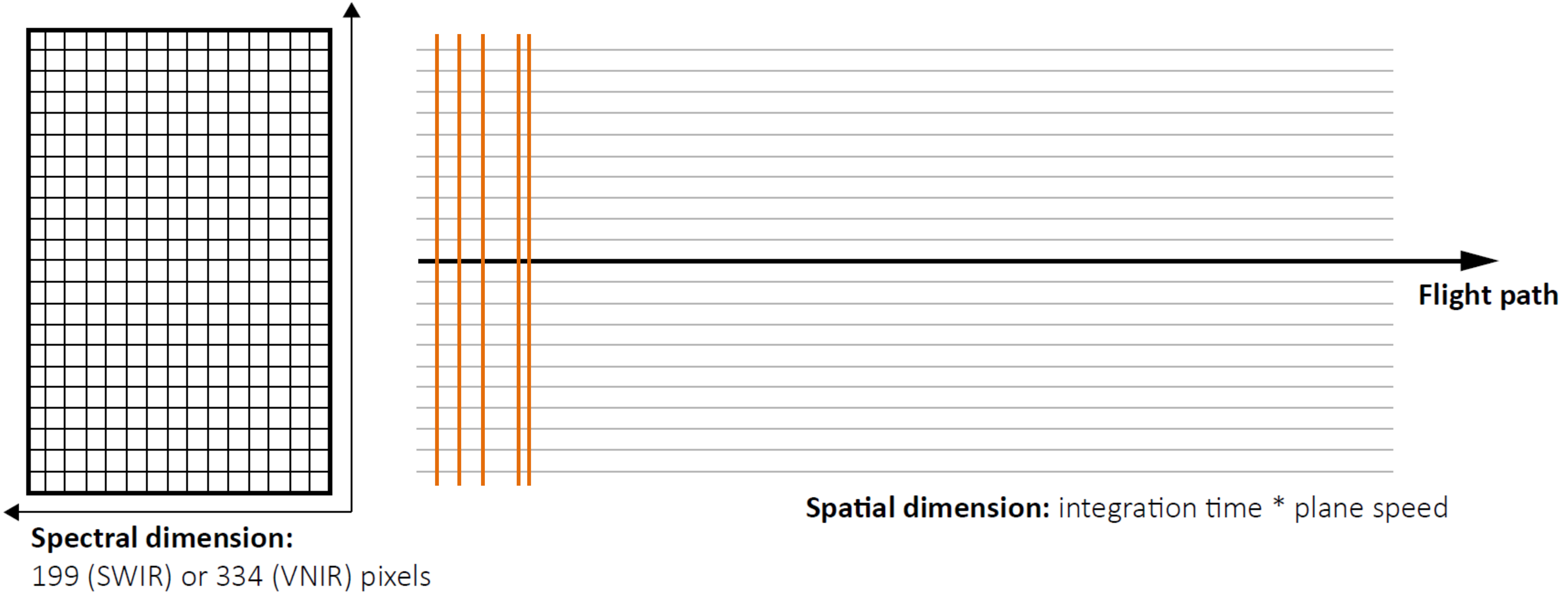
Airborne Prism Experiment - APEX (380-2500 nm, up to 532 bands)



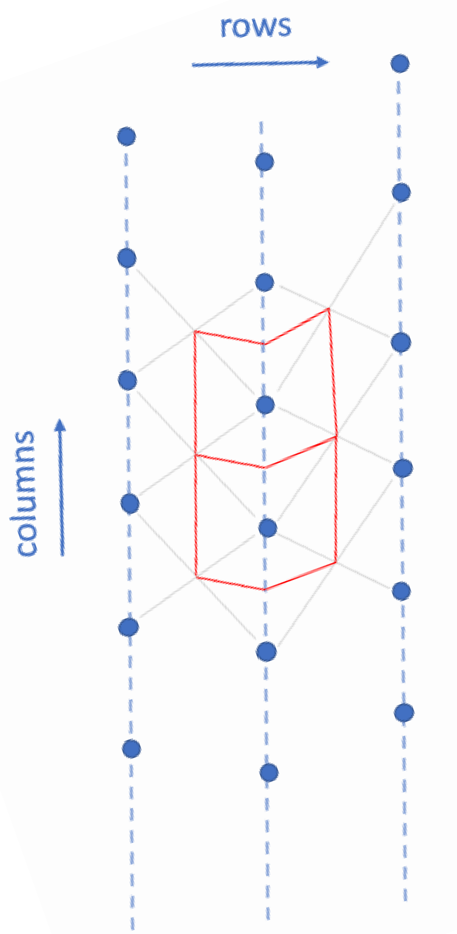
Source: https://twitter.com/APEX_RSL/status/450568985386303488, https://directory.eoportal.org/web/eoportal/airborne-sensors/content/-/article/apex

Sensor technology: line scanner

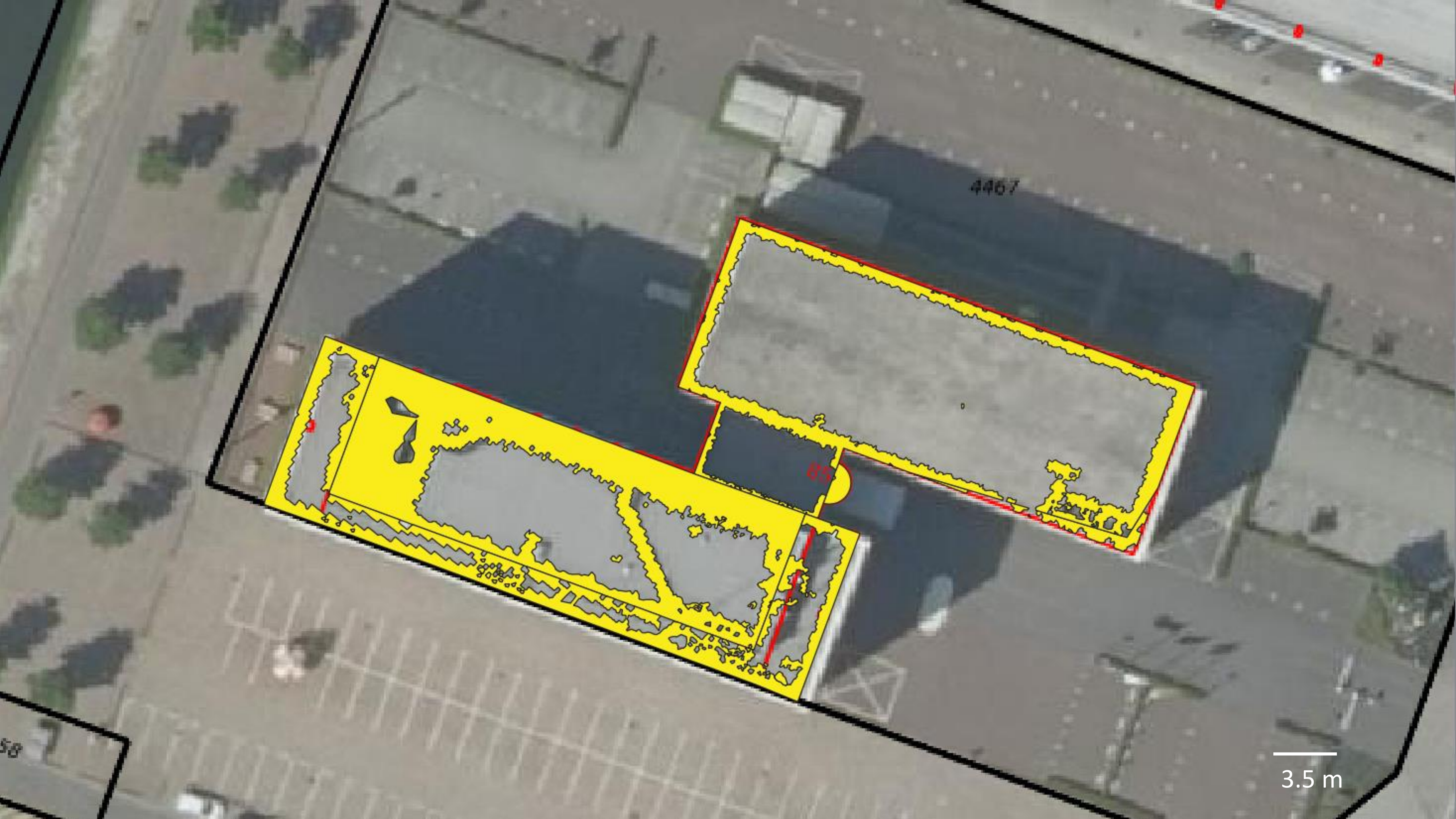
Sensors:
SWIR (940-2500 nm): CMOS - 1000*199 pixels
VNIR (380-970 nm): CCD - 1000*334 pixels



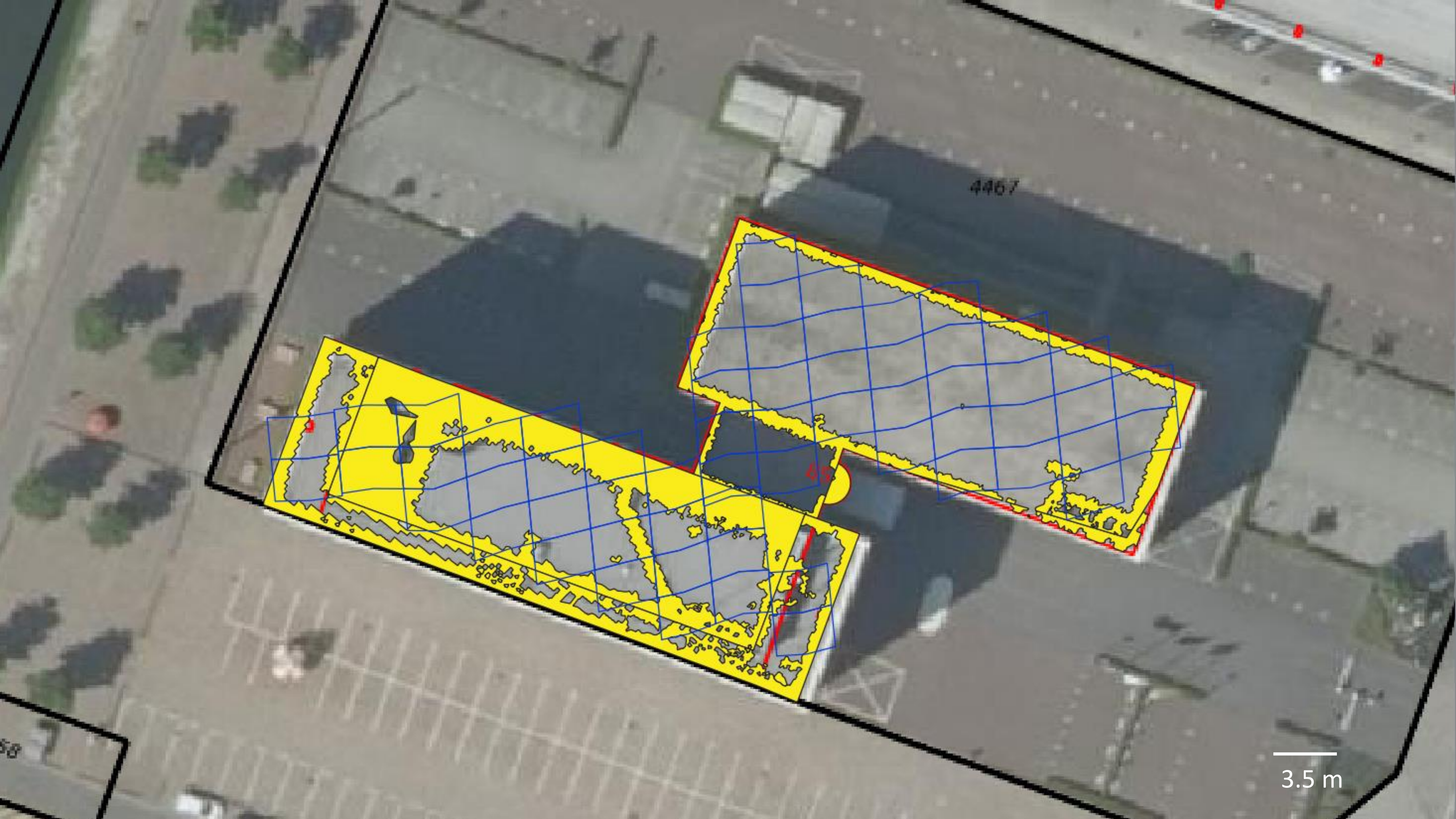
From pixel to mesh




4467
85
3.5 m



4467
85
58
3.5 m


4467
3.5 m

pixels_0.2_0.9994_ID_0599100000422432 :: Features Total: 48, Filtered: 48, Selected: 0

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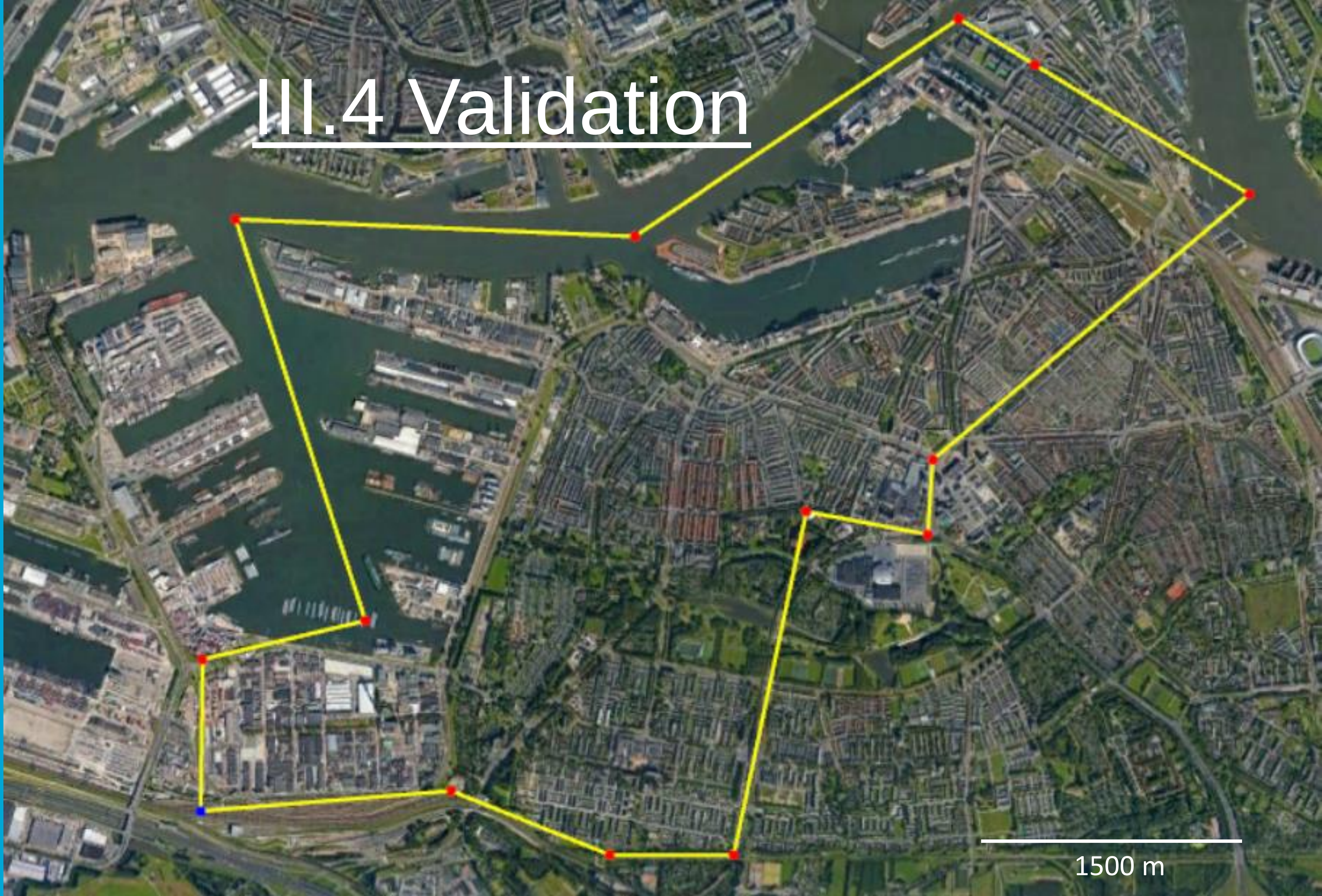
29	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6634	288	15.29554931764578	0.383443159895518	0.8988928567266443
30	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6634	287	15.29916221256968	0.0010693754828837807	1
31	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6639	289	14.335818835706...	0.024945794063467294	1.0000000000000002
32	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6638	289	16.07770587344237	0.17155123723252663	1
33	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6640	290	16.738973672388...	0.21897873445585644	0.870184833107257
34	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6640	289	16.561445723163...	0.306504829538554	0.7101994084037123
35	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6637	288	17.605116002197...	0	0.9999999999999998
36	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6637	287	17.6104585216051	0.3193616884693755	0.7745981073477008
37	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6638	288	16.08278441055711	0.5352957748956251	0.9770337101024849
38	ID_0599100000422432	RCID_28845666-21bc-40c5-8f6b-a7b746baa1a5	south	6637	289	17.5997833447767	0.26746259412850204	0.7689971277413774
39	ID_0599100000422432	RCID_b7ad193e-b9b6-43c6-a263-3b6d24d143b8	south	6641	292	16.218508029249...	0.27010374574896373	0.9038385214757328

III.4 Validation



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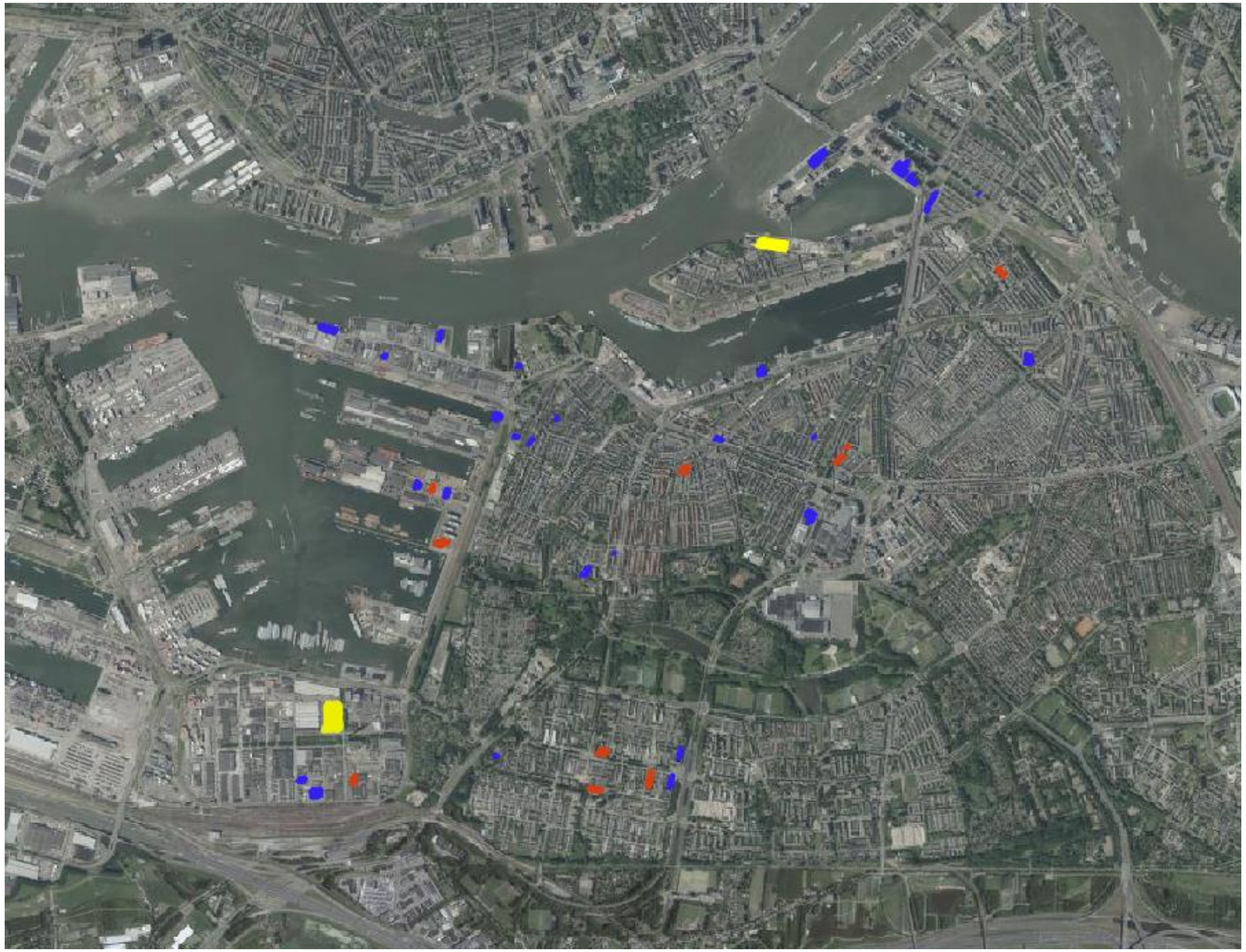
Validation sample



Legend:

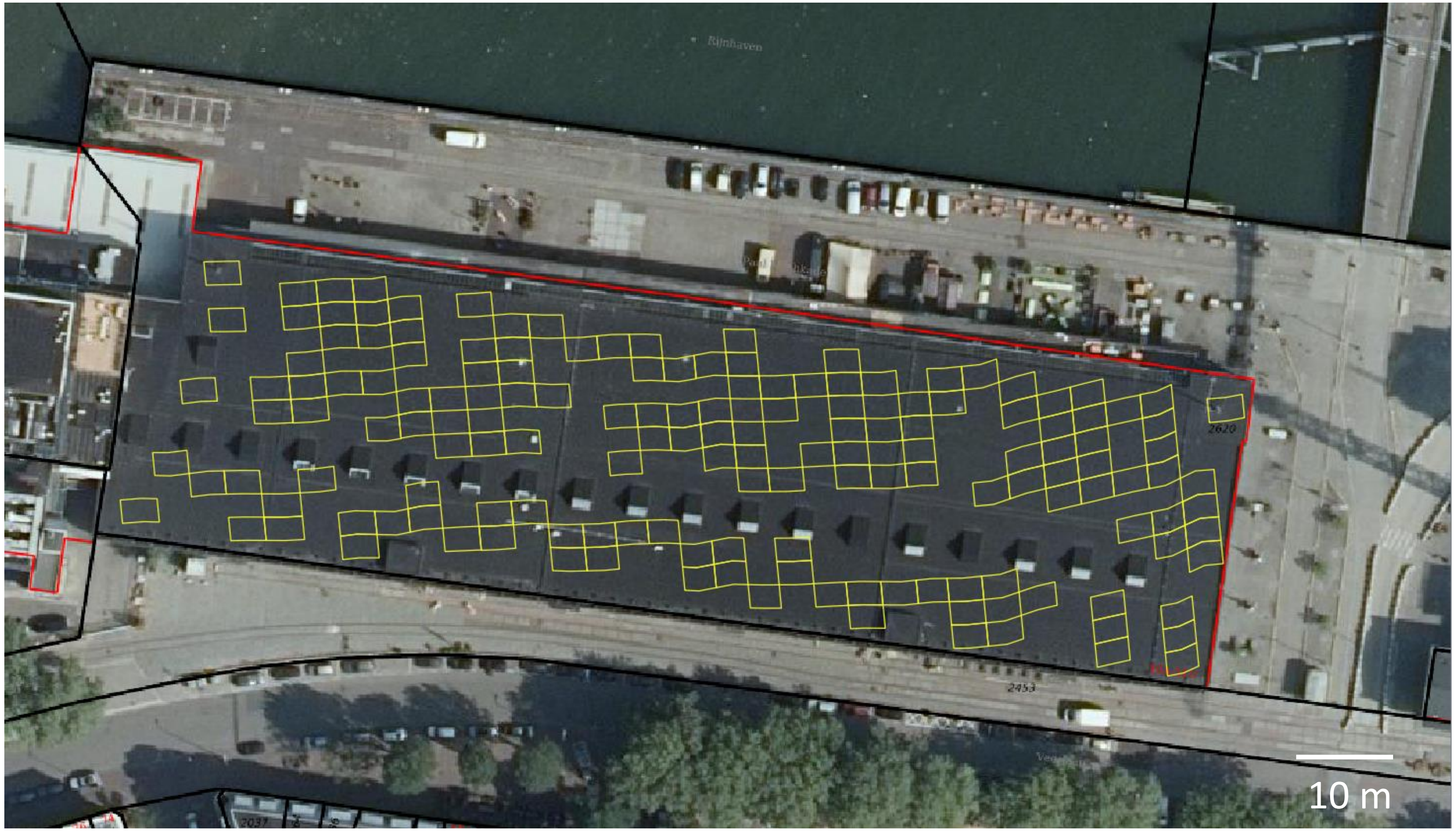
 Used for all 4 validations incl. cells partially outside roof

 Used only for validations with cells 100% inside roof (A&B)

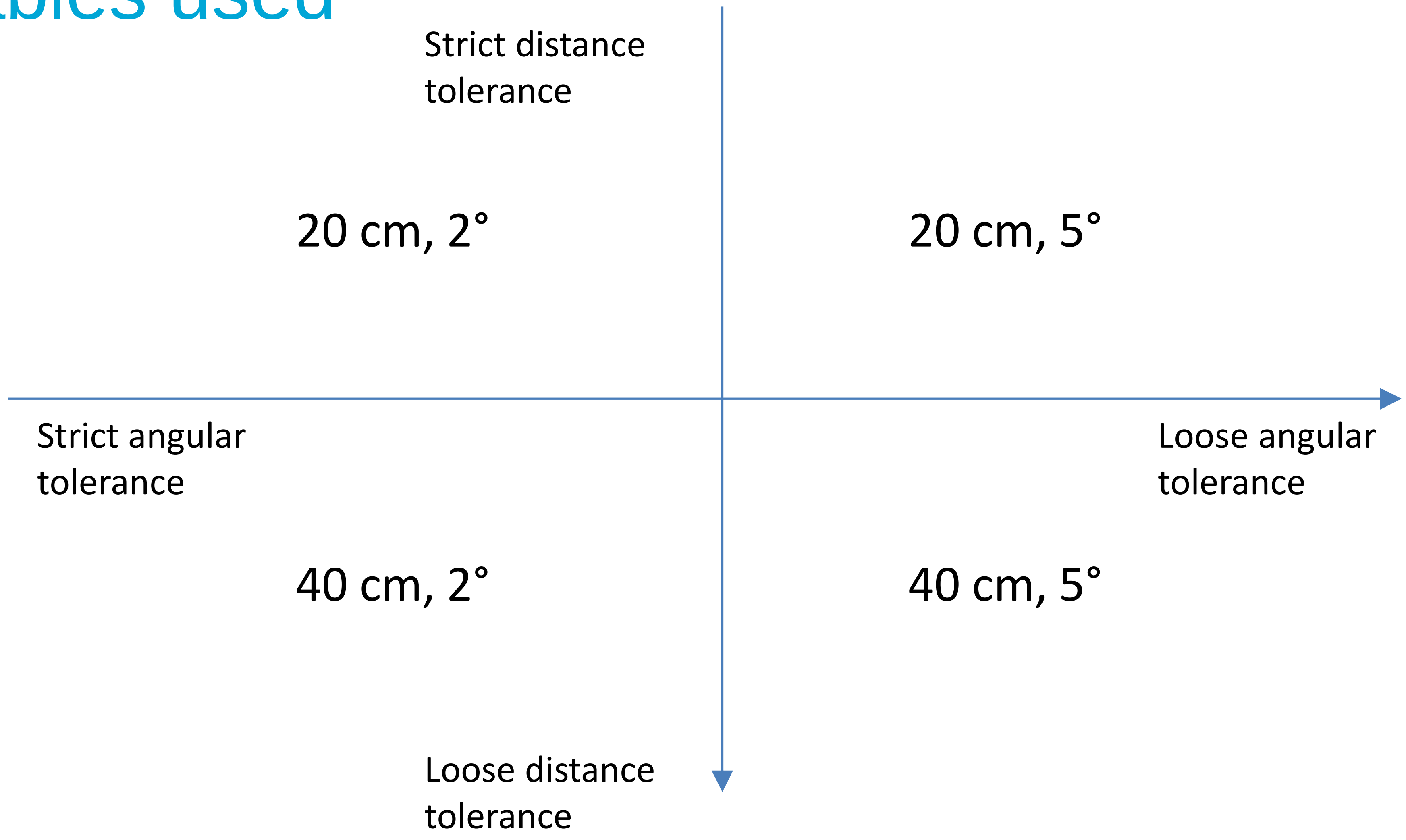
 Only used for level A (cell number bias)

1500 m

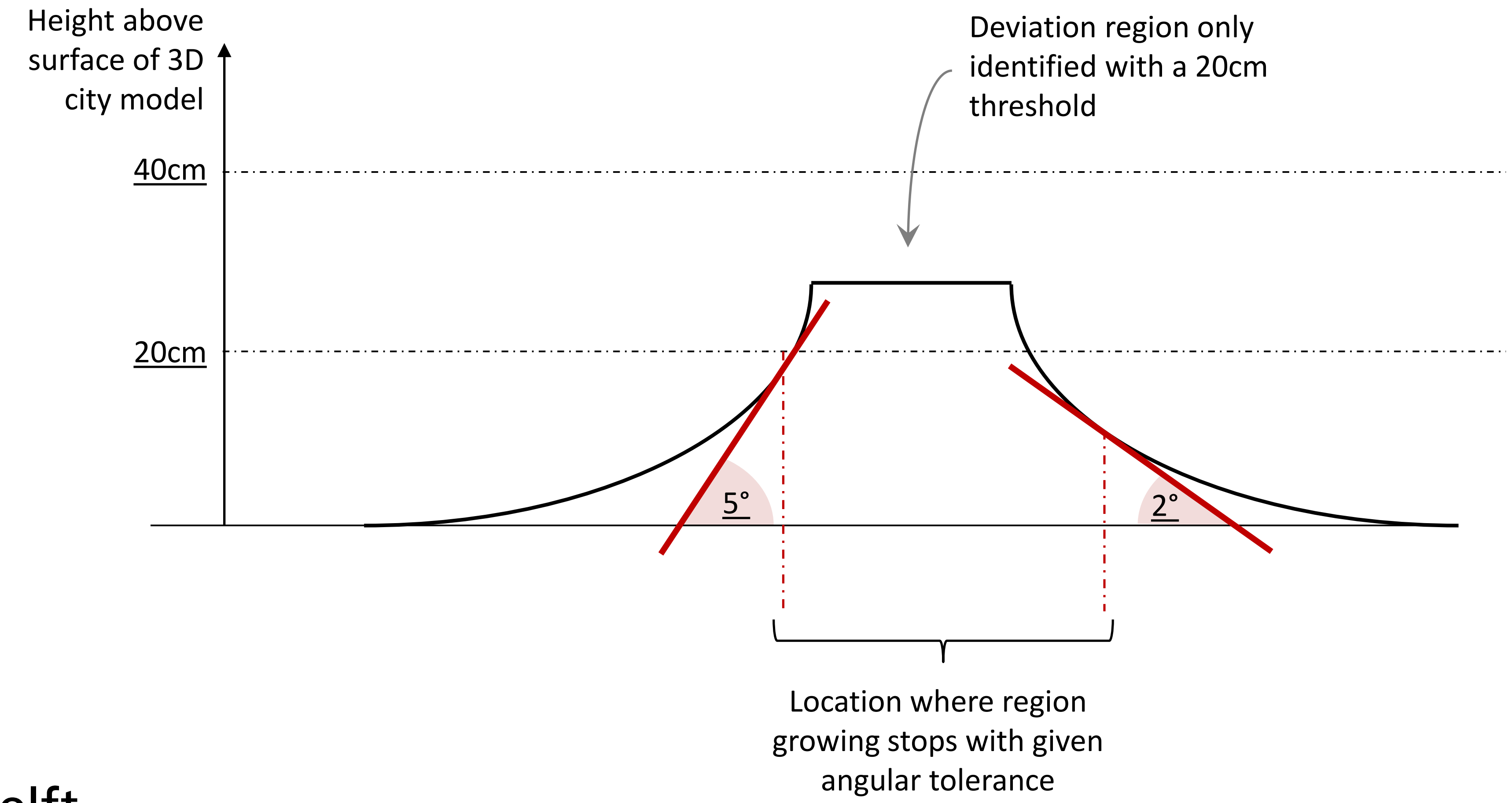
Ground ‘truth’



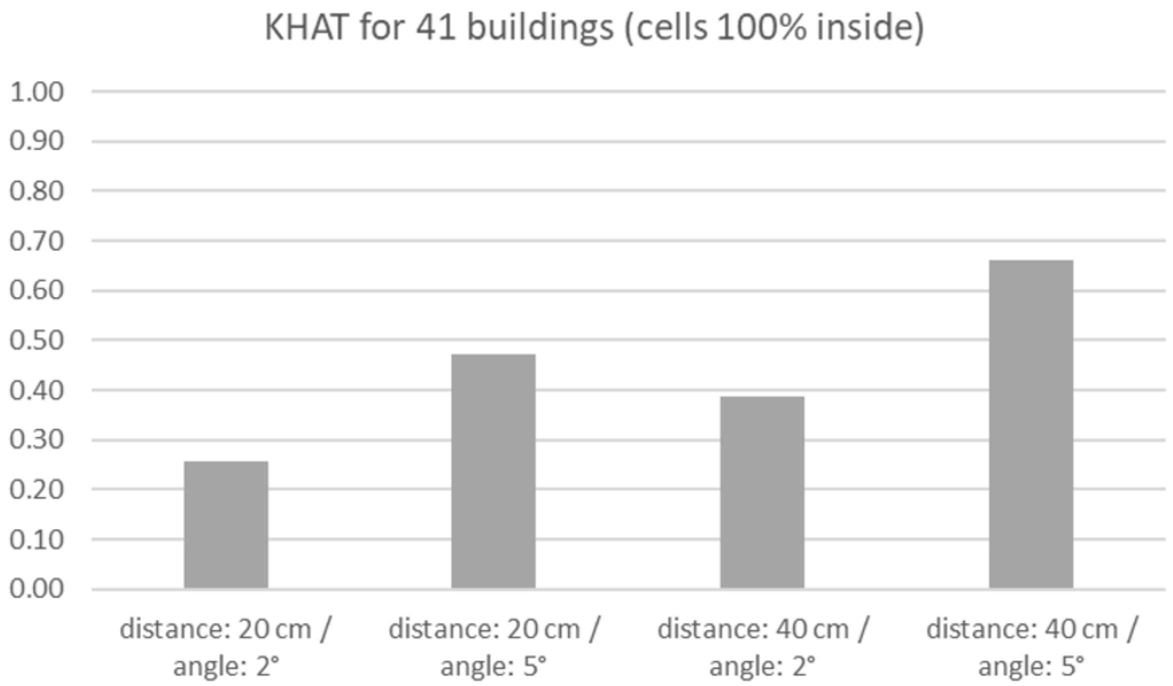
Variables used

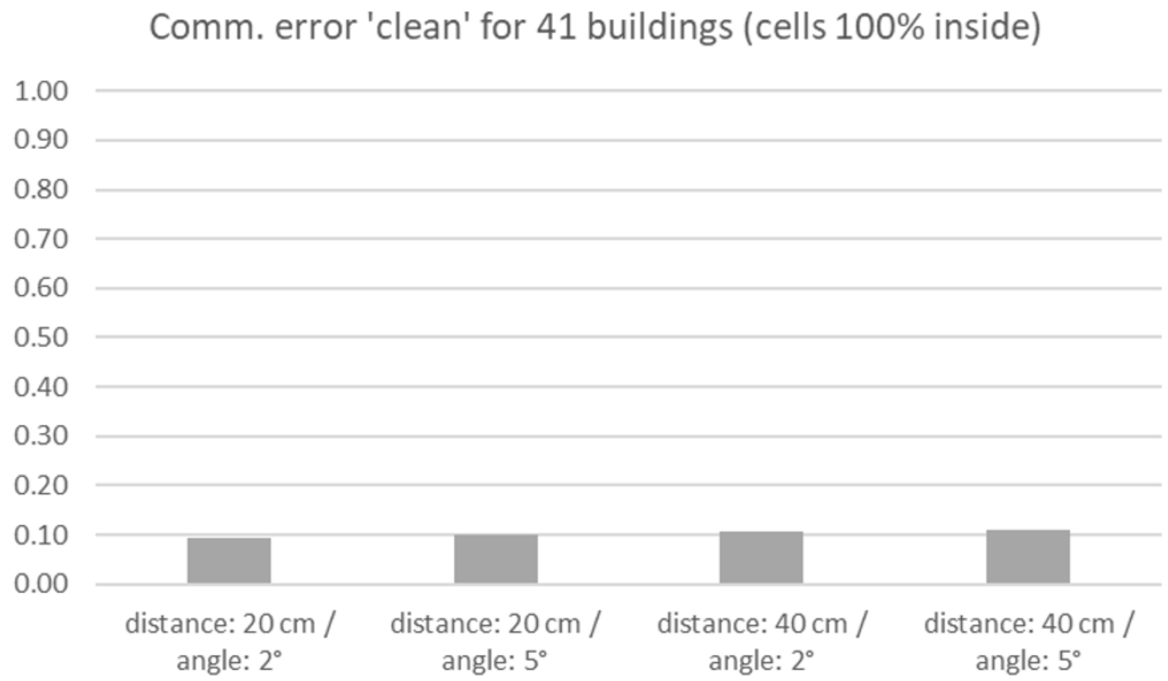


Variable impact



Level A (nominal & building level -cells 100% inside)





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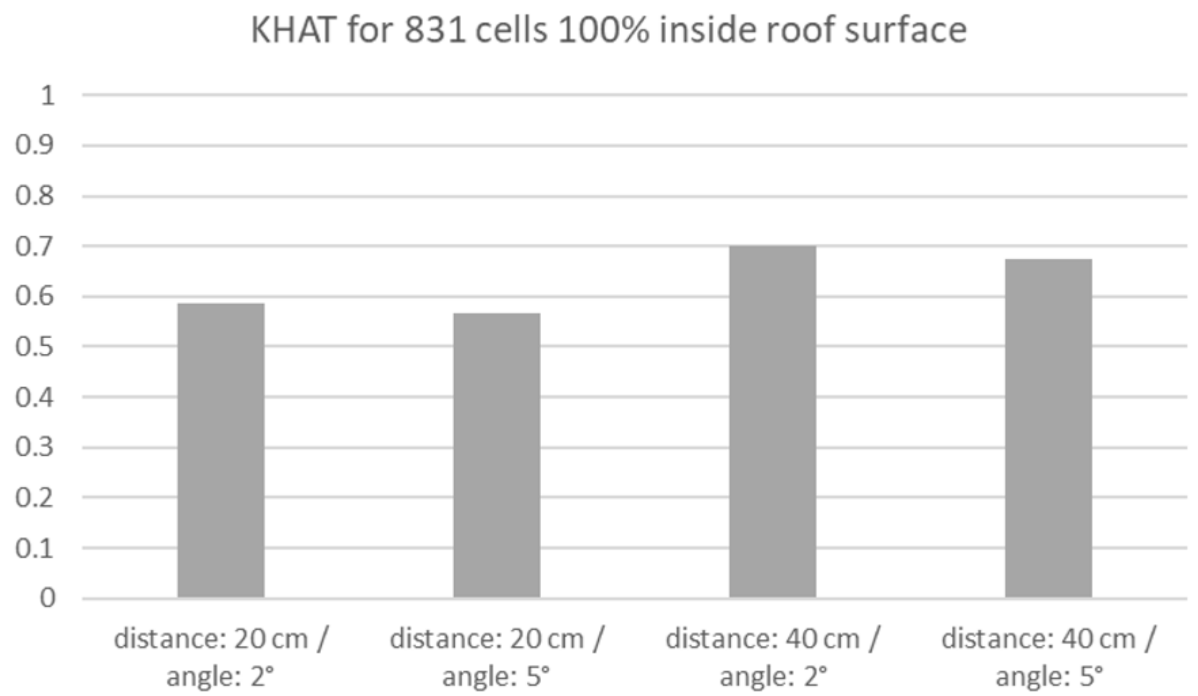
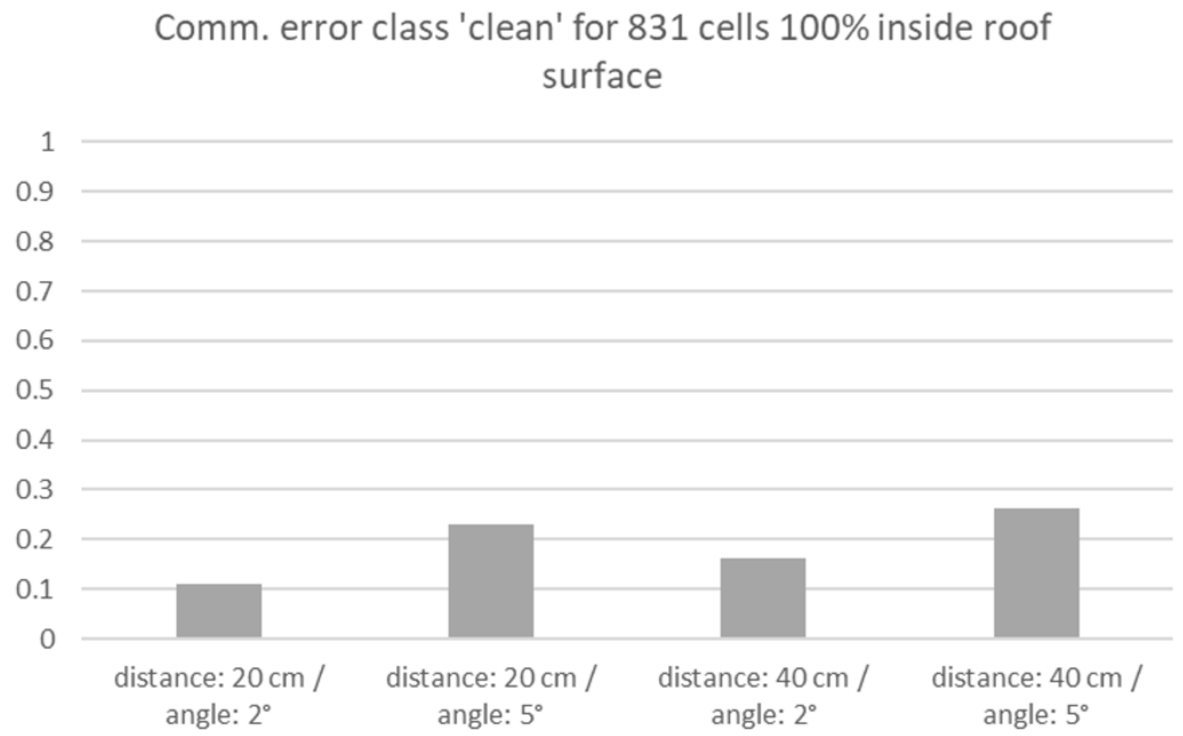
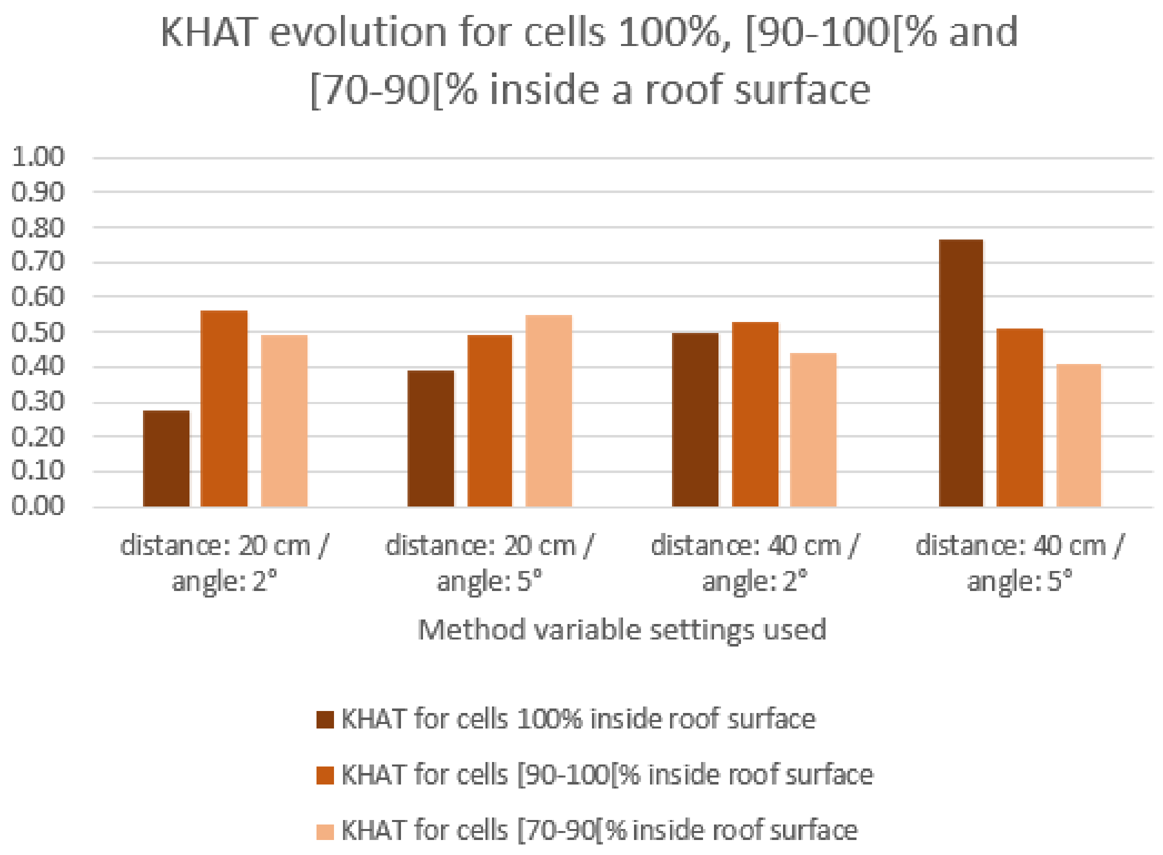
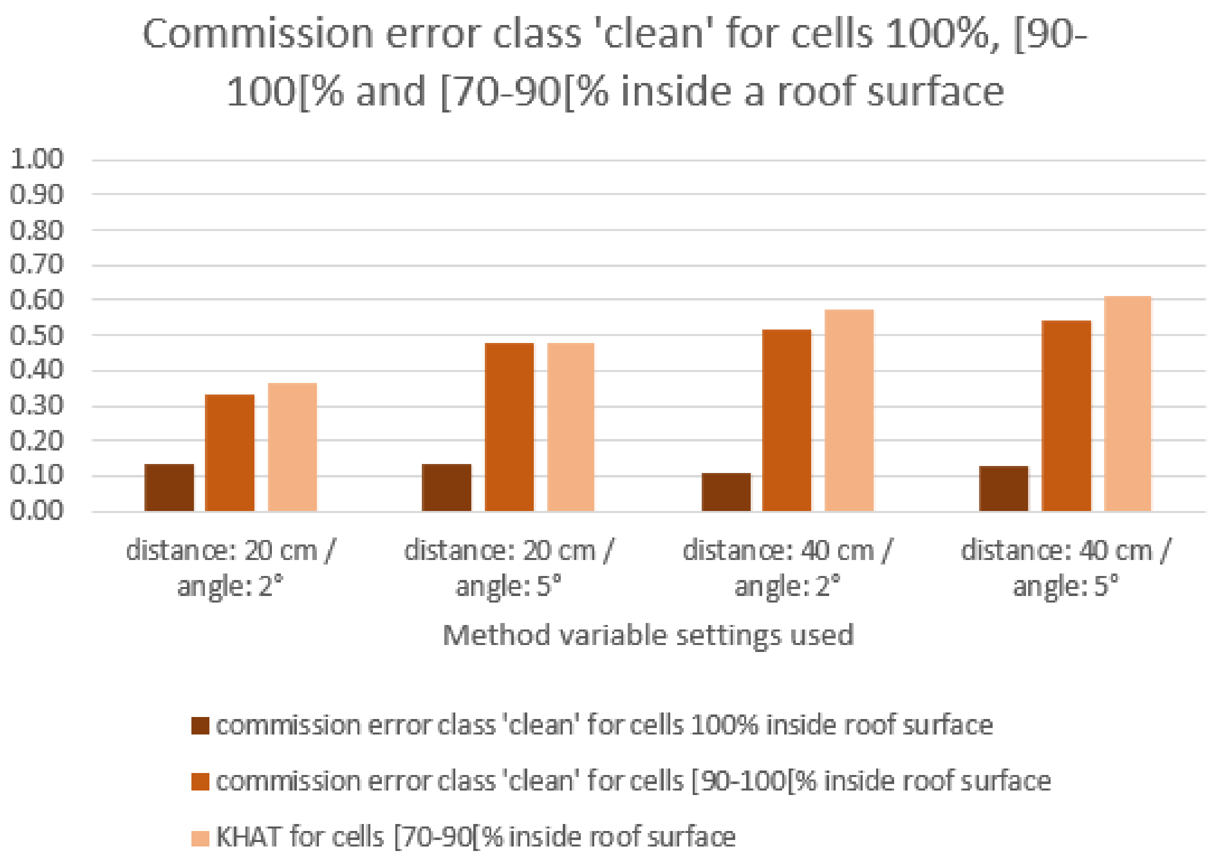
Level B (nominal & cells 100% inside roof)





Level C (nominal & cells ≥70% inside roof)





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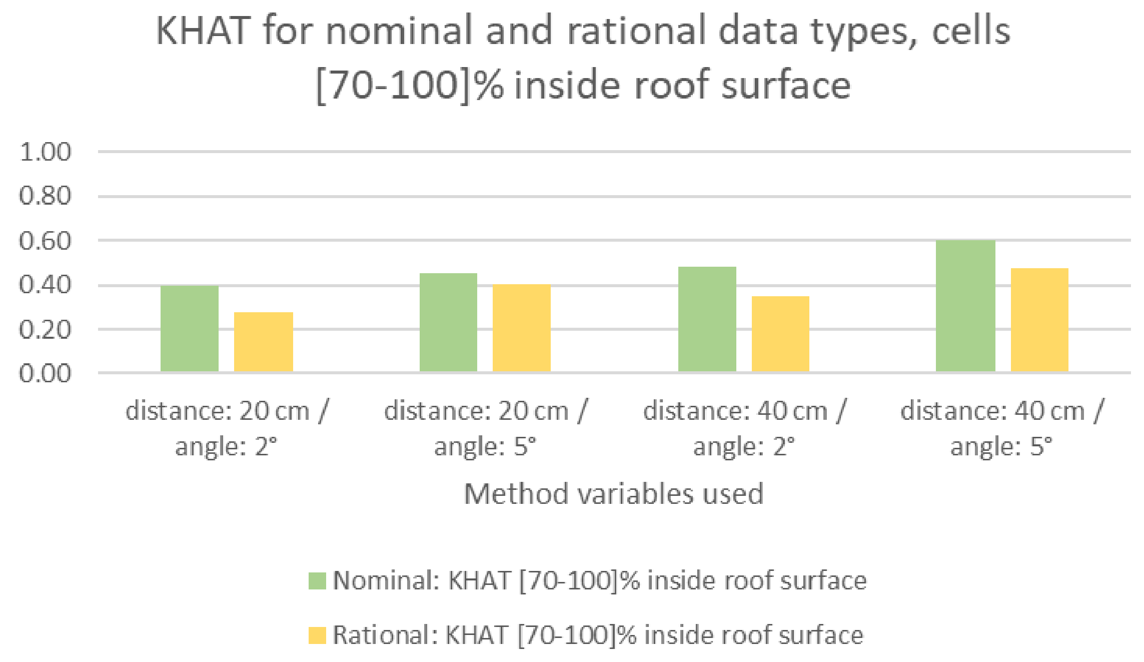
Outcome

	Approach 1: ‘geographer’	**Approach 2: ‘goldminer’**
Aim	<u>Quantify</u> materials	<u>Identify</u> material presence
Strategy	Maximum overall accuracy/khat	Avoid commission errors
Recommendation	Loose settings (e.g. 40cm)	Strict settings (e.g 20cm, 2°)
Limitation	Not suited for small quantities	Small surfaces might be missed

Level D (rational & cells ≥70% inside roof)



[20cm, 2 degrees] accuracy of deviation cleanliness in %					
	truth				
	100%	[90-100[%	[70-90[%	<70%	total
100%	30	9	2	0	41
[90-100[%	25	48	11	0	84
[70-90[%	9	62	54	3	128
<70%	16	5	32	22	75
total	80	124	99	25	328

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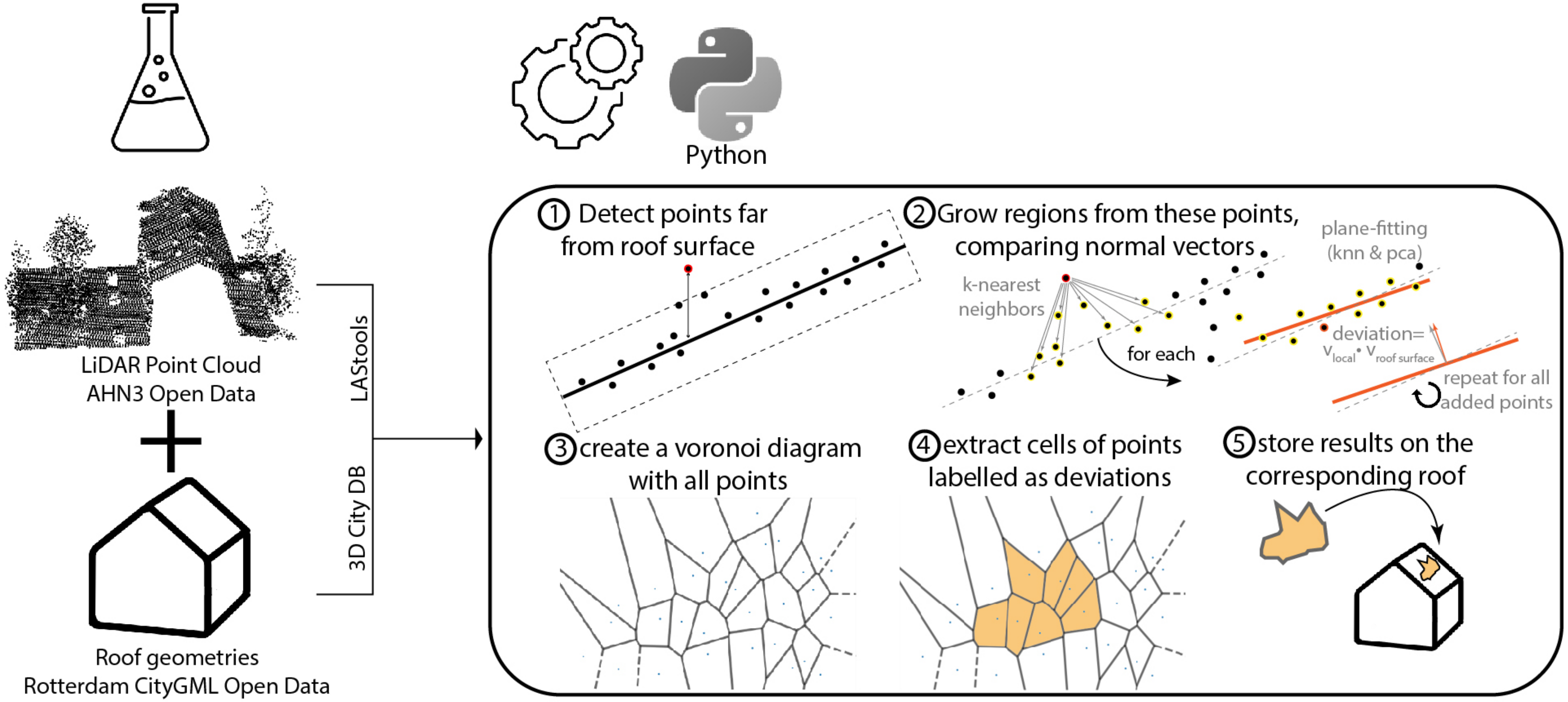
IV. Conclusions

Research questions

1. Which method is suitable to 'identify' deviations of LiDAR point clouds compared to LOD2?

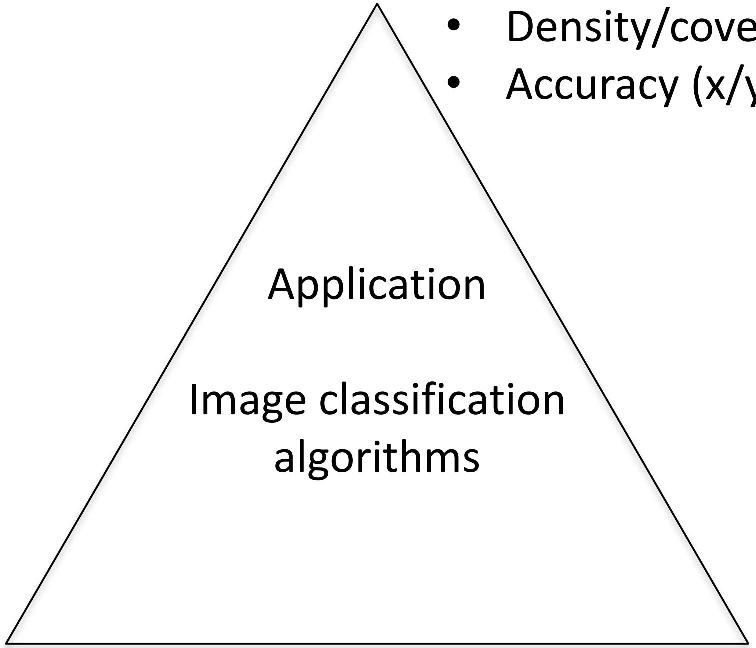


Research questions

2. What are the requirements with regard to CityGML LOD2, LiDAR point clouds and hyperspectral imagery data?

<u>LiDAR point cloud</u>

- Density/coverage
- Accuracy (x/y and z)



<u>Hyperspectral imagery</u>

- Resolution
- Accuracy (x/y)

<u>3D city model</u>

- LOD ≥ 2
- Accuracy (x/y and z)
- Input and output quality

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Research questions

3. To which extent does such a method support the identification of clean pixels?

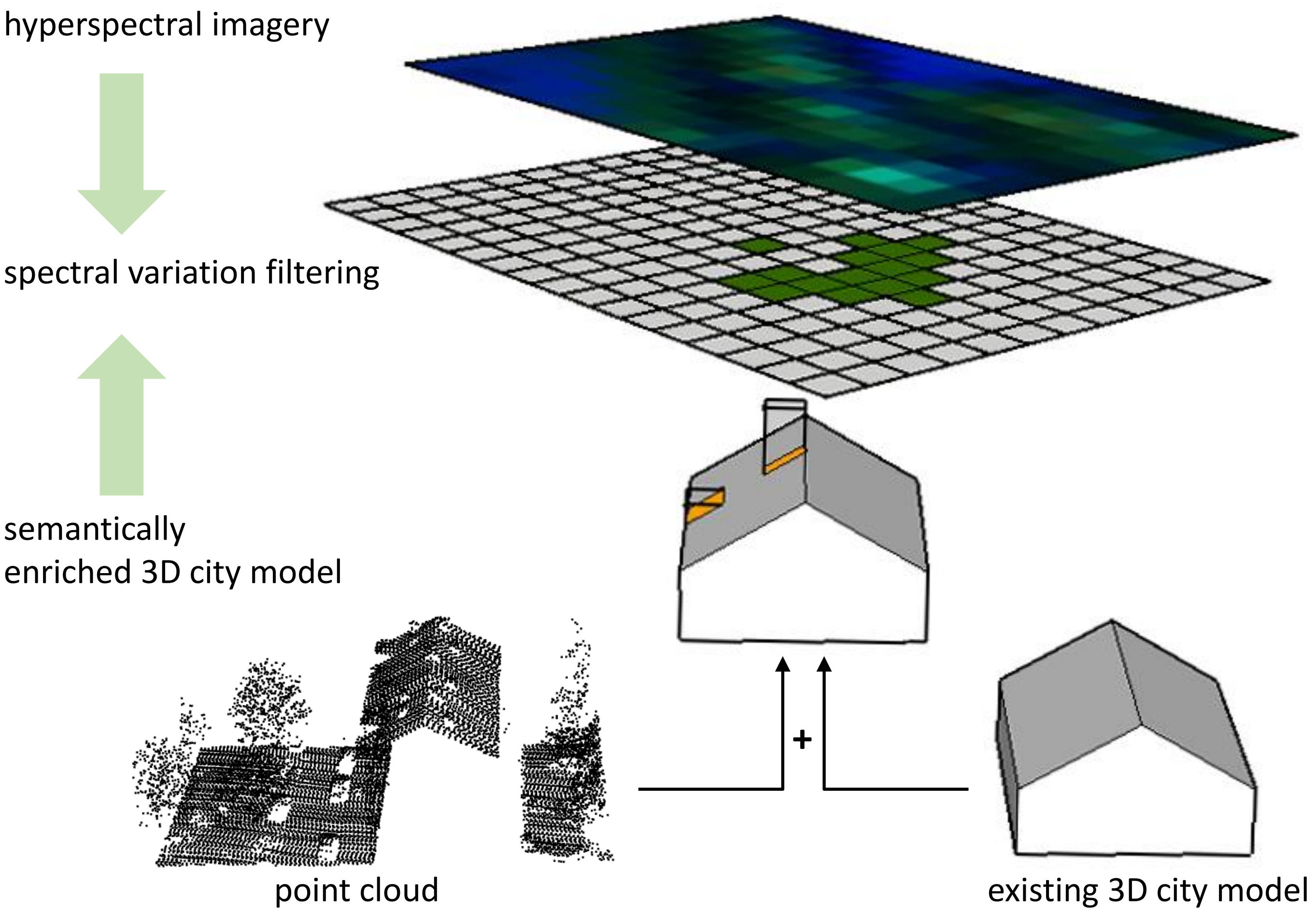
- Validation: 40%<KHAT<70% - ‘moderate’ agreement
- Commission errors: as low as 10%
- Limitations: sample, ground ‘truth’

Main research question

How can a CityGML LOD2 model be semantically enriched in order to improve material classification performed on roof surfaces?

- ‘Semantic’ enrichment, thus 2D projection in LOD2 is sufficient
- Potential is present, but improvements possible
- Variant: count points in cell directly
- Focus was on overall ‘completeness’ & clean cells
- Out of scope: shadowed pixel identification, orthocorrection

Relevance


hyperspectral imagery
spectral variation filtering
semantically
enriched 3D city model
+
point cloud
existing 3D city model

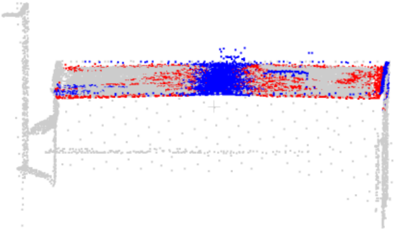
Recommendations to data suppliers

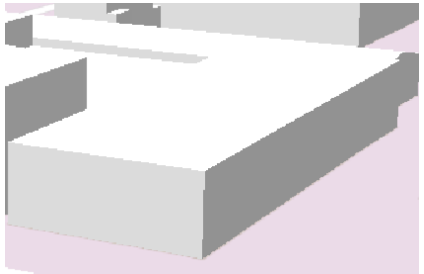
- LiDAR point clouds:
  - provide more **metadata** on classification algorithms

- CityGML Standard
  - roof **edges**
  - storage of **materials**

Recommendations to data suppliers

- 3D model of Rotterdam
  - make **specifications open**
  - accuracy indicators (e.g. ‘**flatness**’ tolerance)





  - quality information (e.g. **detail coherence**)

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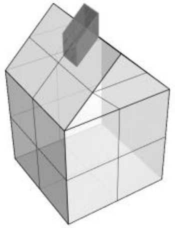
Future research

- Automated quality checks
- Shadow estimation and solar potential
- LOD3 model production



“Don’t reinvent the wheel,
but shuffle the puzzle!”

Thank you very much!

Picture credits

#2
- https://en.wikipedia.org/wiki/Hashima_Island#/media/File:Nagasaki_Hashima_01.png

#3
- https://upload.wikimedia.org/wikipedia/commons/f/f8/Erasmusbrug_seen_from_Euromast.jpg

#6
- https://upload.wikimedia.org/wikipedia/commons/f/f4/Bitumen-Schwei%C3%9FbahnenFl%C3%A4mmenAufbringen_03.jpg

#7
- Tanikawa, H., & Hashimoto, S. (2009). Urban stock over time: spatial material stock analysis using 4d-GIS. *Building Research & Information*, *37*(5-6), 483-502.

#8
- https://en.wikipedia.org/wiki/Human_eye#/media/File:Human_eye_with_blood_vessels.jpg
- https://en.wikipedia.org/wiki/Spectral_sensitivity#/media/File:Cones_SMJ2_E.svg
- https://commons.wikimedia.org/wiki/File:Diretmus_argenteus2.jpg
- Musilova, Z., Cortesi, F., Matschiner, M., Davies, W. I., Patel, J. S., Stieb, S. M., ... & Mountford, J. K. (2019). Vision using multiple distinct rod opsins in deep-sea fishes. *Science*, *364*(6440), 588-592.

#9
- https://www.gfz-potsdam.de/en/section/remote-sensing-and-geoinformatics/projects/enmap/enmap-requirements-and-technical-outline/

#10
- Heiden, U., Segl, K., Roessner, S., & Kaufmann, H. (2007). Determination of robust spectral features for identification of urban surface materials in hyperspectral remote sensing data. *Remote Sensing of Environment*, *111*(4), 537-552.

#11, 13, 43
- APEX flight above Rotterdam

Picture credits

#15
- https://www.goodfreephotos.com/albums/netherlands/rotterdam/city-view-of-rotterdam-netherlands.jpg

#16
- https://www.flickr.com/photos/victortsu/5175960711/in/photostream/

#17
- https://3drotterdam.nl/#/

#18
- Gröger, G., Kolbe, T. H., Nagel, C., & Häfele, K. H. (2012). OGC city geography markup language (CityGML) encoding standard.

#22
- https://www.tern.org.au/Newsletter-2014-Jun-Airborne-Infrastructure-pg29230.html

#24
- https://commons.wikimedia.org/wiki/File:Chimney_red.jpg

#28
- https://3drotterdam.nl/#/

#39,40,45-48, 51, 52
- PDOK luchtfotos

#50
- Google earth

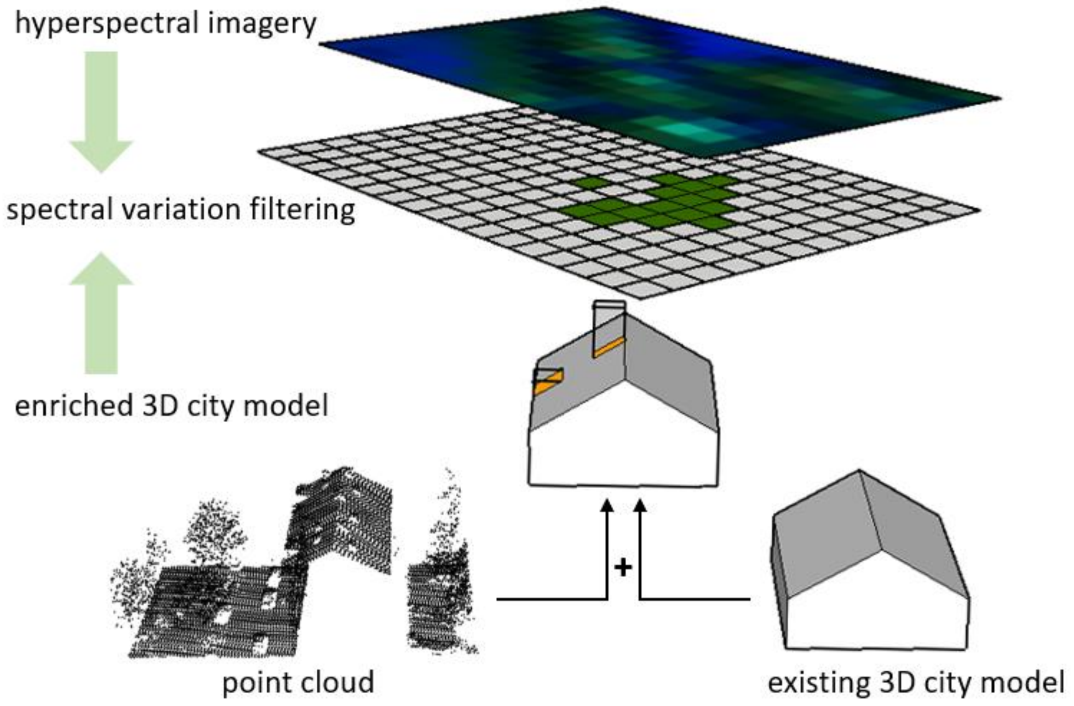
#69
- https://www.maxpixel.net/Unfinished-Puzzle-Unresolved-Chaos-Mess-55877

3D City Models in the context of Urban Mining

Final Presentation

Pablo Ruben – tutors: Rusnė Šilerytė and Giorgio Agugiaro

Co-reader: Kaixuan Zhou – Delegate: Regina Bokel



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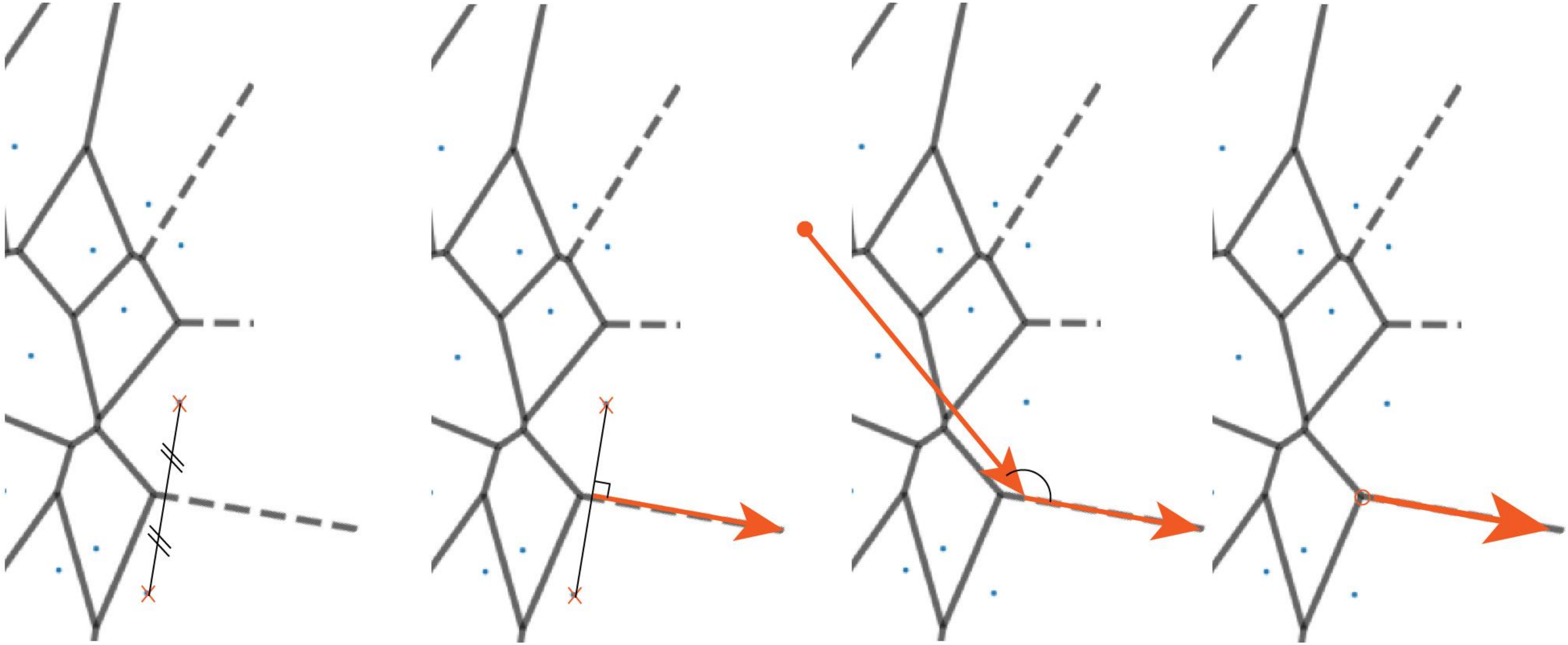
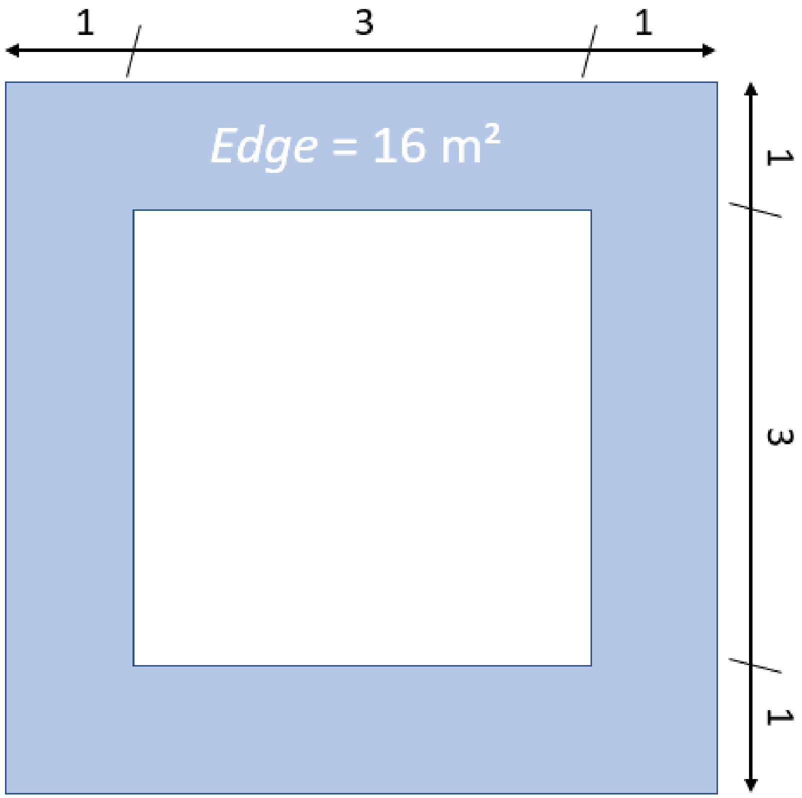
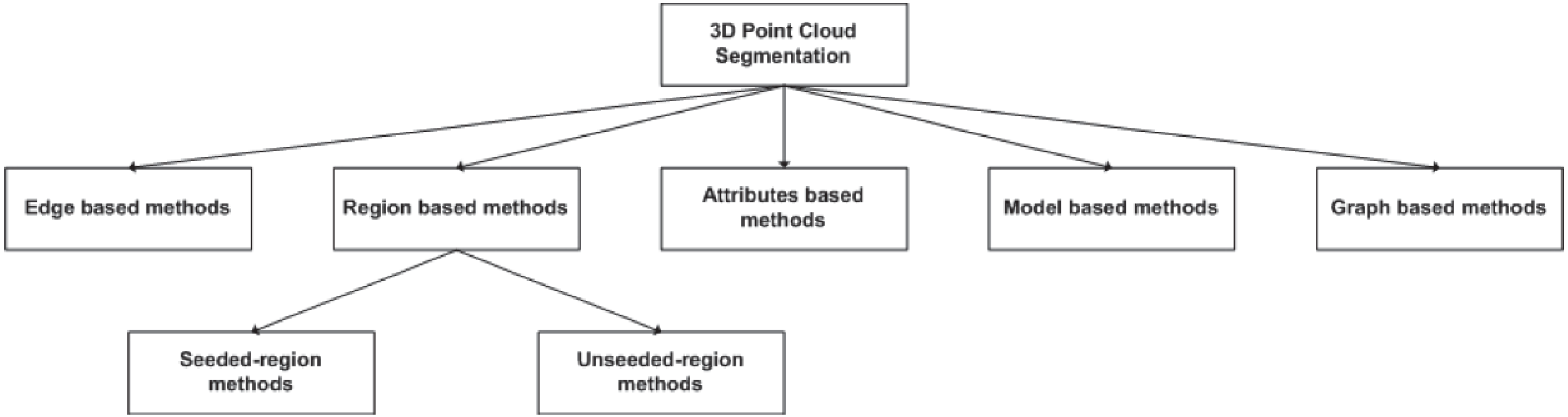


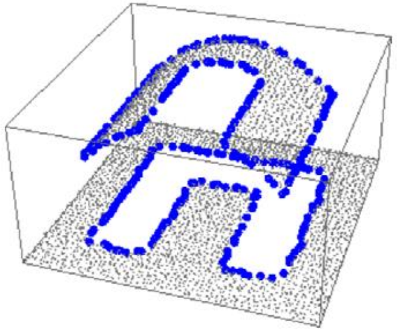
Roof edges



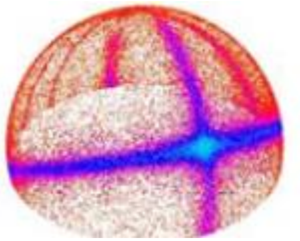
Taxonomy of point cloud segmentation



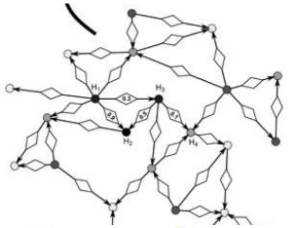
Edge-based
“Boundaries first – surfaces second”



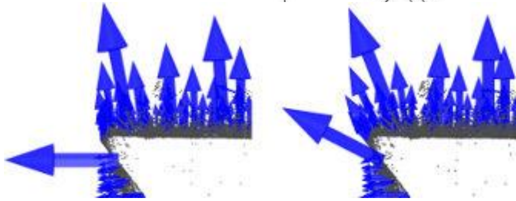
Model-based
“Check if a plane, cylinder or sphere fits”



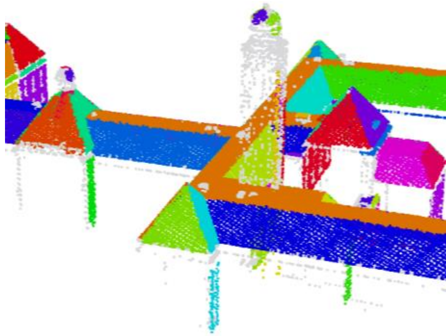
Graph-based
“Generate neighbourhoods and identify weak connections”



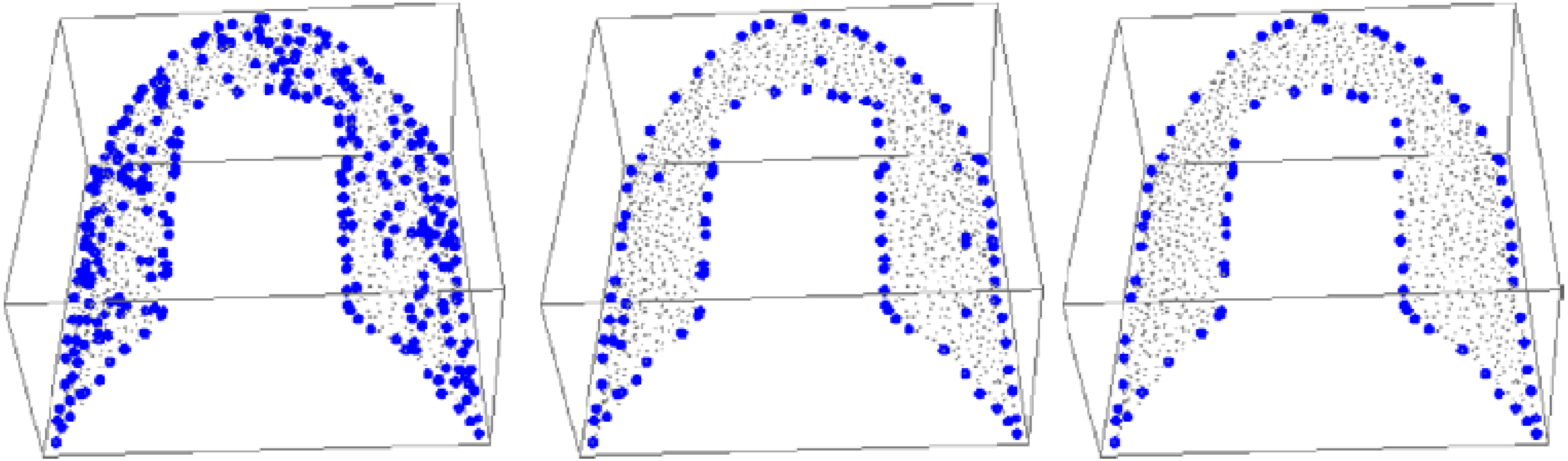
Attribute-based
“Compute attributes from data dimensions - use them to classify”



Region-based
“Points with similar neighbours belong together”



Wang & Shan 2009; https://3d.bk.tudelft.nl/courses/geo1015/hw/04/
http://pointclouds.org/documentation/tutorials/normal_estimation.php
Vosselman et al. 2004;https://www.sciencedirect.com/science/article/pii/S0924271615000544#f0085



n=5
288 boundary points

n=7
103 boundary points

n=9
80 boundary points

Wang & Shan 2009