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iLab @ HKURBANlab
the urban big data lab

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Semantic Enrichment for Rooftop Modeling using Aerial LiDAR Reflectance

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Outline

1 Background

2 Semantic Enrichment using LiDAR

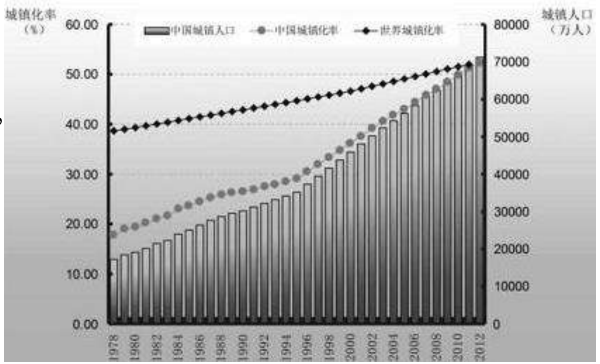
3 Discussion

Section 1

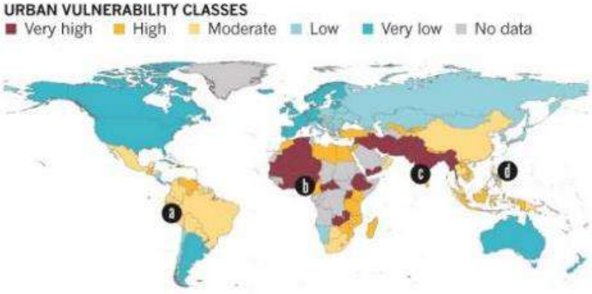
BACKGROUND

1.1 Background

- Global urbanization
  - By 2050, 65% world's population will live in cities (WHO, 2015)
  - Irreversible; Even faster in China
- Leads to urban vulnerability (a.k.a. 'city diseases')
  - 'Dead' space/landscape, low familiarity with surroundings,
  - Poor waste treatment, environment (air, water) pollution,
  - Heritage destruction, aging town blocks, inefficient traffic,
  - Disasters (earthquake, climate change), resource crisis, …
- Demands smarter and more resilient development
  - (a) Smarter decision supports in multiple disciplines
  - (b) On basis of accurate, timely urban semantics



China's and global urbanization rates
source: gov.cn

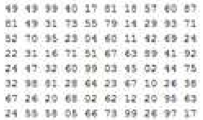


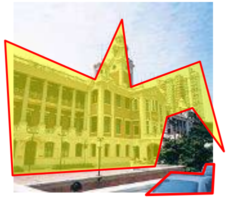
Global urban vulnerability level (Birkmann et al, 2016) *source: nature.com*

1.2 Urban semantics

- Why semantics from signals? (Rowley & Hartley, 2017)
  - Answering interrogative questions (*what, who, where, when*)
  - Enabling automated reasoning / checking
  - Abstracted, processed from data and signals
- Types of urban semantics
  - Geometric: Dimension, location, rotation, color, …
  - Non-geometric facts: Function, materials, history, owner, …
  - Instructions (how-to): Manufacturing, installation, access, …
- Common databases / interfaces
  - BIM: building information model
  - GIS: geographic information system

Data: Digital pixels (0~255 R, G, B)





Semantics: Car, building, tree, …

1.3 Motivation and aims

- LiDAR data
  - Light Detection and Ranging
    - Different devices: total station, vehicle-borne, drone
  - Aerial LiDAR from drones / fixed-wing aircraft
    - Large-scale
    - Uniform point density (4~1,000 pts/m^2)
    - Laser reflectance (received photons from object surface)
    - Rooftop details
- Semantic enrichment using LiDAR ?
  - Geometry
  - Non-geometric, e.g., green roof
  - topology

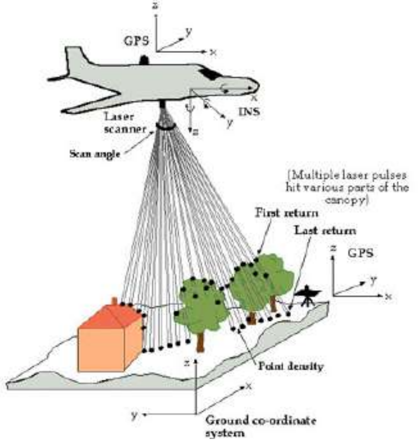
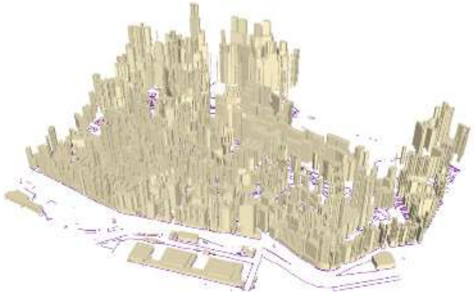
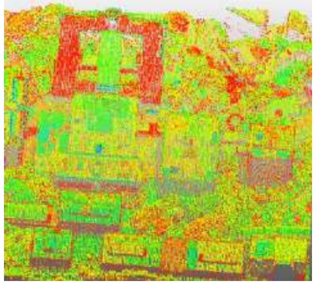


Illustration of aerial LiDAR



2.5D “block” map



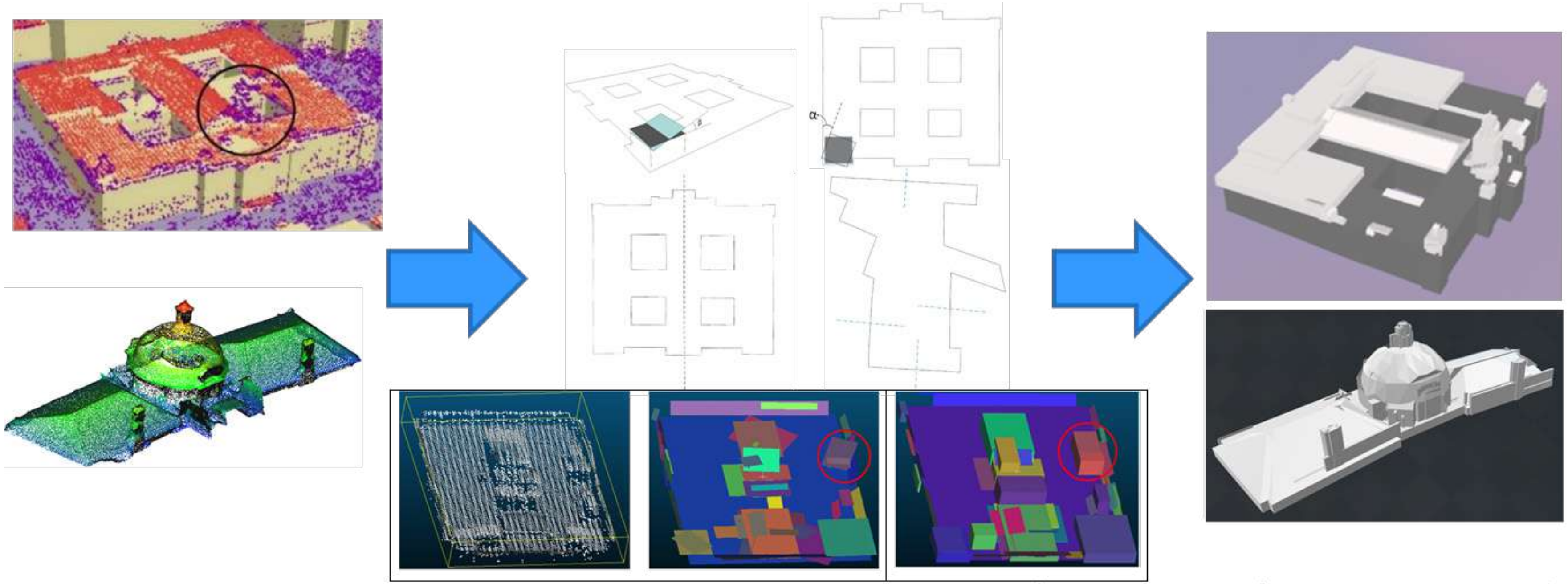
Infrared laser reflectance (warmer color = less received)

Section 2

SEMANTIC ENRICHMENT USING LIDAR

2.1 Semantic enrichment: Geometry

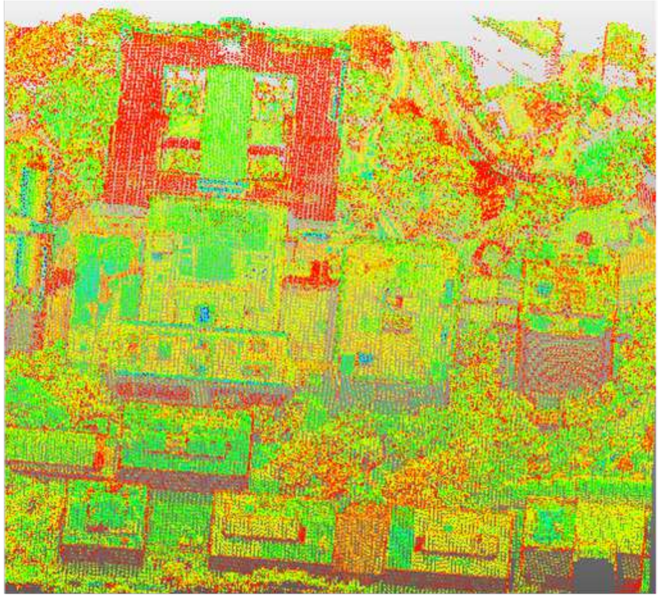
◈ LiDAR → RANSAC → rectification → LoD2 model (Chen et al. 2018)



(Language: C++; Data formats: COLLADA, Las, csv)

2.2 Semantic enrichment: Green roofs (1/3)

- Inputs of a pilot area: (a) LiDAR
  - Intermediate input: (b) Rooftop elements from geometric modeling (previous page)



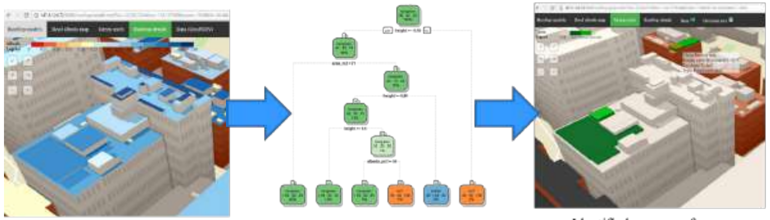
(a) Input LiDAR point cloud of 55,000m² pilot area (298,126 points), where color indicates the laser reflectance (warmer = less)

(b) 158 reconstructed rooftop elements using [2], where color indicates average reflectance (warmer = less)

2.2 Semantic enrichment: Green roofs (2/3)

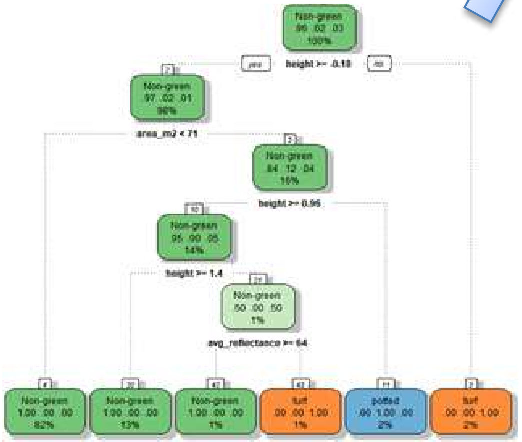
- A supervised learning method
  - Decision tree (*ctree* on R)
    - Human readable result
  - Label: Potted, turf, non-green

Label	Avg. reflectance (%)	Top area (m^2)	height (m)
Non-green	54.5	123.6	2.47
Non-green	53.6	66.2	2.39
Non-green	36.7	400.5	3.53
Non-green	34.6	58.6	3.52
Non-green	50.8	12.5	2.84
Non-green	29.5	5.0	0.80
Non-green	30.5	9.5	0.72
Non-green	33.5	29.1	0.63
Non-green	28.1	5.3	0.72
potted	35.1	74.0	0.35
turf	54.9	61.9	–0.35
turf	53.7	529.3	–0.34
…	….	…	…
turf	50.4	74. 4	–0.39


Generated rooftop objects from point clouds

Identified green roof areas by machine learning

(Language: C++, R; Data formats: GeoJSON, Las, csv)



2.2 Semantic enrichment: Green roofs (3/3)

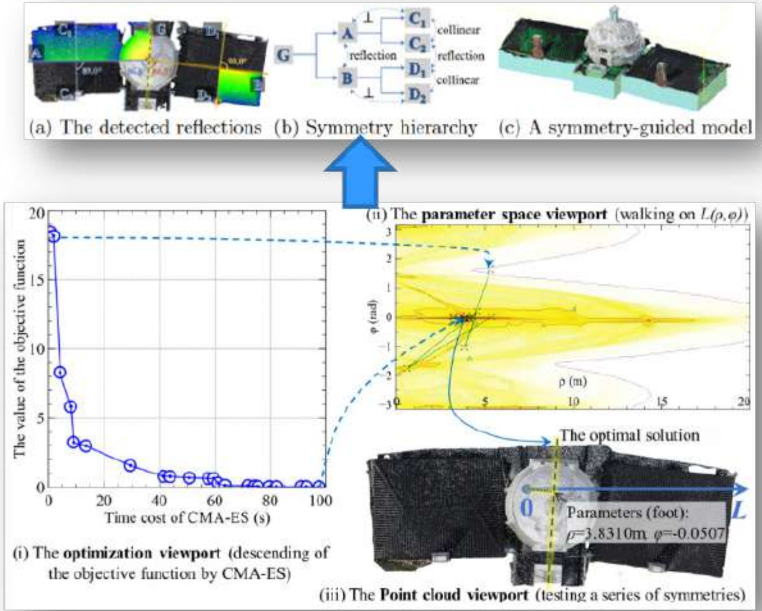
- Output: (a) green roof prediction
- Validation: (b) screenshot of Google Earth

(a) Prediction results (dark green = turf, light green = potted) (b) Screenshot of the mesh models on Google Maps

2.3 Semantic enrichment: Symmetry

- 3D point cloud → symmetry hierarchy (Xue et al., 2019)
  - A knowledge discovery tool for further 3D modeling

- Time = 98.6s
- PCR = 93.7%



Section 3

DISCUSSION

3.1 Discussion

- A pilot study of predicting rooftop materials
  - From LiDAR
    - Using geometric features (from LiDAR)
    - Using laser reflectance (from LiDAR)
  - For smart city
- Pros
  - Automated
  - Data readiness
- Cons
  - A small-scale test
  - No benchmarking against other methods
    - More supervised, unsupervised, reinforcement learning methods

References

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Thank you !

Q&A time