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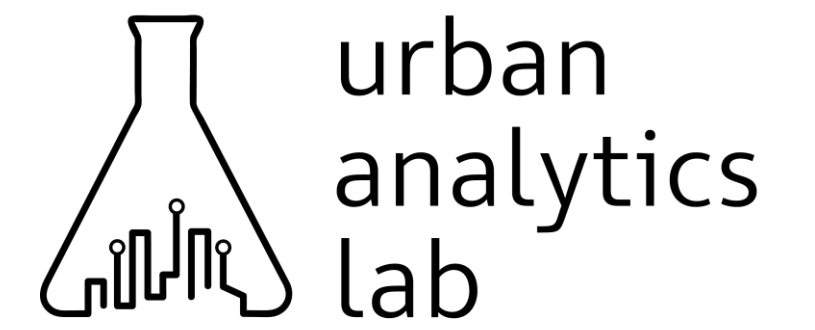
urban
analytics
lab

Research Insights and Perspectives of Urban Digital Twins

Filip Biljecki
Assistant Professor
National University of Singapore
Urban Analytics Lab

This mosaic was formed using 5,720 street view images contributed by Mapillary and KartaView users.

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Urban informatics with a strong geospatial foundation

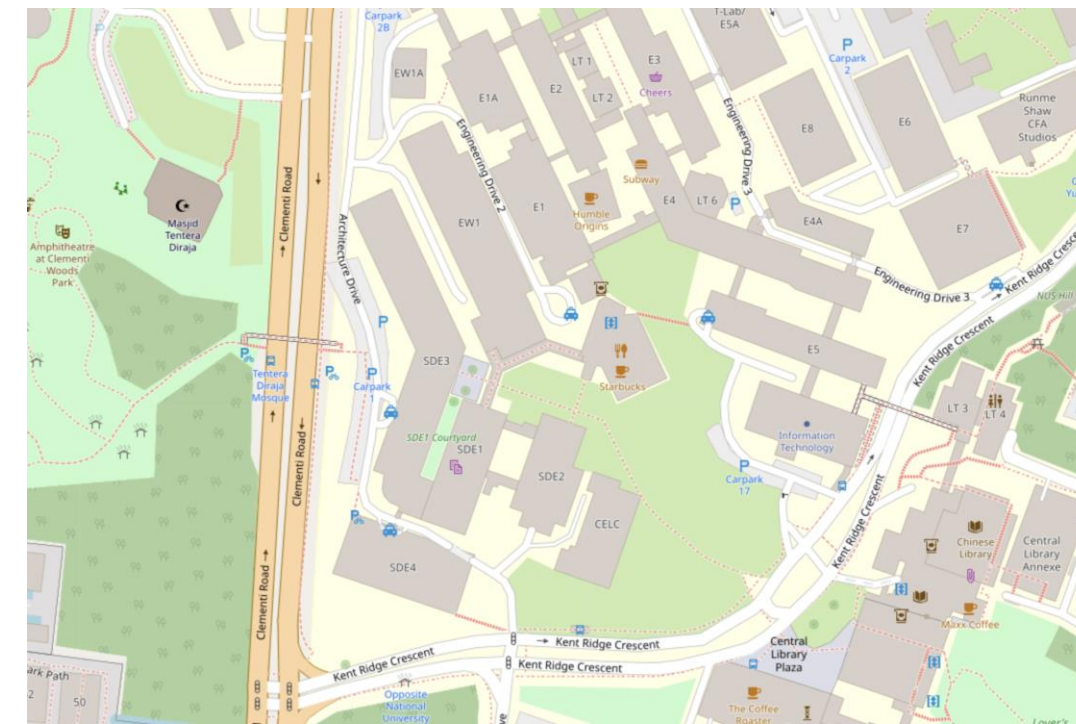
Research strands



Buildings / 3D GIS / DT



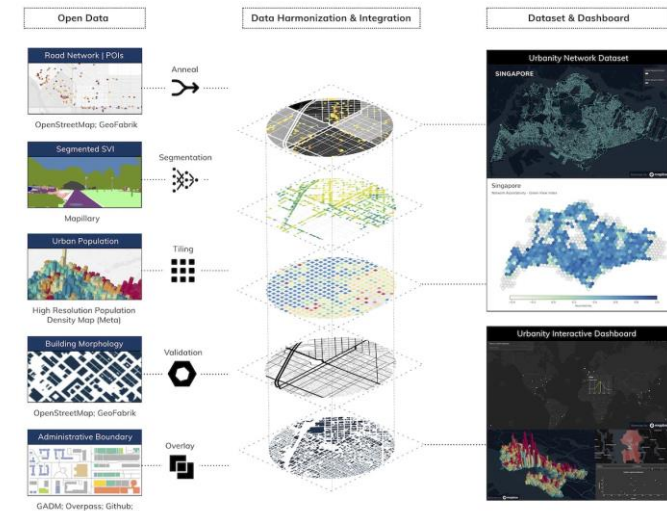
Street view imagery



VGI, spatial data quality



Some of our open-source software / open data



Global Building Morphology Indicators; Roofpedia; Urbanity

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Urban informatics with a strong geospatial foundation

Research strands

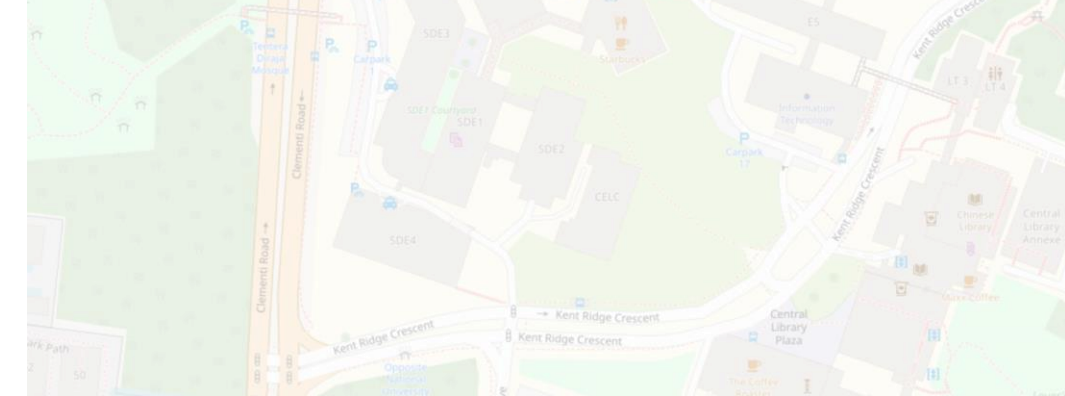


Buildings / 3D GIS / DT

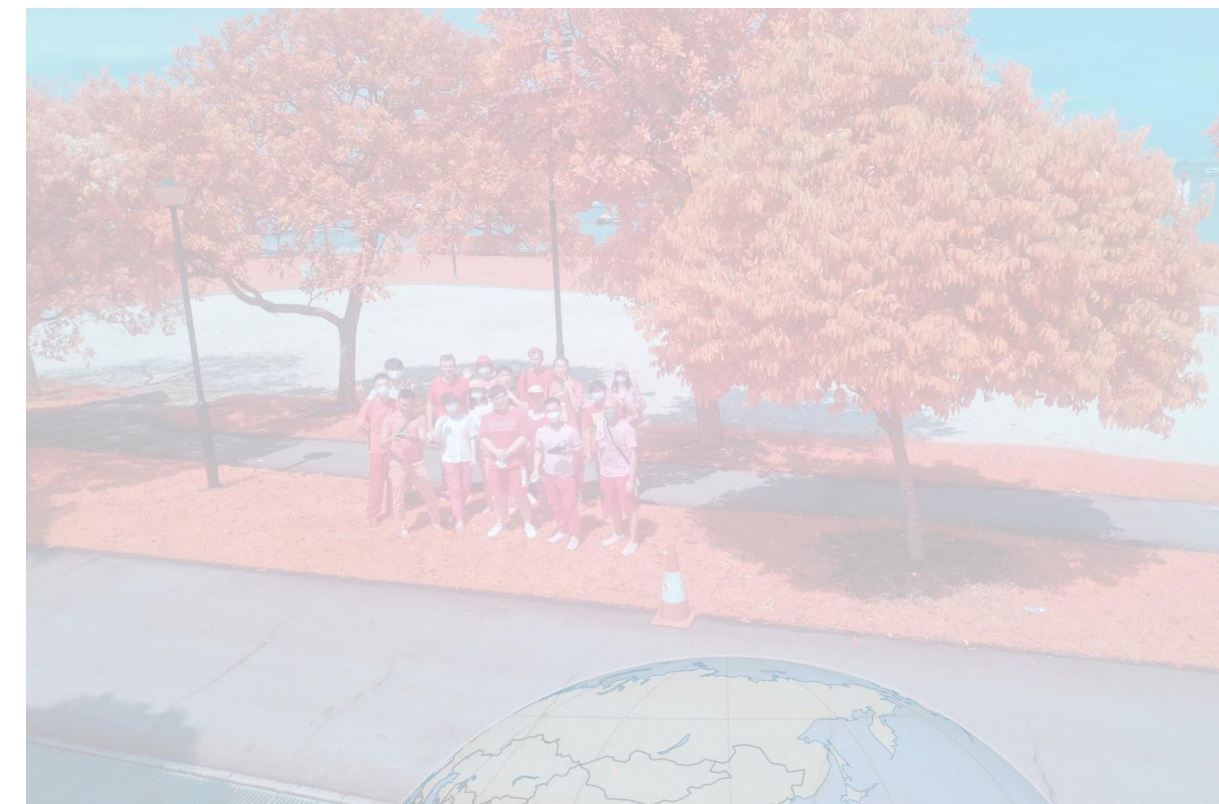
Data acquisition,
Data quality,
Data harmonisation



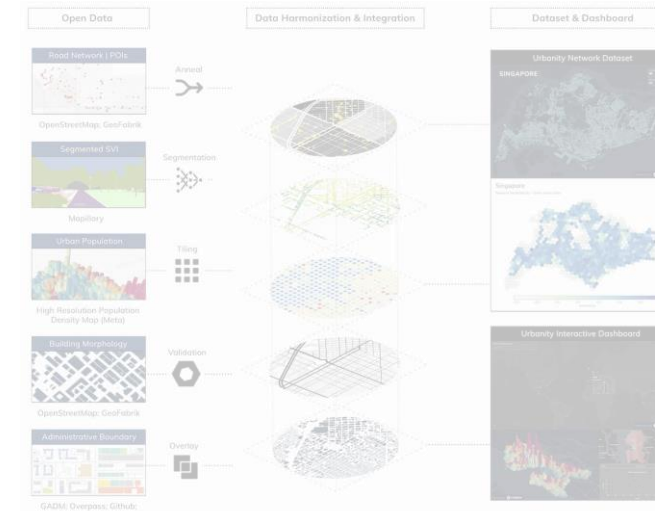
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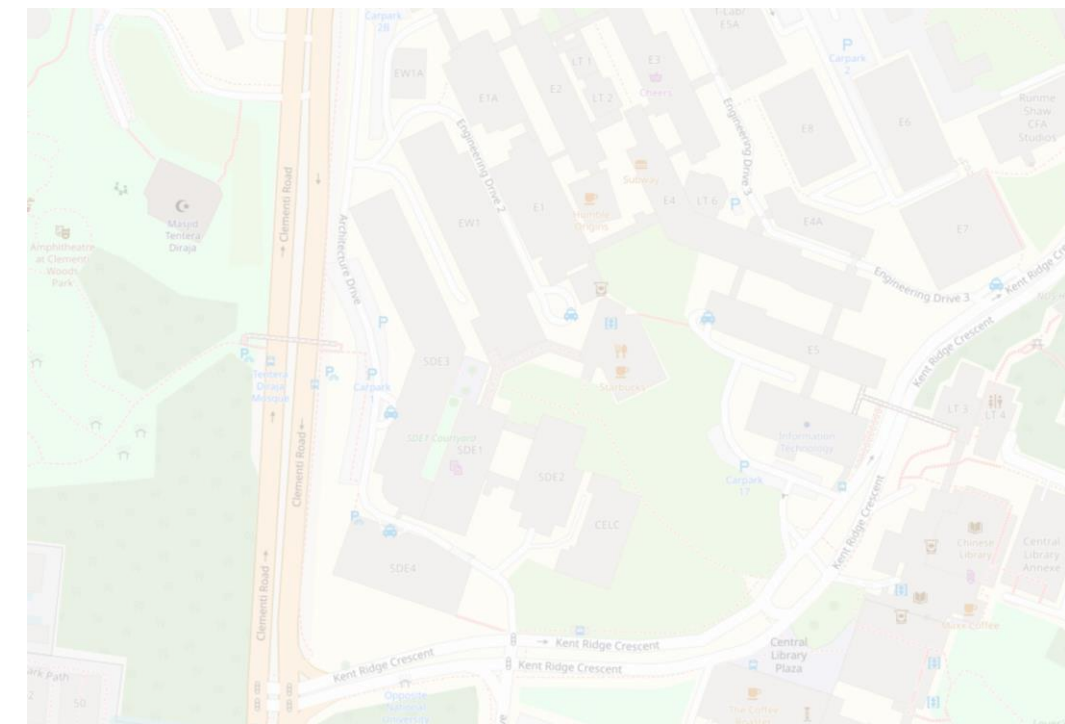
Research strands



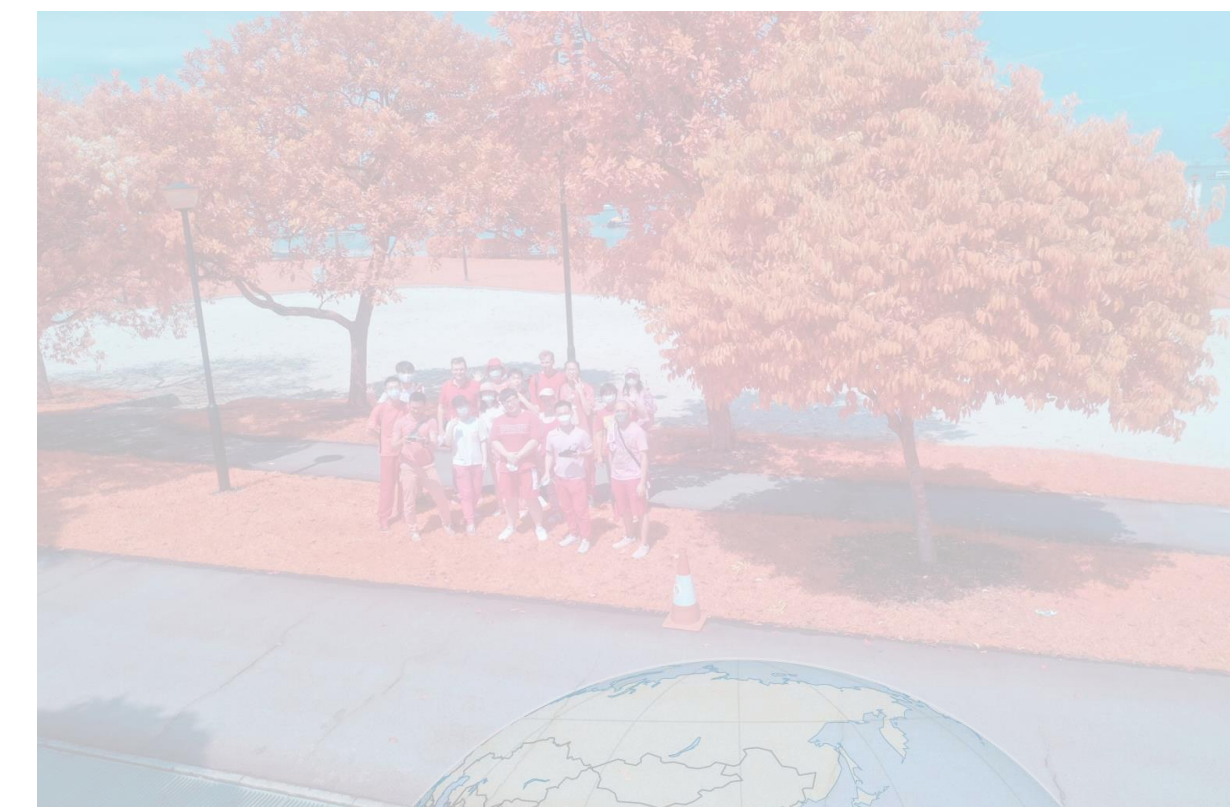
Buildings / 3D GIS / DT



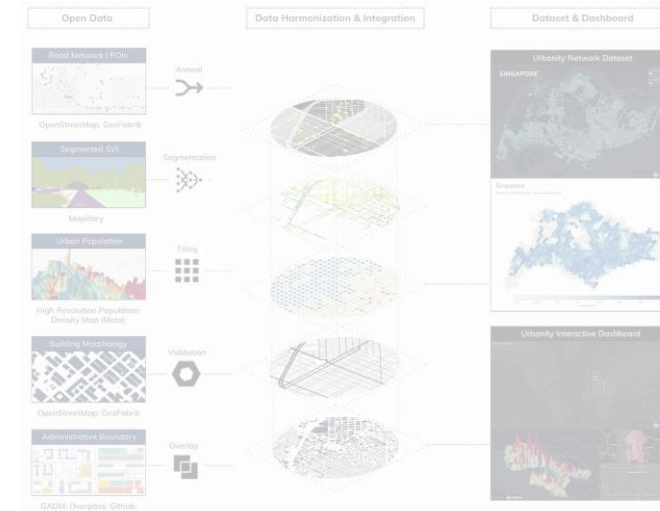
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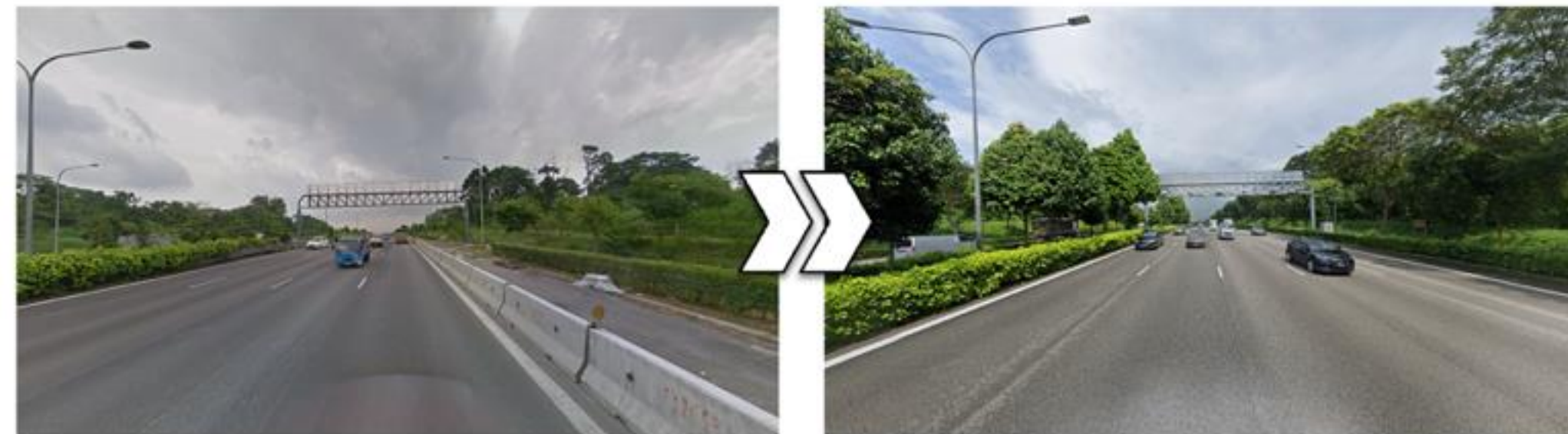
Global Building Morphology Indicators; Roofpedia; Urbanity

Change detection with SVI

Research by Xiucheng Liang & Zeyu Wang

Physical measures

Perceptual measures



Tampines (East)



Worsening
→
Pavement
Façade



Bronx (North)



Worsening
→
Pavement
Façade



Overall

Cluster 6



Cluster 4



Cluster 3



Cluster 5



Period 1 to 2

Cluster 6



Cluster 2



Cluster 1



Cluster 5



Period 2 to 3

Cluster 5



Cluster 1



Cluster 6



Cluster 3



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Urban informatics with a strong geospatial foundation

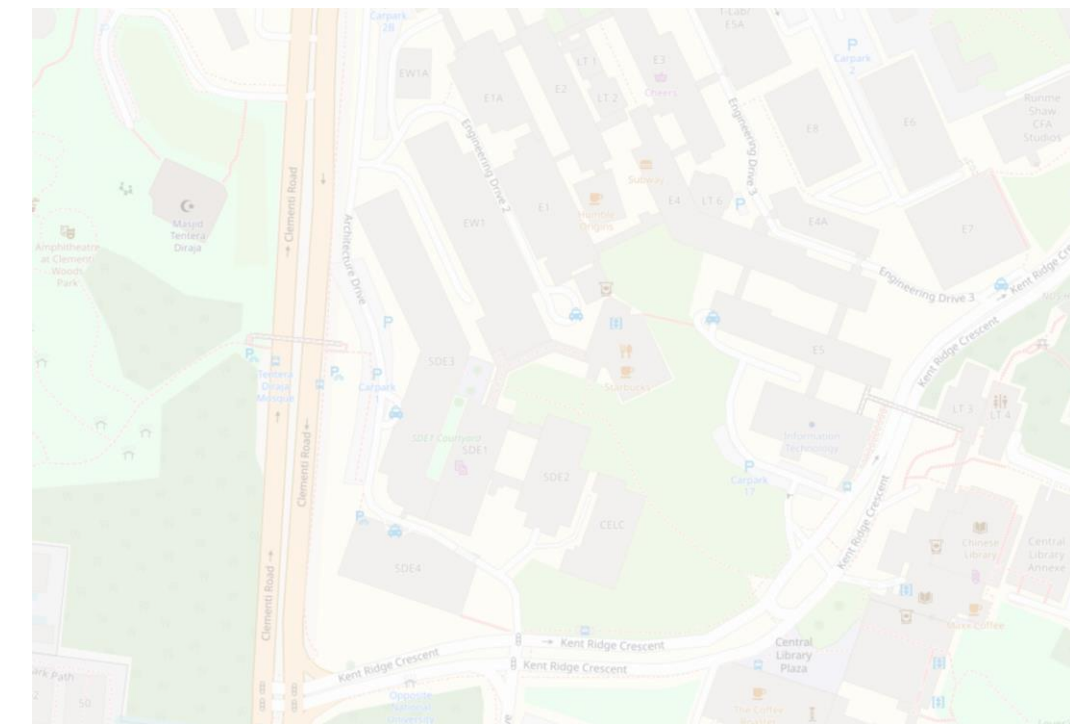
Research strands



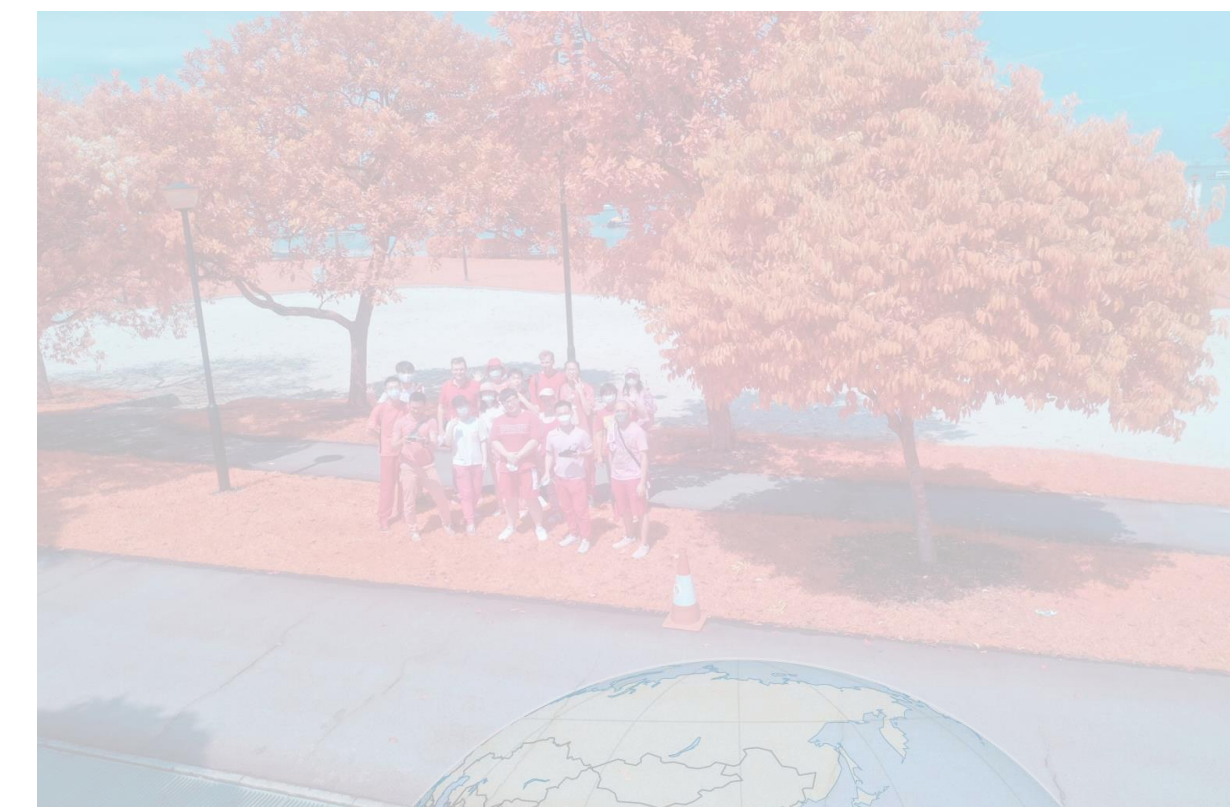
Buildings / 3D GIS / DT



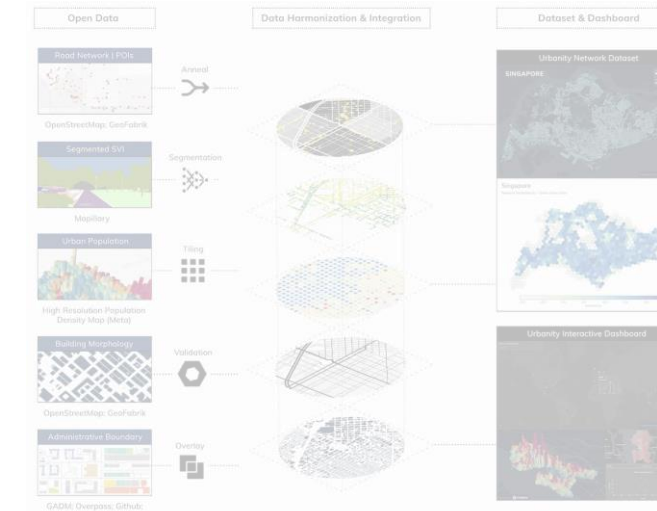
Street view imagery



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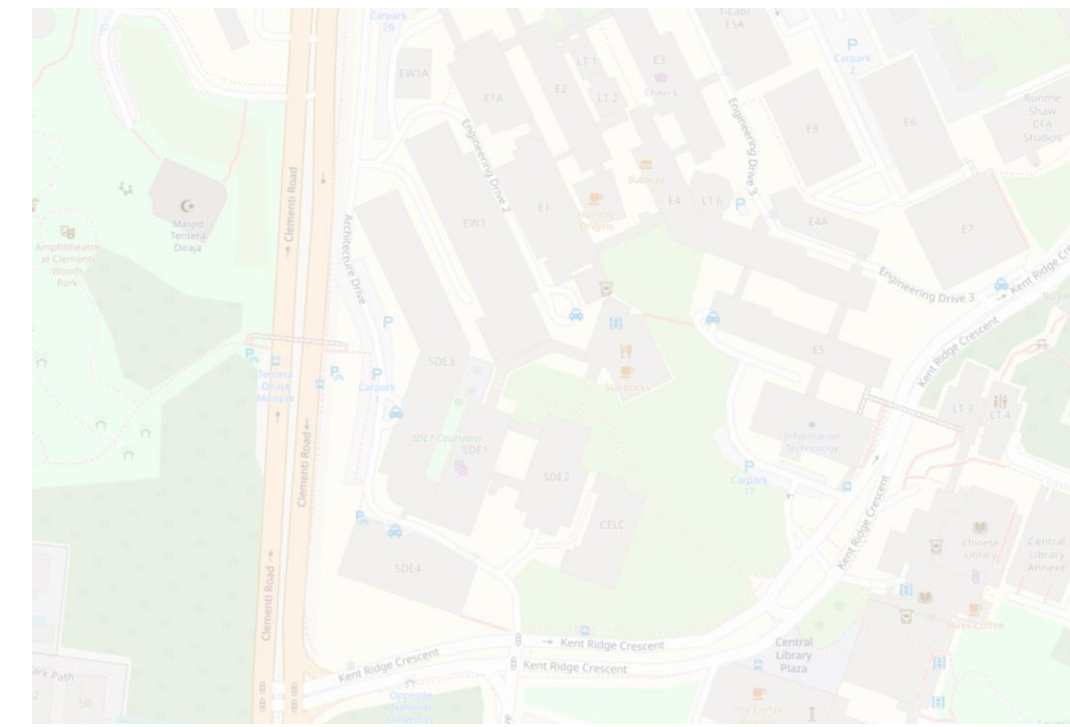
Research strands



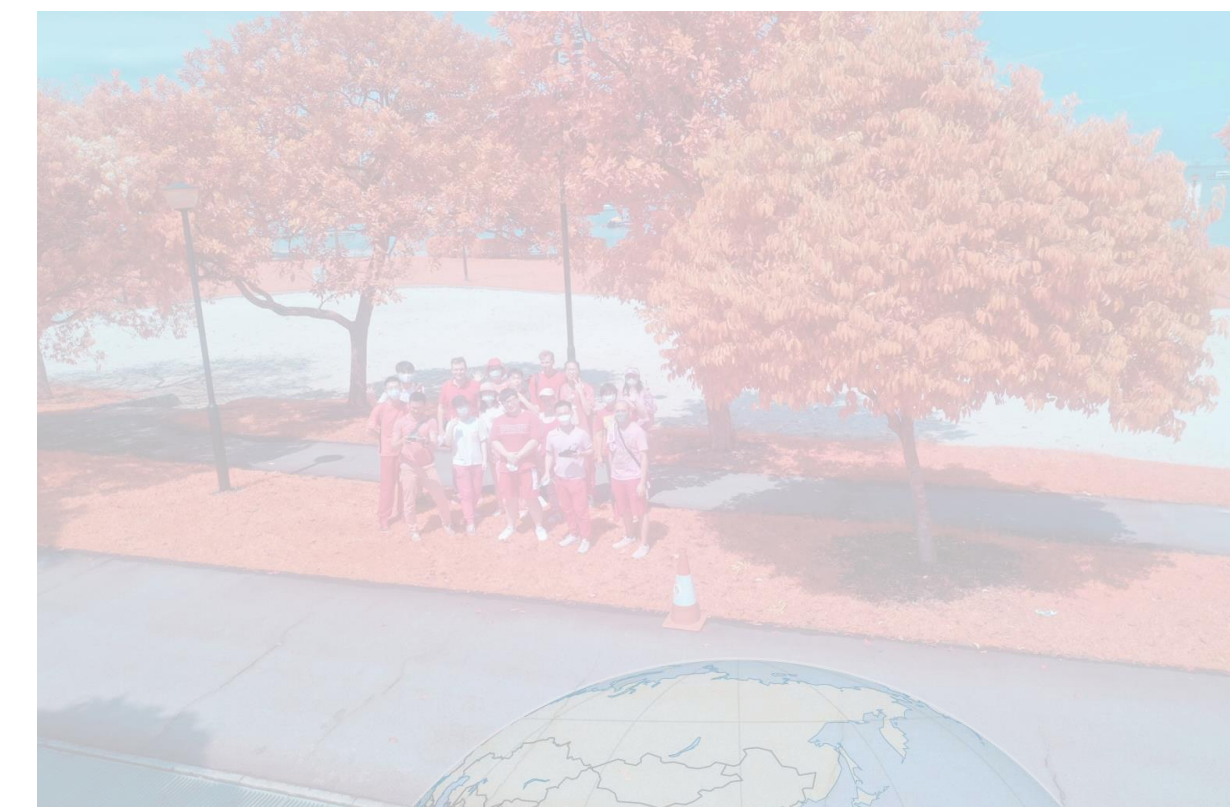
Buildings / 3D GIS / DT



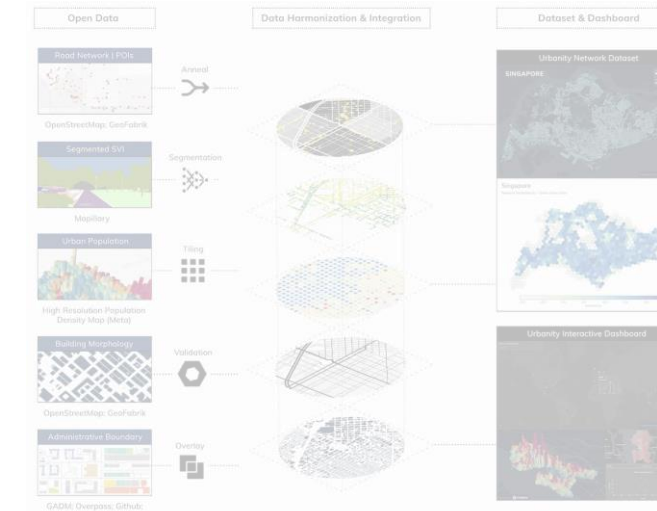
Street view imagery



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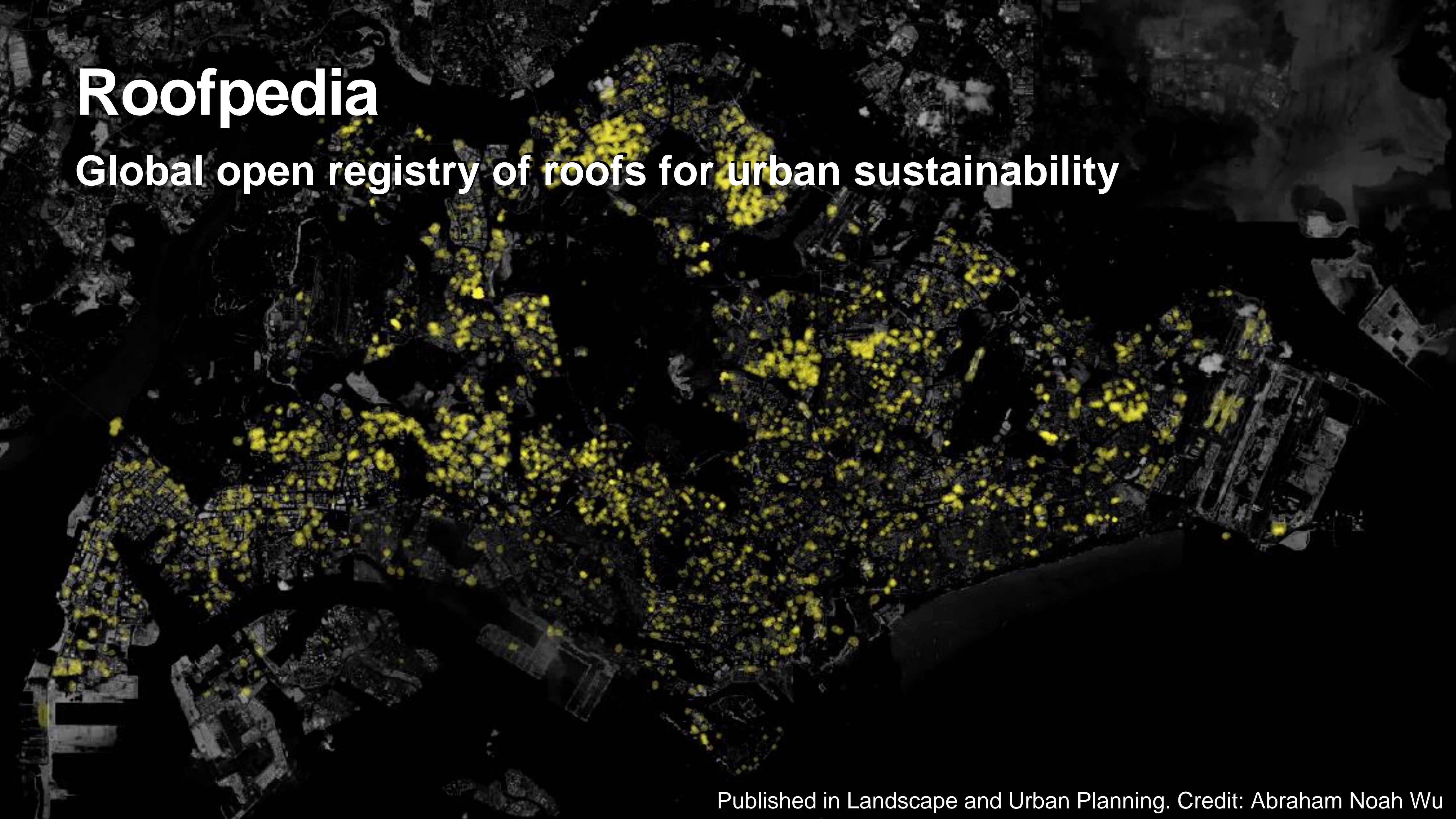
Roofpedia

Global open registry of roofs for urban sustainability



Roofpedia

Global open registry of roofs for urban sustainability



ROOFPEDIA

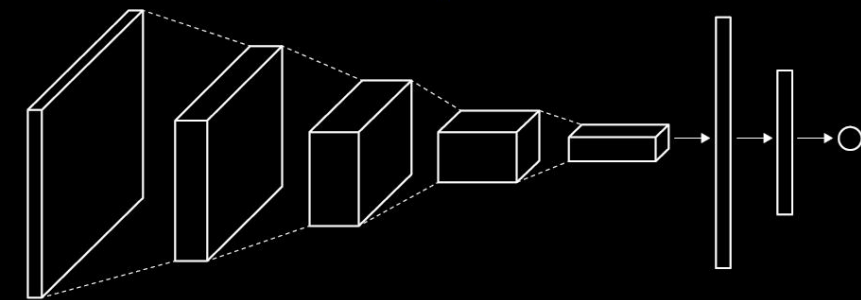
Automated Roof Mapping + Geospatial Roof Registry + Sustainable Roof Index



Automated Classification



Satellite Images



Convolutional Neural Network



Rooftop Solar Panels

Rooftop Vegetation

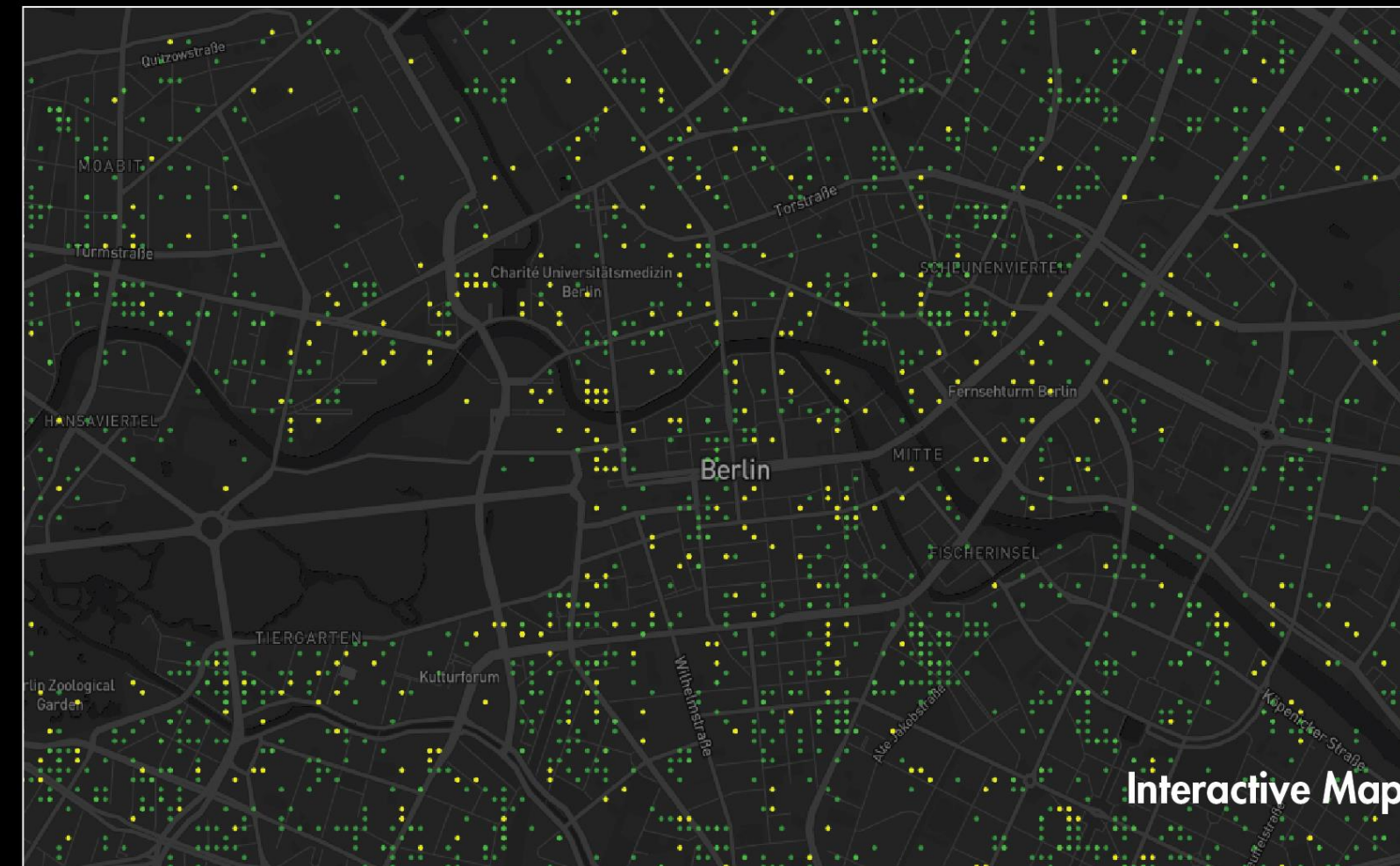
GIS Processing



Solar Roofs

Green Roofs

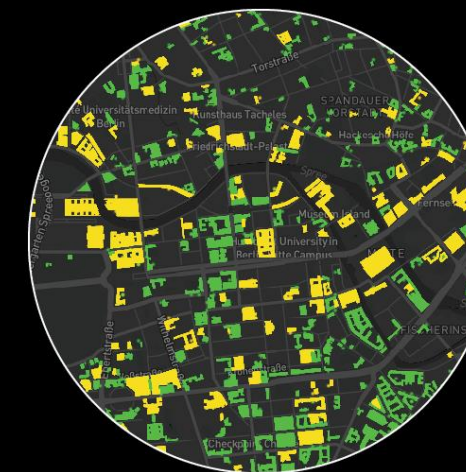
Roofpedia Registry



Interactive Map



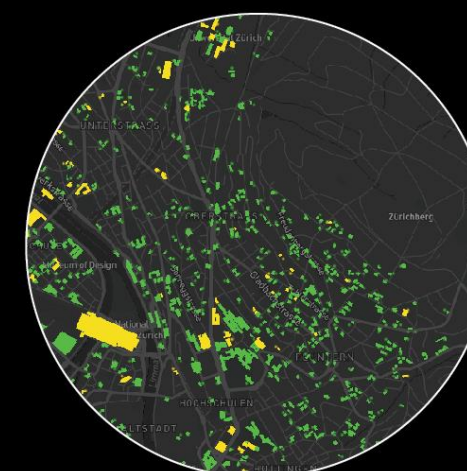
New York



Berlin



Melbourne



Zurich



Las Vegas



Copenhagen

Roofpedia Indices

Solar Roof Index

Las Vegas	86
Zurich	81
Singapore	75
Phoenix	75
Melbourne	74
Berlin	57
Copenhagen	45
New York	42
Paris	42
San Diego	24
Los Angeles	20
Seattle	13
San Jose	12
Portland	10
San Francisco	9
Luxembourg City	7
Vancouver	0

Green Roof Index

Zurich	100
Berlin	51
New York	28
Copenhagen	22
Paris	18
San Diego	14
San Jose	13
Phoenix	13
Melbourne	11
Las Vegas	9
Seattle	6
Los Angeles	6
Luxembourg City	4
Portland	3
San Francisco	2
Vancouver	0

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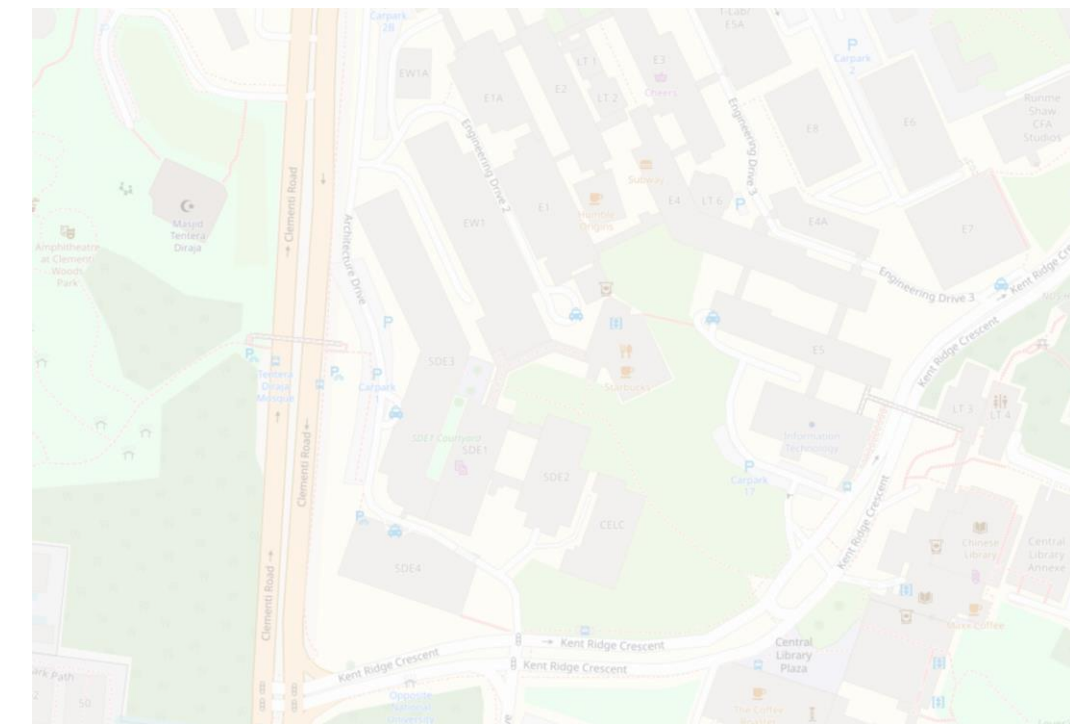
Research strands



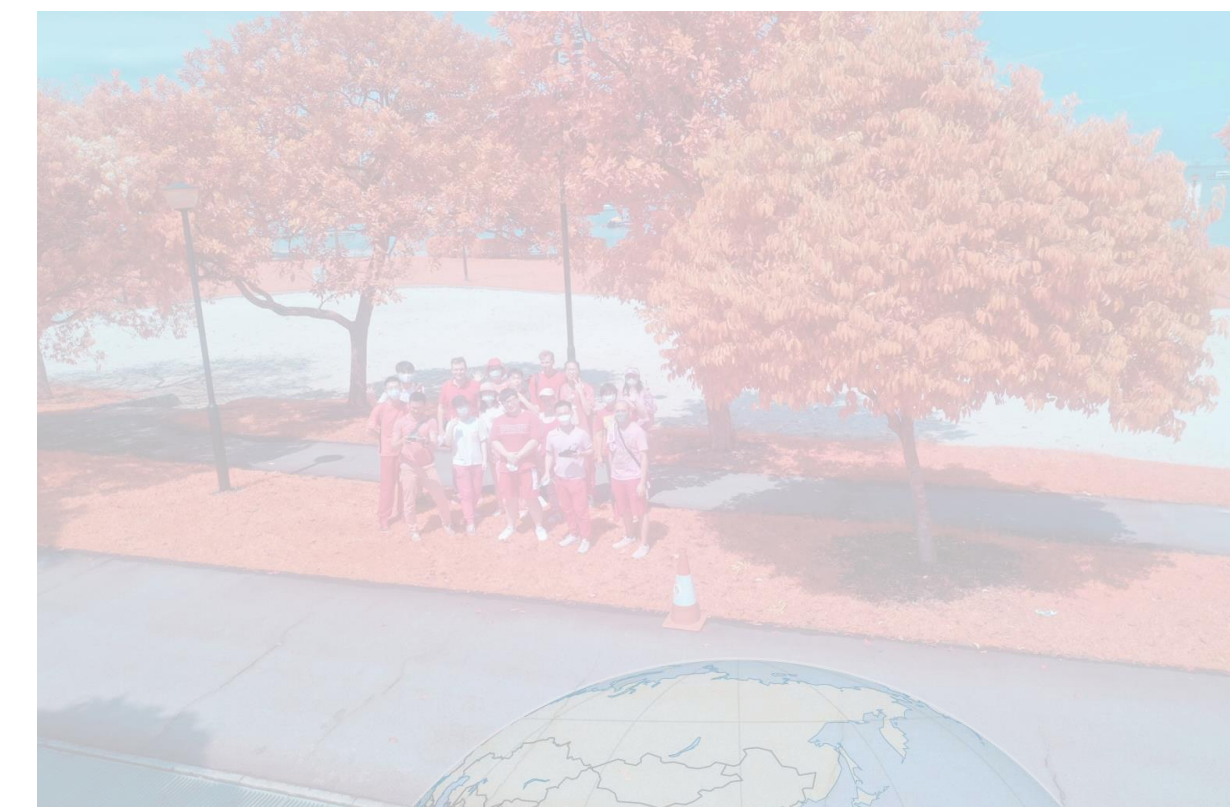
Buildings / 3D GIS / DT



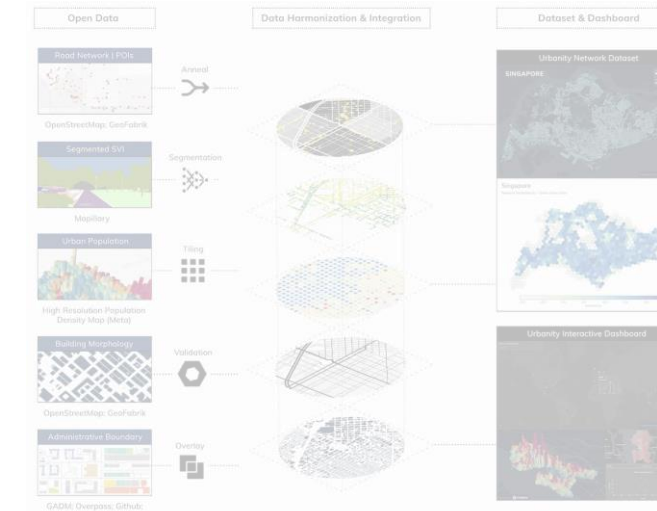
Street view imagery



VGI, spatial data quality

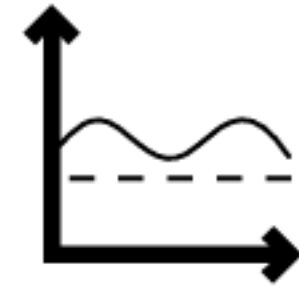


Some of our open-source software / open data



Global Building Morphology Indicators; Roofpedia; Urbanity

BEAM



Establishing the Baseline

FY22

B

BASELINING



Identifying hot and cool spots

E

EVALUATING



Simulation, planning & application of mitigation measures

A

ACTION

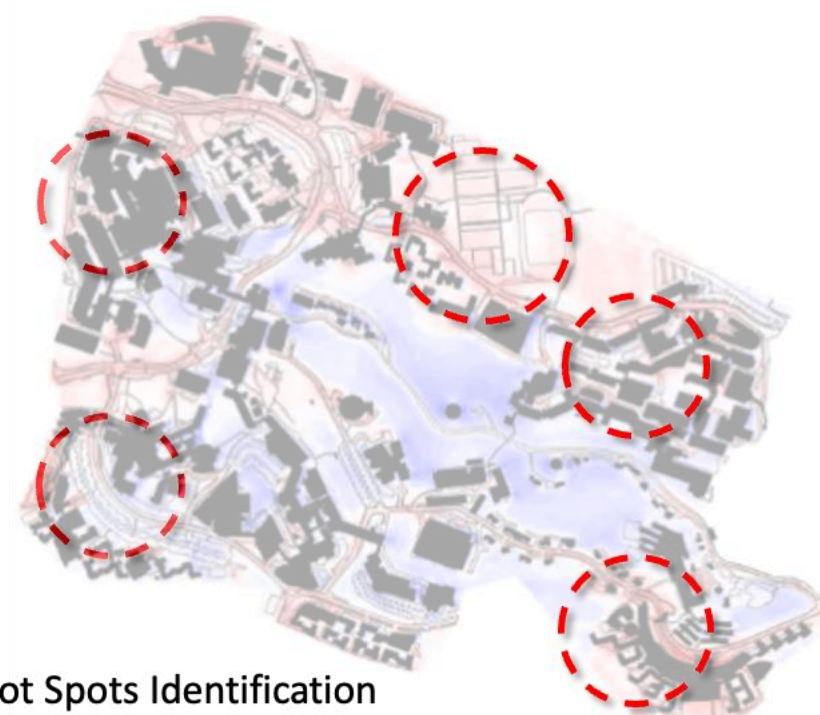
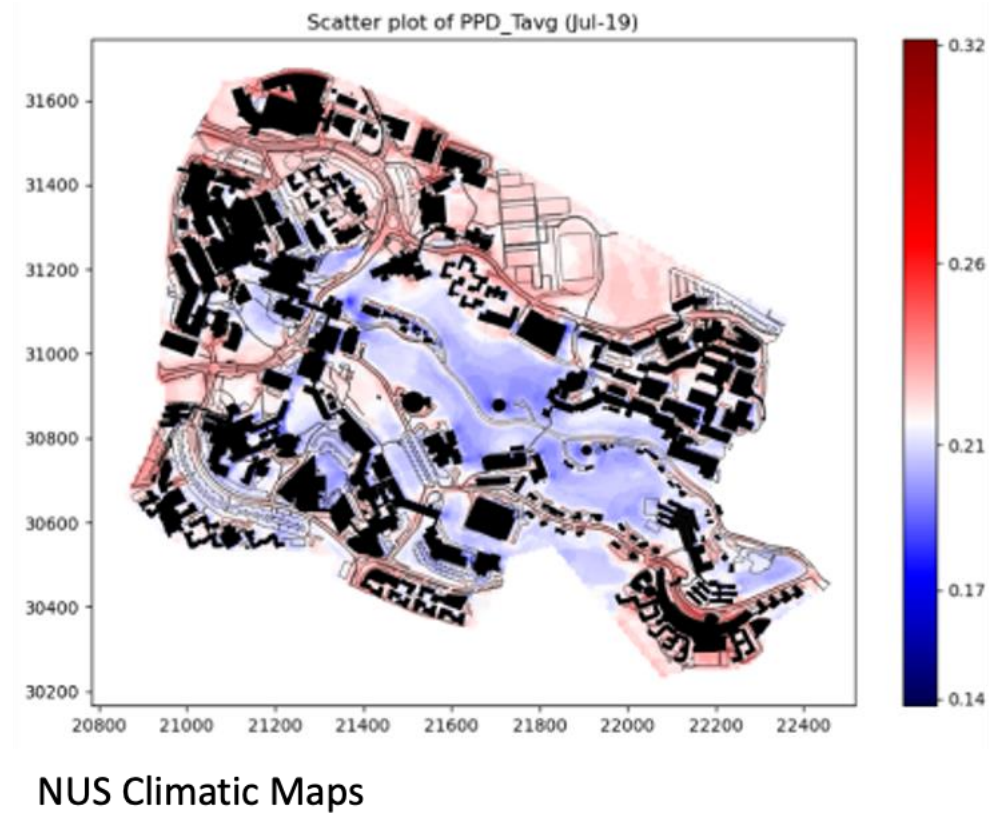
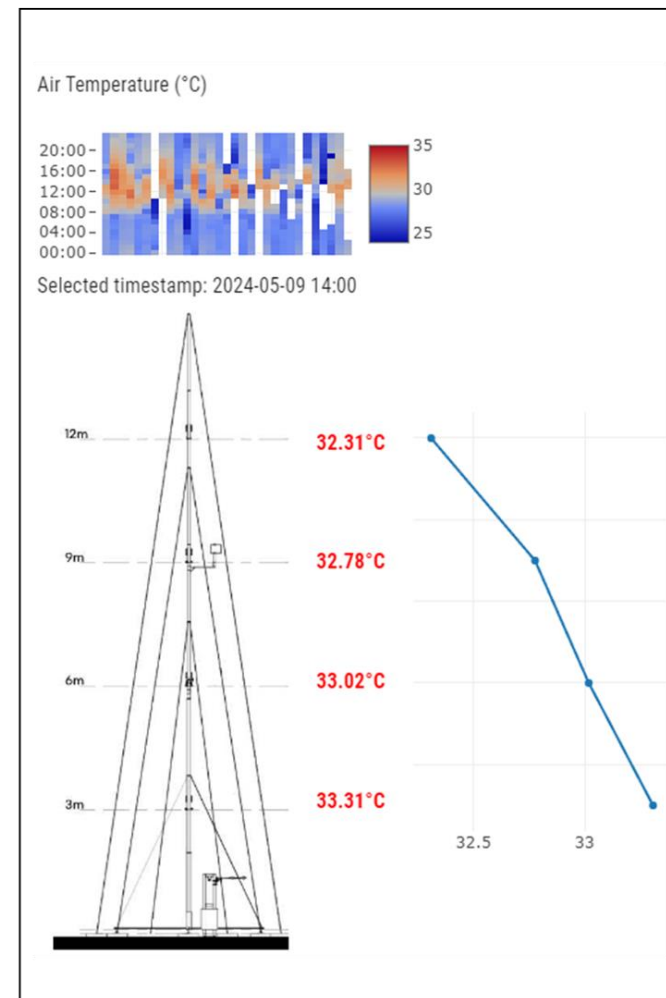
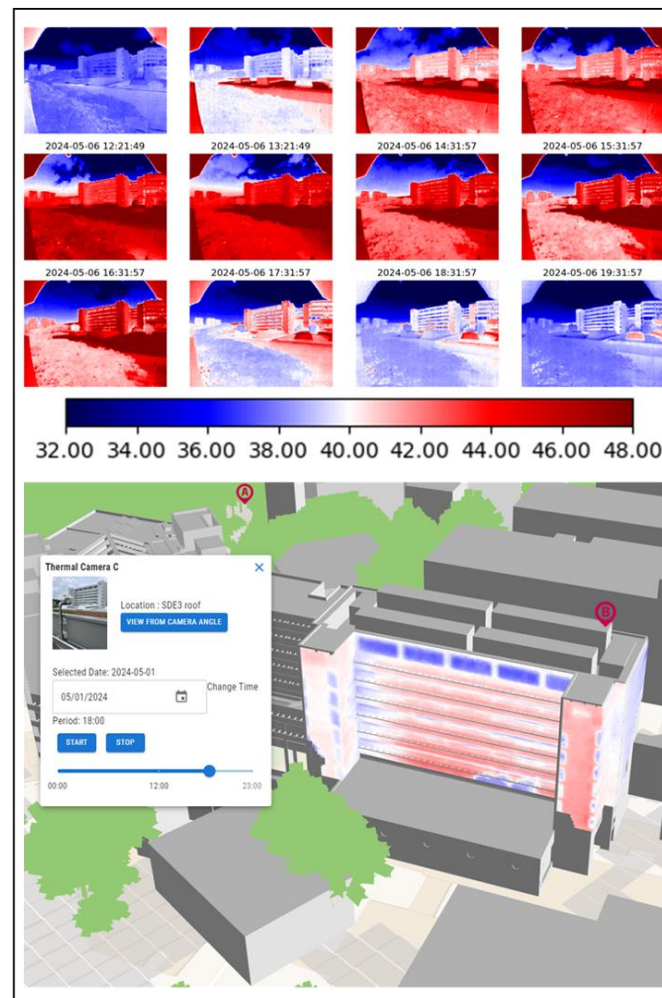
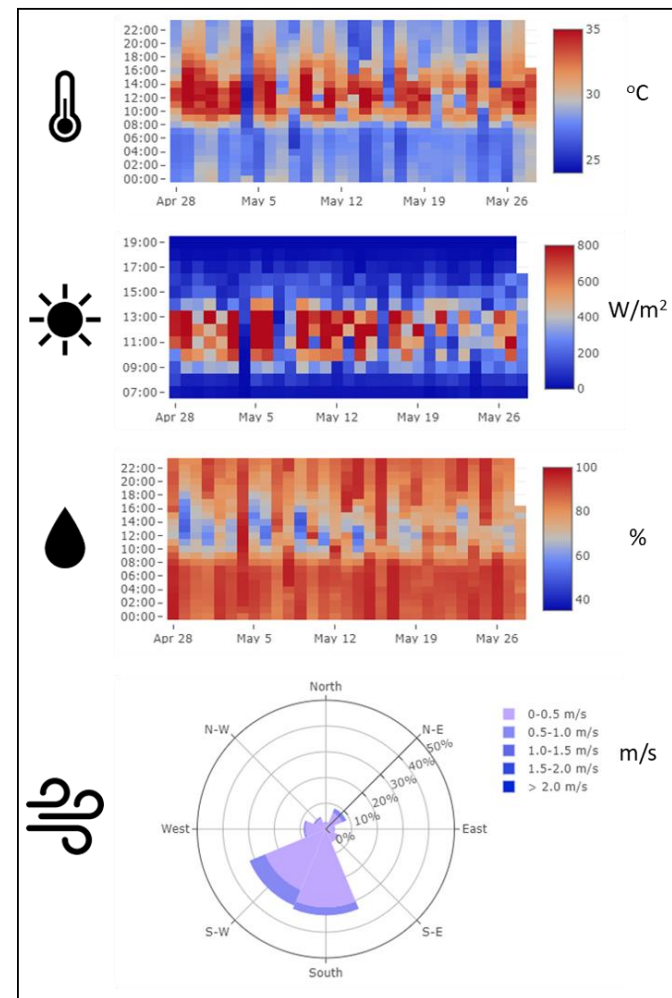


Monitoring and benchmarking of applied mitigation measures

M

MONITORING

FY25



What is a Digital Twin Anyway? Deriving the Definition for the Built Environment from over 15,000 Scientific Publications

Mahmoud Abdelrahman^a, Edgardo Macatulad^{a,b}, Binyu Lei^a, Matias Quintana^c, Clayton Miller^d, Filip Biljecki^{a,e,*}

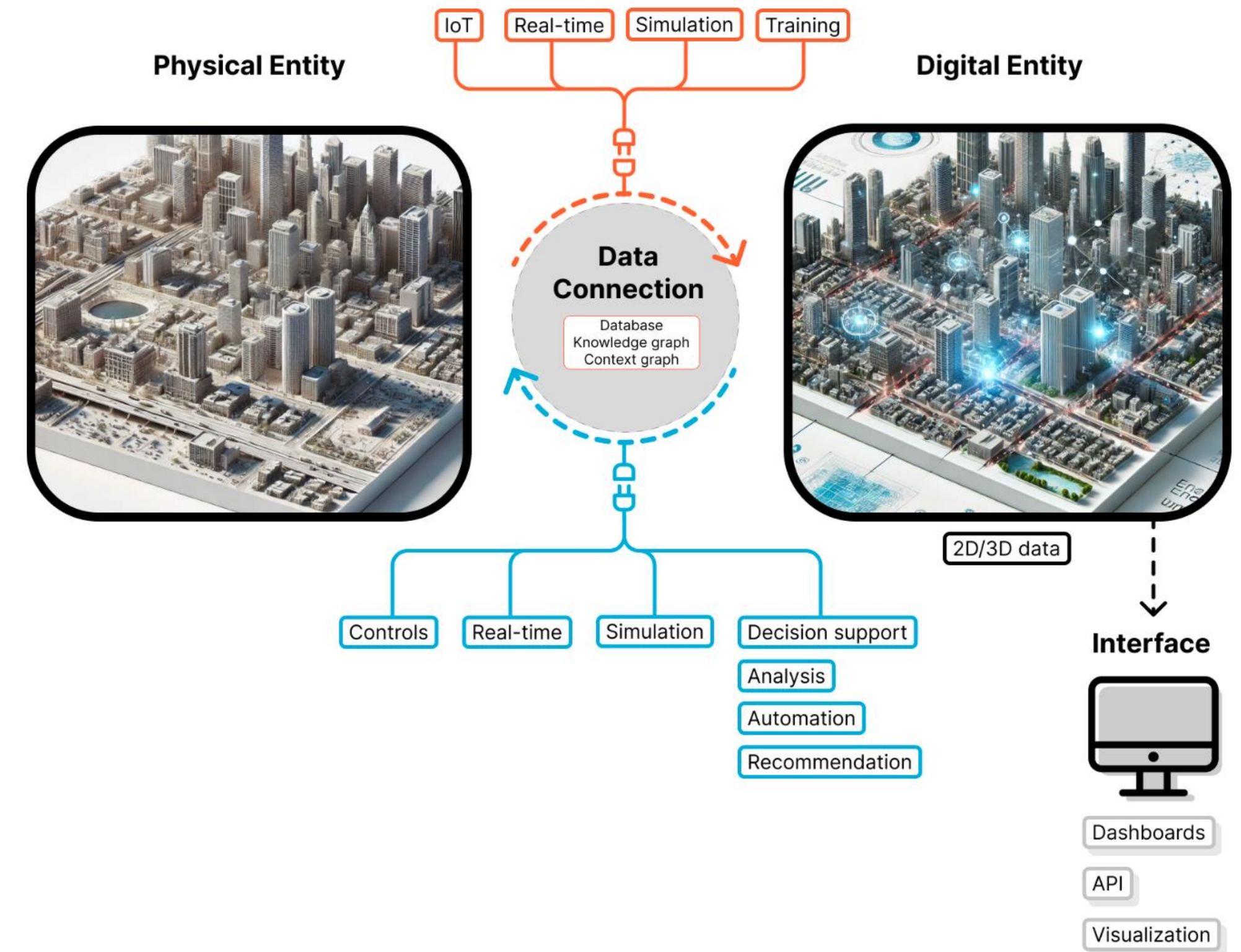
^aDepartment of Architecture, National University of Singapore, 4 Architecture Drive, Singapore, 117566, Singapore

^bDepartment of Geodetic Engineering, University of the Philippines, Diliman, Quezon City, 1101, Philippines

^cSingapore-ETH Centre, Future Cities Lab Global Programme, CREATE campus, #06-01 CREATE Tower, Singapore, 138602, Singapore

^dDepartment of the Built Environment, National University of Singapore, 4 Architecture Drive, Singapore, 117566, Singapore

^eDepartment of Real Estate, National University of Singapore, 15 Kent Ridge Dr, Singapore, 119245, Singapore



Definition *A City/Urban Digital Twin is a spatial-temporal virtual representation of a real-world urban area or city, mirroring its states during its lifecycle through IoT sensors. It is used to monitor and analyze urban systems across different time spans to aid in decision-making and can be extended to simulate and predict various states and scenarios.*

Gaps & opportunities in digital twins

- Potential for integrating new data streams — wearables, **crowdsourced** data, dynamic data, street view imagery
- Human-centric DTs
- More use cases
- Lack of data to build and maintain them



Some recent efforts

1. Inferring information from real estate ads (crowdsourcing building data)
2. Integration of dynamic data / wearables / comfort information
3. Integration of perception (another human-centric focus)
4. Development of localised use cases



TAKENAKA



Search Where is this? Go

Way: Preston Residential College (264858358)

Version #4

Columbia changes

Edited over 6 years ago by Royoriti
Changeset #50817763

Tags

addr:city	Columbia
addr:housenumber	1323
addr:postcode	29225
addr:street	Greene Street
building	dormitory
building:levels	3
name	Preston Residential College

Nodes

► 17 nodes

[Download XML](#) · [View History](#)



Search Where is this? Go

Way: 1025420137

Version #2

동대문구 답십리동 일대 건물 수정

Edited about 1 year ago by Dingo0034
Changeset #116695520

Tags

addr:street	서울시립대로4길
building	yes

Nodes

► 14 nodes

[Download XML](#) · [View History](#)



Hedges Park Condominium

Condominium



[Overview](#) [Home Finance](#) [Price Insights](#) [Location](#)

[Shortlist](#) [Share](#)

s\$ 2,088,888 Negotiable

[Shortlist](#) [Hide](#) [Share](#) [PDF](#)

4 **4** **1539 sqft** **s\$ 1,357.30 psf**

[Report Listing](#)

Est. Repayment S\$ 5,791 /mo [Get the best rates](#)

Hedges Park Condominium

81 Flora Drive 506886 Changi Airport / Changi Village (D17)



Details

Property Type

Condominium For Sale

Floor Size

1539 sqft

Developer

Tripartite Developers Pte Limited

PSF

S\$ 1,357.30 psf

Furnishing

Unfurnished

Floor Level

Ground Floor

Tenure

99-year Leasehold

TOP

June, 2015

Listing ID

24359099

Currently Tenanted

No

Listed On

32 seconds ago

Maintenance Fee

S\$ 450.00 /mo

Are real estate ads a type of user-generated geographic information that has been ignored in GIScience?

Introducing new means of acquisition of building data

By Xinyu Chen

Urban Informatics Paper of the Year Award (2023)



Chen and Biljecki *Urban Informatics* (2022) 1:12
<https://doi.org/10.1007/s44212-022-00012-2>



Urban Informatics

ORIGINAL ARTICLE

Open Access

Mining real estate ads and property transactions for building and amenity data acquisition



Xinyu Chen¹ and Filip Biljecki^{2,3*}

Abstract

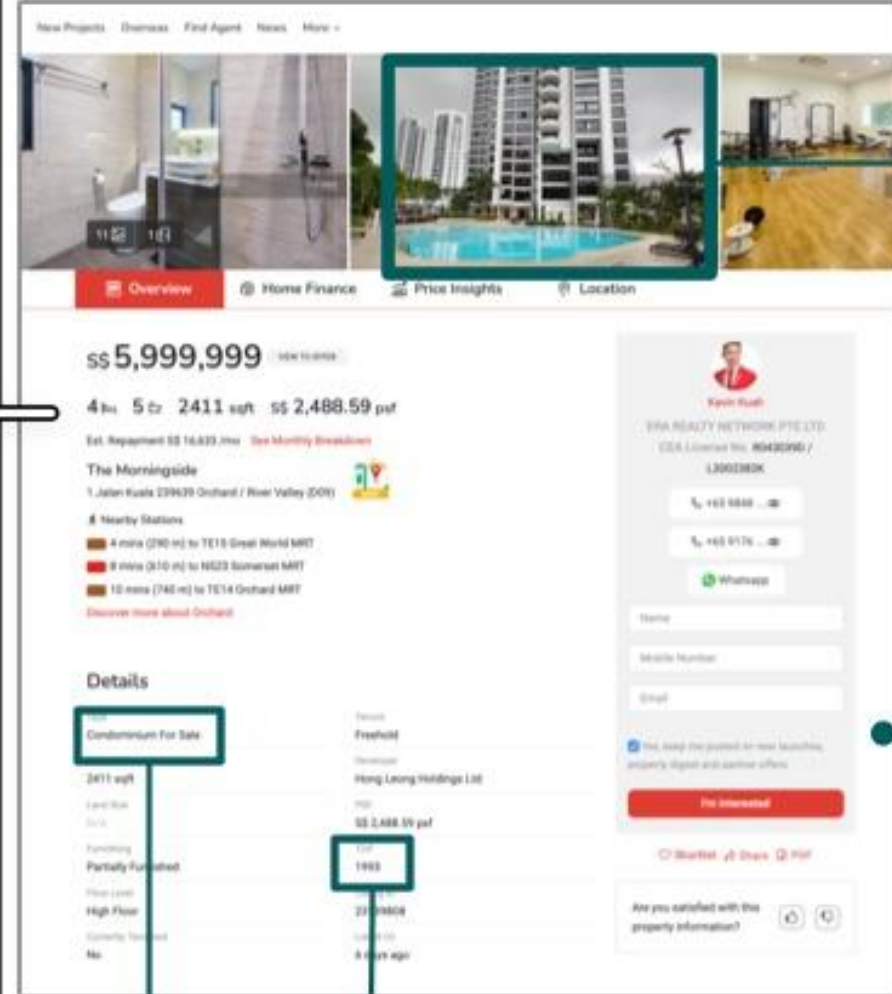
Acquiring spatial data of fine and dynamic urban features such as buildings remains challenging. This paper brings attention to real estate advertisements and property sales data as valuable and dynamic sources of geoinformation in the built environment, but unutilised in spatial data infrastructures. Given the wealth of information they hold and their user-generated nature, we put forward the idea of real estate data as an instance of implicit volunteered geographic information and bring attention to their spatial aspect, potentially alleviating the challenge of acquiring spatial data of fine and dynamic urban features. We develop a mechanism of facilitating continuous acquisition, maintenance, and quality assurance of building data and associated amenities from real estate data. The results of the experiments conducted in Singapore reveal that one month of property listings provides information on 7% of the national building stock and about half of the residential subset, e.g. age, type, and storeys, which are often not available in sources such as OpenStreetMap, potentially supporting applications such as 3D city modelling and energy simulations. The method may serve as a novel means to spatial data quality control as it detects missing amenities and maps future buildings, which are advertised and transacted before they are built, but it exhibits mixed results in

Situation



Real estate data

(1) Real estate ads



(2) Property transactions

Transacted Price (\$)	Address	Area (SQM)	Property Type
747,000		42	Apartment
1,738,000		97	Apartment
1,472,000		84	Apartment
790,000		42	Apartment
1,166,000		85	Apartment
713,000		42	Apartment
720,000		42	Apartment
700,000		42	Apartment
1,456,000		85	Apartment
1,226,000		69	Apartment

Extracting relevant data

(A) Detecting features (computer vision)



(B) Collecting the location of a building

N1.295423, E103.8357

(C) Mining descriptions/characteristics

e.g. building type and year of construction

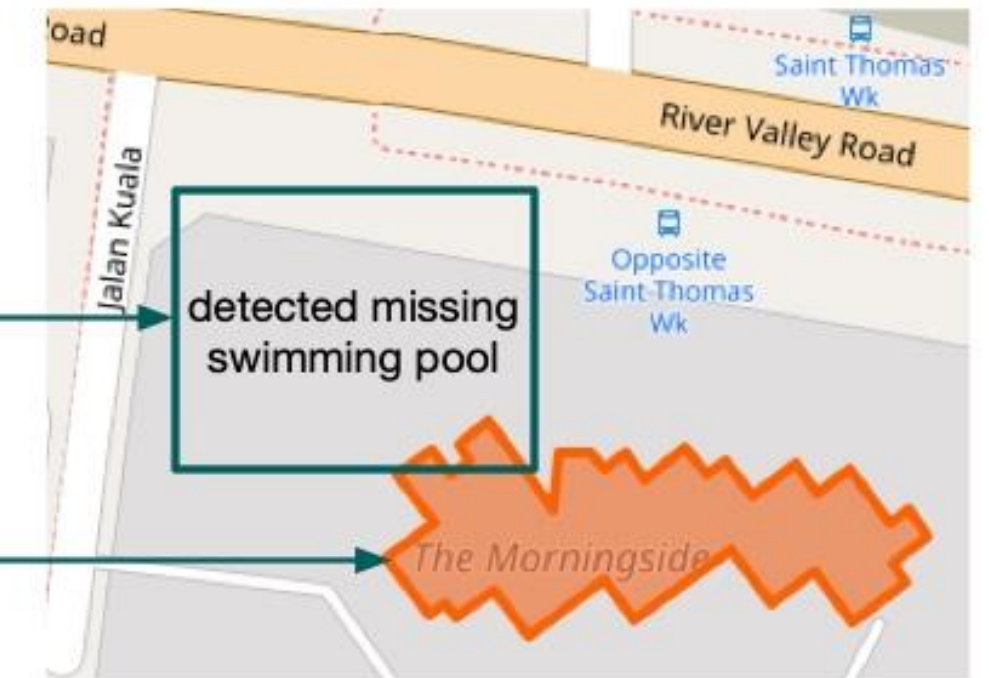
Type	TOP
Condominium For Sale	1993

e.g. height from address and floor area

#24-63	42
#23-65	97
#23-64	84
#23-63	42

Spatial database and downstream applications

(i) Quality control: revealing unmapped features



(ii) Sensing future buildings (e.g. planned ones that are not yet mapped)

(iii) Quality control of existing attributes

type	condominium	✓
start_date	1997	✗

(iv) Data enrichment: new attributes


levels	24
avg_floor_area	80

Example use cases: supporting energy simulations and 3D model generation



Floor area provides value for energy consumption estimations

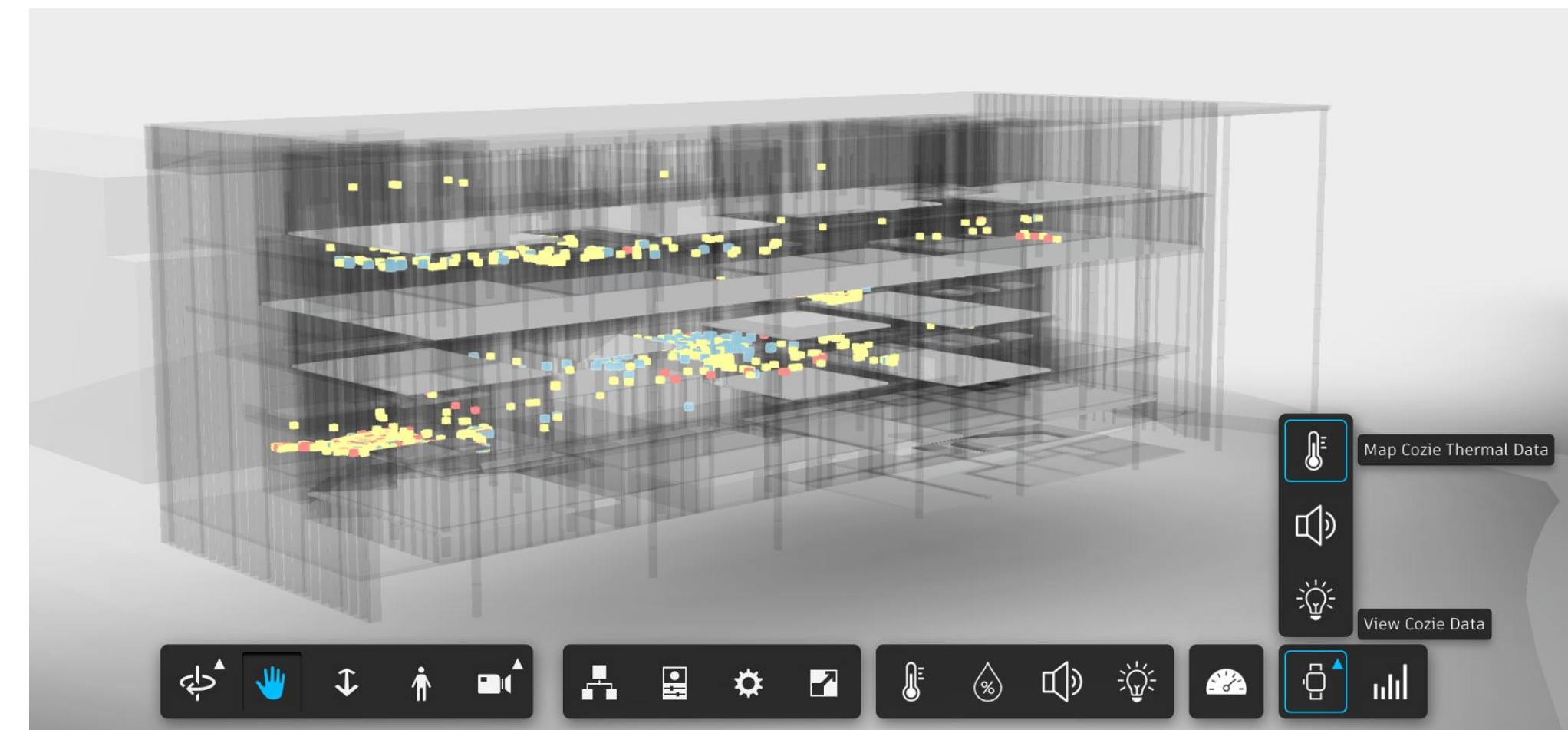
Number of floors, which can be inferred from corresponding property transactions, can be used to extrude existing footprints, resulting in 3D building models



Cozie - An iOS application for watch surveys and physiological data collection

Non-intrusive feedback in real-time

[Forum](#) [Download on the App Store](#)



<https://cozie-apple.app/>

Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 10: 174, 2020.

<https://doi.org/10.3390/buildings10100174>

- Momentum in research on comfort in the built environment
- Comfort is more than thermal comfort
- Comfort is influenced by myriads of factors

Towards Human-centric Digital Twins: Leveraging Computer Vision and Graph Models to Predict Outdoor Comfort

Pengyuan Liu^a, Tianhong Zhao^{a,b}, Junjie Luo^{a,c}, Binyu Lei^d, Mario Frei^e, Clayton Miller^f, Filip Biljecki^{a,g}

^a Department of Architecture, National University of Singapore, Singapore
^b School of Architecture and Urban Planning, Shenzhen University, Shenzhen, China
^c Department of Landscape Architecture, Tsinghua University, Beijing, China
^d Department of The Built Environment, National University of Singapore, Singapore
^e Department of Real Estate, National University of Singapore, Singapore

ARTICLE INFO **ABSTRACT**

Keywords:
 Spatial analysis
 Walkability
 Built environment
 Graph neural network
 Urban study

ABSTRACT
 Conventional sidewalk studies focused on quantitative analysis of sidewalk walkability at a large scale which cannot capture the dynamic interactions between the environment and individual factors. Embracing the idea of Tech for Social Good, Urban Digital Twins seek AI-empowered approaches to bridge humans with digitally-mediated technologies to enhance their prediction ability. We employ GraphSAGE-LSTM, a geo-spatial artificial intelligence (GeoAI) framework on crowdsourced data and computer vision to predict human comfort on the sidewalks. Conceptualizing the pedestrians and their interactions with surrounding built and outdoor environments as human-centric dynamic graphs, our model captures such spatio-temporal variations given by the sequential movements of human walking, enabling the GraphSAGE-LSTM to be spatio-temporal-explicit. Our experiments suggest that the proposed model provides higher accuracy by more than 20% than a traditional machine learning model and two state-of-art deep learning frameworks, thus, enhancing the prediction power of Urban Digital Twin. The source code for the model is shared openly on GitHub.

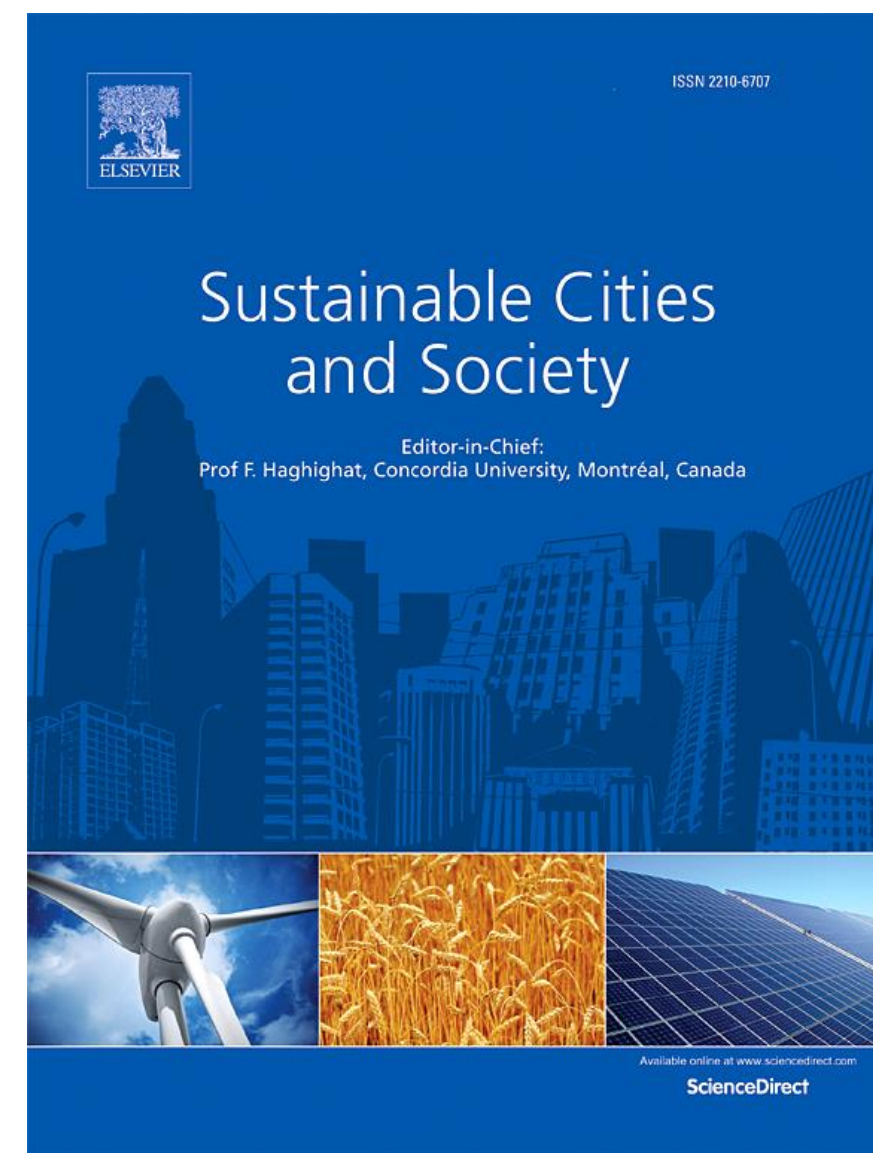
1. Introduction

Cities are the systems of networks and flows (Batty, 2013) of which urban sidewalks are a crucial component (Hosseini, Miranda, Liu, & Silva, 2022; Ning, Ye, Chen, Liu, & Cao, 2022). Sidewalks function not only for transportation and everyday commute but also as a carrier for social interactions and recreational physical activities (Liu, Zhang, Jin, & Liu, 2020), i.e., walking, that promote active lifestyles (Daly, Schwanman, Baber, Barndrage, & James, 2007). In the urban environment, increased walking activities benefit the city from various perspectives, from air pollution reduction to urban spaces safety maintenance; it is also an essential measure of the life quality of a community (Kusman & Tuncer, 2022; Bicycle, 2008; Blacklock, Rhodes, & Brown, 2007; Cottrill, Gagliardi, Gargiulo, & Zucaro, 2020; Gotato, Morillas, Gonzalez, & Moraga, 2018; Patterson & Chapman, 2016). Therefore, designing and maintaining sidewalks for pedestrians is one of the key focuses of urban planners to develop a healthier and happier city.

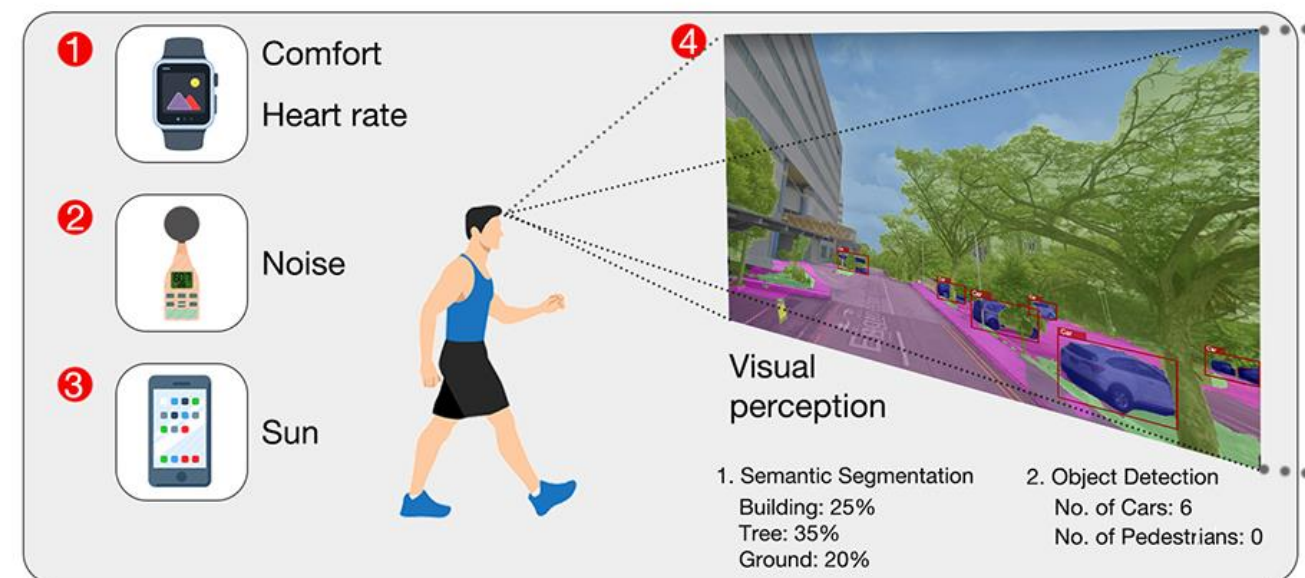
In recent years, human perceptions have become a useful measurement to assess urban outdoor environment (Abdollahzadeh & Biloria, 2021; Bivina & Parida, 2022; Deng et al., 2021; Florio et al., 2021; Luo, Liu, & Cao, 2022; Nazarian & Lee, 2021; Zhang et al., 2018). During the walking activity on the sidewalks, people perceive multi-sensory experiences (e.g., thermal experience, surrounding traffics) interacting with a series of urban spatial objects (e.g., buildings, trees, road conditions) that impact their state of comfort when navigating and path-finding in the urban realm (Gao et al., 2022). Previous research primarily focused on the thermal experiences (i.e., thermal comfort) of the pedestrians, which are essential to understanding the relationship between urban micro-climate and spatial urban morphology (Gao et al., 2022; Vasilidou & Nikolopoulos, 2020) and also as an indicator of the sidewalk quality (Abdollahzadeh & Biloria, 2021). However, thermal comfort measures do not capture a complete comprehension of the walking experience in the environment, particularly in the outdoor settings where the inter-play between pedestrians and spatial objects along the walking is constantly changing (Bivina & Parida, 2022). The sense of the crowdedness of the road, safety, fear or willingness to walk in the sun, the slope condition of the roads, and other factors can heavily affect human comfort when walking on the routes (Gao et al., 2022; Ming & Kang, 2016; Miranda, Fan, Duarte, & Ratti, 2021; Nanjov

* Corresponding author at: Department of Architecture, National University of Singapore, Singapore.
 E-mail address: pjbilje@nus.edu.sg (F. Biljecki).

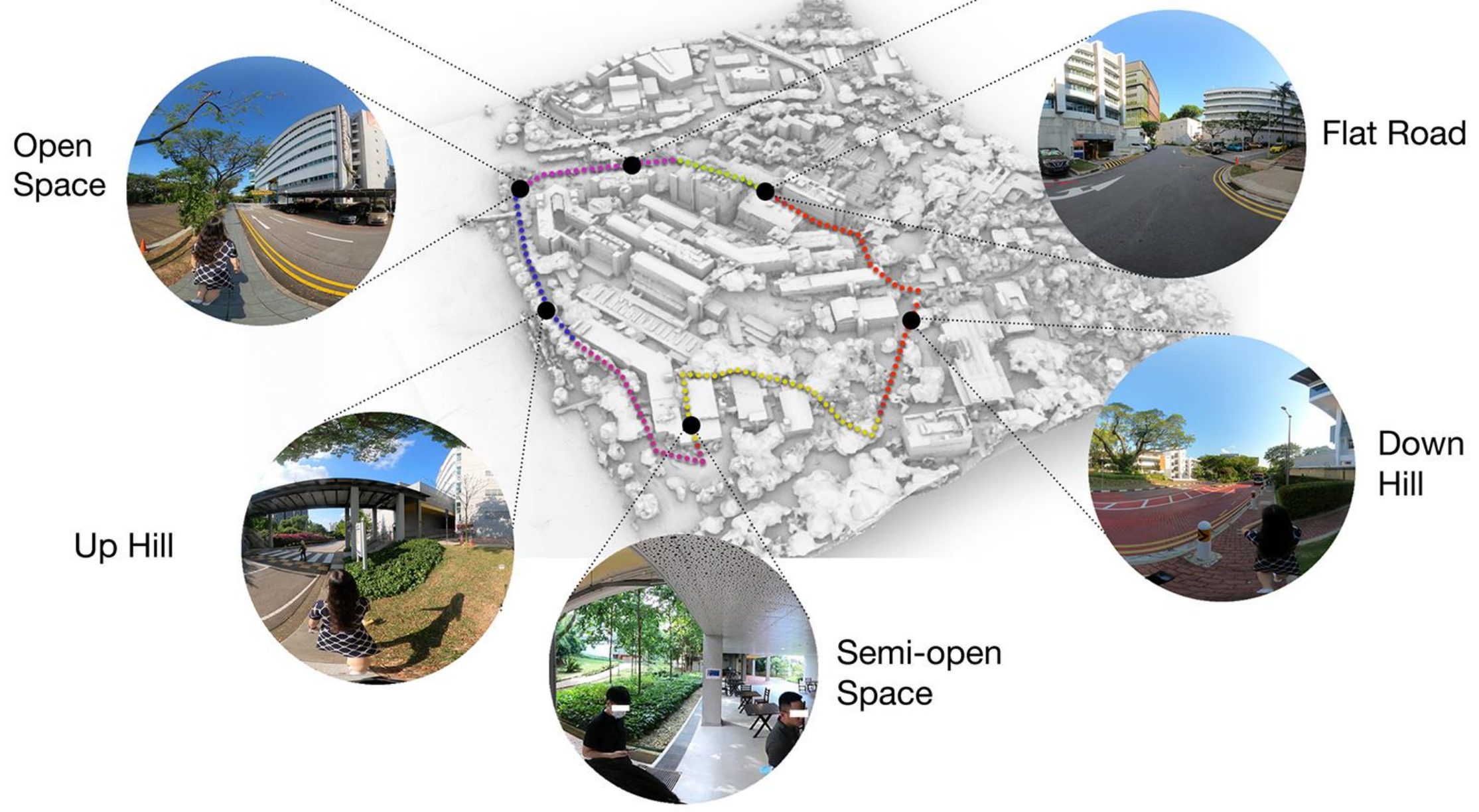
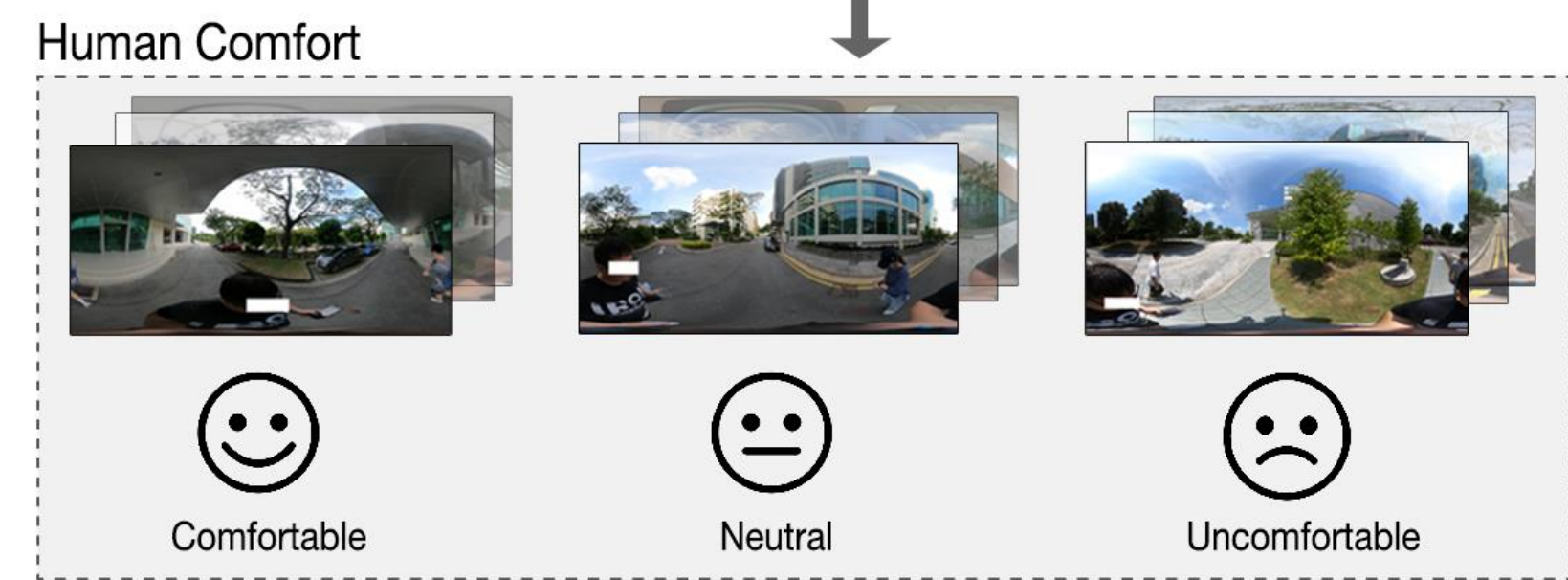
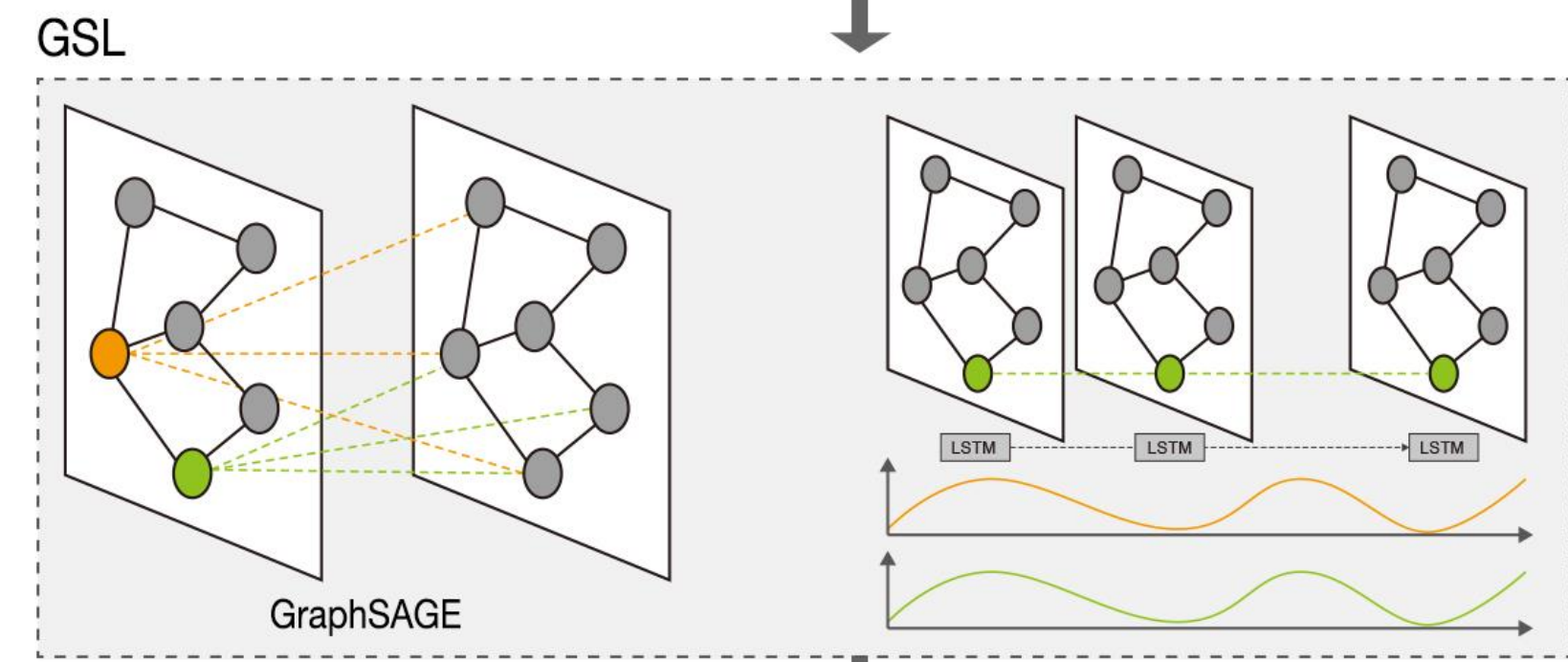
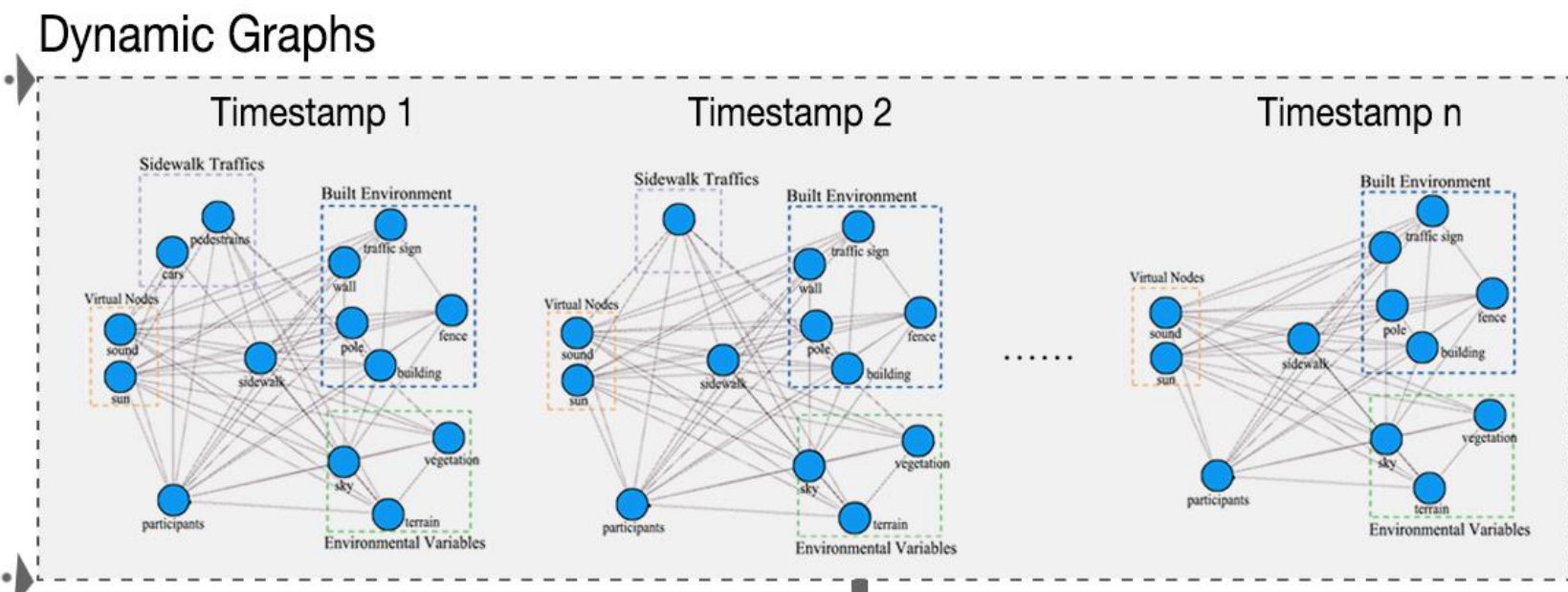
<https://doi.org/10.1016/j.scs.2023.104480>
 Received 30 December 2022; Accepted 8 February 2023
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Predicting Human Comfort on the Sidewalk

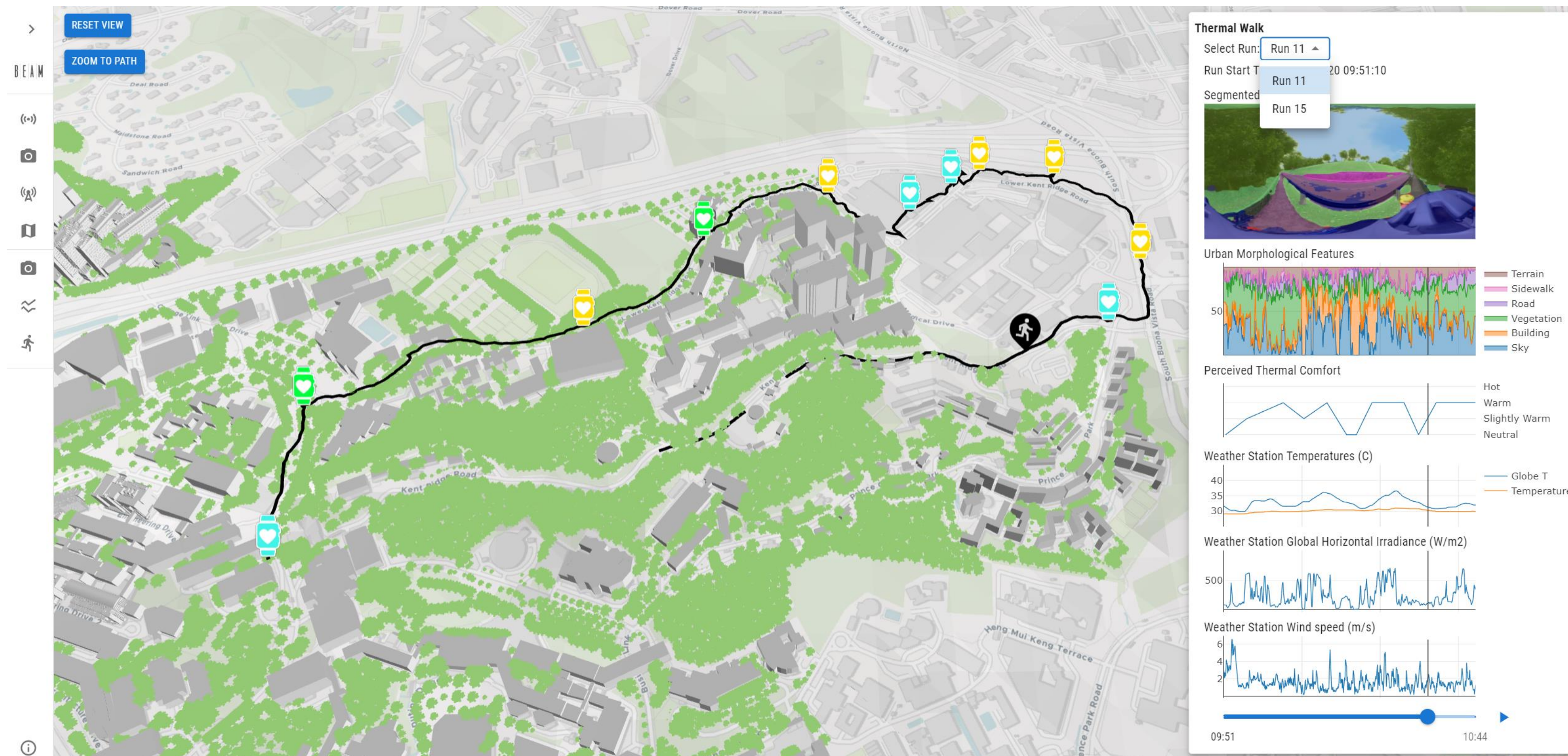


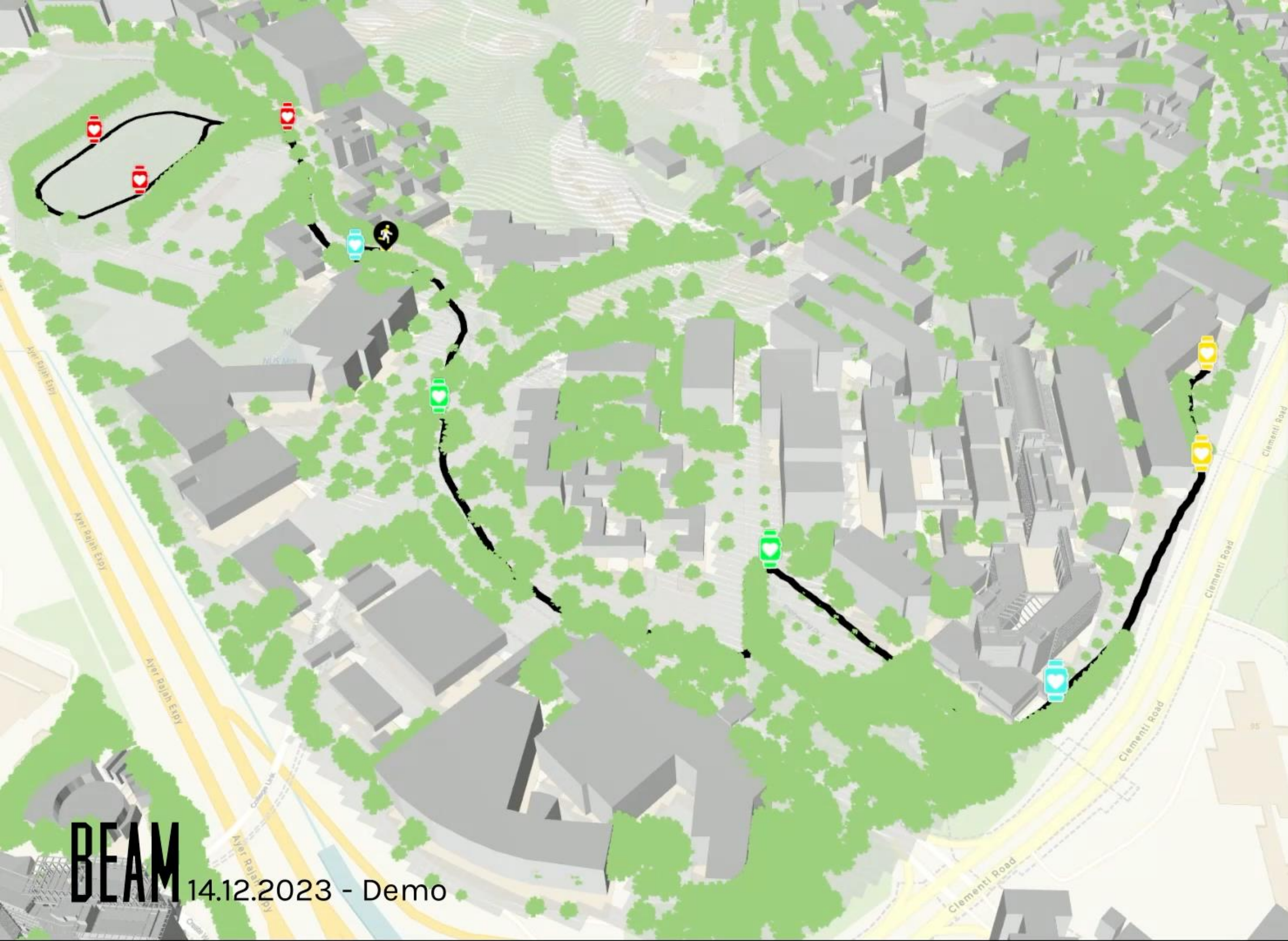
Methodology



Goal of the work

Proof of concept of integrating wearable data, weather information, street view imagery / urban form data, etc. in an urban digital twin to support walkability/comfort studies





Thermal Walk

Segmented Image

Urban Morphological Features

- Terrain
- Sidewalk
- Road
- Vegetation
- Building
- Sky

Perceived Thermal Comfort

Hot
Warm
Slightly Warm
Neutral

Weather Station Temperatures (C)

40
35
30

— Globe T
— Temperature

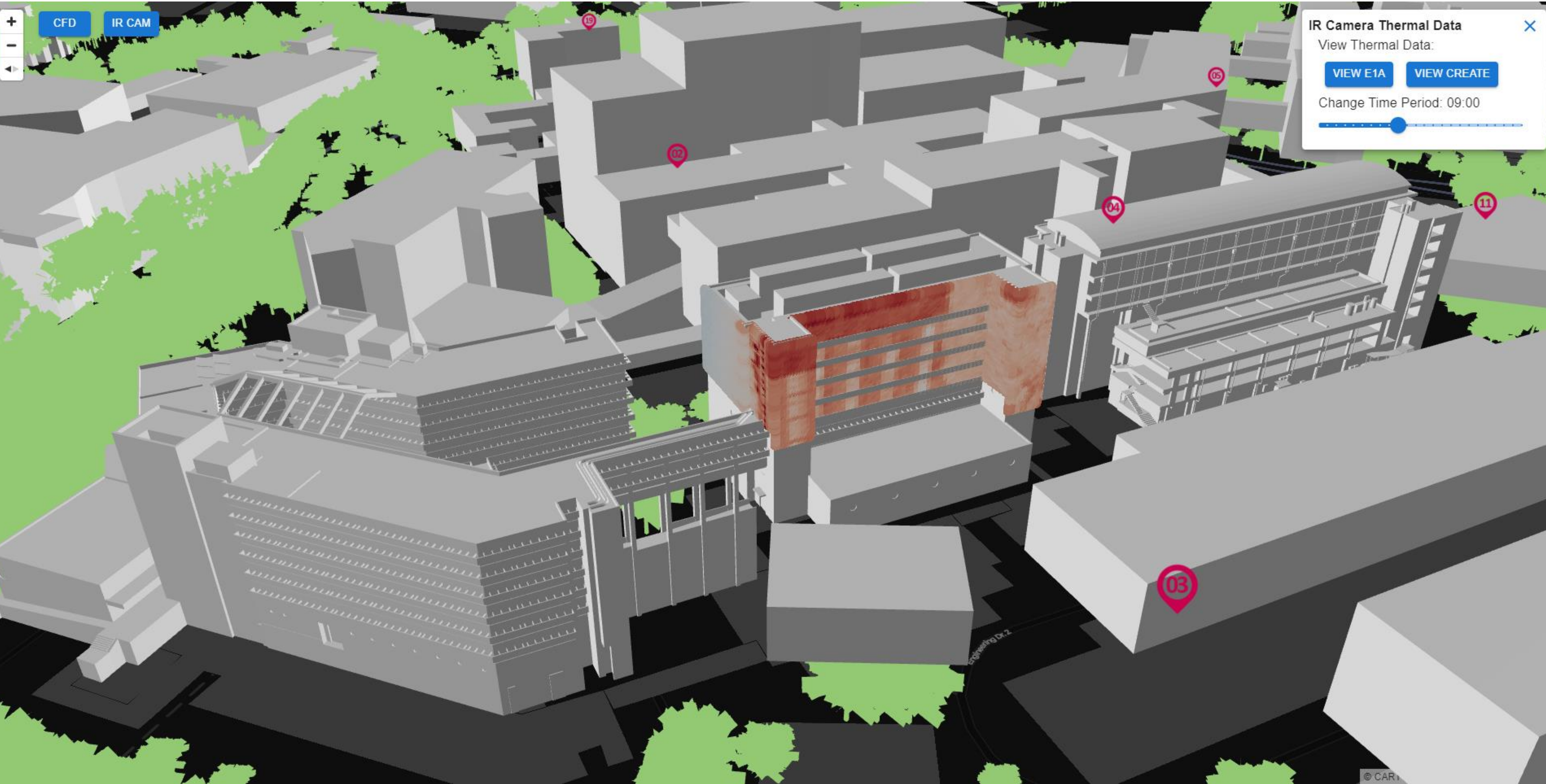
Weather Station Solar Radiation (W/m²)

500

Weather Station Wind speed (m/s)

3
2
1

14:24 14:44 15:05



CFD

IR CAM

IR Camera Thermal Data

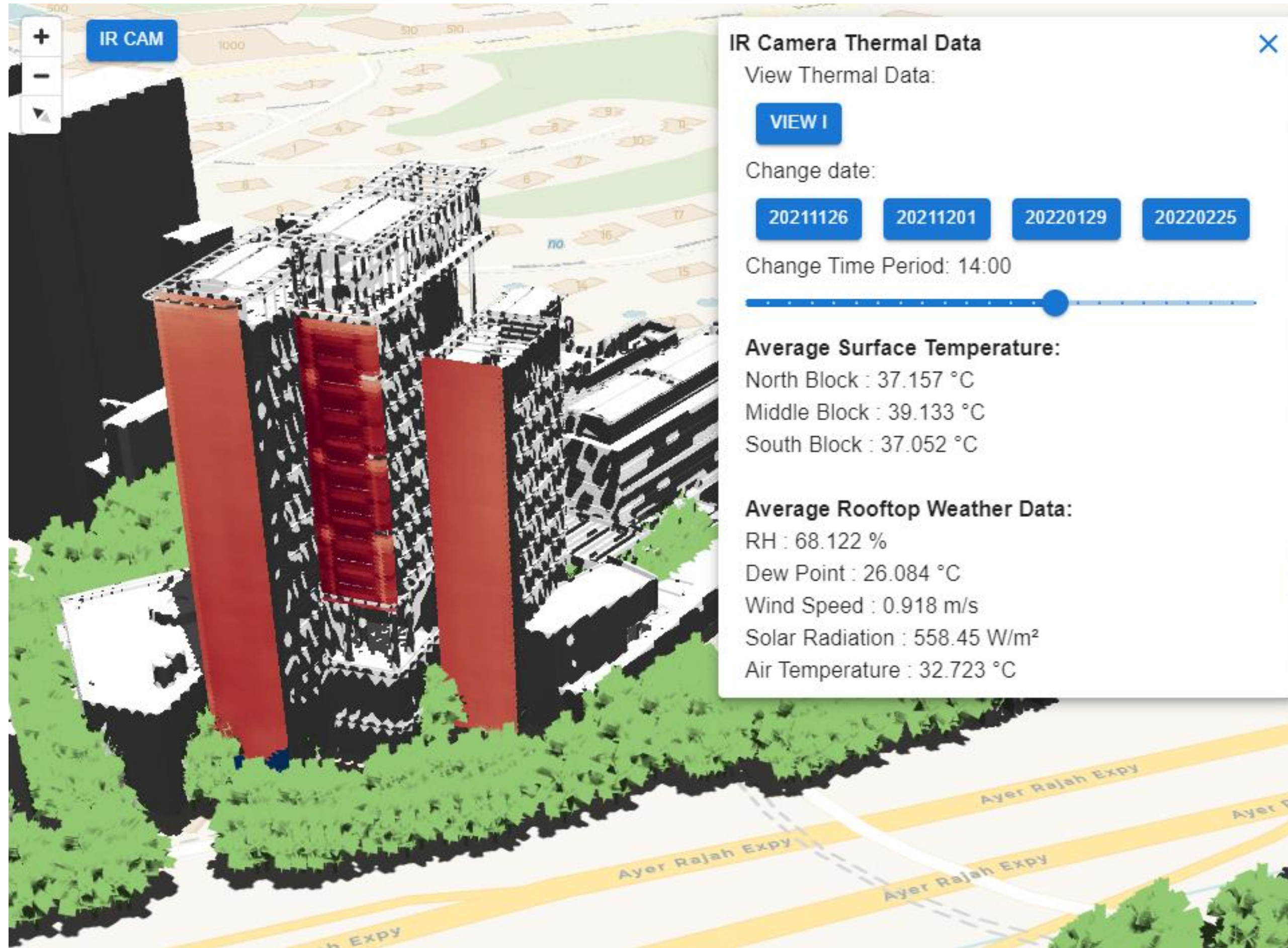
View Thermal Data:

[VIEW E1A](#)

[VIEW CREATE](#)

Change Time Period: 09:00





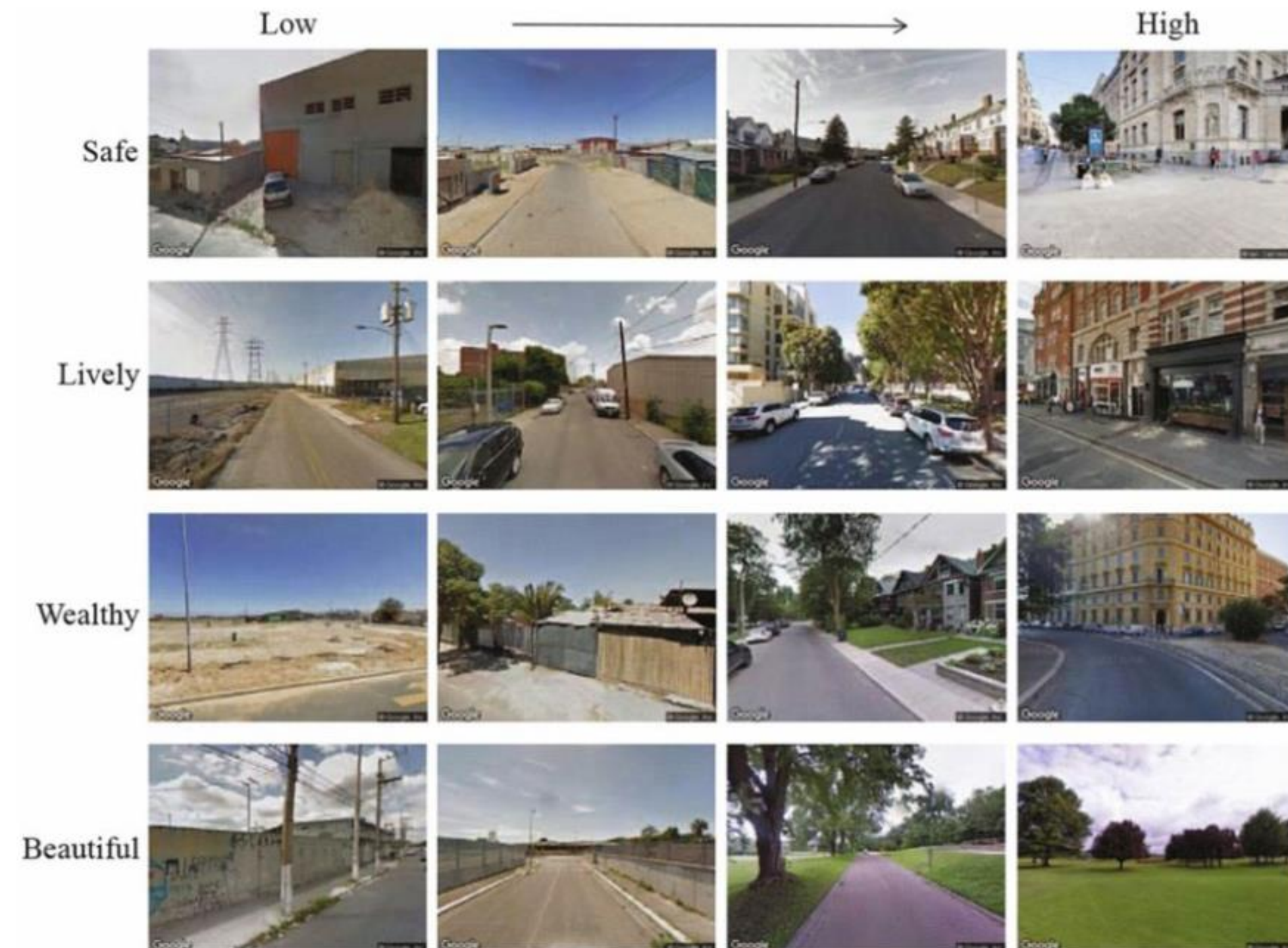
Potential of the work / Why do we need this?

- Work in progress
- Understand drivers of comfort in the built environment
- Support walkability studies
- Predicting comfort at detailed resolution — both spatially and temporally
- Human-centric aspect - tailored models based on profiles and personal preferences

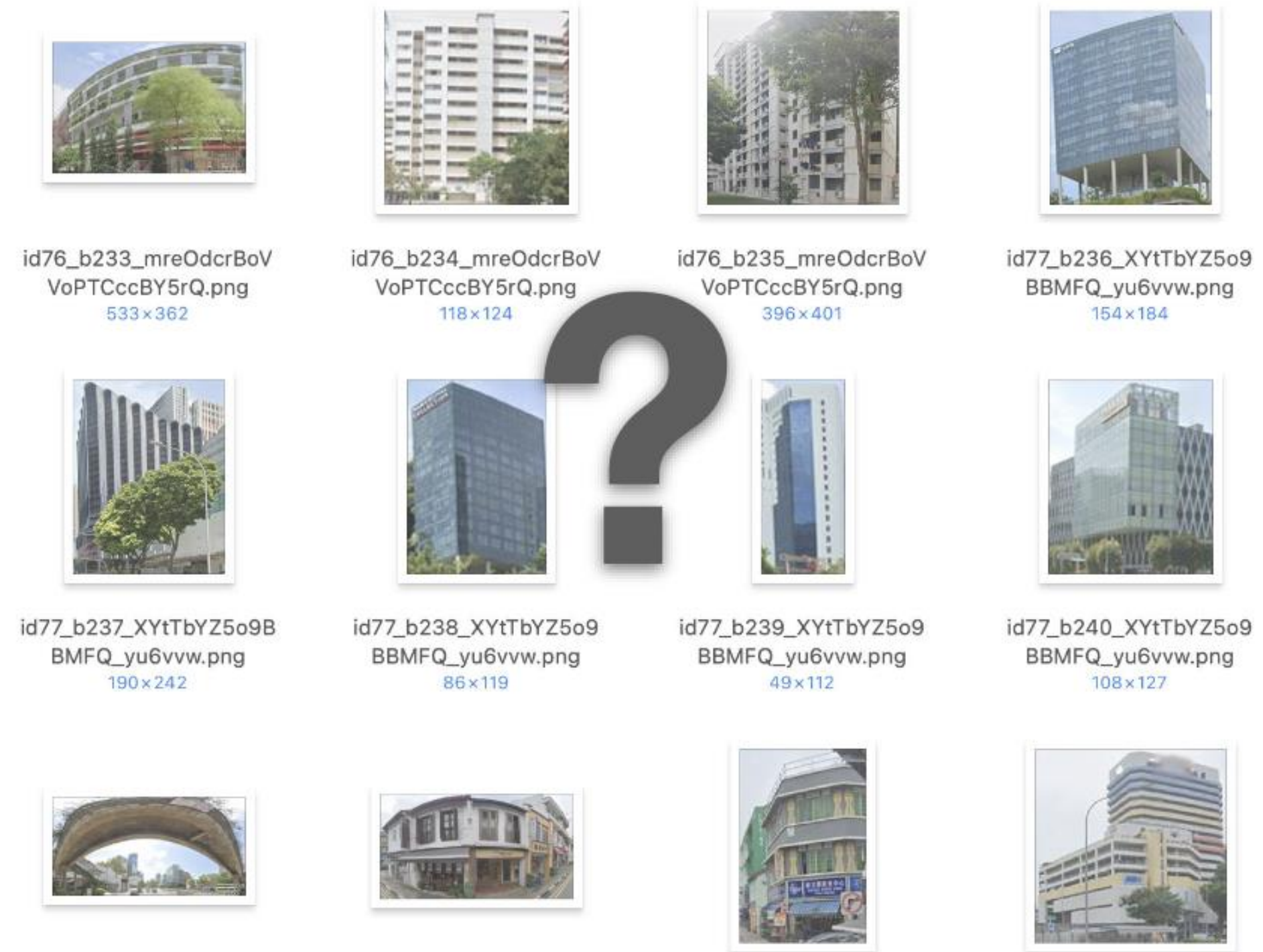


Evaluating Human Perception of Building Exteriors Using Street View Imagery

— Xiucheng Liang, Jiat Hwee Chang, Song Gao, Tianhong Zhao, Filip Biljecki *



Urban streetscape perception dataset: Place Pulse 2.0



Building Facade ?

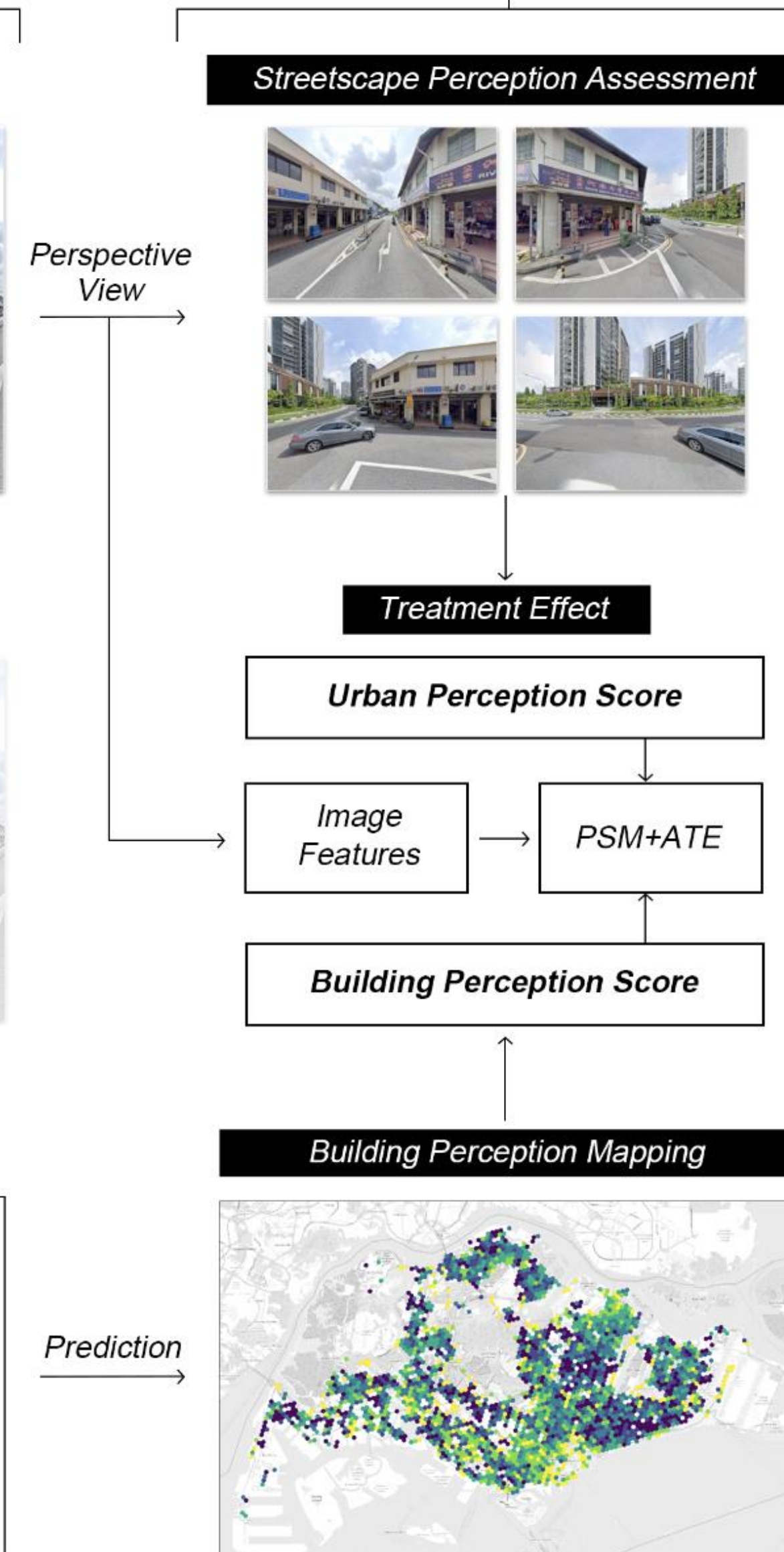
- + How well can machine learning be leveraged to describe and compare the exteriors of buildings in a detailed and scalable manner?
- + How do the human perceptions vary across cities that are constituted by different types of building exteriors?

Research Framework

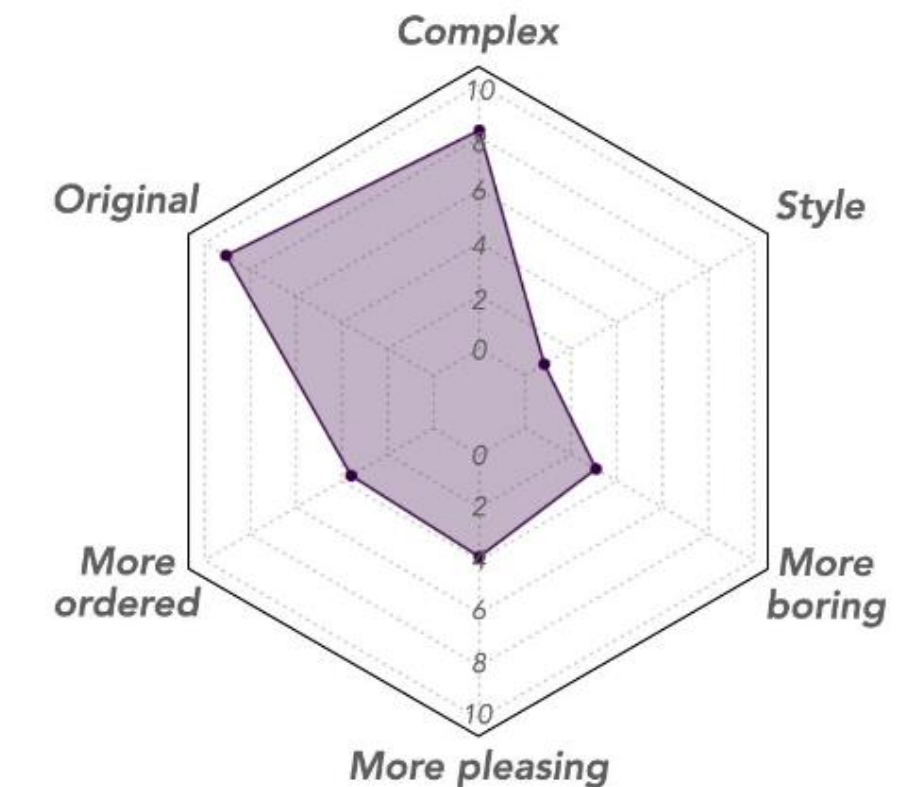
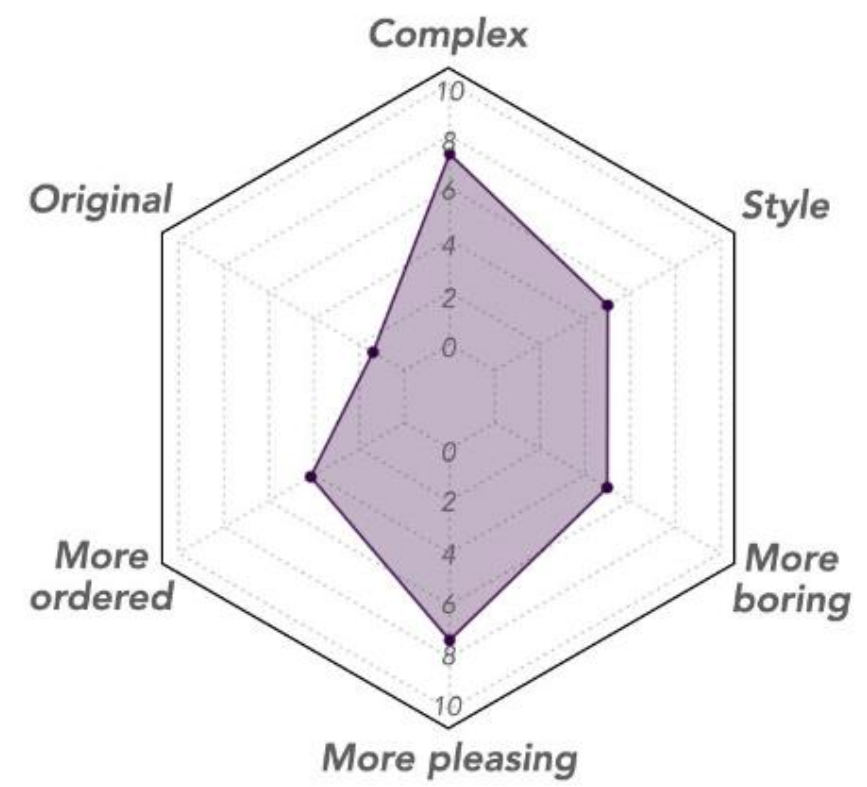
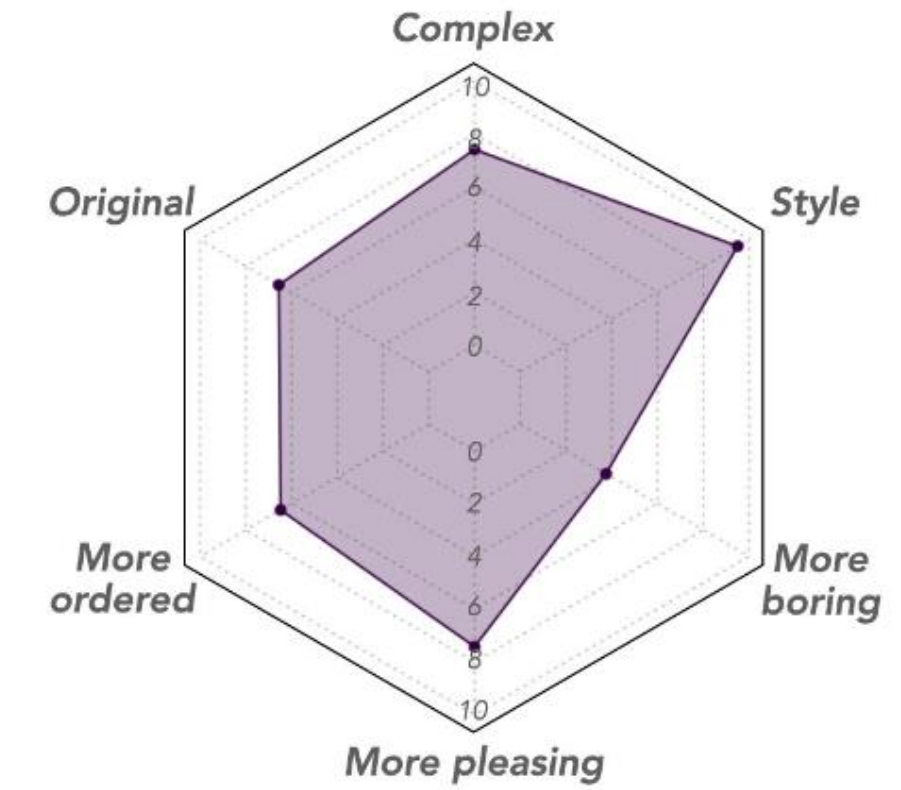
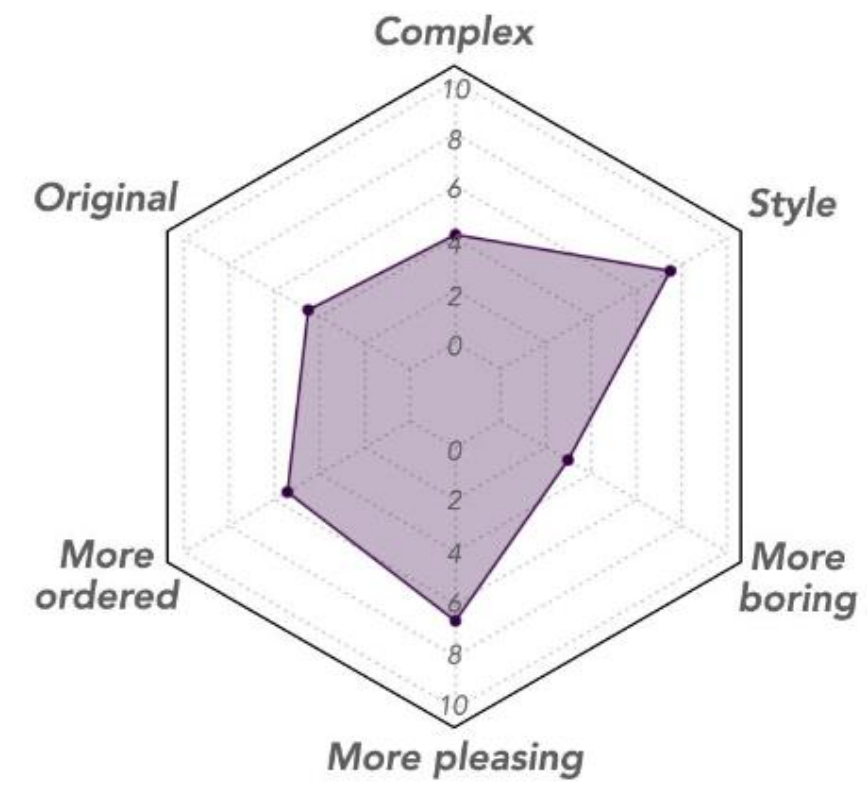
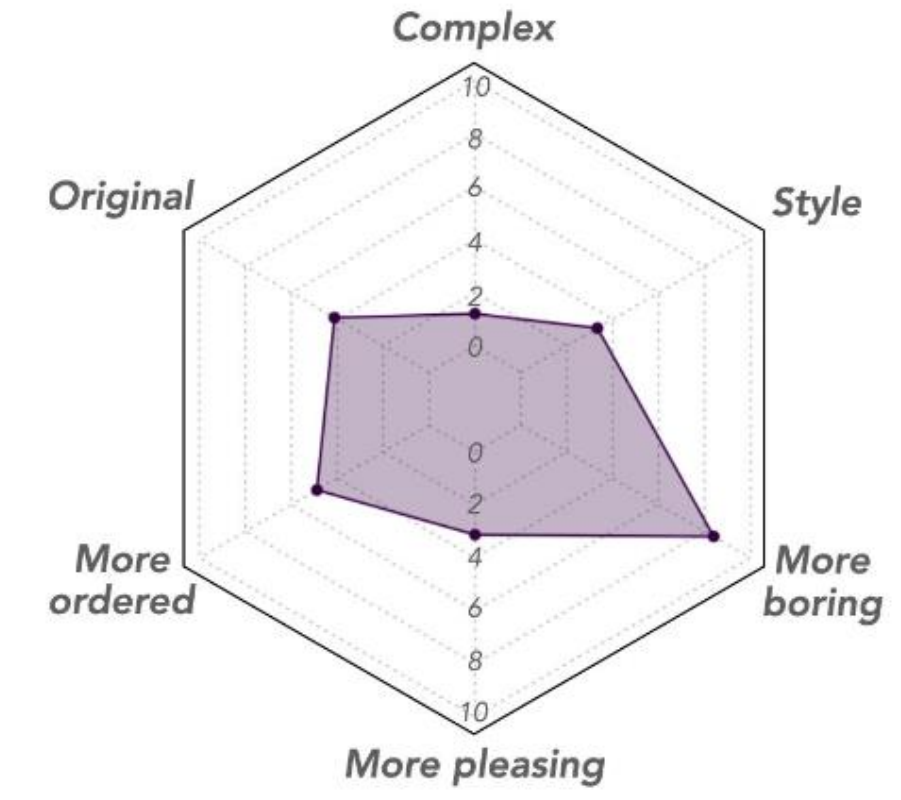
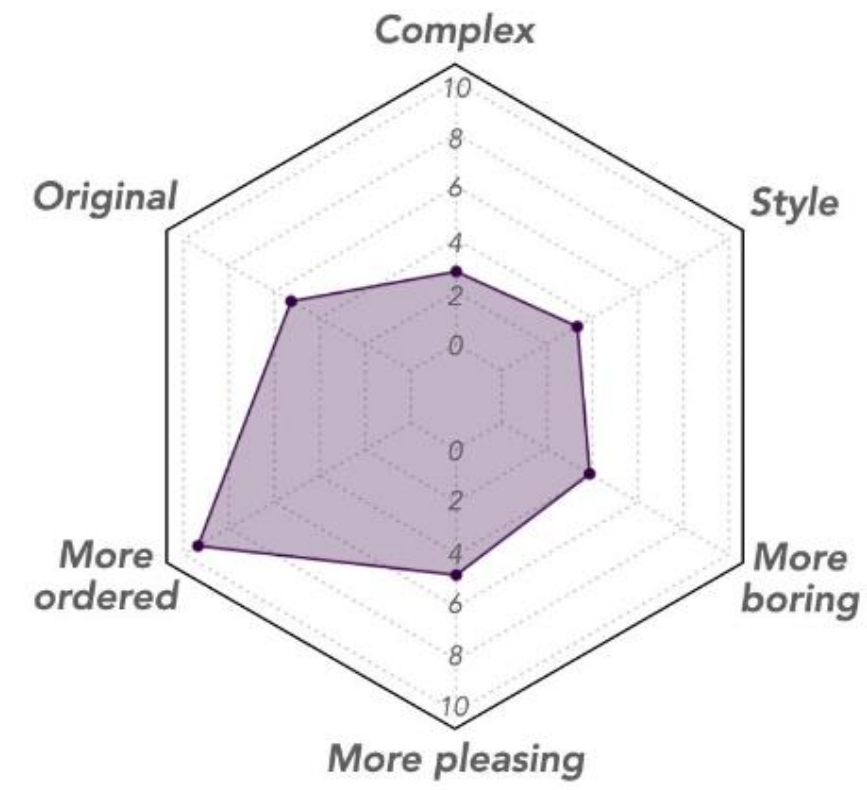
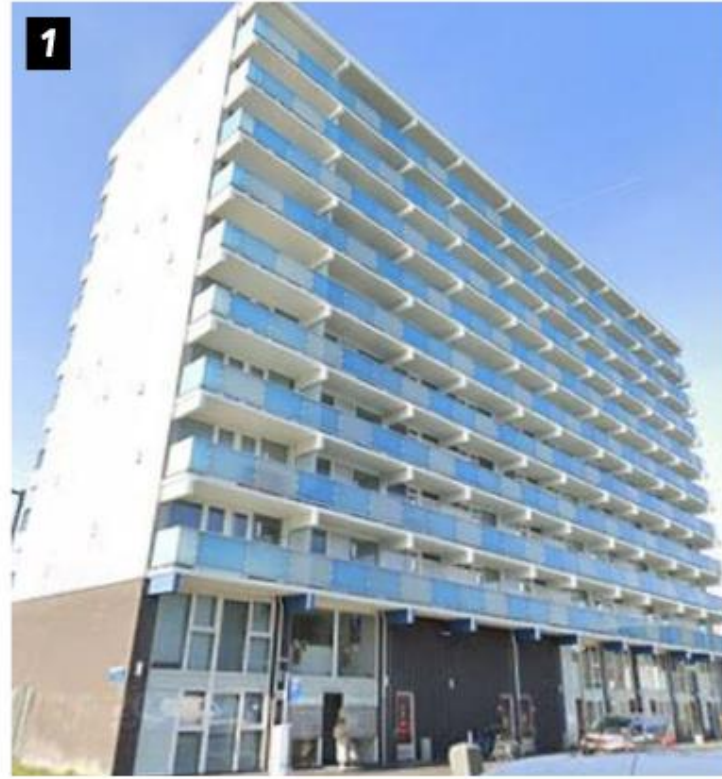
1. Dataset and Perception Models Establishment



2. Understanding of Urban Perception



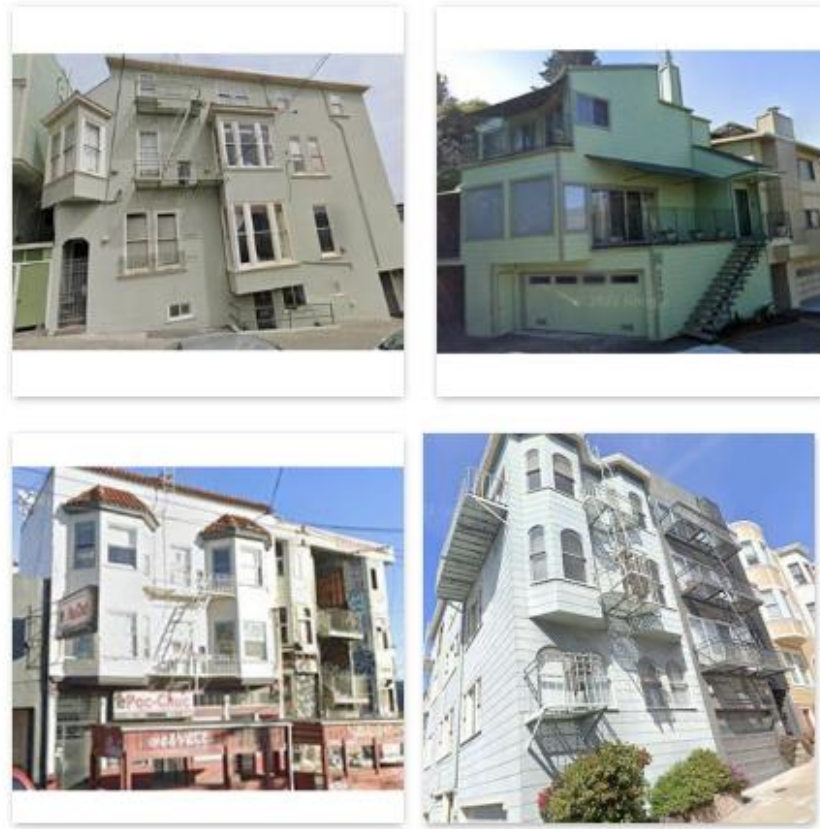
Survey result



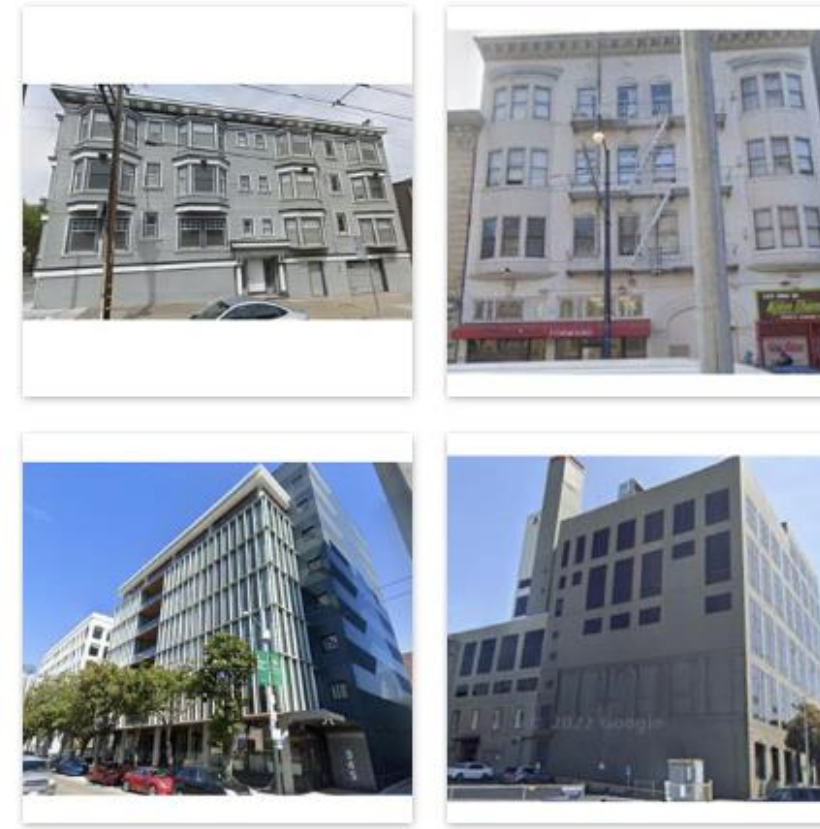
Singapore



San Francisco



Amsterdam



Low ordered score (≤ 3)

Medium ordered score ($> 3 \ \& \ \leq 7$)

High ordered score (> 7)

Integration in DT/3D

WORKFLOW

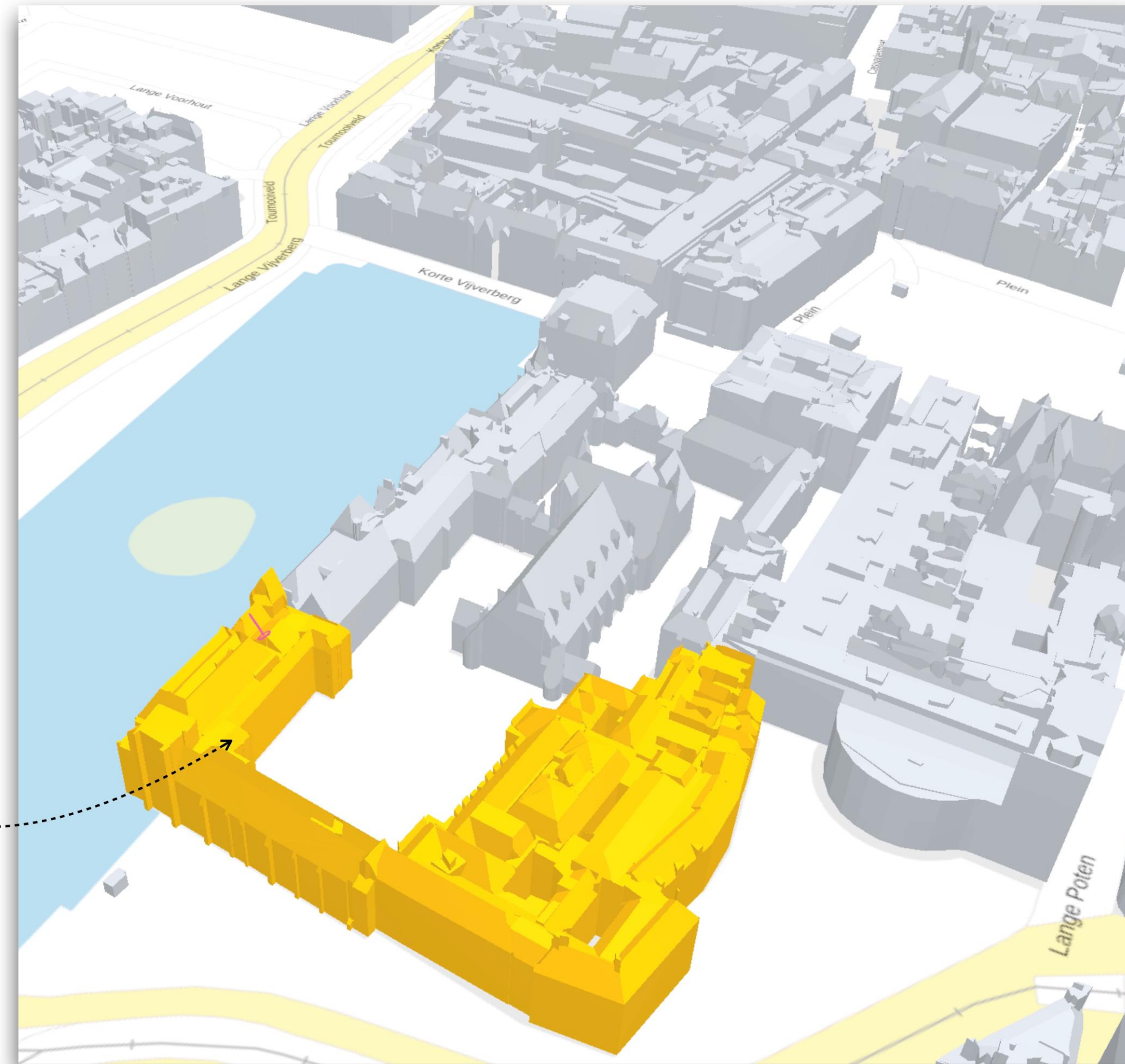
STREET VIEW IMAGERY



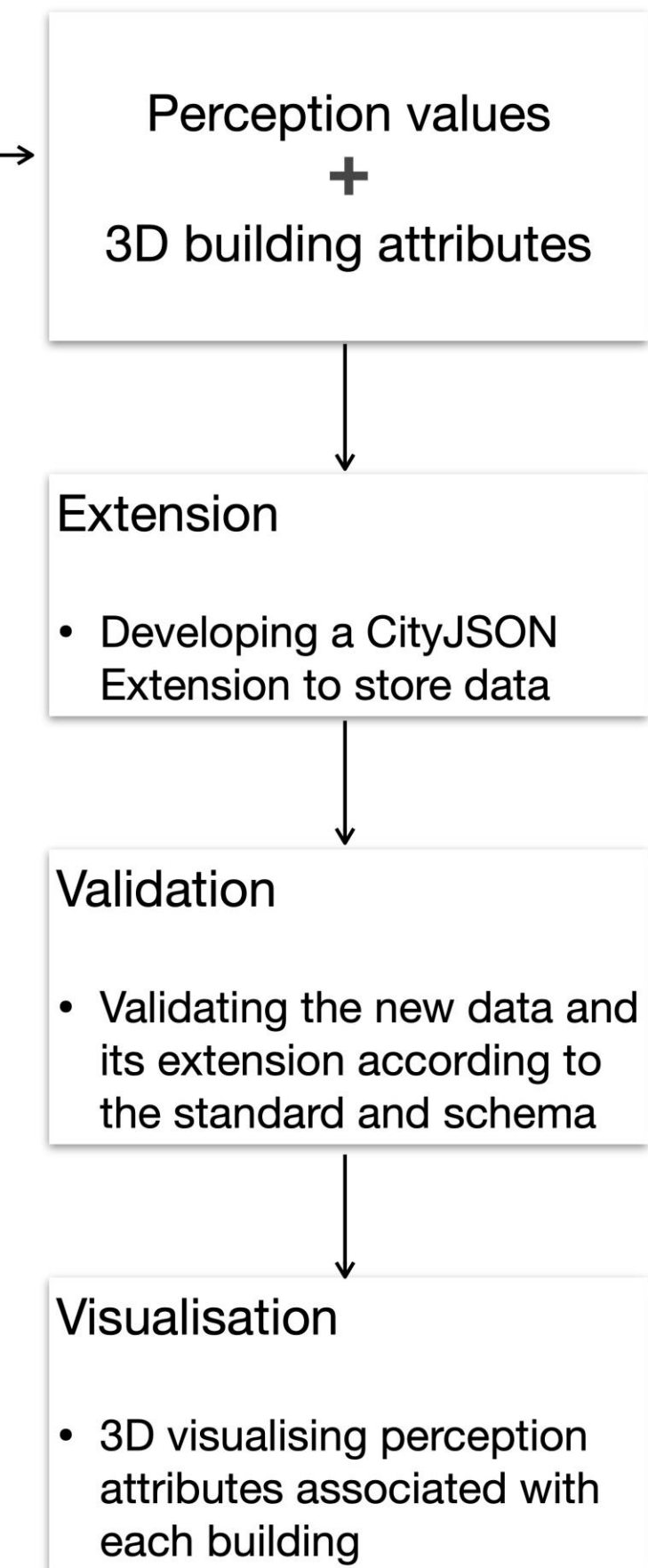
How do you perceive the building?

Indicator	Score
Original	5.2
Pleasing	5.1
Ordered	4.7
Boring	3.4
Complex	5.1

3D BUILDING MODEL



INTEGRATION



ADOPTION

RESULTS

BuildingPart Edit ×

NL.IMBAG.Pand.0363100012170202-0

Parents: ⌵

65 Attributes ^ 3 Geometries ∨

morphology_cluster	0
perception_cluster	0_0
+perception-originality	{ "originality": 4.278324889 }
+perception-pleasing	{ "pleasing": 4.76029276 }
+perception-ordered	{ "ordered": 3.77965274 }
+perception-boring	{ "boring": 5.227181812 }
+perception-complexity	{ "complexity": 5.11609989 }

Parent attributes

b3_bag_bag_overlap	0
b3_dak_type	slanted
b3_h_dak_50p	14.460000038146973
b3_h_dak_70p	15

Select surface

Semantics

All LoD0 LoD1.2 LoD1.3 LoD2.2

CityJSON

ninja v0.7.0



ADOPTION

USE CASES

An attribute-based query of buildings

The screenshot shows a GIS application interface with a 3D building model. A 'Query Builder' window is open, displaying a list of fields and a filter expression. The filter expression is: `"attribute.pleasing" > 5 AND "attribute.year" < 1950`. The interface includes a toolbar, a layers panel, and a status bar at the bottom.

Query Builder

Set provider filter on example.city

Fields

- uid
- type
- parents
- children
- attribute.b3_bag_bag_overlap
- attribute.b3_dak_type
- attribute.b3_h_dak_50p
- attribute.b3_h_dak_70p
- attribute.b3_h_dak_max
- attribute.b3_h_dak_min
- attribute.b3_h_maaiveld
- attribute.b3_kas_warenhuis

Values

Search...

Sample All

Use unfiltered layer

Operators

= < > LIKE % IN NOT IN

<= >= != ILIKE AND OR NOT

Provider Specific Filter Expression

`"attribute.pleasing" > 5 AND "attribute.year" < 1950`

Help Test Clear Save... Load... Cancel OK



Incorporating Human Perception in Digital Twins

by Junjie Luo

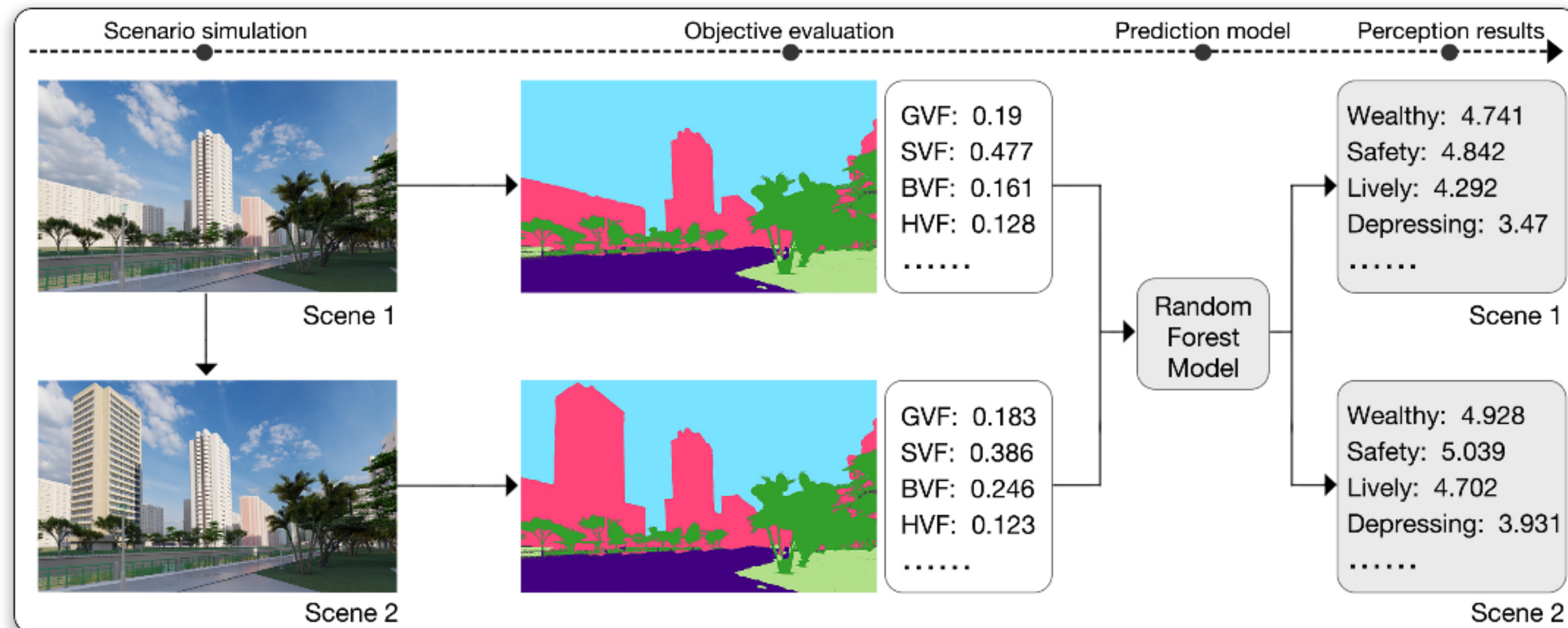


(A). Photograph of an example location



(B). Virtual counterpart in UDT

A. Adding a new building



Geospatial technologies in urban farming

Supporting the 30 by 30 vision — Singapore's 30% of nutritional needs by 2030



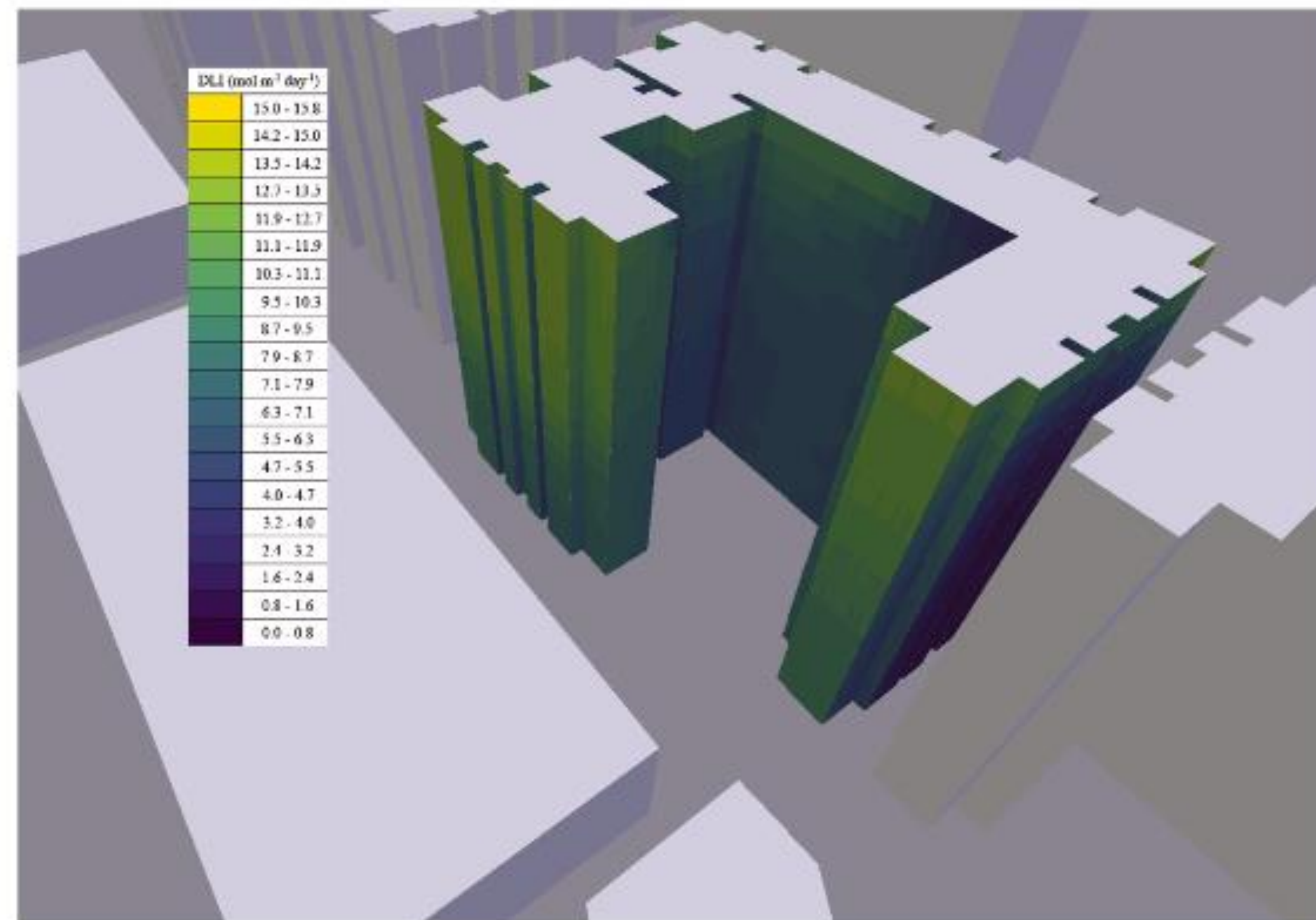
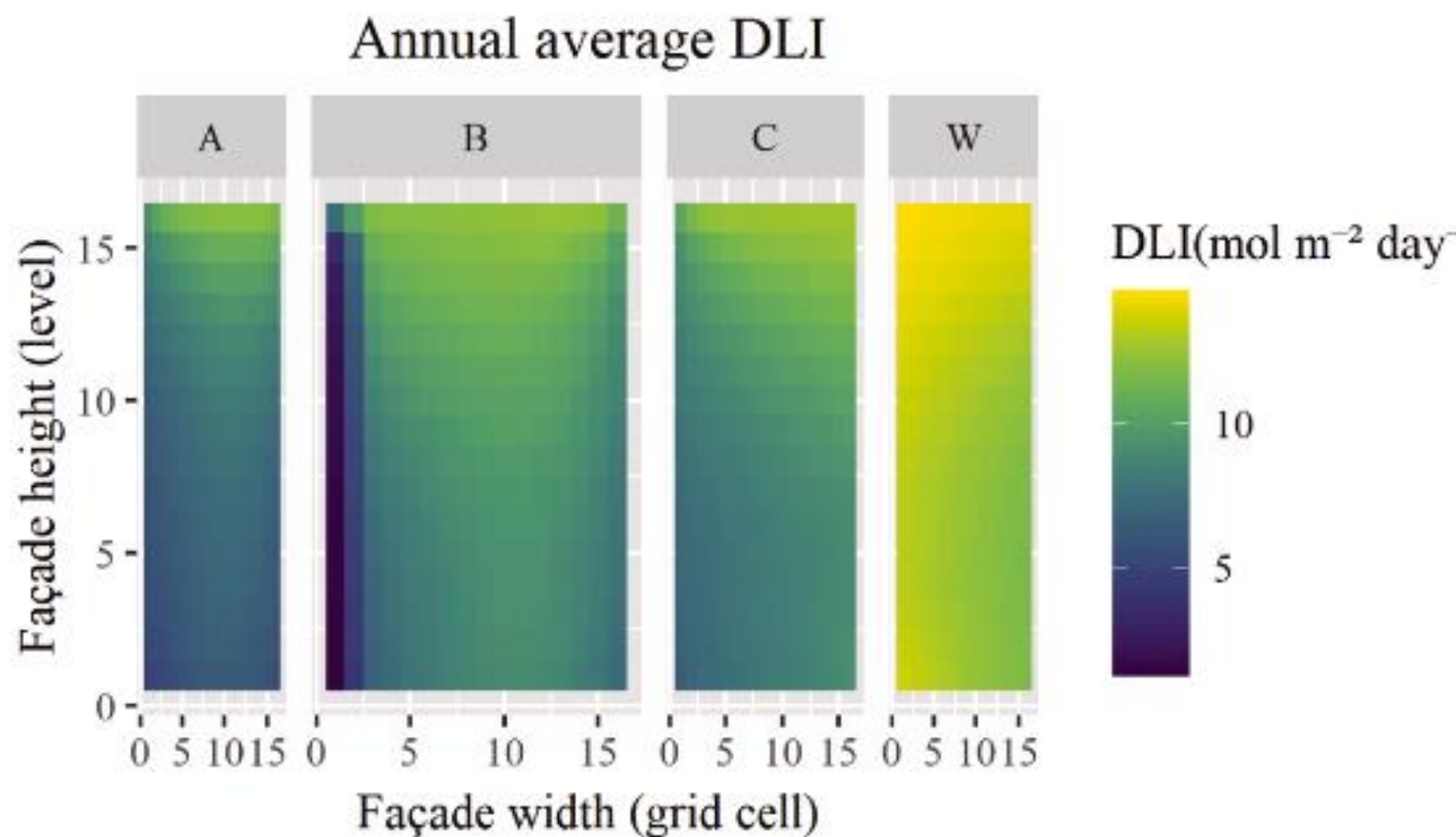
Geospatial technologies in urban farming

Supporting the 30 by 30 vision — Singapore's 30% of nutritional needs by 2030



New 3D GIS use case: urban farming simulations

by Ankit Palliwal



(a) PAR sensor placement along the corridors.



(b) PAR sensor placement on the window ledge.



Credit: Song Shuang

Conclusion and lessons learned

- Achieving a mature ('true') digital twin is difficult. Real-time/dynamic data and feedback loop remain the key obstacles
- Breaking silos is *de facto* 'a must' but challenging
- DT is well beyond 3D. Marriage of lots of data sources and types that are difficult to integrate and make sense of
 - Novel integration of thermal walks into urban digital twins to analyse and improve pedestrian thermal comfort and walkability in urban environments
 - Wearables, street view imagery, precise weather data, ...
- Unlike traditional 3D GIS, DTs entail more attention on stakeholders, organisational issues, business models, ...

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