URBAN CLIMATE AND MOBILITY:

A Graph Neural Network-based Approach to Predict the Effect of Urban Climate on Personal Mobility Choices

Michele Giampaolo

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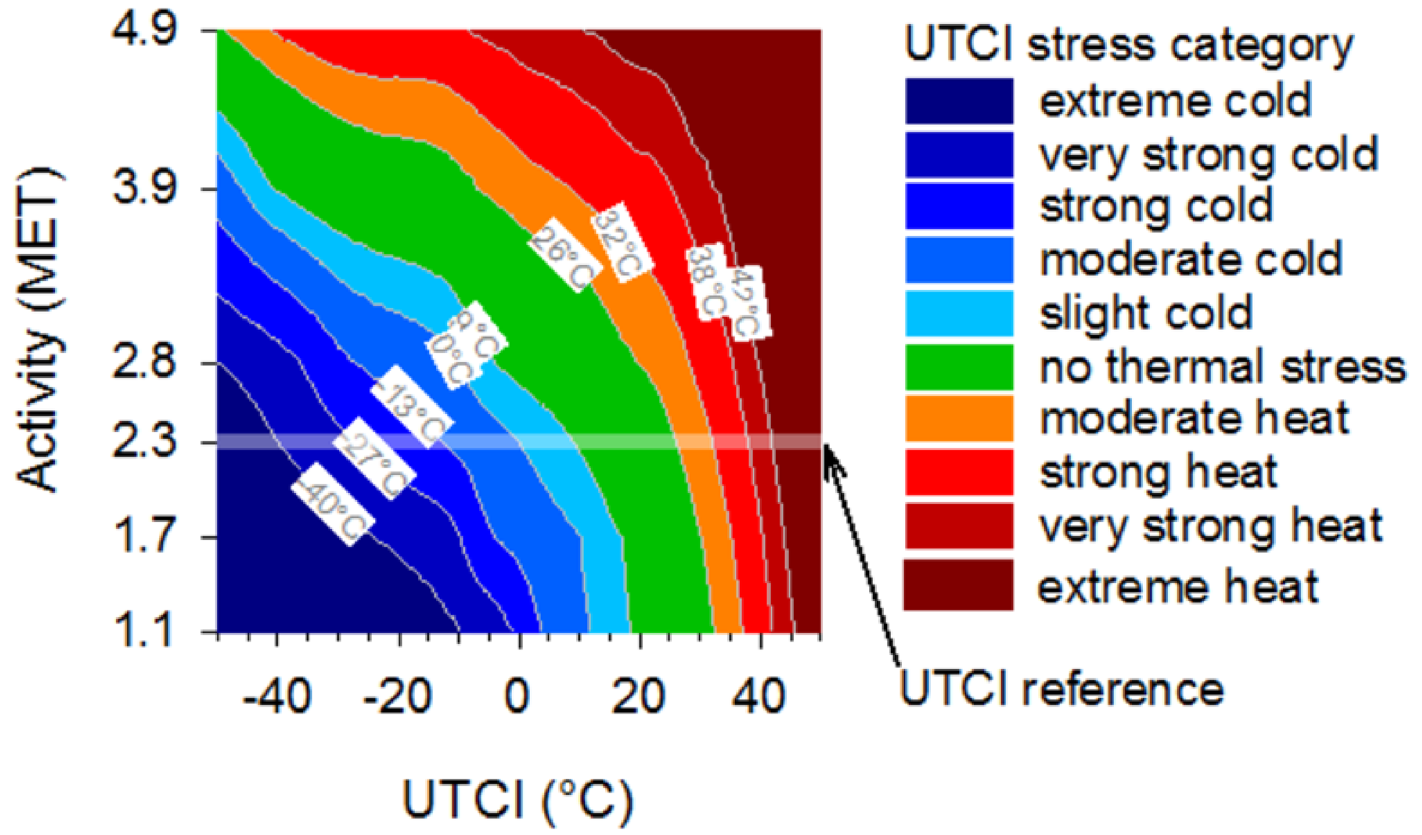
TU Delft

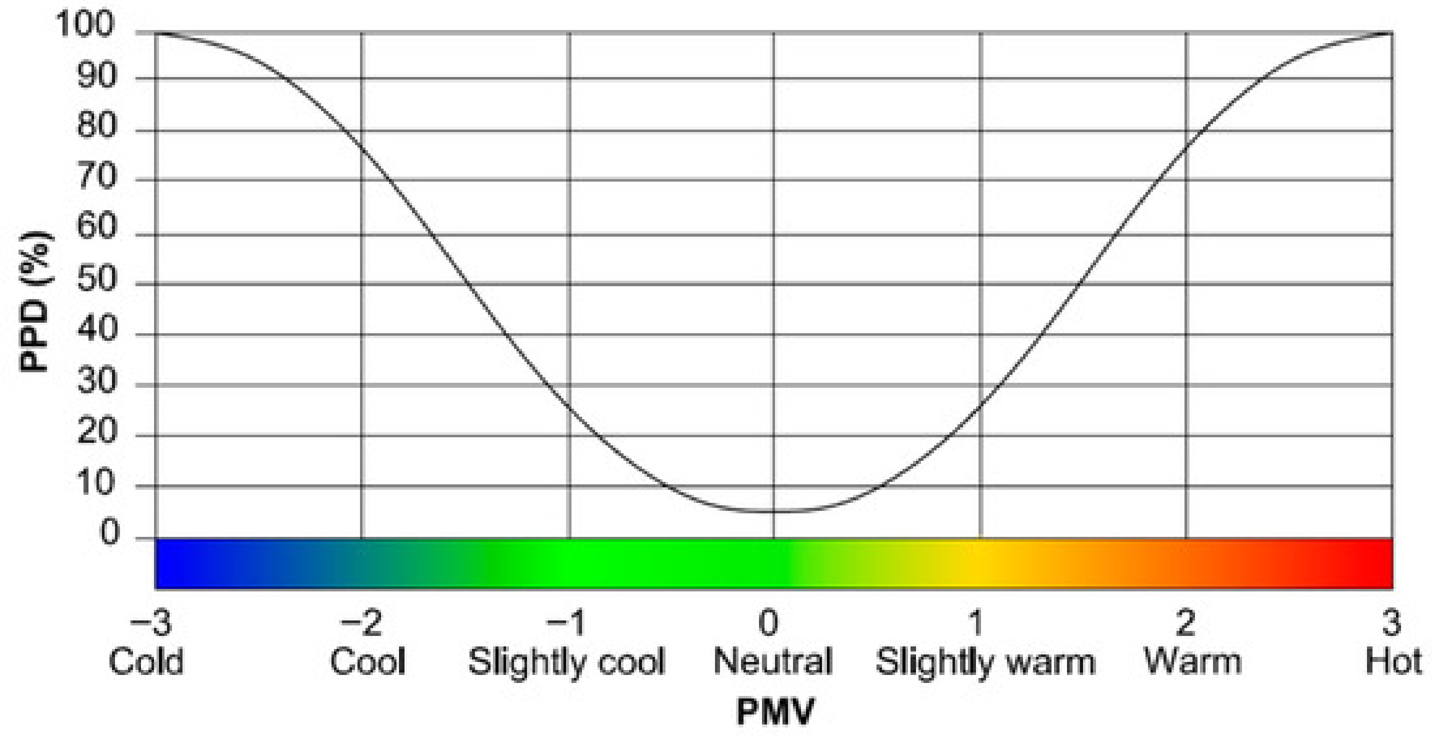
Master of Science in
Geomatics for the Built Environment

Climate Comfort in Urban Applications

- Climate essential in modern city design
- Conventional deterministic models (PMV, PET, UTCI)
- Good at generalisable standard value based on high-level weather parameters
- But they miss personal human influences:
  - activity
  - clothing
  - culture
  - personal preferences
  - eating habits
  - body composition

PET (°C)	Thermal Perception	Grade of Physiological Stress
<4	Very cold	Extreme cold stress
4–8	Cold	Strong cold stress
8–13	Cool	Moderate cold stress
13–18	Slightly cool	Slight cold stress
18–23	Comfortable	No thermal stress
23–29	Slightly warm	Slight heat stress
29–35	Warm	Moderate heat stress
35–41	Hot	Strong heat stress
>41	Very hot	Extreme heat stress

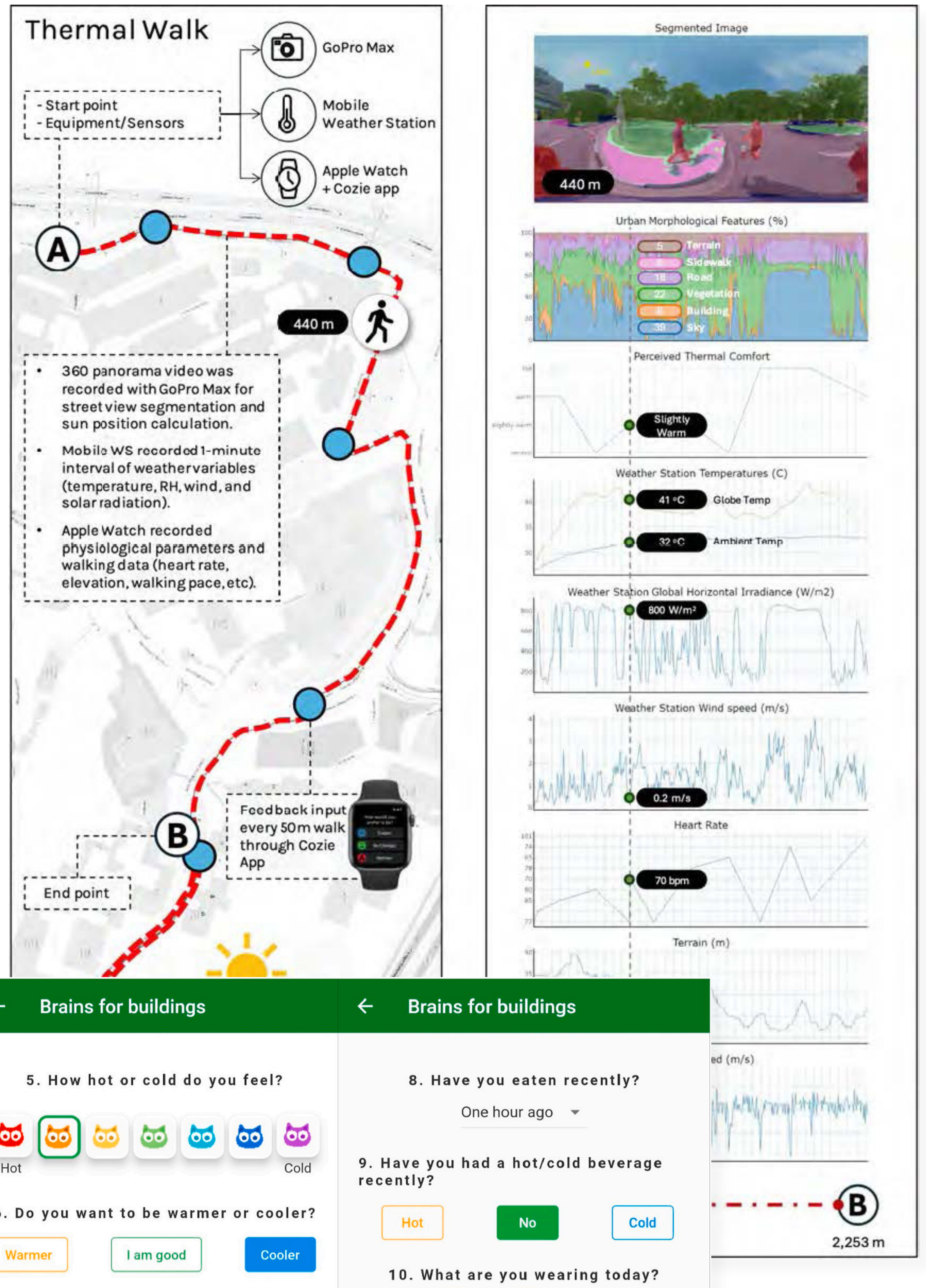


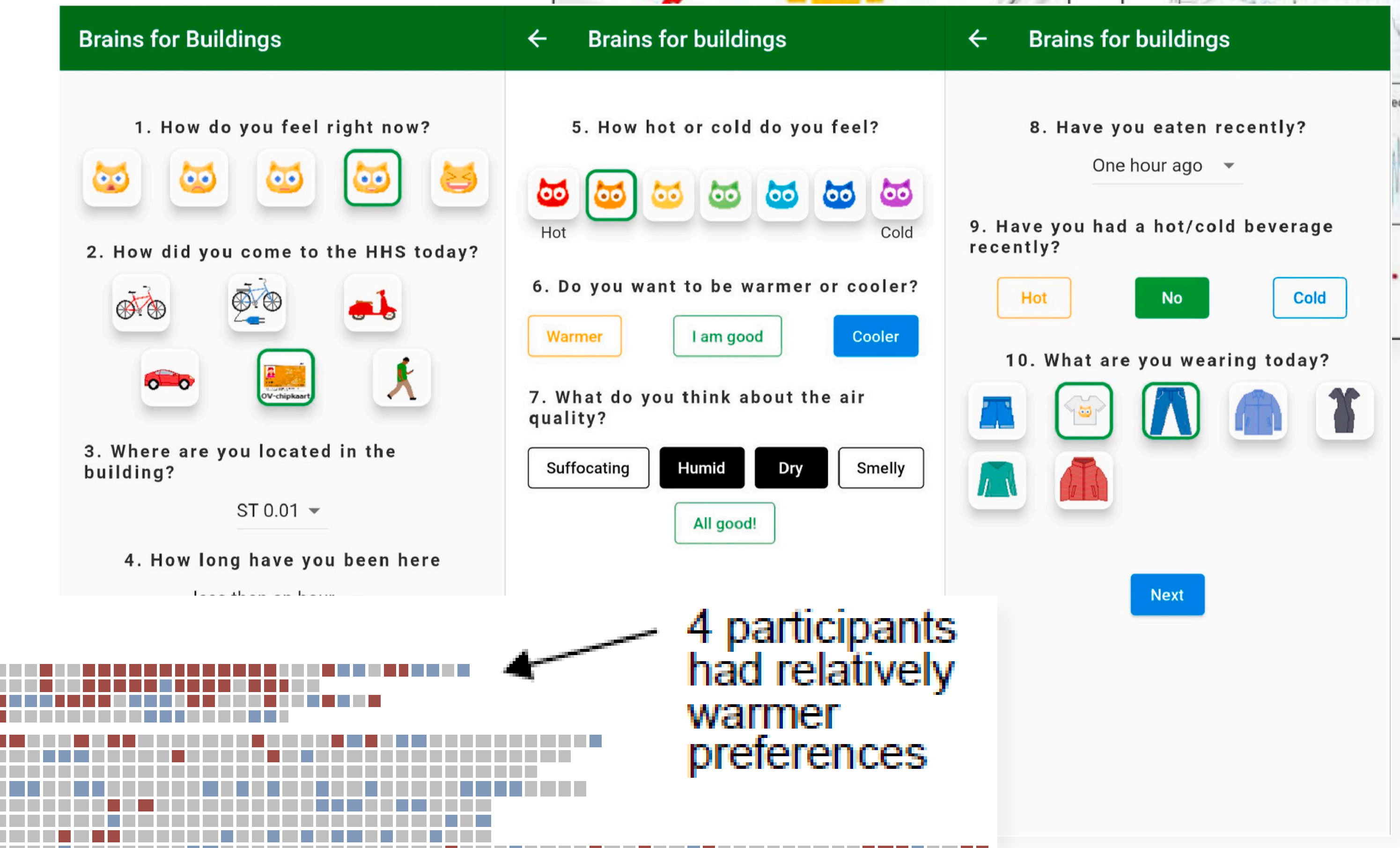


Human-centric Methods

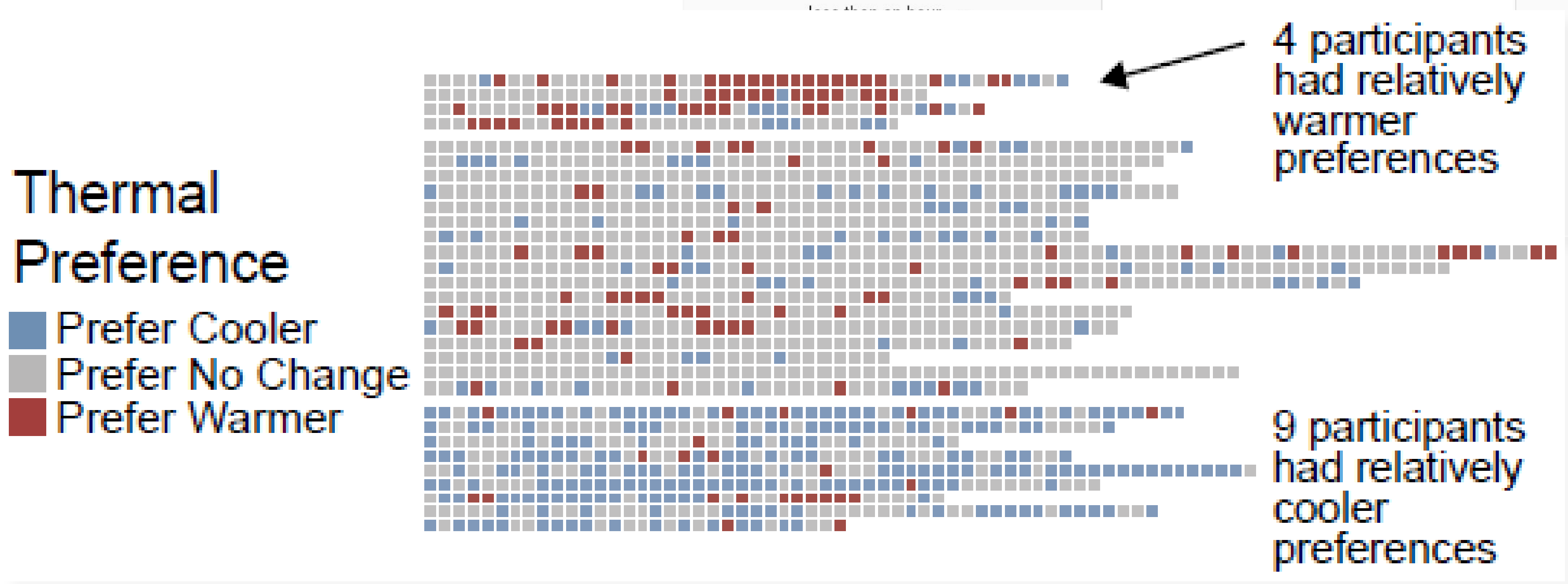
- Bottom-up approaches reverse this approach
- Use more personalized, low-level datasets to model human behaviour as it relates to climate
- Usually using wearables and survey data
- Often limited to indoor spaces or to a small outdoors scale
- There is a gap for this approach on an the urban scale!

Ignatius et al. (2024)





Upasani et al. (2024)



Jayathissa et al. (2020)

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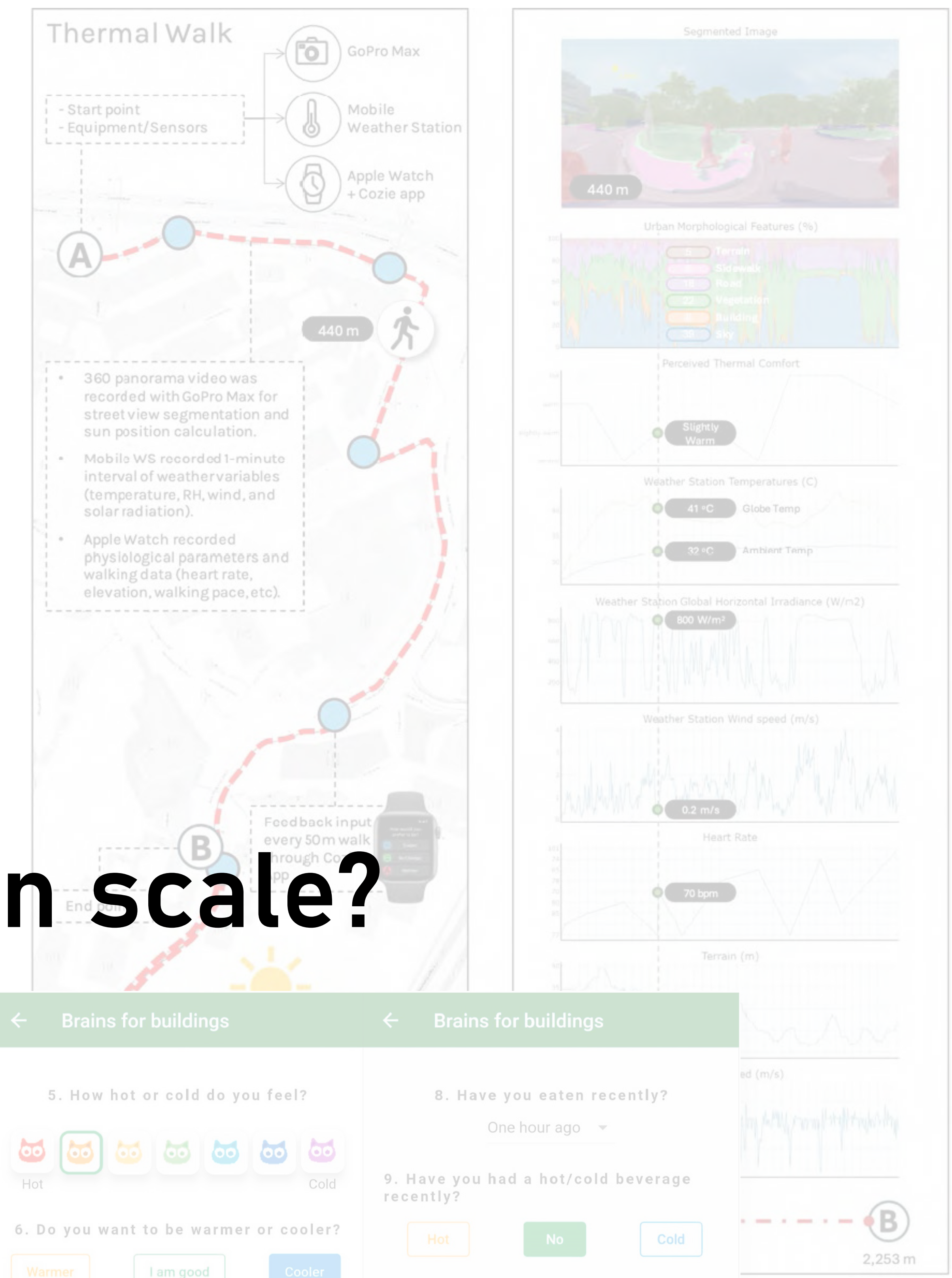
How to apply this approach to the urban scale?



Ignatius et al. (2024)

Upasani et al. (2024)

Jayathissa et al. (2020)

CONTEXT

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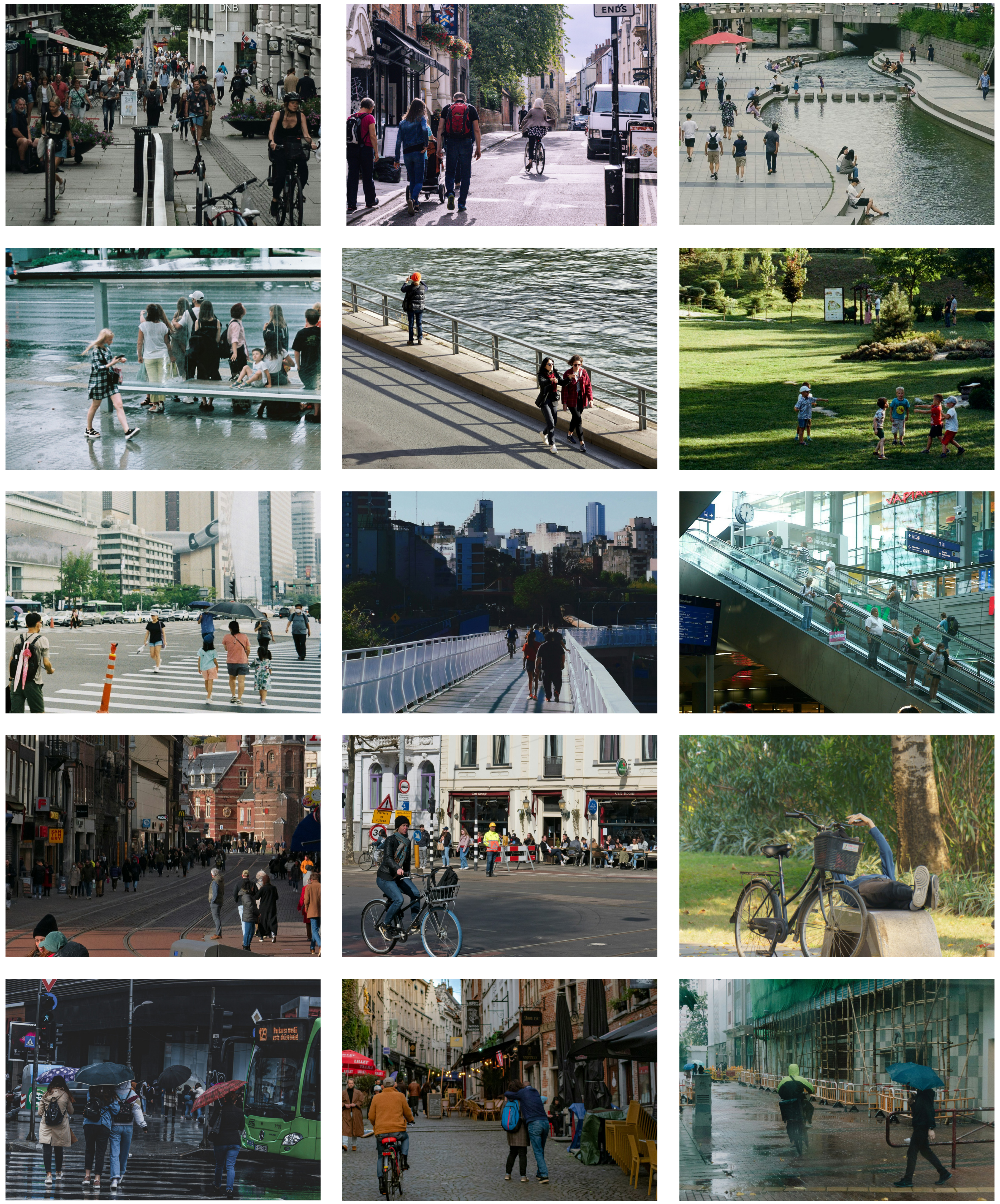
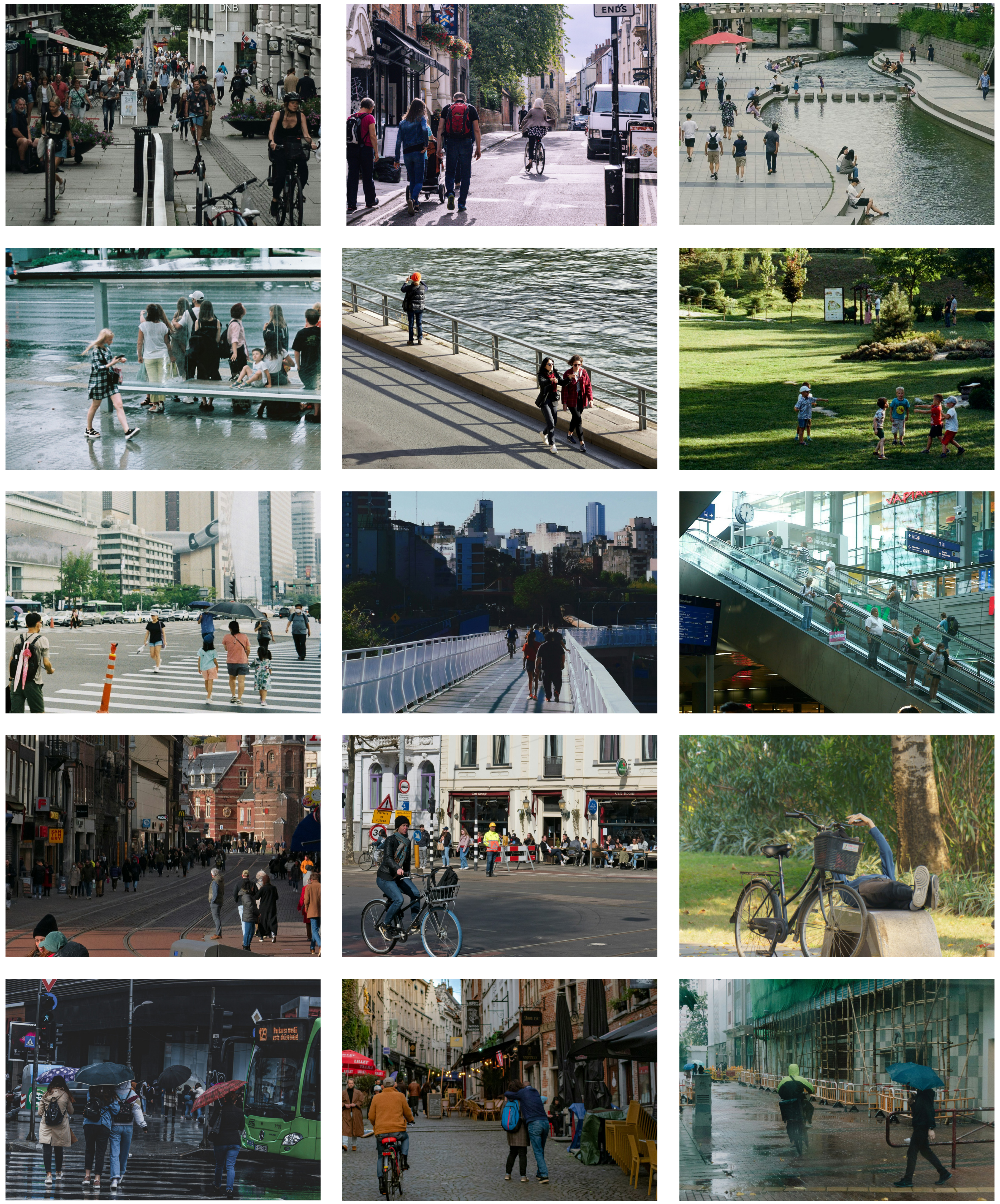
Mobility!

- Can record individual people's movements with similar bottom-up approaches
- Intrinsically includes personal influences
- Can be analysed along with climate



Urban Mobility Forecasting & GNNs

- Wide application in modeling cities as graphs
- Spatial and Temporal dependencies can be captured
- Mostly used with static graphs:
    - Traffic sensor networks
    - Origin-destination networks
    - Point of Interest networks
- Gap with personal mobility network modeling



Research Questions

How do urban climate factors impact people's mobility choices in the urban landscape of Seoul and how can this be captured using a STGNN model?

- *To what extent and how reliably can a GNN model be used to predict urban mobility?*
- *How is the STGNN graph structure constructed and how does this impact the insights the model is able to give on mobility?*
- *How can a personal mobility dataset, like the Seoul Cozie dataset, be integrated in a STGNN framework and what are its limitations?*

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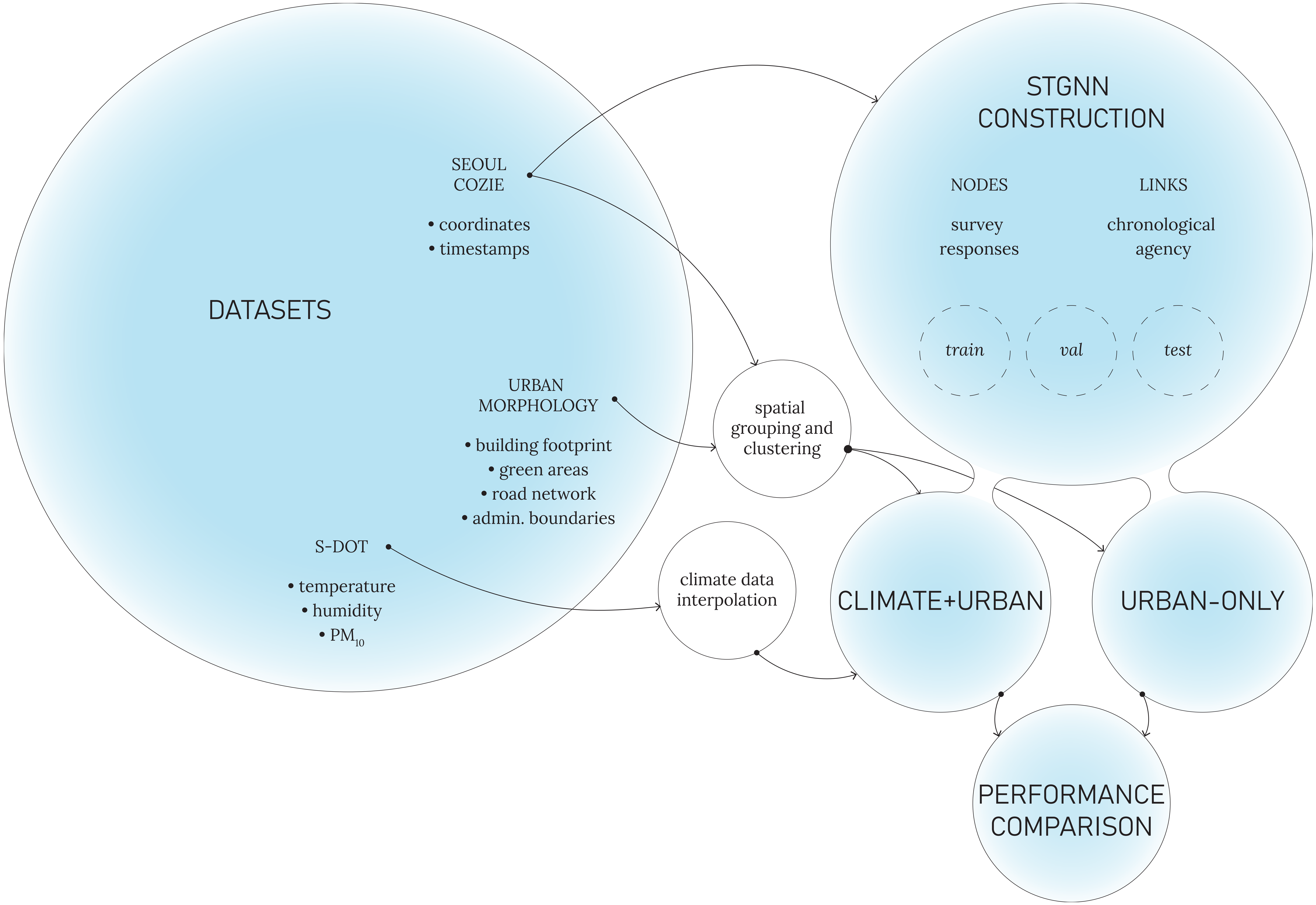
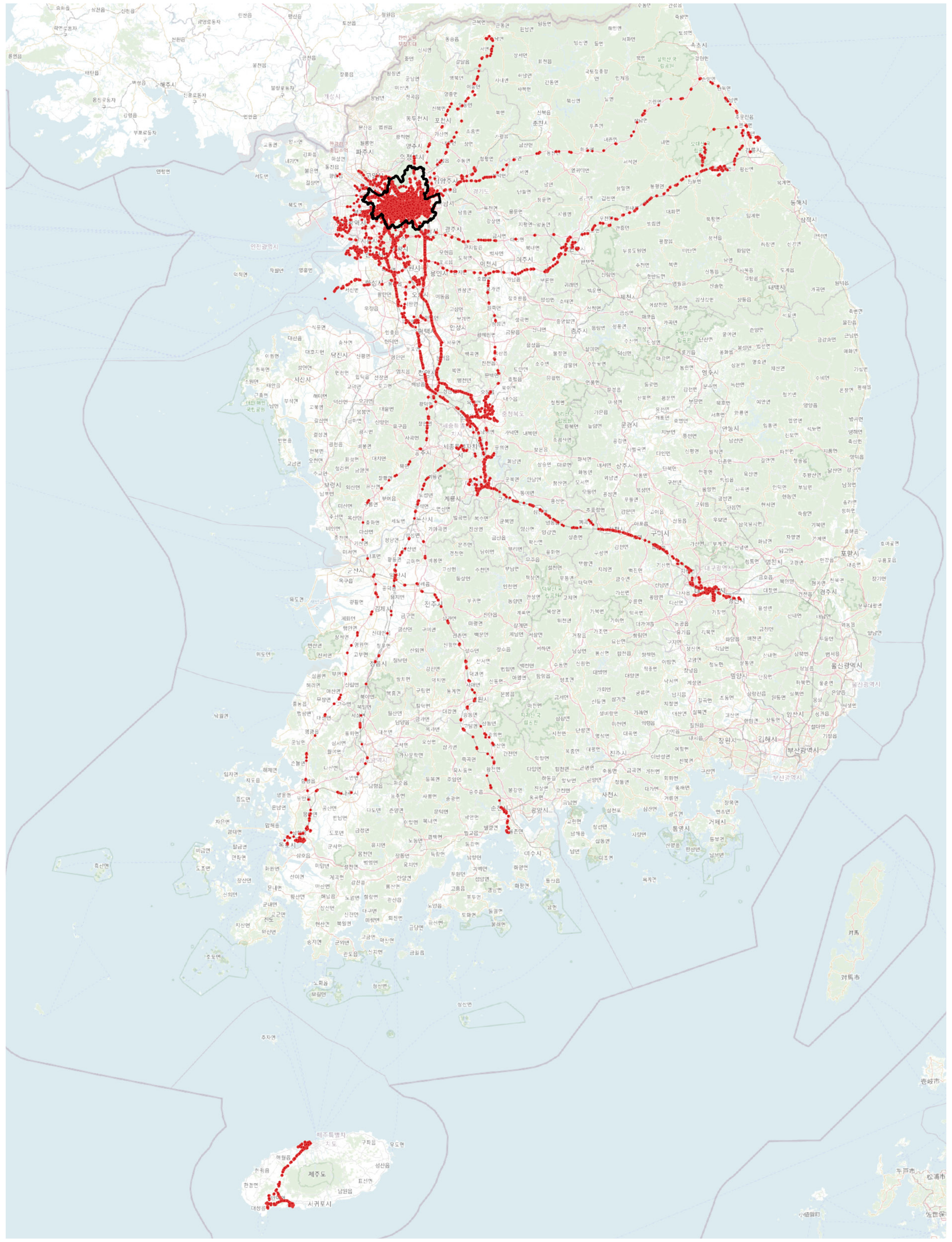
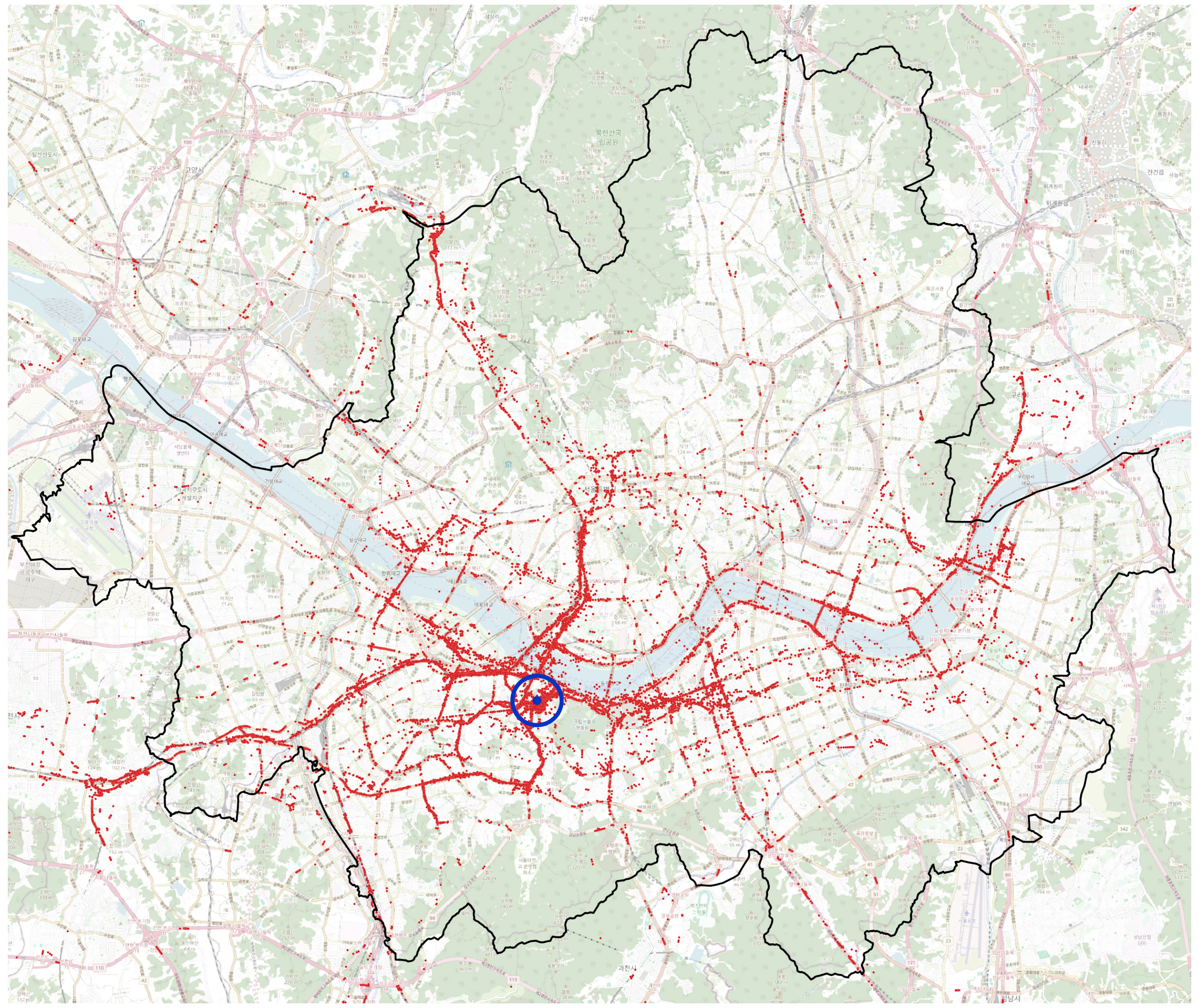


Seoul Cozie Dataset





- **22 particpants**
  CAU students 20-31yrs.
- **6 weeks**
  Oct./Nov. 2024
- **15000+** individual recorded coordinates

Tartarini et al. (2023)

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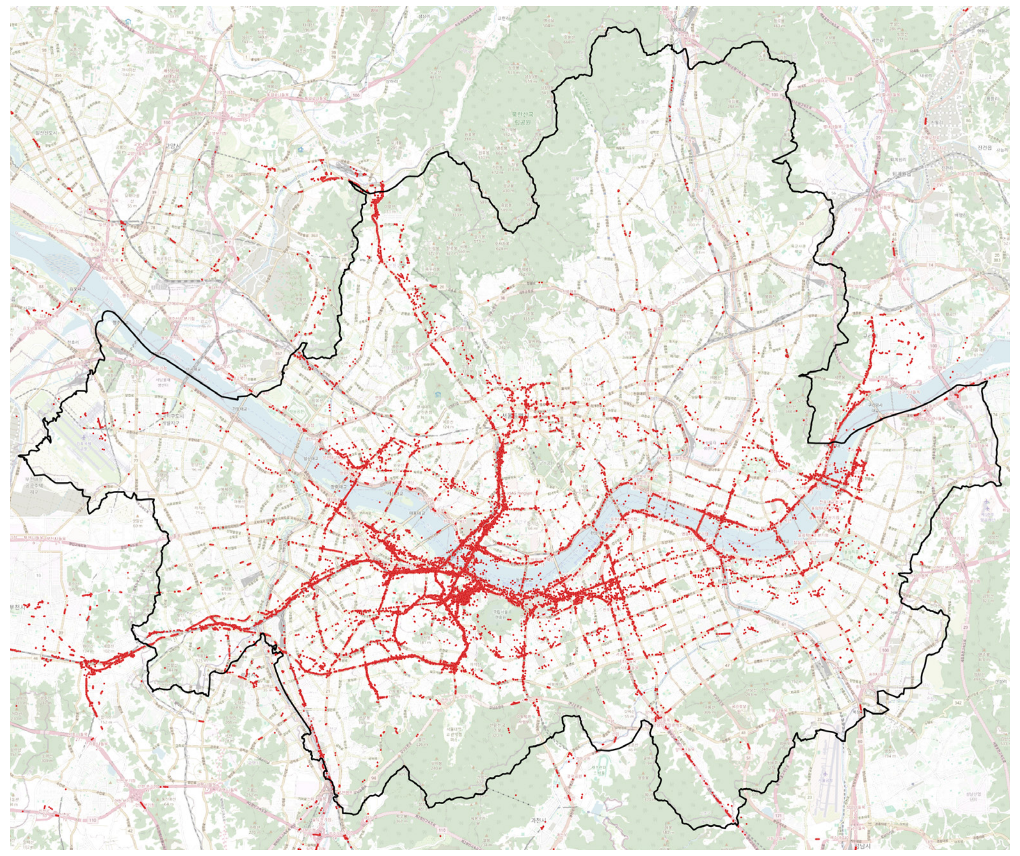
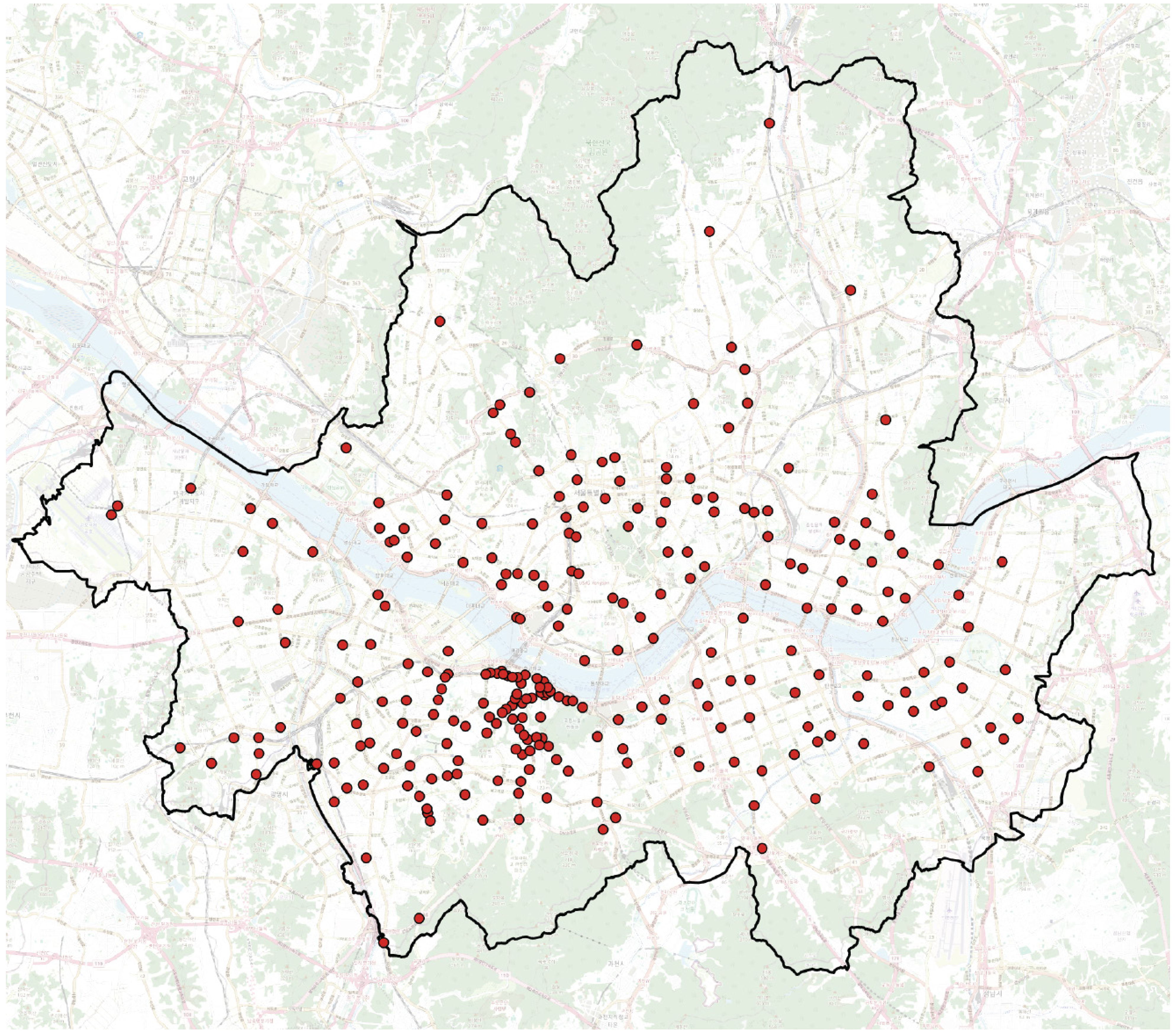
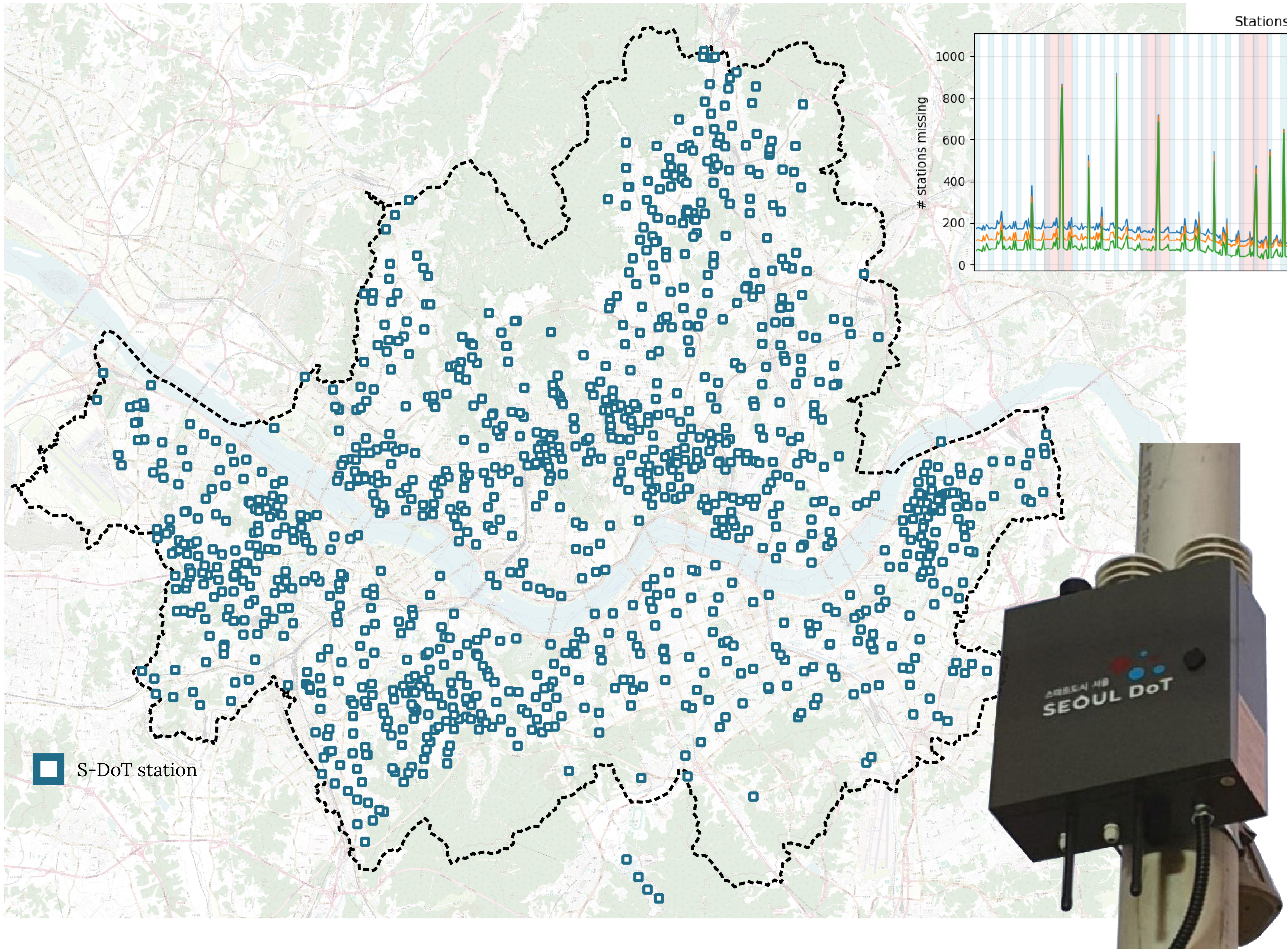


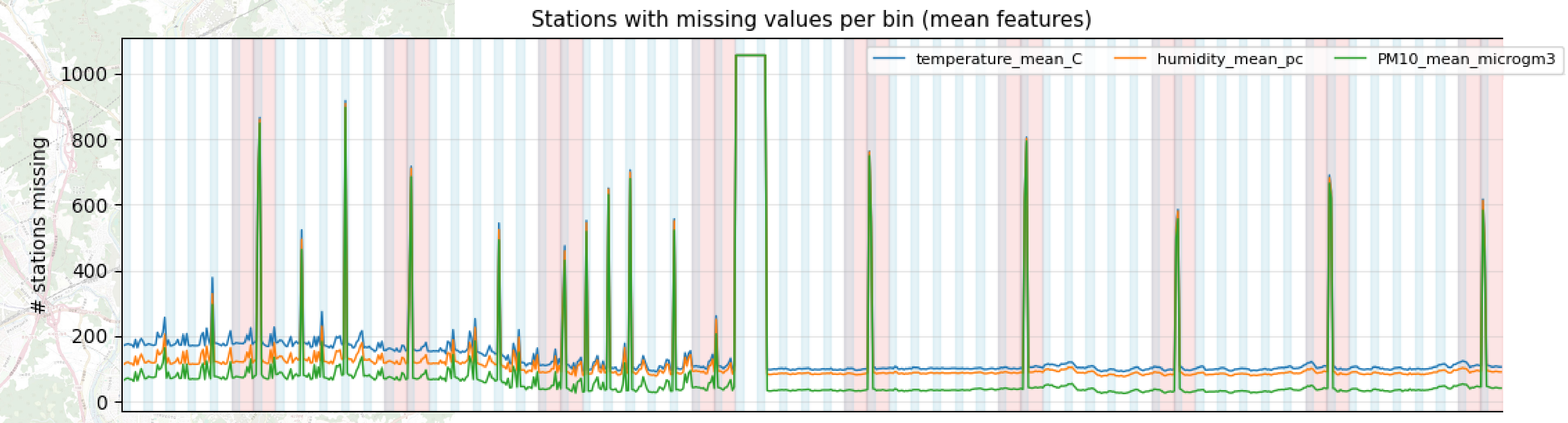


271 nodes
of 4 types:

- *municipality* node
- *sub-municipality* node
- *main road intersection* node
- *local road intersection* node

S-DoT Dataset





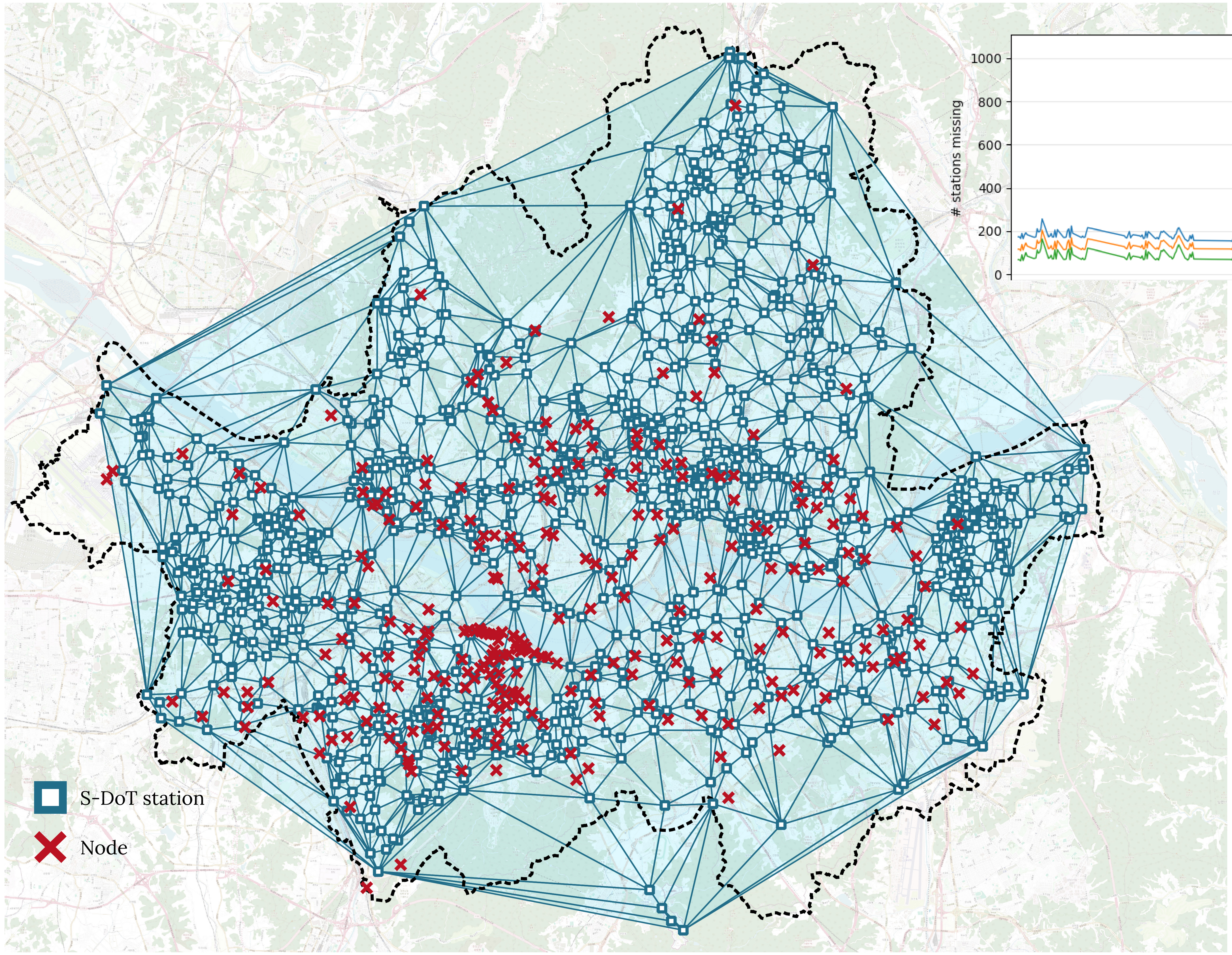
1000+ weather stations across Seoul:

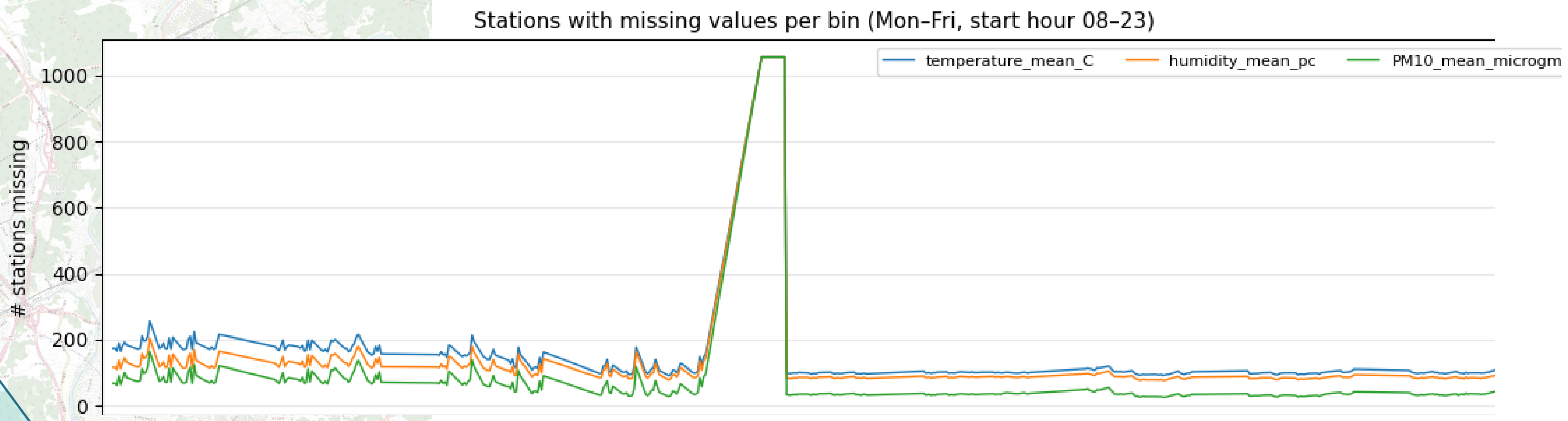
- temperature
- humidity
- air quality

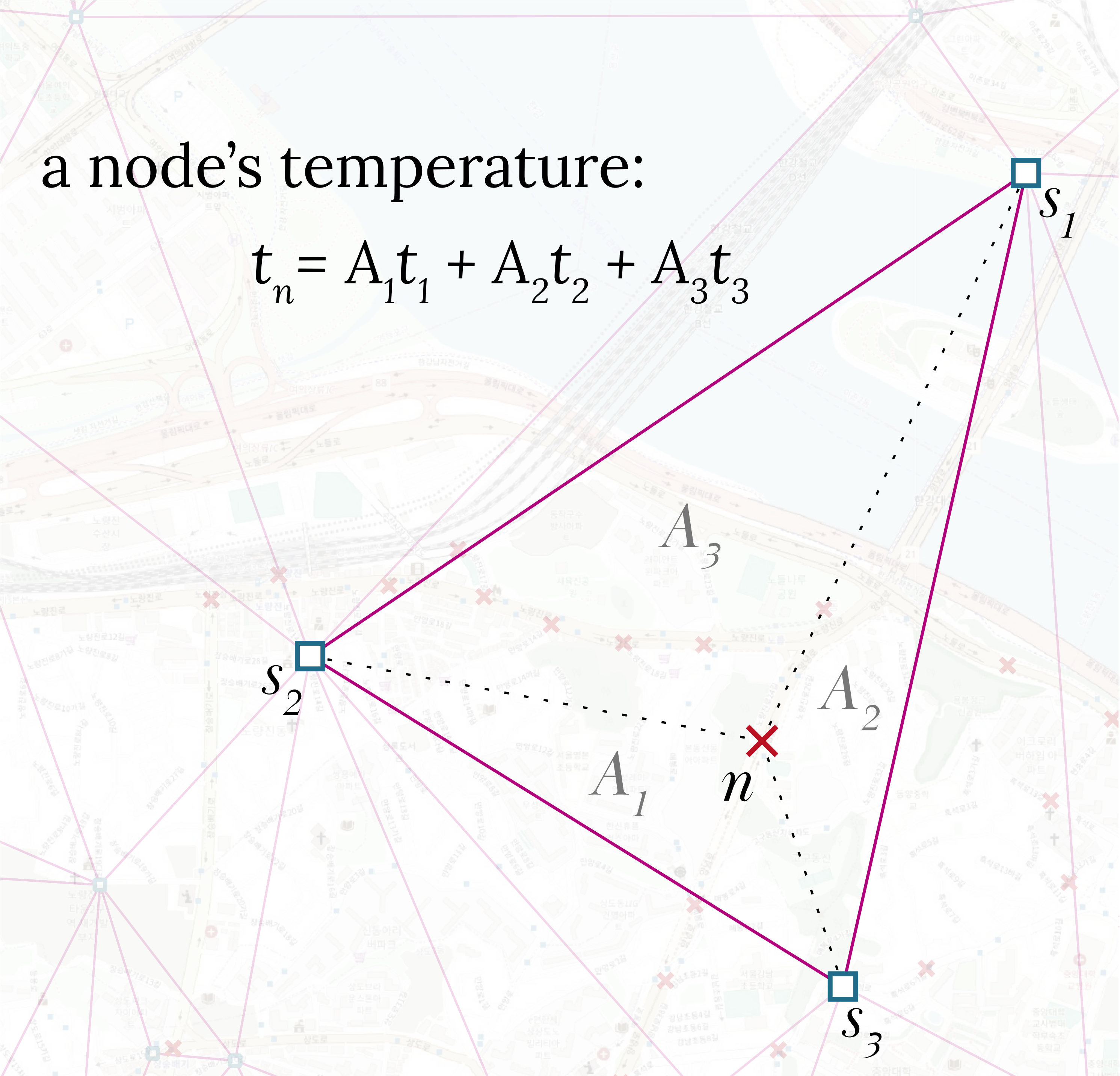
- wind
- light
- UV
- noise
- vibration
- pollutants

Seoul Metropolitan Government (2021)

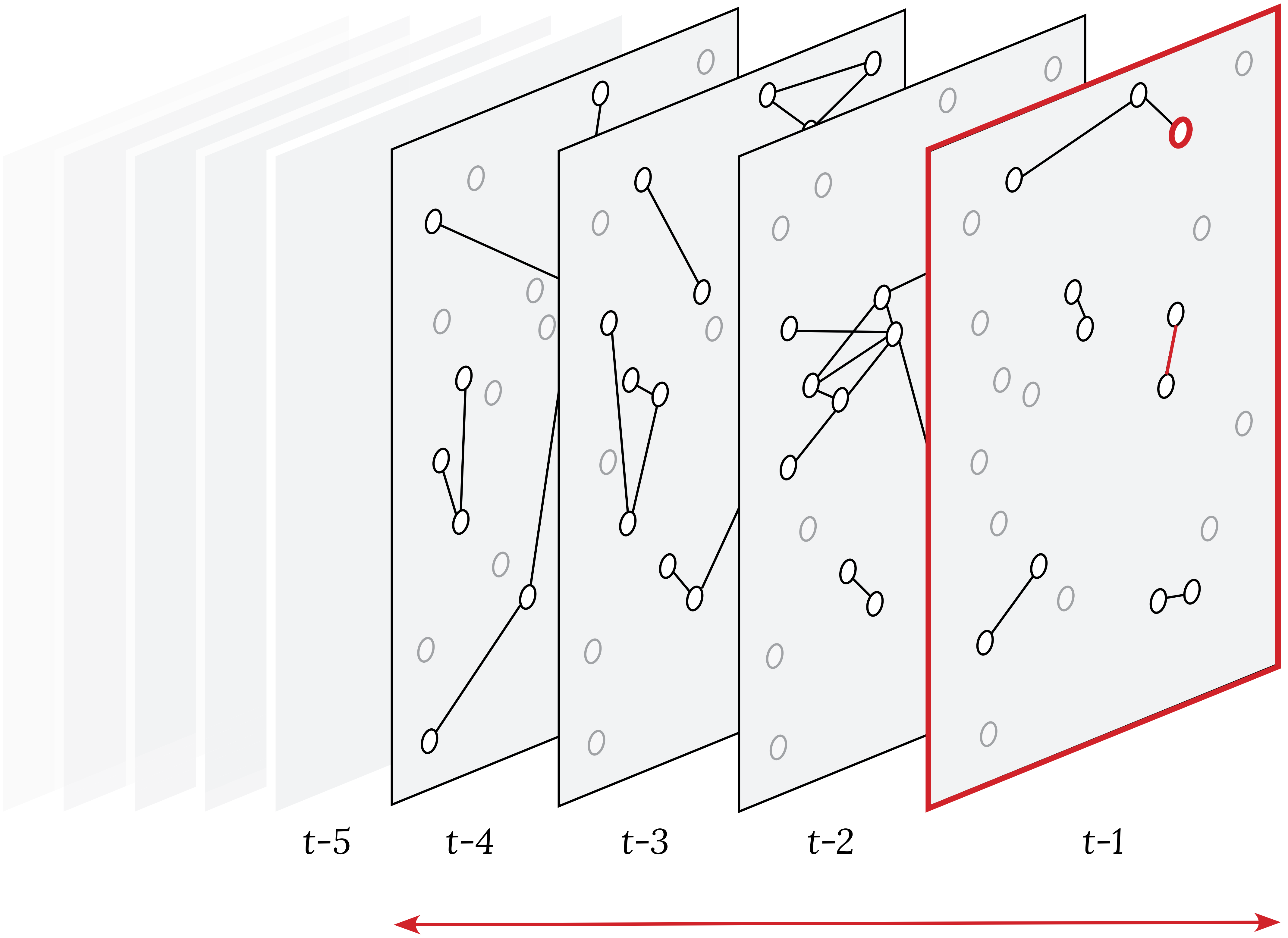
S-DoT Dataset







STGNN Structure

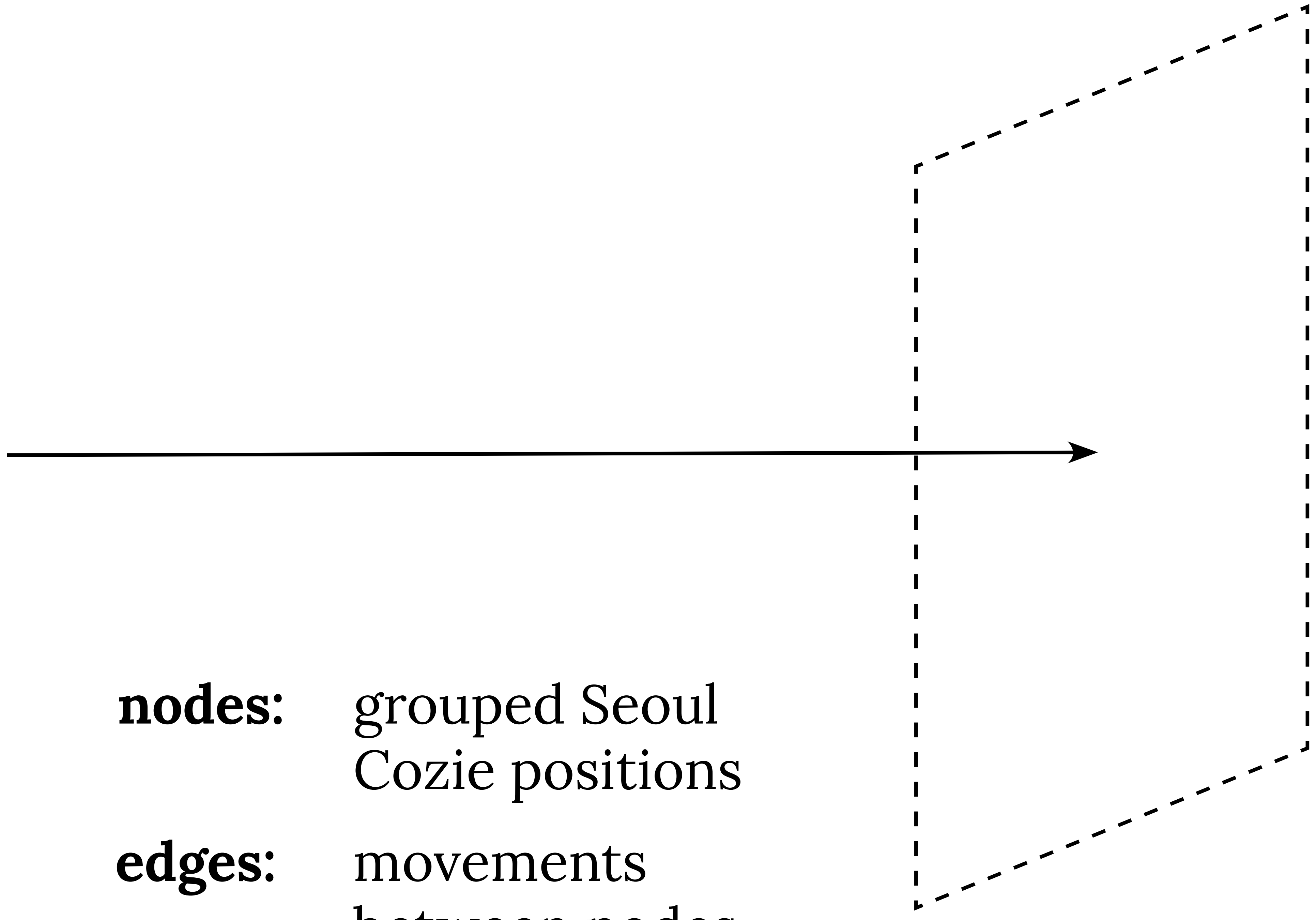


nodes: grouped Seoul Cozie positions

edges: movements between nodes

time bin: snapshot of graph every 2 hours

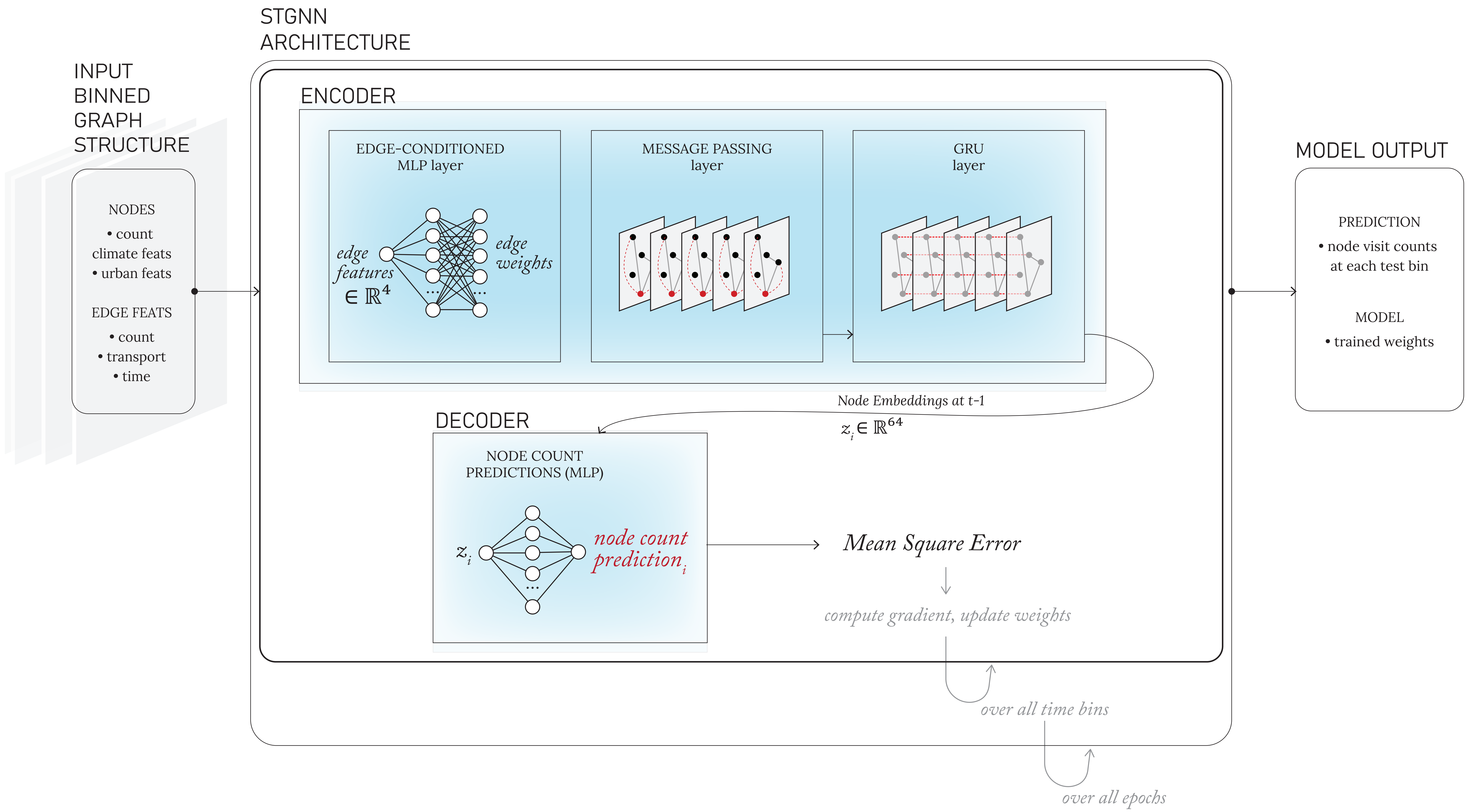
window size: 5 bins used for prediction (10 hours)



Node & Edge Features

	CLIMATE+URBAN STGNN	URBAN-ONLY STGNN
node features	coords urban feats visit count	
	temperature humidity PM_{10}	
edge features	visit count avg. transport method (from avg. speed)	

STGNN Architecture



Results

CONFIGURATION	NODE COUNT ACCURACY (MSE)	NODE PRESENCE ACCURACY (%)	NODE PRESENCE PRECISION (%)	NODE PRESENCE RECALL (%)
Climate+Urban	0.1250	98.09	76.41	56.51
Urban-only	0.1314	98.04	75.33	55.53

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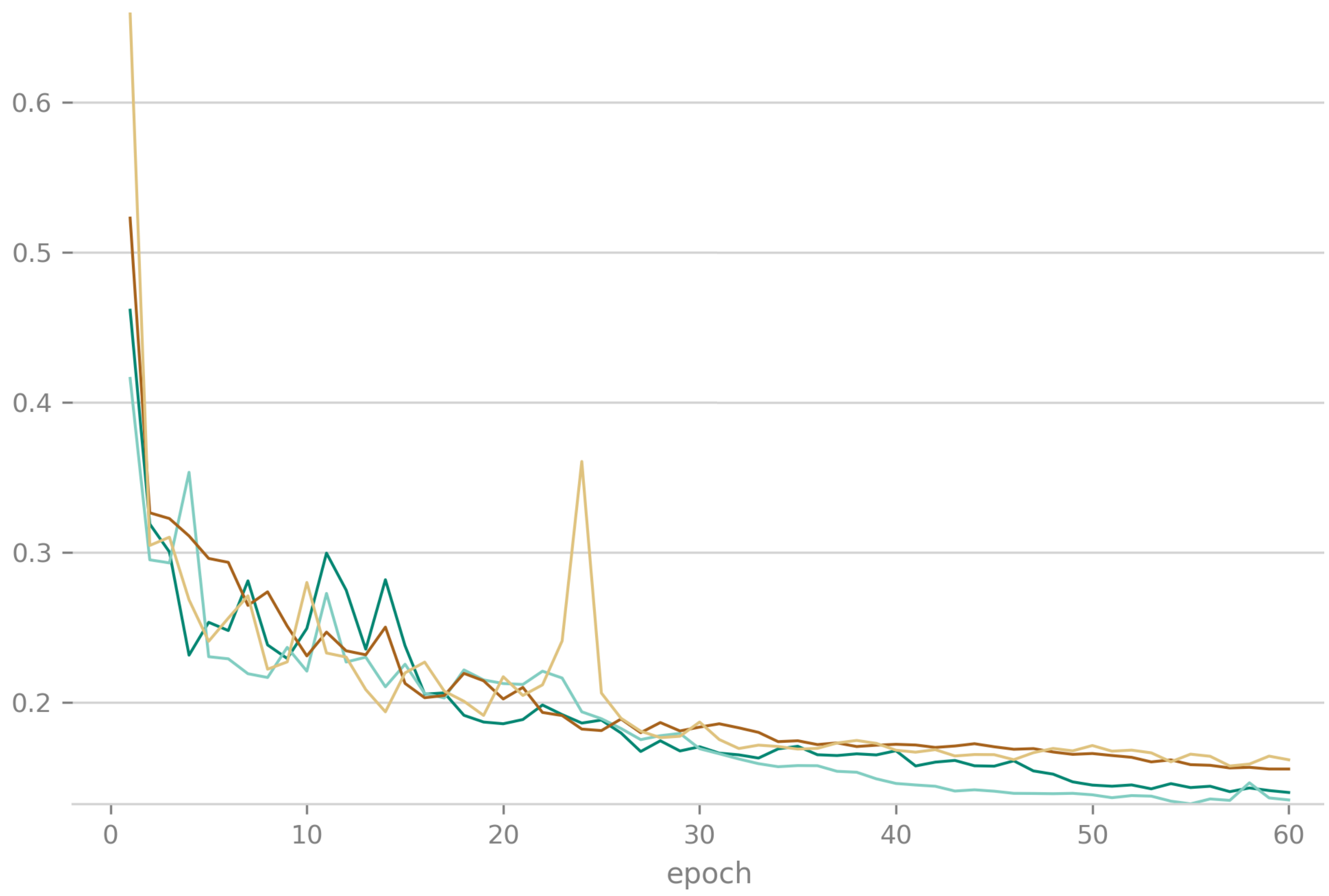
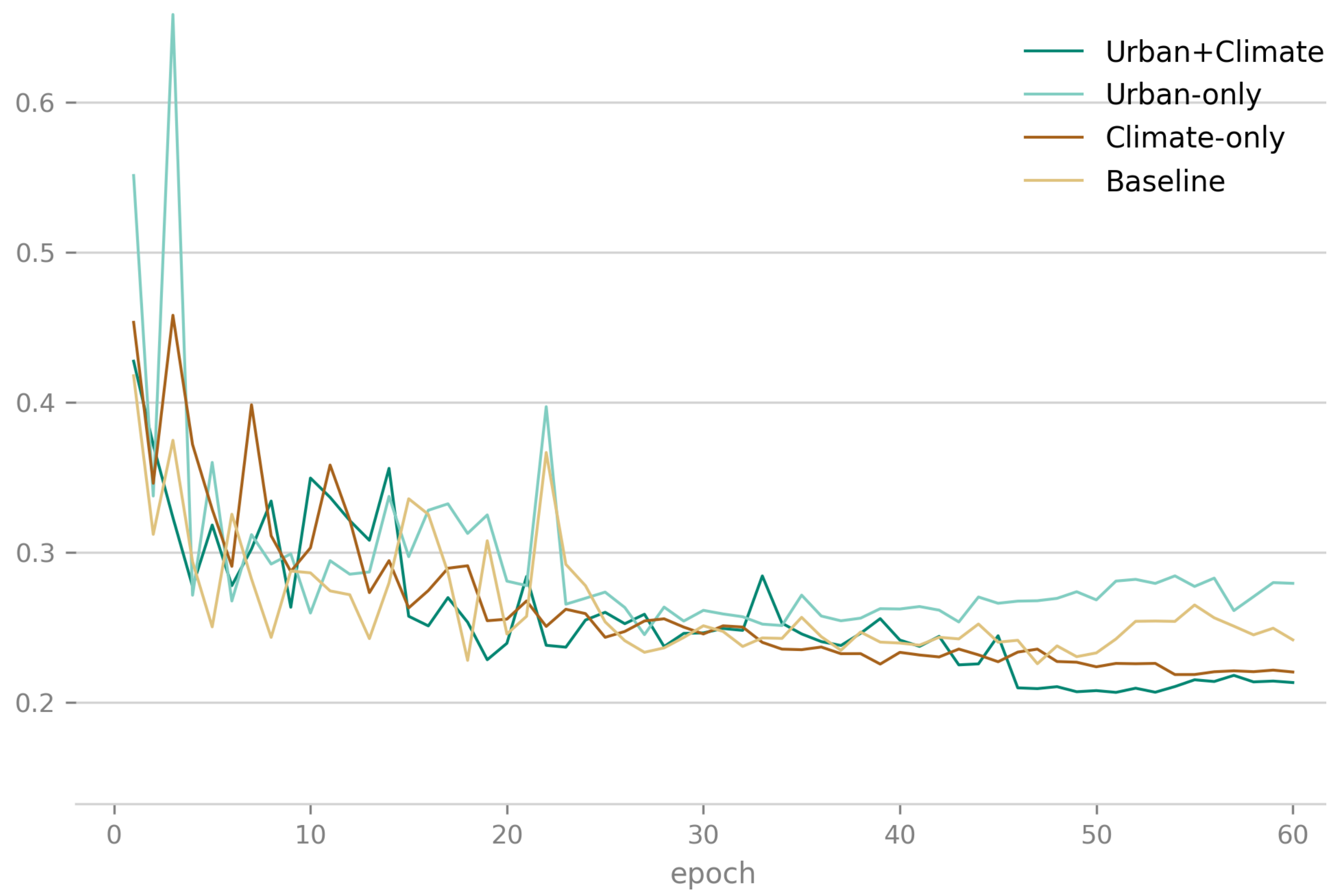
Urban-only	0.1314	98.04	75.33	55.53
Climate-only	0.1240	97.77	67.16	56.27
Baseline	0.1174	97.99	74.33	54.79



Training losses (MSE)



Validation losses (MSE)

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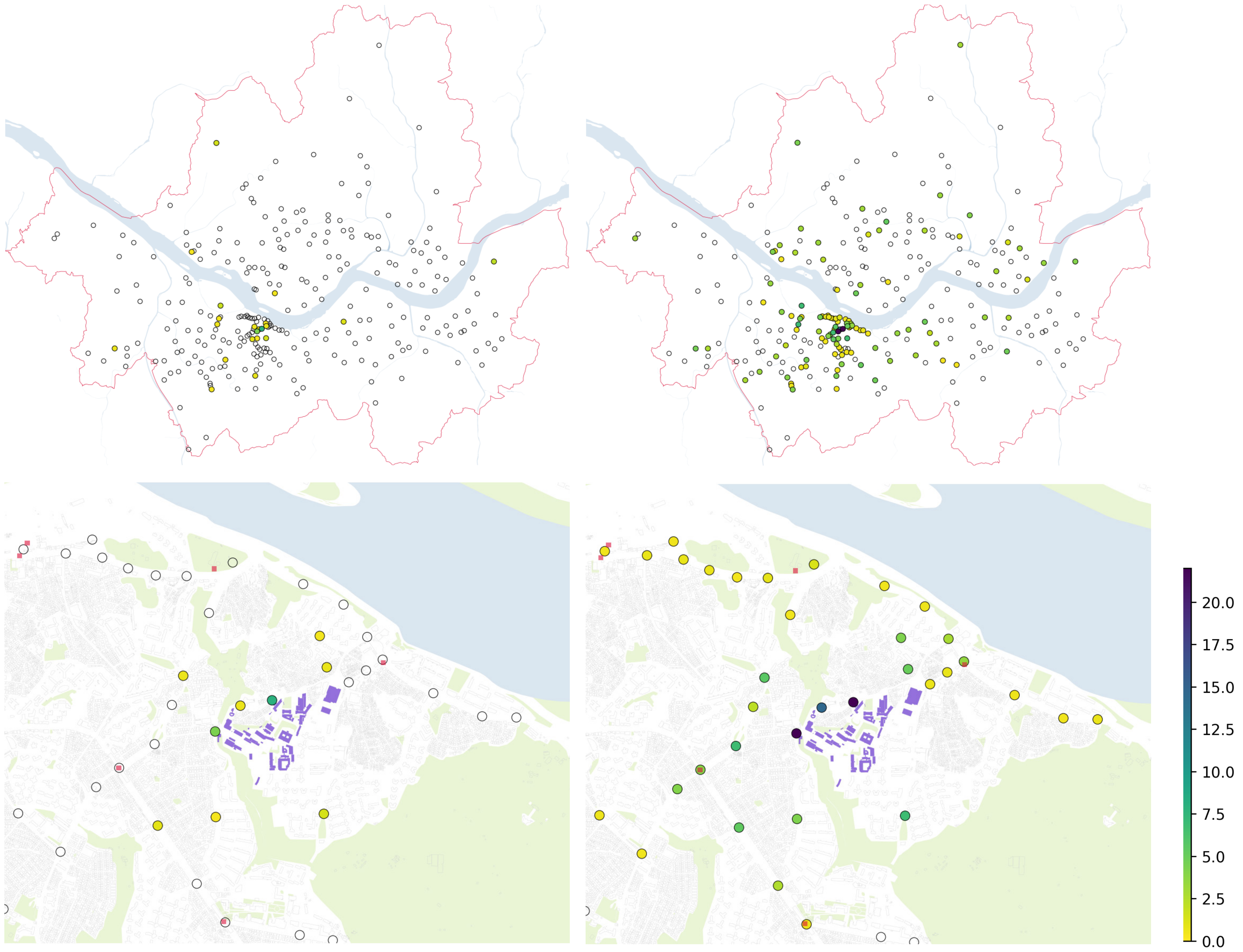

Mean values

Peak values

Scenario Definition

Time-of-day

• Morning	08:00-10:00
• Mid-day	12:00-14:00
• Afternoon	16:00-18:00
• Evening	18:00-20:00

Weather

• Hot days	≥ 23°C
• Cold days	≤ 10°C
• Humid days	≥ 70%

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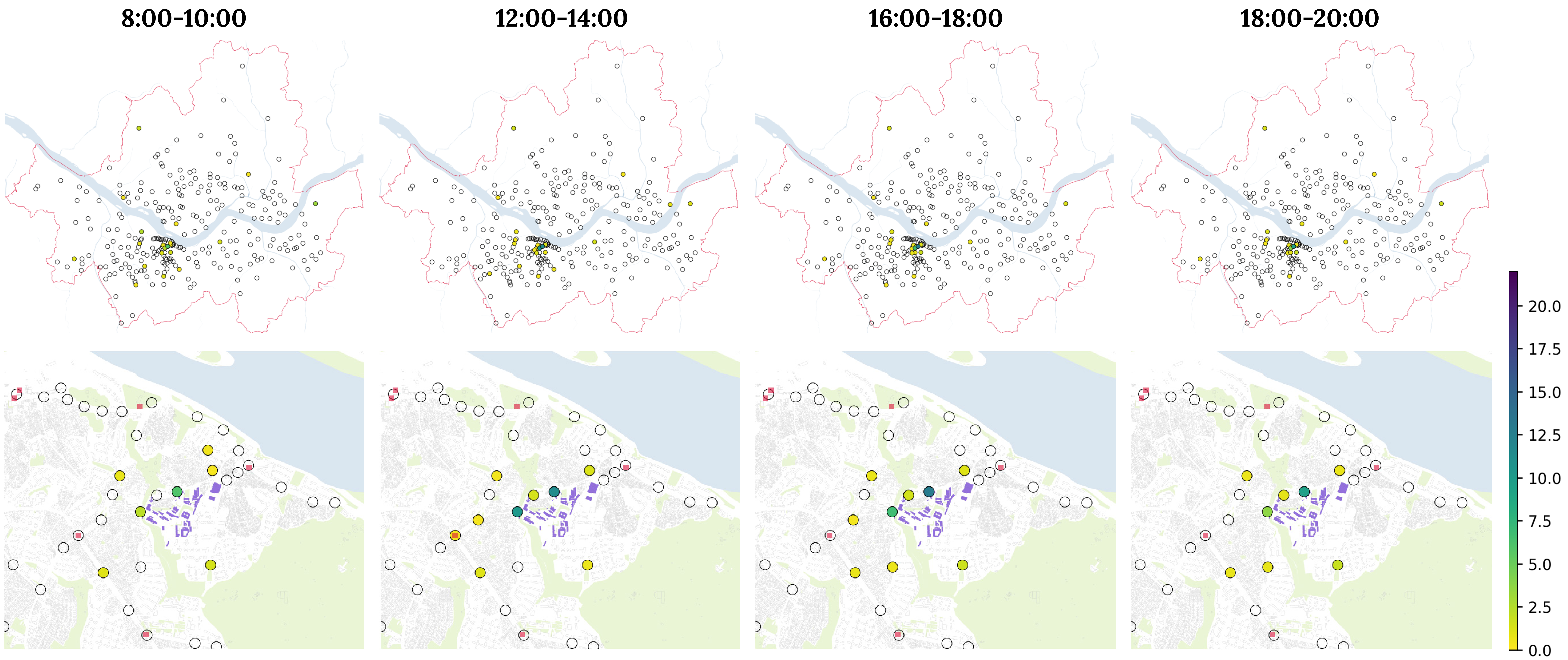
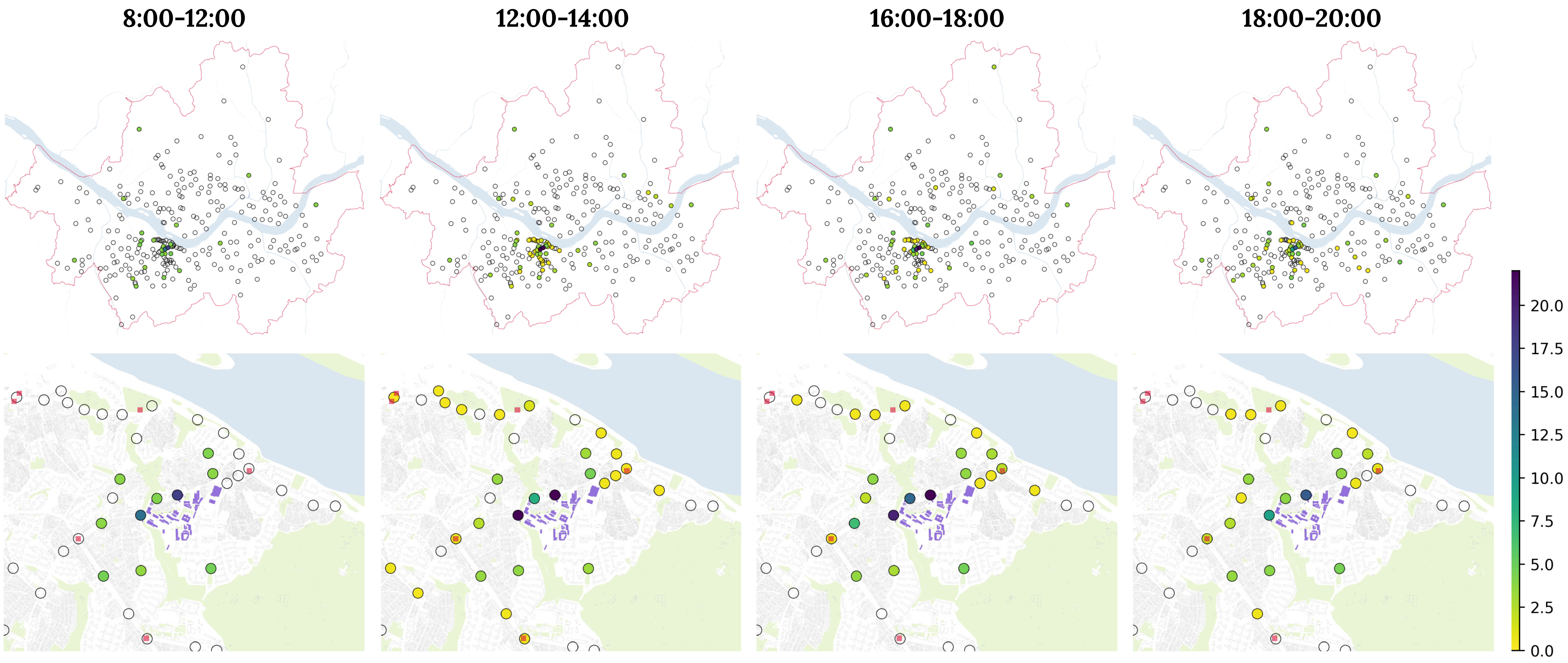
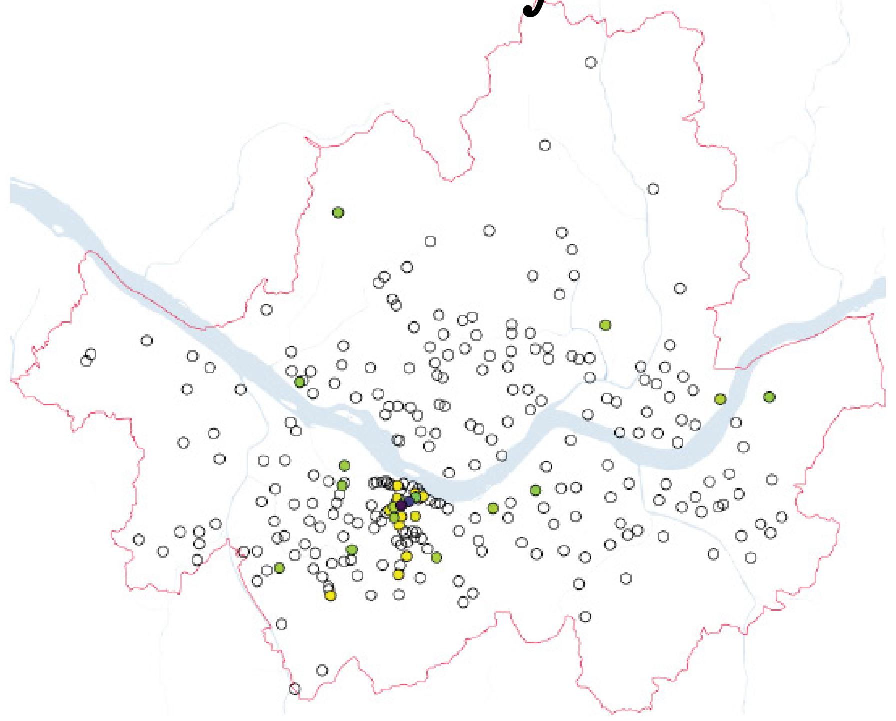
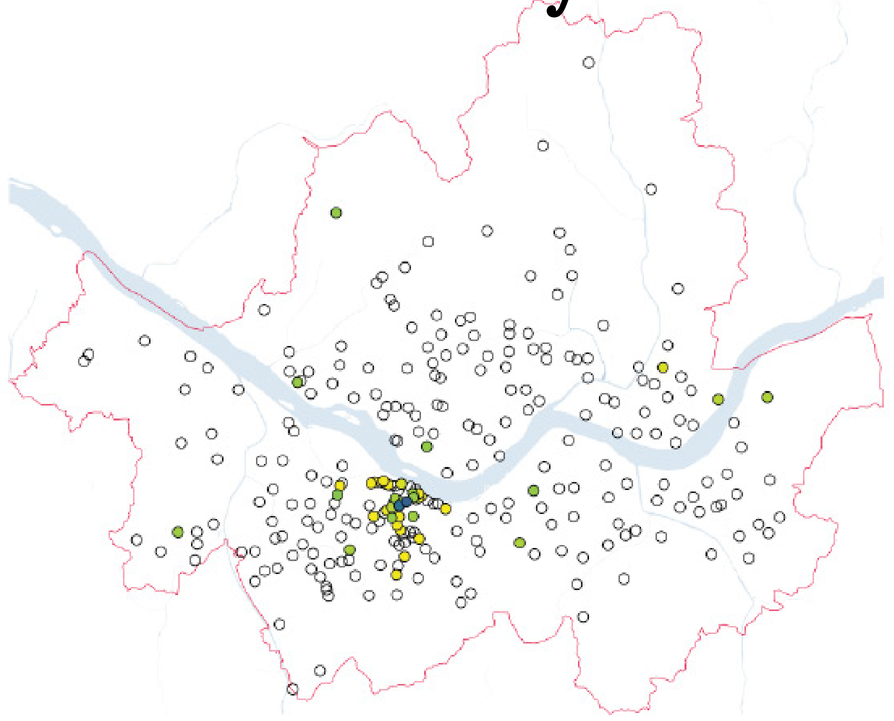
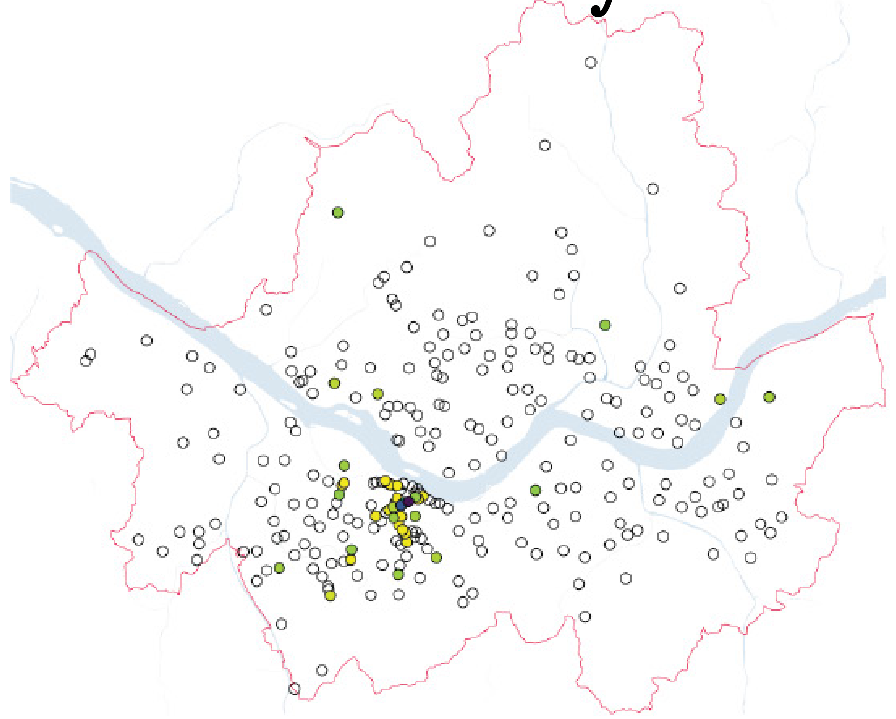
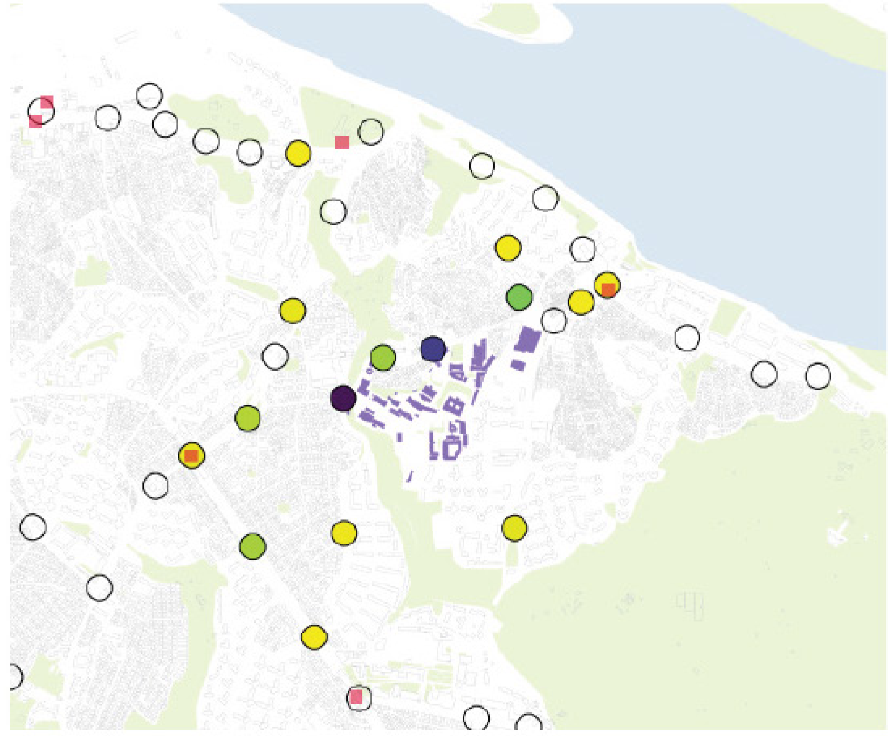
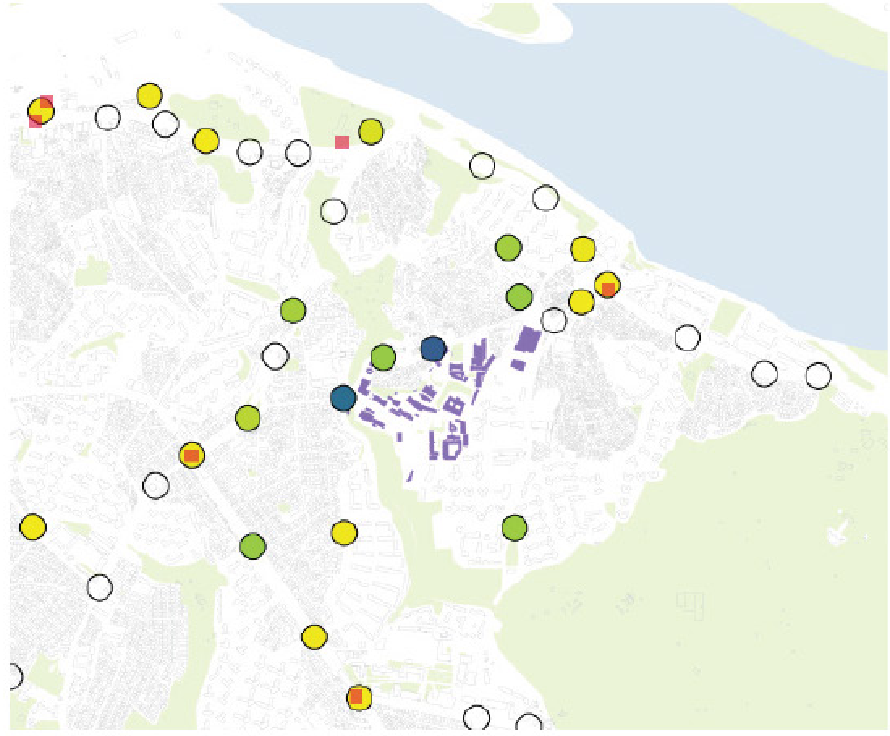
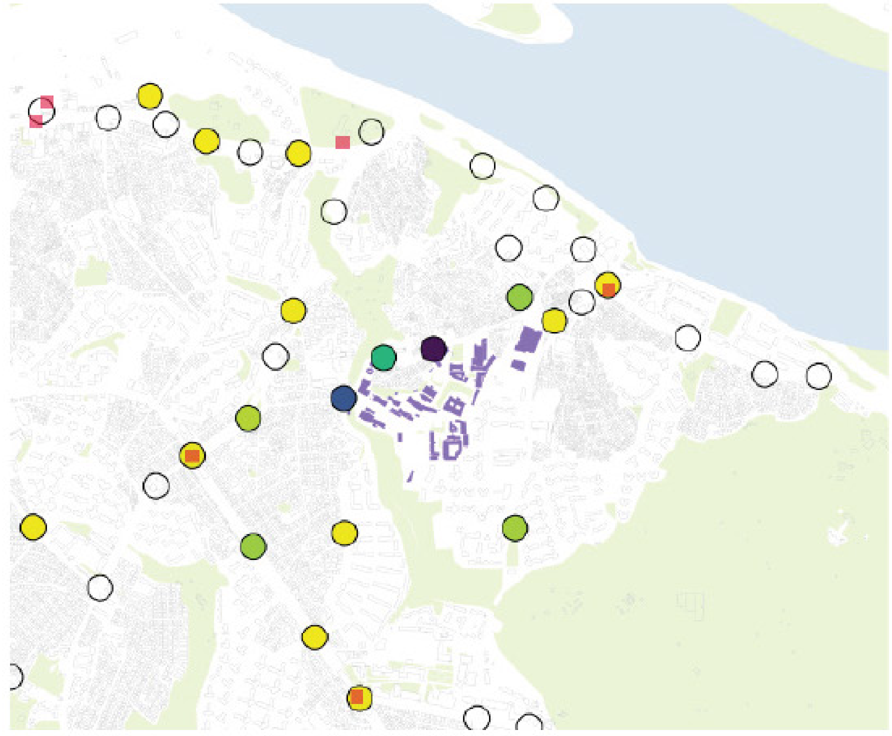
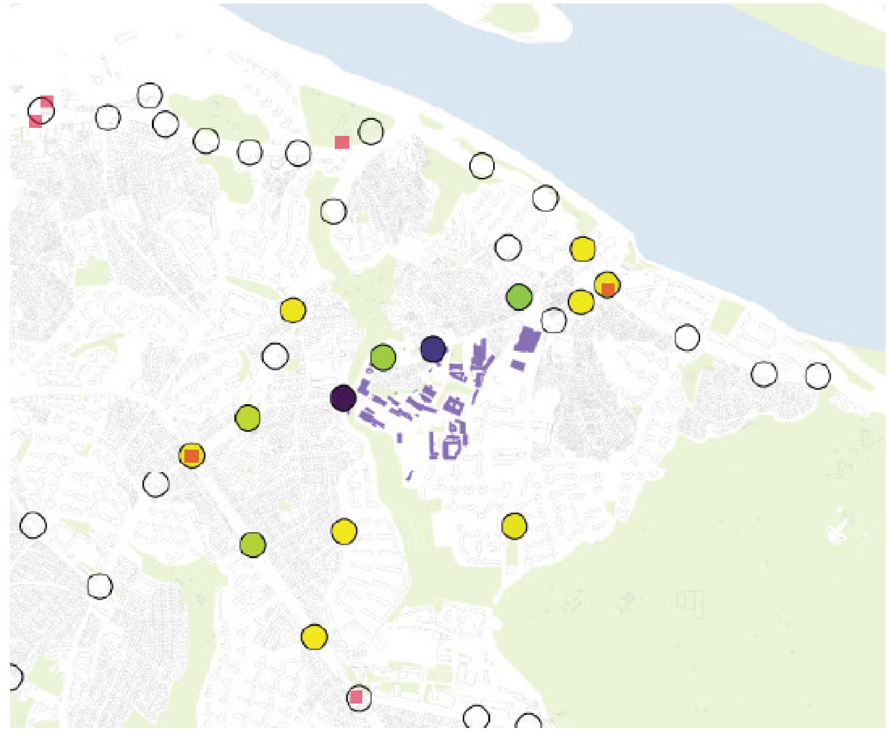
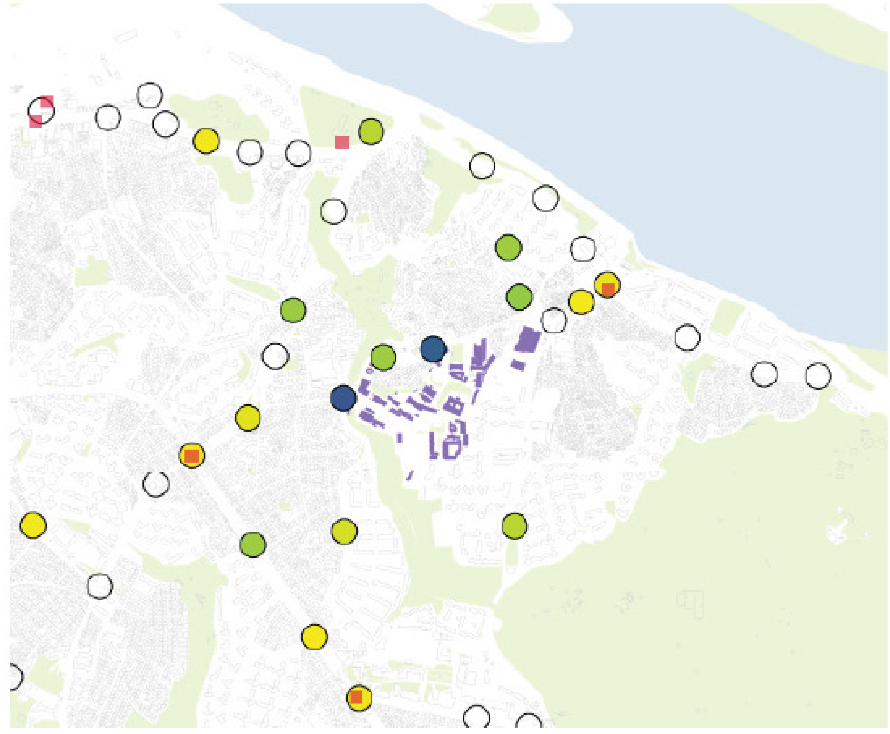
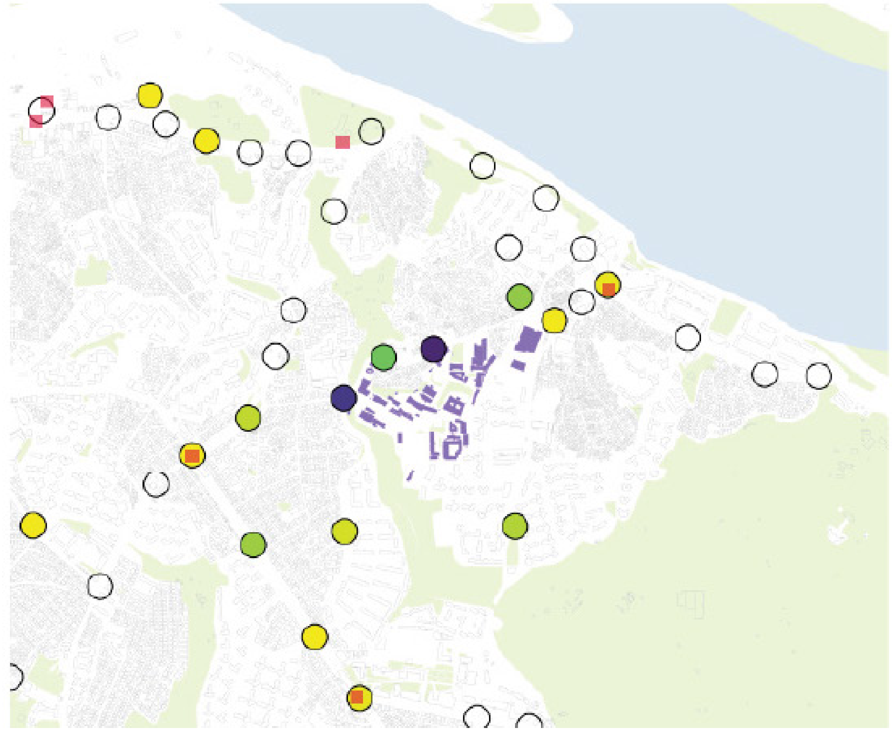
Time-of-day Scenarios Mean (Urban+Climate)



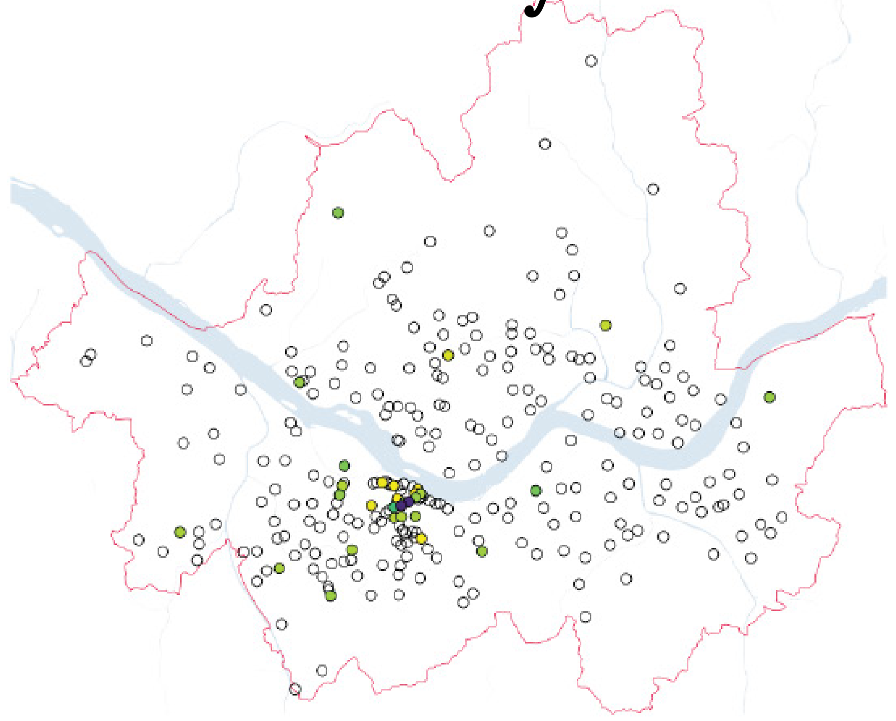
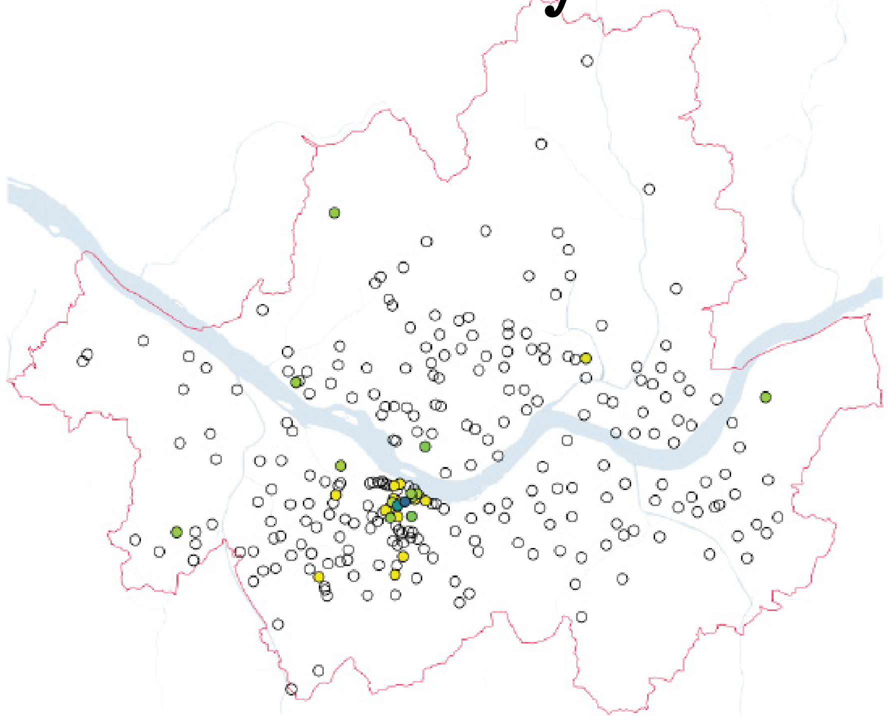
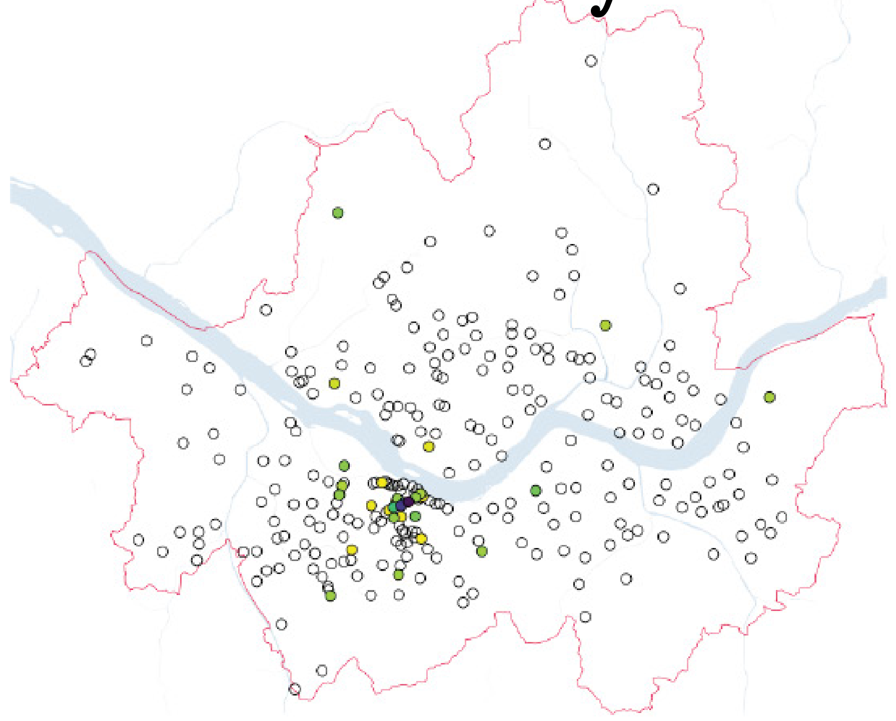
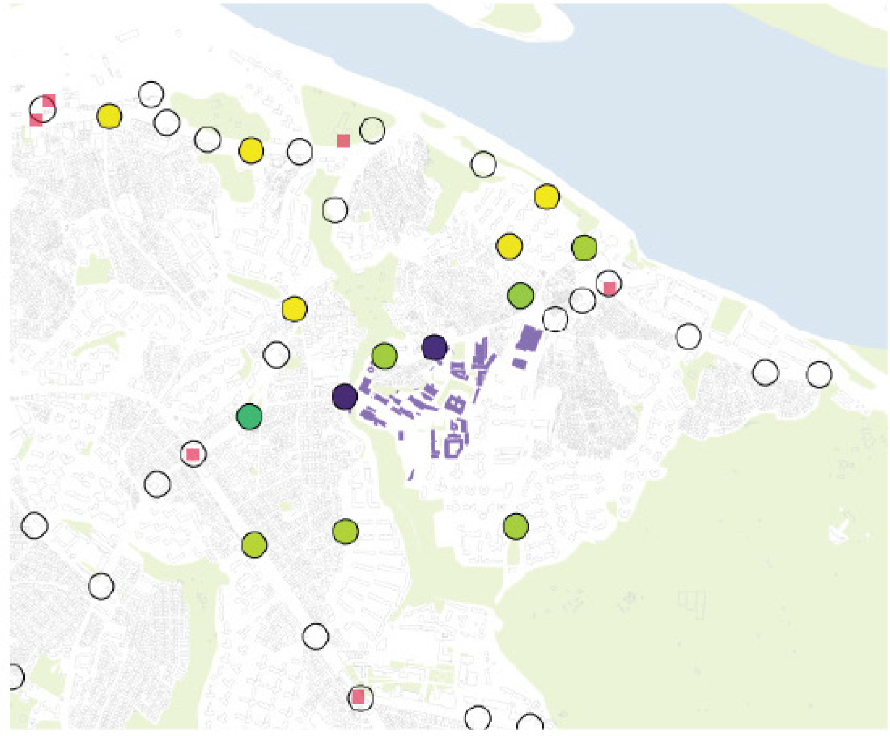
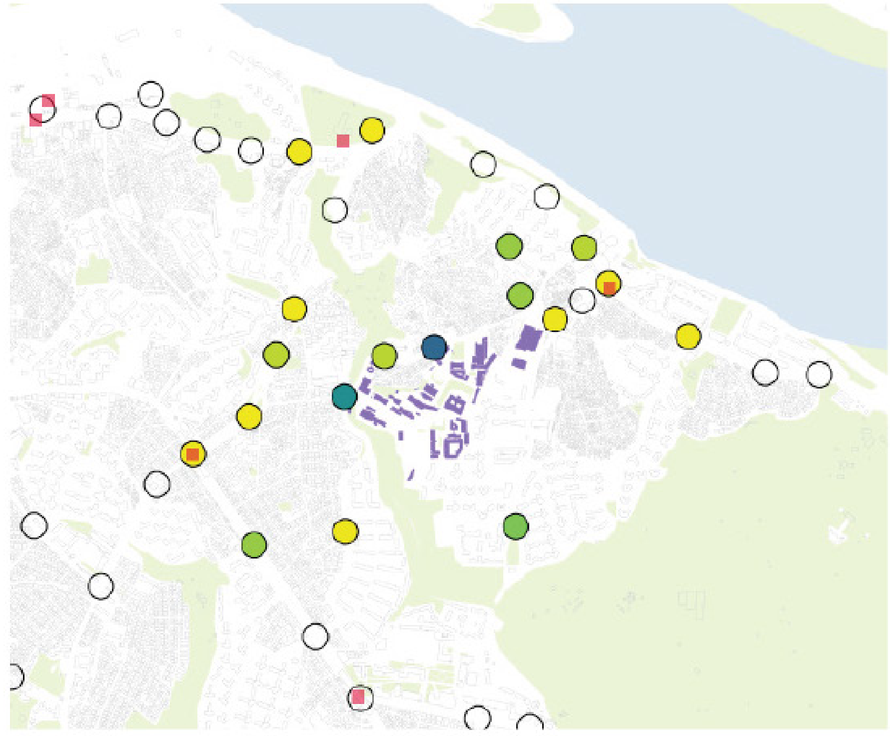
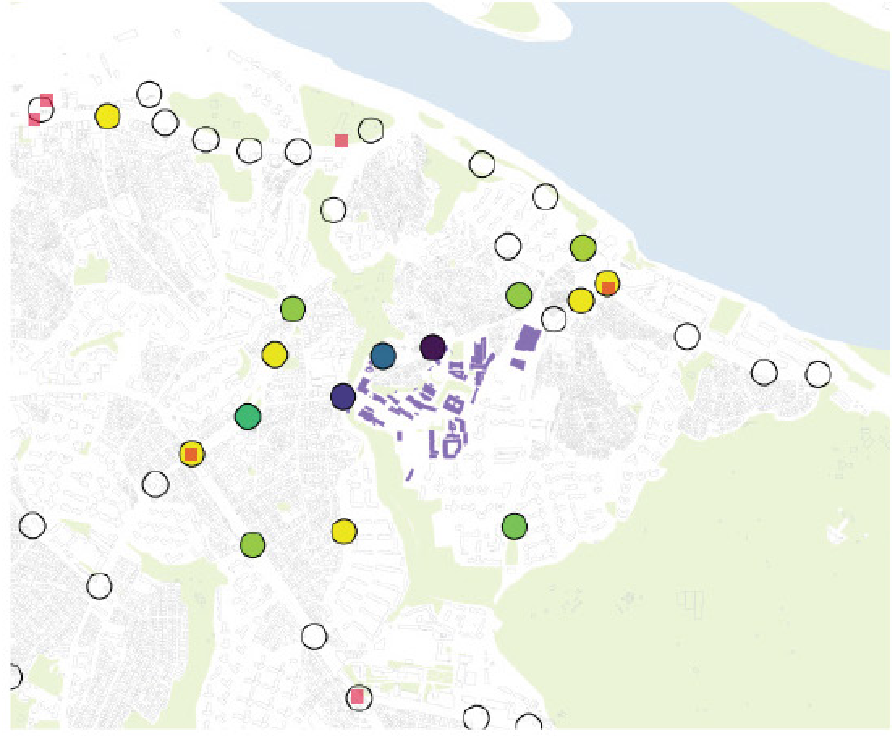
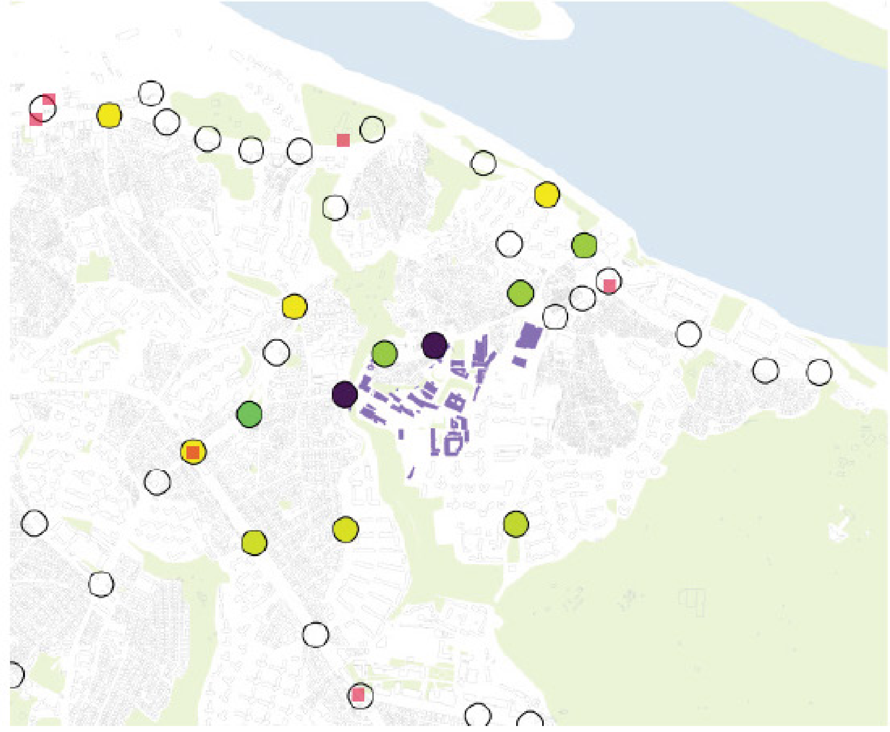
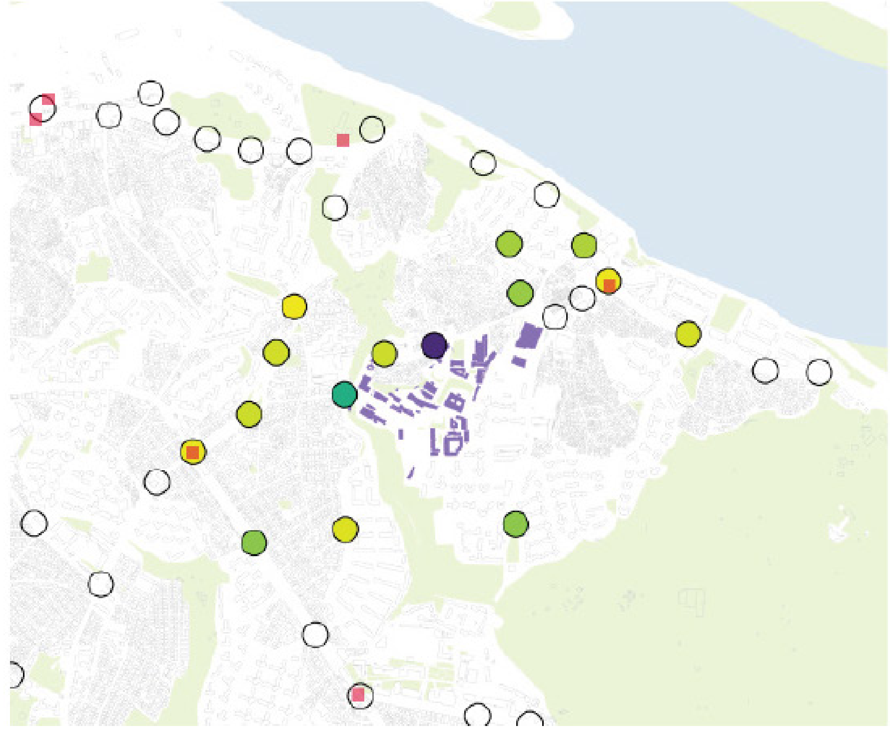
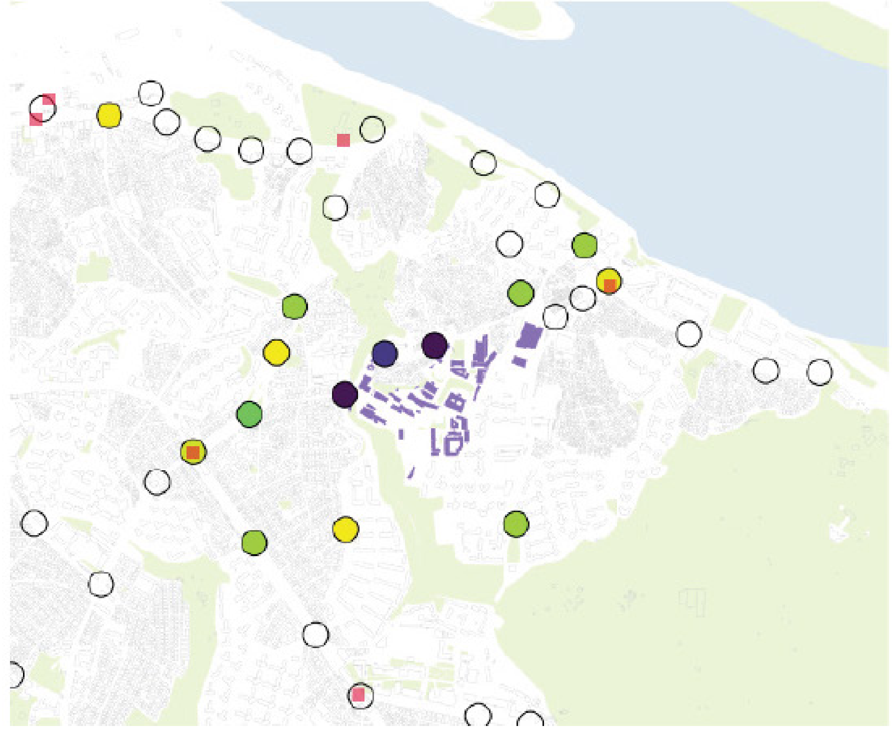
Time-of-day Scenarios Peaks (Urban+Climate)



Weather Scenarios 12:00-14:00 Peaks

	Hot days	Cold days	Humid days
Climate+ Urban			
Climate+ Urban			
Urban-only			

Weather Scenarios 16:00-18:00 Peaks

	Hot days	**Cold days**	**Humid days**
Climate+ Urban			
Climate+ Urban			
Urban-only			

Weather Scenarios 18:00-20:00 Peaks

	Hot days	**Cold days**	**Humid days**
Climate+ Urban			
Climate+ Urban			
Urban-only			

Takeaways

- Stable next-bin predictions, but “inactive” is over-predicted
- Class imbalance between visited and unvisited nodes greatly impacted
- Climate and Urban features yield small gains, but not decisive effects
- Intersection-based node grouping led to workable graph, but still left strong class imbalance
- Time and weather scenarios show some qualitative mobility trends
- Framework shows feasibility of fusing personal GNSS, climate and morphology with a STGNN pipeline

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Limitations

- Small, short dataset (22 participants, 6 weeks)
- GNSS irregularities and timestamp issues required cleaning, noise likely remained
- Intersection-based node grouping reduced place-level detail and feature impact
- Sparse graph and class imbalance biased learning toward zeros
- Simple encoder (edge-conditioned + GRU) and short input window (10h) limited temporal pattern capture
- Climate inputs were restricted to Temp, Humidity, PM10. TIN smoothing missed micro-scale microclimate.
- Omitted times when most mobility choices might differ (nights and weekends)

Future Work

- Larger, longer, more diverse datasets with standardized coordinate sampling
- Improve localization (Wi-Fi fingerprinting) and indoor/outdoor labeling frequency
- Explore alternative graph structure (dynamic/event-based) to limit class imbalance
- Additional graph features: distance-aware edges, expanded urban features (terrain, SVF, shading, tree cover)
- Additional climate metrics (wind, solar radiation) and higher-resolution microclimate data

Thank you

for your attention!