August 3–7, 2025 KDD2025

香港科技大學(廣州) THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY (GUANGZHOU)

Fine–grained Urban Heat Island Effect Forecasting: A Context–aware Thermodynamic Modeling Framework

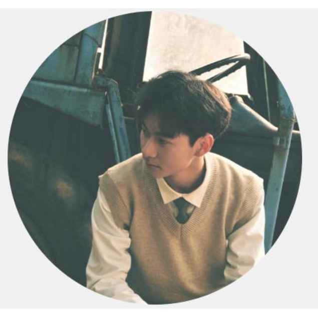
Xingchen Zou, Weilin Ruan, Siru Zhong, Yuehong Hu, & Yuxuan Liang

GitHub

WeChat

Key Points

- We propose *DeepUHI*, a **data-driven** context-aware framework for modeling **urban thermodynamics**.
- We carried experiments on **real-world dataset** to test the effectiveness.
- We release **SeoulTemp**, the first **fine-grained** urban temperature dataset.
- We deployed our model on the SeoUHI platform to provide public services



Presenter: Xingchen Zou @HKUST(GZ)

Can we use data-driven methods to modeling Urban Heat Island?

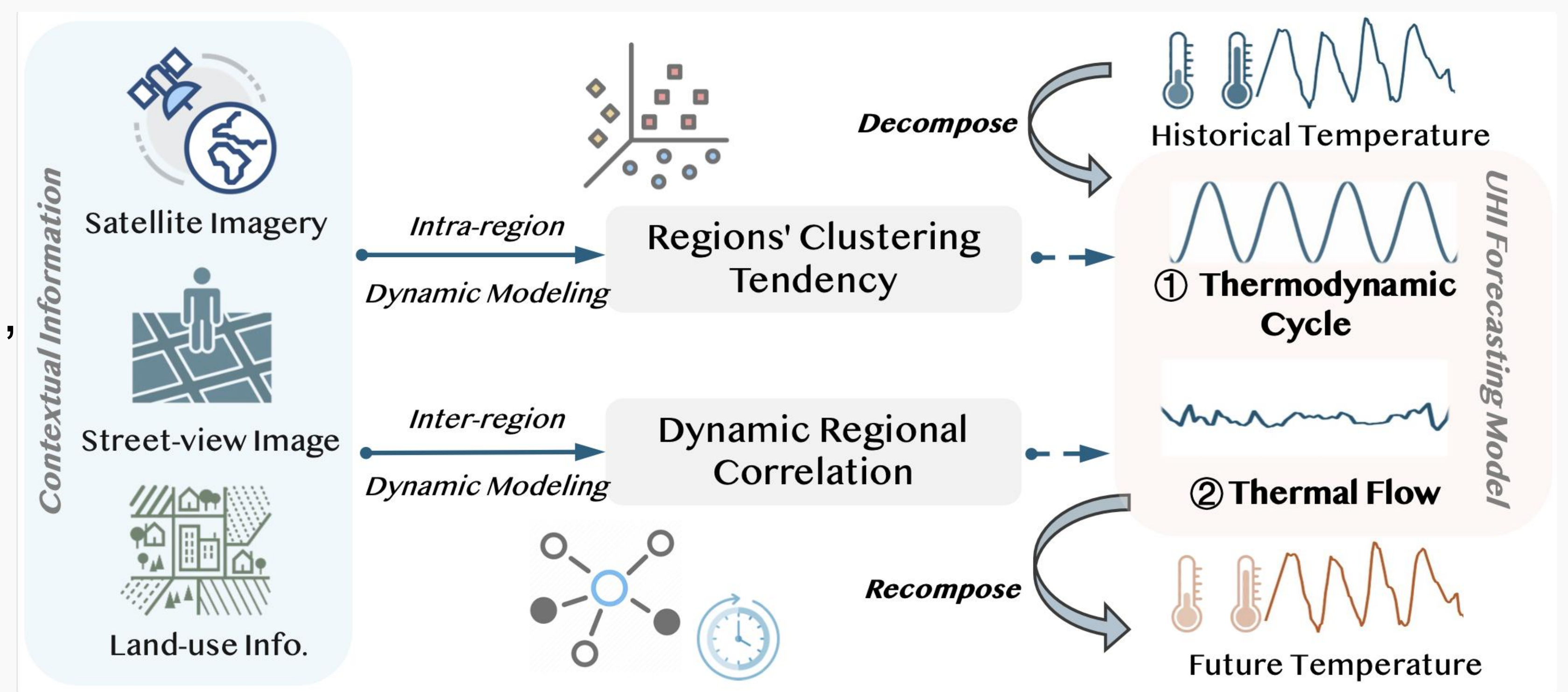
1. Urban Thermodynamics Decomposition

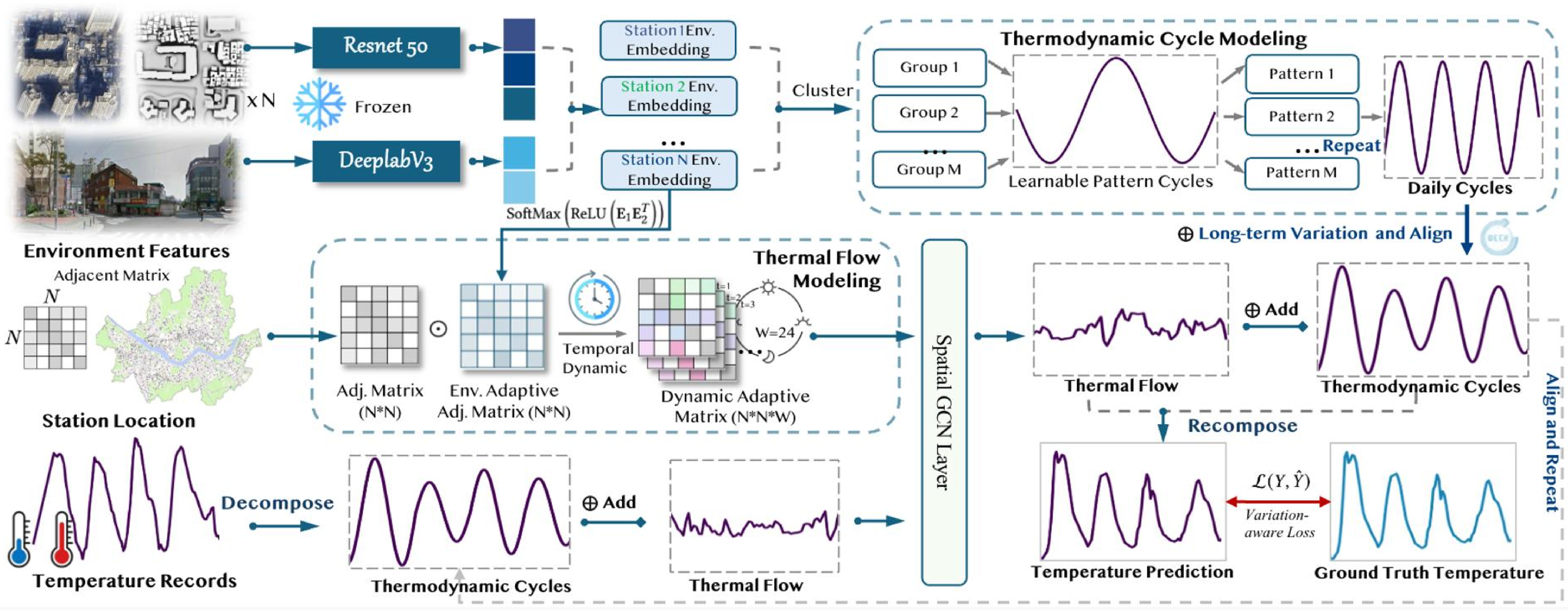
$$\frac{\partial u}{\partial t} = \frac{\partial}{\partial x}\left(\alpha(x,y,z)\frac{\partial u}{\partial x}\right) + \frac{\partial}{\partial y}\left(\alpha(x,y,z)\frac{\partial u}{\partial y}\right) + \frac{\partial}{\partial z}\left(\alpha(x,y,z)\frac{\partial u}{\partial z}\right)$$

To enable data-driven **instantiation** of the partial differential equation, local thermodynamics are **decomposed** into:

- **a. *Intra-region Thermal Cycle*** $\frac{\partial u}{\partial t} = 0$
- **b. *Inter-region Thermal Flow*** $\frac{\partial u}{\partial t} \neq 0$

We unitize *temporal periodicity modeling block* and *spatial dynamic convolutional block* to separately model these two components.



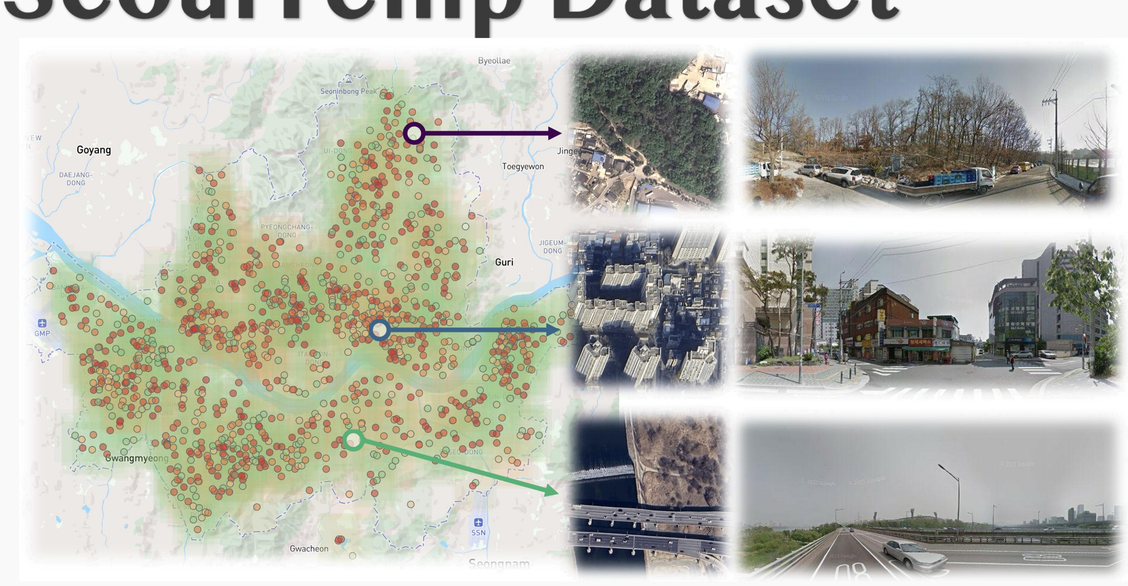


2. *DeepUHI*

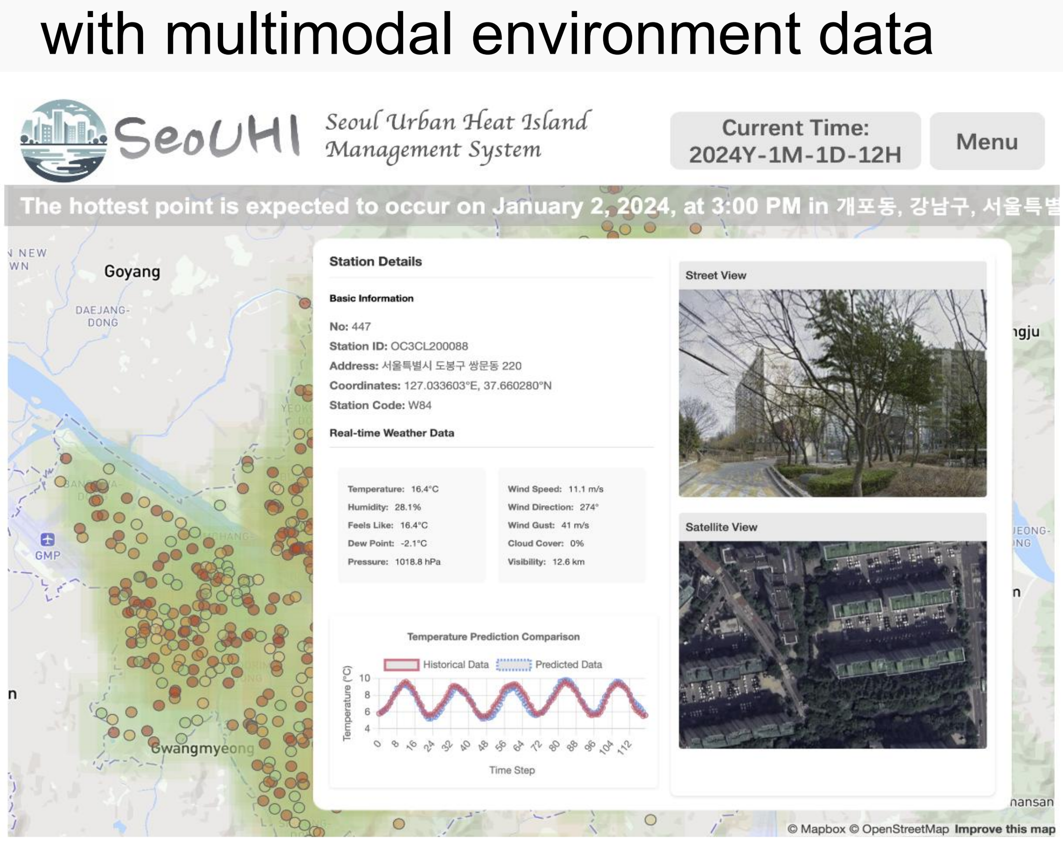
- An explainable heat **decomposition** framework to represent thermodynamics.
- Environment representation contribute to **cluster** regional thermal cycle patterns.
- Environment and spatial matrix contribute to **modeling** dynamic thermal flow relations.

How can we evaluate our model on real-world dataset?

3. SeoulTemp Dataset



Street level hourly Temperature Record with multimodal environment data



Deployment demo of **DeepUHI** on web

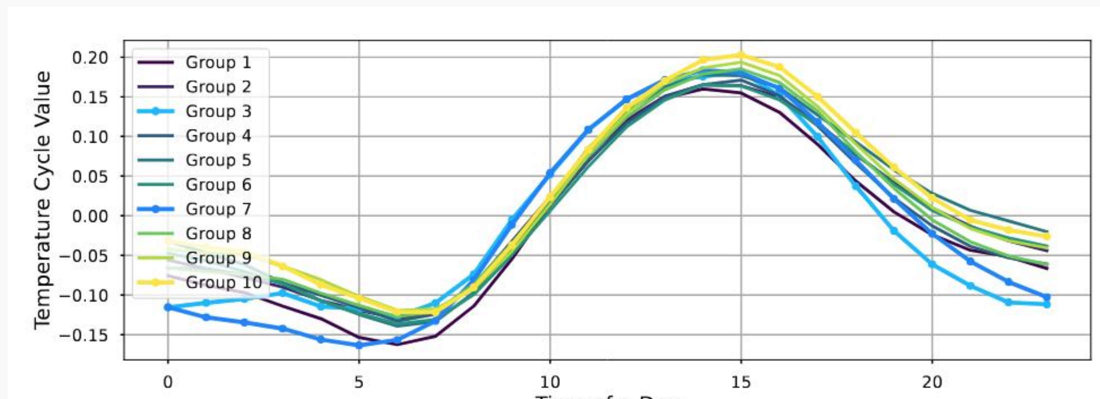
4. Experiment Result

Horizons	Metric	*Traditional Methods*			*Time-series Methods*		*Spatio-temporal Methods*				DeepUHI
		HA	LR	ARIMA	DLinear	PatchTST	GWN	MTGNN	STID	STAEformer	
12	MAE	3.535	1.599	3.453	1.653	1.774	1.642	1.639	**1.431**	1.456	1.433
	sMAPE	0.485	0.408	0.486	0.256	0.309	0.257	0.261	0.242	0.244	**0.241**
24	MAE	3.672	2.031	3.563	2.015	2.111	2.014	1.987	1.875	1.944	**1.811**
	sMAPE	0.497	0.332	0.499	0.321	0.344	0.322	0.309	0.305	0.312	**0.303**
48	MAE	3.884	2.693	3.991	2.735	2.748	2.601	2.552	2.495	2.499	**2.367**
	sMAPE	0.514	0.403	0.524	0.412	0.434	0.405	0.392	0.387	0.382	**0.375**
96	MAE	4.210	3.431	4.325	3.428	3.670	3.419	3.335	3.331	3.264	**3.231**
	sMAPE	0.543	0.484	0.555	0.477	0.513	0.493	0.477	0.483	0.478	**0.464**

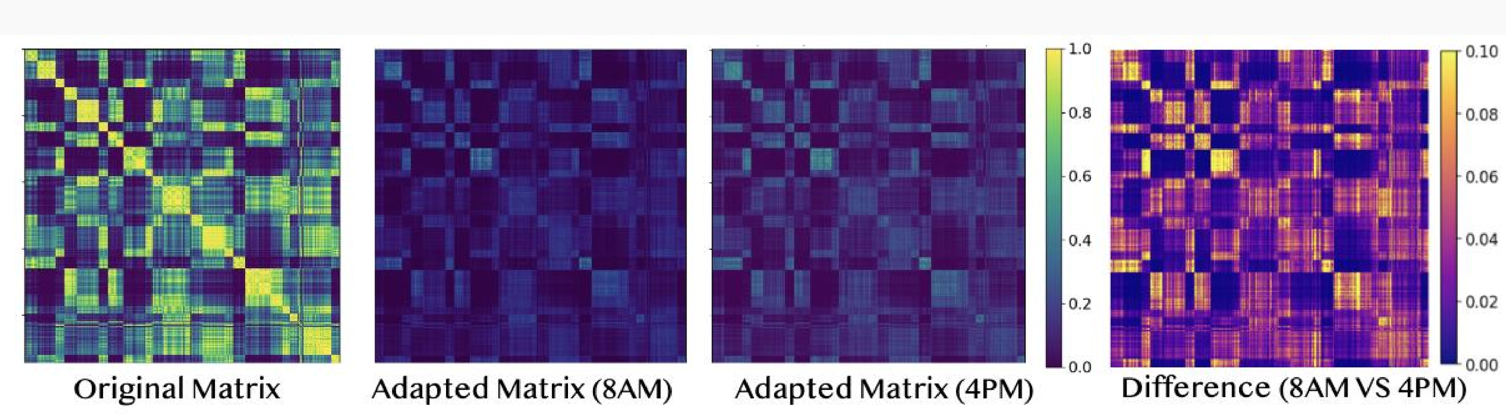
Best **prediction** accuracy compare with ST and TS models.

Method	Complexity (multi-adds)	24 Hours		48 Hours	
		k=3	k=9	k=3	k=9
LR	1.69 M	0.395	0.513	0.294	0.331
DLinear	1.69 M	0.414	0.532	0.322	0.359
GWN	297,160 M	0.459	0.593	0.355	0.386
STID	7,560 M	0.421	0.556	0.331	0.358
SATEformer	236,330 M	0.472	0.604	0.376	0.423
Contextual Features Augmented Variants					
DLinear+Context	13.01M	0.423	0.545	0.329	0.365
SATEformer+Context	236,352M	0.481	0.644	0.389	0.452
DeepUHI	20.95 M	**0.653**	**0.802**	**0.495**	**0.569**

Best spatial temporal **warning accuracy** and efficiency



DeepUHI **clearly** modeling the **thermal cycle patterns** with the city.



DeepUHI capture the **daily variations** of spatial relations within urban **thermal flows**.