

# Heterogeneity-Informed Meta-Parameter Learning for Spatiotemporal Time Series Forecasting

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## Contributions

- We propose a novel **Heterogeneity-Informed Meta-Parameter Learning** scheme for spatiotemporal forecasting.
- It not only captures but explicitly leverages **spatiotemporal heterogeneity** to **inform** the learning of spatiotemporal-specific model parameters from **meta-parameter** pools.
- We develop a forecasting model **HimNet** that achieves SOTA performance and superior **interpretability**.

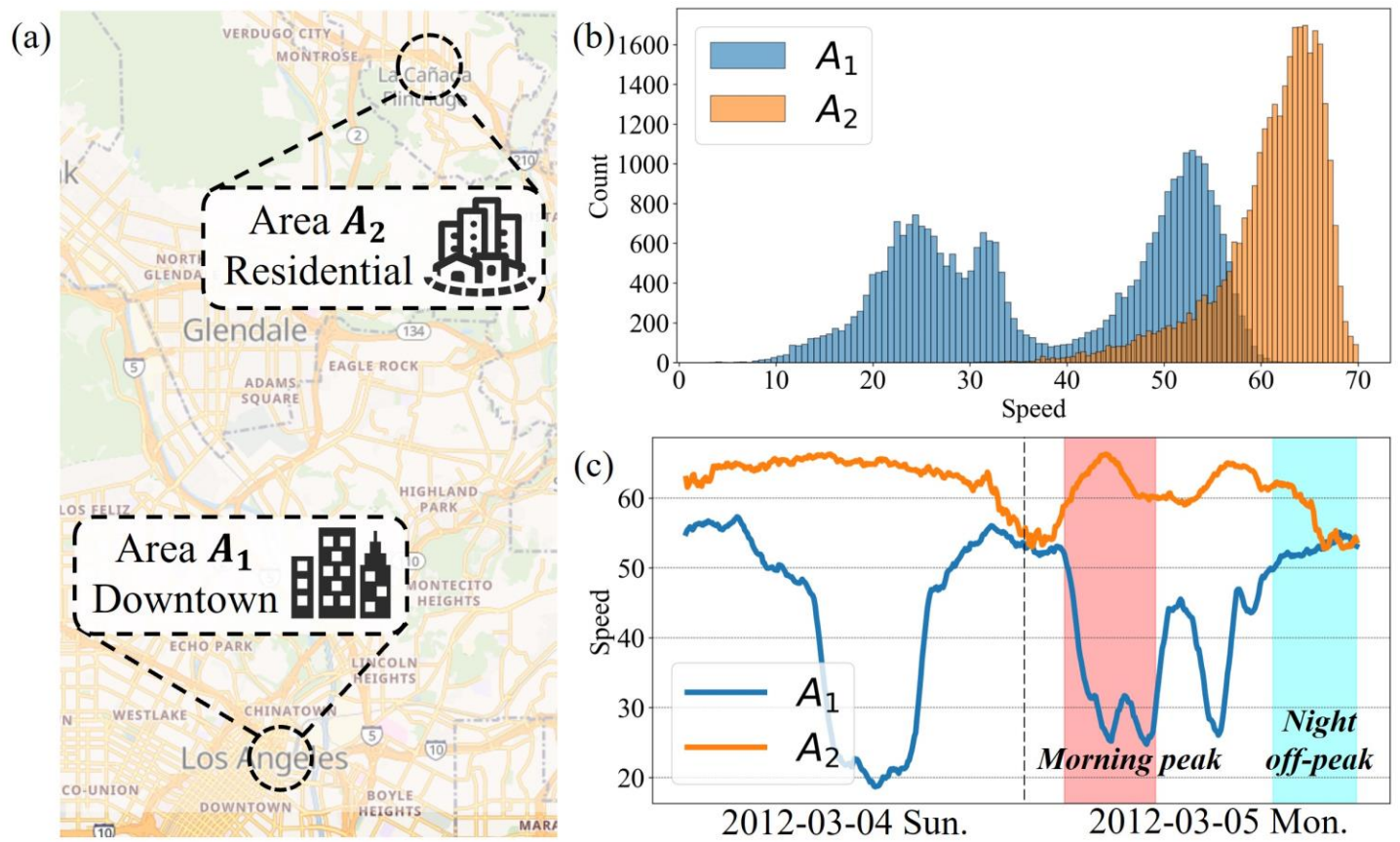
## Introduction

### ■ Spatial Heterogeneity:

- **Different locations** + same time = different patterns  
*e.g.* different traffic speed distribution of  $A_1$  and  $A_2$

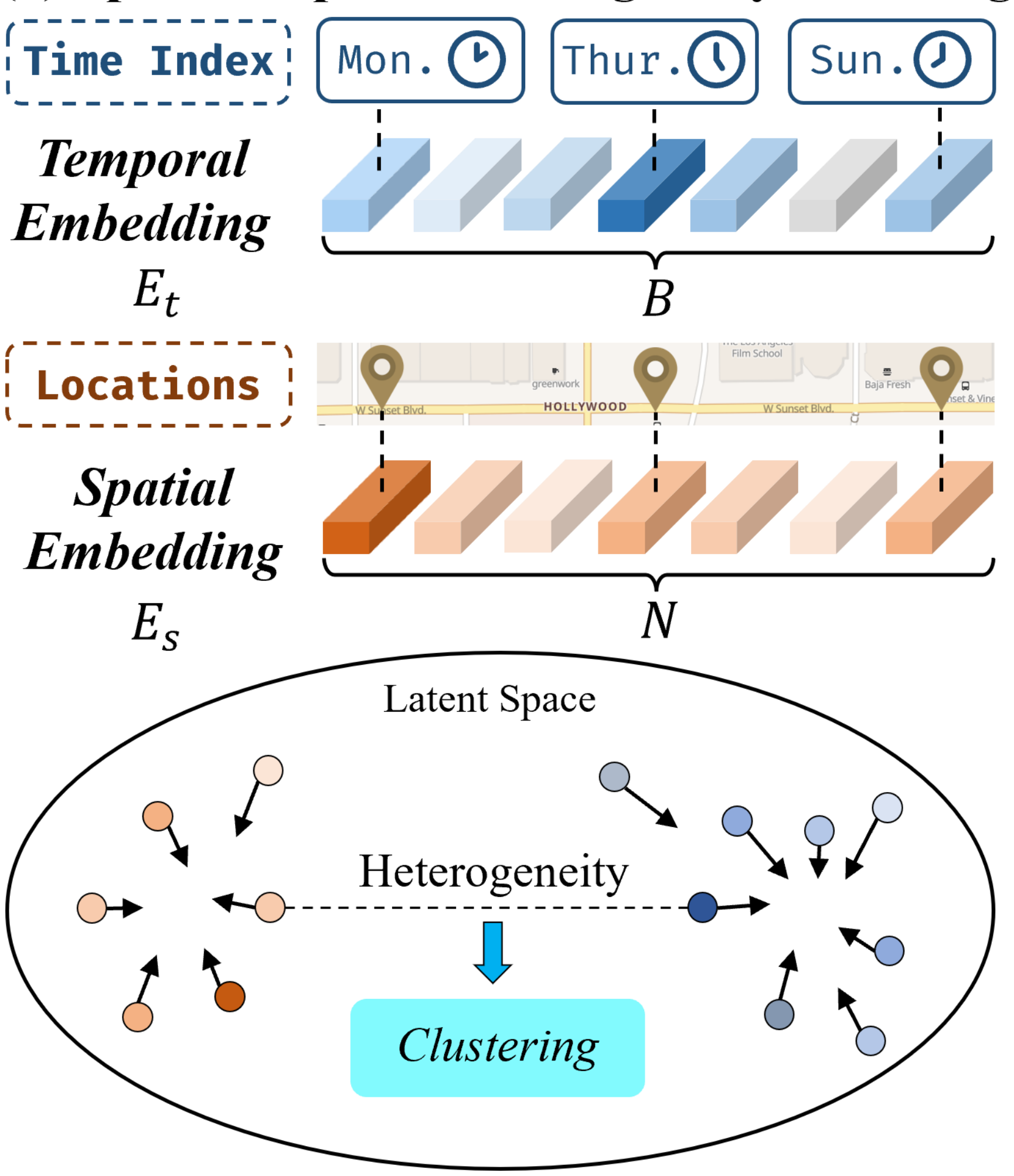
### ■ Temporal Heterogeneity:

- **Same location** + **different times** = different patterns  
*e.g.* different speed patterns between Sun. and Mon.

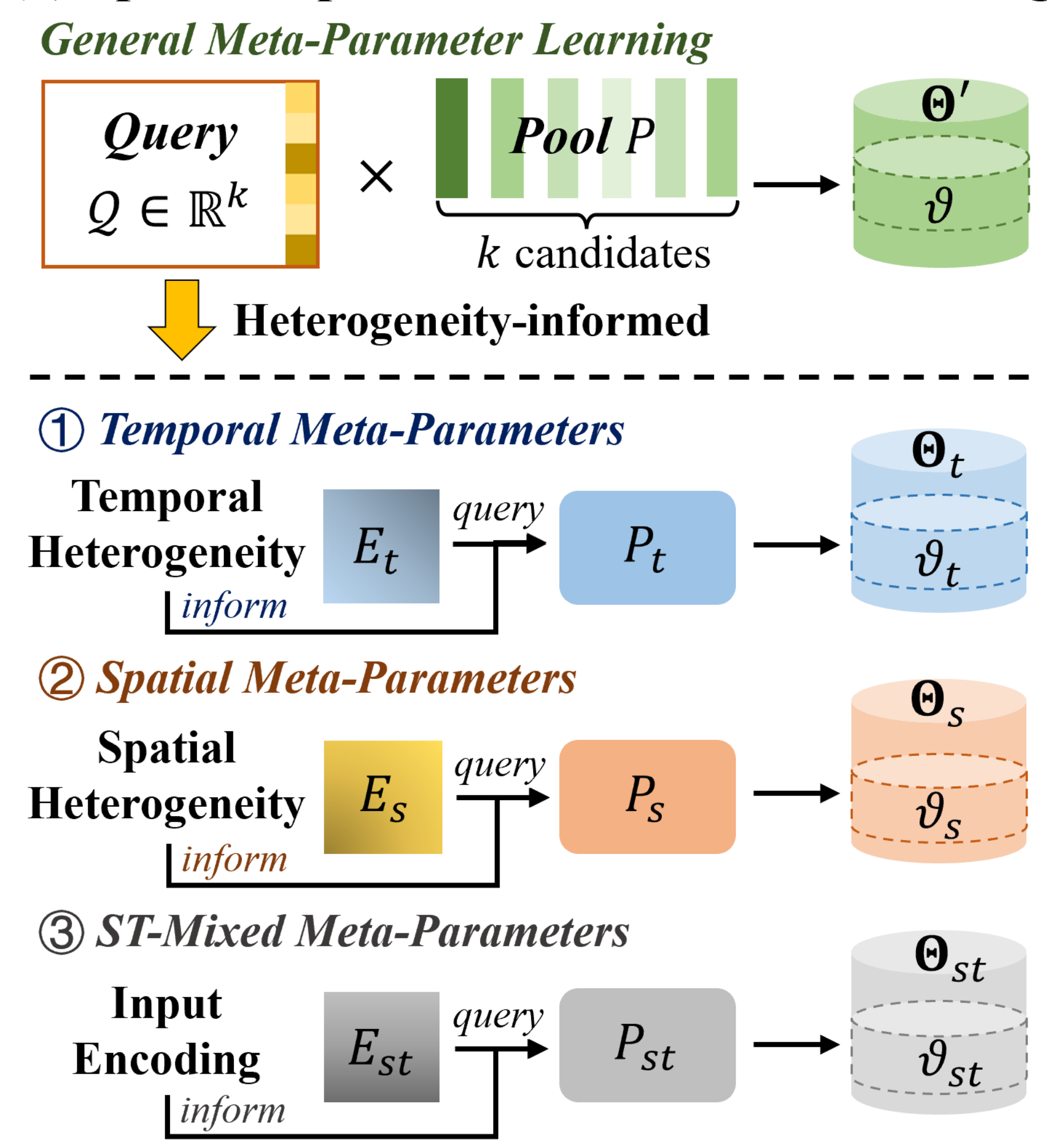


## Methodology: Heterogeneity-Informed Meta-Parameter Learning

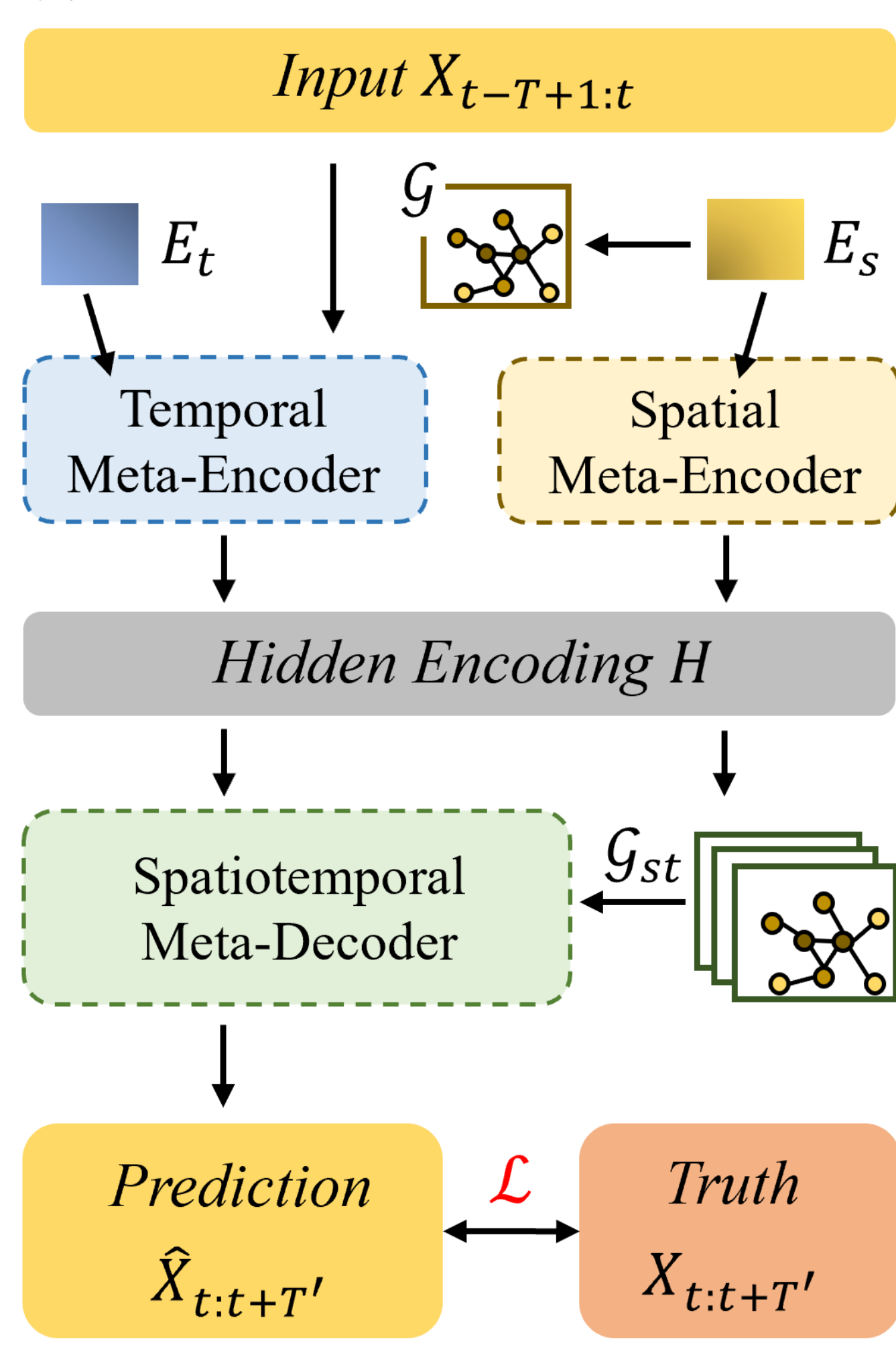
### (a) Spatiotemporal Heterogeneity Modeling



### (b) Spatiotemporal Meta-Parameter Learning



### (c) HimNet Architecture



### ■ Modeling Heterogeneity

- The **clustering** view
- Hetero. of ST data  $\rightarrow$  Hetero. of embeddings
- **Learning Meta-Parameter**
- Meta-parameter pool  $P = [\vartheta_1, \vartheta_2, \dots, \vartheta_k]$
- General formulation  $\vartheta = QP = \sum Q_i \vartheta_i$
- **Spatial/Temporal/ST-Mixed**  
 $\vartheta_{\{s,t,st\}} = E_{\{s,t,st\}} P_{\{s,t,st\}}$   
 $E_{st}$ : encoding of input  $X$
- **Heterogeneity-Informed ST Meta-Network**
- GCRU-based architecture
- Parameters are **dynamically generated** on each input via Meta-Parameter Learning

## Experiments

### ■ Forecasting Performance on METRLA, PEMSBA, and PEMS04/07/08

Dataset	Metric	HI	GRU	STGCN	DCRNN	GWNet	AGCRN	GTS	STNorm	STID	ST-WA	PDFormer	MegaCRN	HimNet
METRLA	Step 3 15 min	MAE	6.80	3.07	2.75	2.67	2.69	2.85	2.75	2.81	2.82	2.89	2.83	2.60
		RMSE	14.21	6.09	5.29	5.16	5.15	5.53	5.27	5.57	5.53	5.62	5.45	5.02
		MAPE	16.72%	8.14%	7.10%	6.86%	6.99%	7.63%	7.12%	7.40%	7.75%	7.66%	7.77%	6.70%
	Step 6 30 min	MAE	6.80	3.77	3.15	3.12	3.08	3.20	3.14	3.18	3.19	3.25	3.20	2.95
		RMSE	14.21	7.69	6.35	6.27	6.20	6.52	6.33	6.59	6.57	6.61	6.46	6.06
		MAPE	16.72%	10.71%	8.62%	8.42%	8.47%	9.00%	8.62%	8.47%	9.39%	9.22%	9.19%	8.11%
PEMSBA	Step 12 60 min	MAE	6.80	4.88	3.60	3.54	3.51	3.59	3.59	3.57	3.55	3.68	3.62	3.37
		RMSE	14.21	9.75	7.43	7.47	7.28	7.45	7.44	7.51	7.55	7.59	7.47	7.22
		MAPE	16.71%	14.91%	10.35%	10.32%	9.96%	10.47%	10.25%	10.24%	10.95%	10.78%	10.91%	9.79%
	Step 3 15 min	MAE	3.05	1.44	1.36	1.31	1.30	1.35	1.37	1.33	1.31	1.37	1.32	1.27
		RMSE	7.03	3.15	2.88	2.76	2.73	2.88	2.92	2.82	2.79	2.88	2.83	2.71
		MAPE	6.85%	3.01%	2.86%	2.73%	2.71%	2.91%	2.85%	2.76%	2.78%	2.86%	2.78%	2.64%
PEMS04	Step 6 30 min	MAE	3.05	1.97	1.70	1.65	1.63	1.67	1.72	1.65	1.64	1.70	1.64	1.57
		RMSE	7.03	4.60	3.84	3.75	3.73	3.82	3.86	3.77	3.73	3.81	3.79	3.60
		MAPE	6.84%	4.45%	3.79%	3.71%	3.73%	3.81%	3.88%	3.66%	3.73%	3.81%	3.71%	3.52%
	Step 12 60 min	MAE	3.05	2.70	2.02	1.97	1.99	1.94	2.06	1.92	1.91	2.00	1.91	1.84
		RMSE	7.01	6.28	4.63	4.60	4.60	4.50	4.60	4.45	4.42	4.52	4.43	4.32
		MAPE	6.83%	6.72%	4.72%	4.68%	4.71%	4.55%	4.88%	4.46%	4.55%	4.63%	4.51%	4.33%
PEMS07	Average	MAE	42.35	25.55	19.57	19.63	18.53	19.38	20.96	18.96	18.38	19.06	18.72	18.14
		RMSE	61.66	39.71	31.38	31.26	29.92	31.25	32.95	30.98	29.95	31.02	30.53	29.88
		MAPE	29.92%	17.35%	13.44%	13.59%	12.89%	13.40%	14.66%	12.69%	12.04%	12.52%	12.00%	12.00%
PEMS08	Average	MAE	49.29	26.74	21.74	21.16	20.47	20.57	22.15	20.50	19.61	20.74	19.97	19.21
		RMSE	71.34	42.78	35.27	34.14	33.47	34.40	35.10	34.66	32.79	34.05	32.95	32.75
		MAPE	22.75%	11.58%	9.24%	9.02%	8.61%	8.74%	9.38%	8.75%	8.30%	8.77%	8.55%	8.03%
PEMS08	Average	MAE	34.66	19.36	16.08	15.22	14.40	15.32	16.49	15.41	14.21	15.41	13.58	13.57
		RMSE	50.45	31.20	25.39	24.17	23.39	24.41	26.08	24.77	23.28	24.62	23.41	23.22
		MAPE	21.63%	12.43%	10.60%	10.21%	9.21%	10.03%	10.54%	9.76%	9.27%	9.94%	9.05%	8.98%

• HimNet achieves SOTA performance on **5 benchmarks** against **12 baselines**

### ■ Ablation Study: Average Prediction MAE

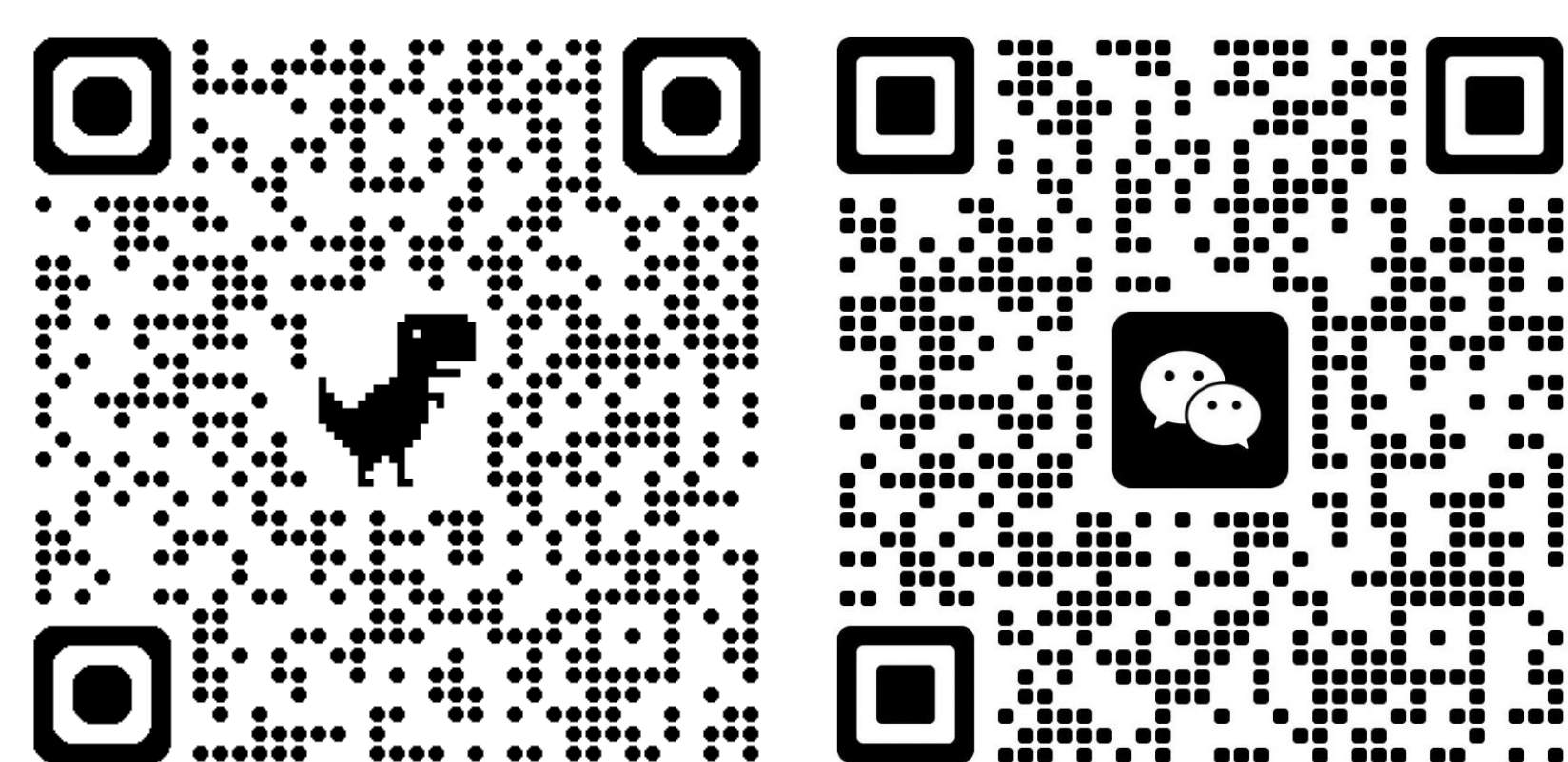
Model	METRLA	PEMSBA	PEMS04	PEMS07	PEMS08
w/o $E_t$	2.94	1.53	18.35	22.00	14.14
w/o $E_s$	3.49	1.74	21.30	19.26	14.79
w/o $E_{st}$	3.07	1.55	18.55	19.77	13.61
w/o TMP	2.94	1.54	18.65	19.58	14.44
w/o SMP	3.53	1.75	21.41	22.26	14.07
w/o STMP	3.01	1.57	18.65	19.86	13.72
HimNet	2.92	1.51	18.14	19.21	13.57

- **w/o  $E$** : replaces embedding with a static matrix of all ones, thus removing heterogeneity modeling
- **w/o MP**: removes meta-parameters by downgrading to randomly initialized parameters

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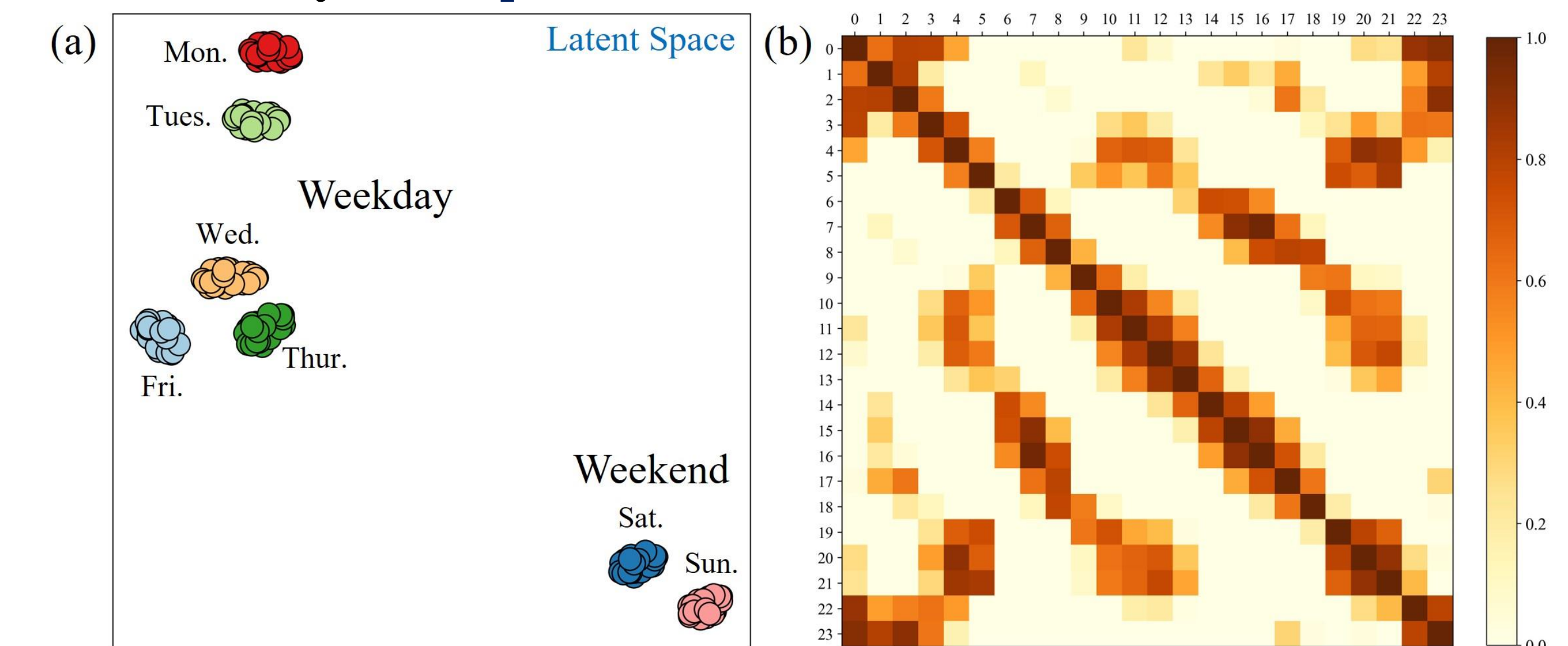


## Efficiency Comparison

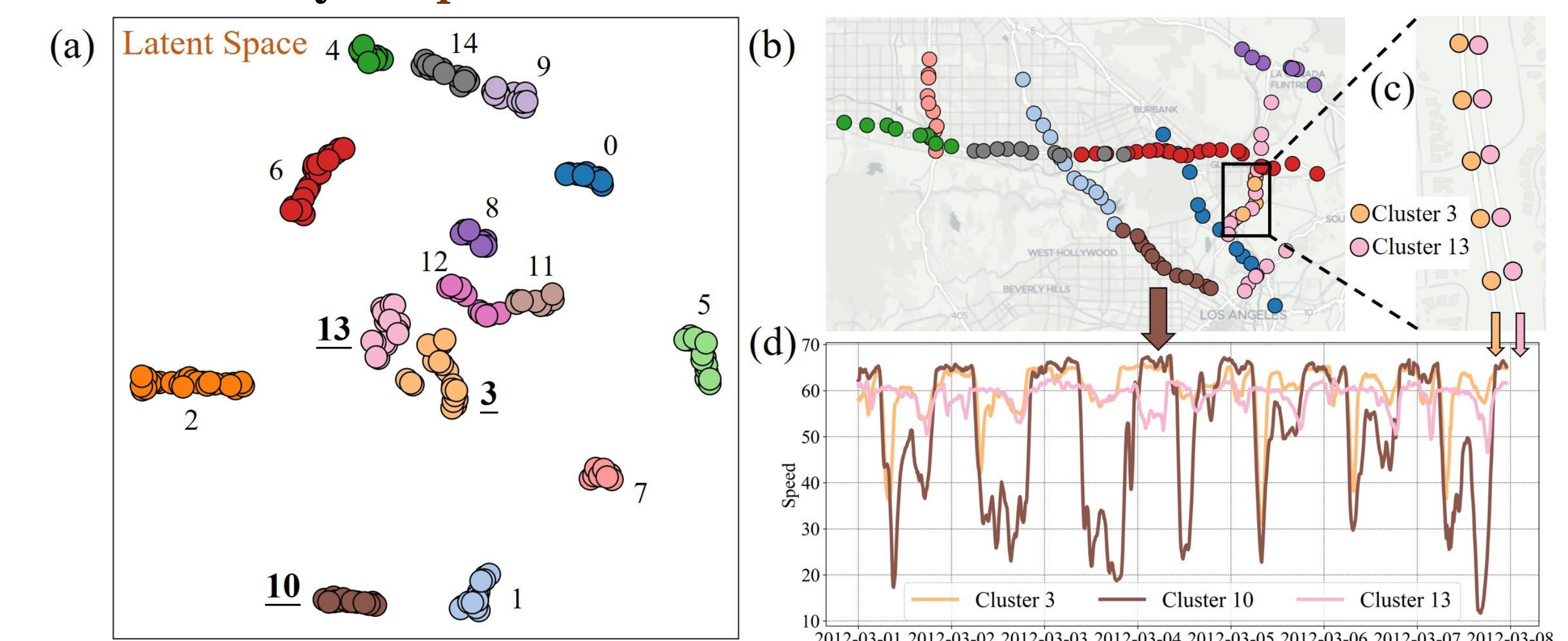
Model	#Params	Time / Batch	Time / Epoch	Mem Usage
STID [51]	118K	8ms	12s	1420MB
STGCN [64]	246K	23ms	34s	1650MB
GWNet [60]	309K	40ms	60s	1994MB
STNorm [11]	224K	39ms	59s	1818MB
DCRNN [36]	372K	189ms	284s	2134MB
AGCRN [2]	752K	54ms	82s	2492MB
GTS [49]	38.5M	114ms	171s	4096MB
MegaCRN [28]	389K	89ms	134s	1962MB
ST-WA [8]	375K	135ms	203s	2668MB
PDFormer [26]	531K	173ms	260s	6938MB
HimNet- $\Theta'$	10.9B	N/A	N/A	N/A
HimNet	1251K	97ms	144s	6056MB

## Interpretability

### ■ Case Study 1: Temporal Meta-Parameters



### ■ Case Study 2: Spatial Meta-Parameters



### ■ Case Study 3: ST-Mixed Meta-Parameters

