

Table 1: Basic properties and statistical information of the datasets.

Dataset	Variable	Spatial Coverage	Time Span	# of Nodes	# of Records	Sampling Rate	Pre-training	Source
Beijing Subway	Metro Flow	Beijing, China	1 month	276	2,980,800	10T, 15T, 30T	Yes	[13]
SHMetro	Metro Flow	Shanghai, China	3 months	288	3,868,416	15T	Yes	[7]
HZMetro	Metro Flow	Hangzhou, China	1 months	80	292,000	15T	Yes	[7]
TaxiBJ	Taxi Demand	Beijing, China	18 months	1,024	65,617,920	30T, H	Yes	[13]
Shenzhen-Taxi	Taxi Demand	Shenzhen, China	1 months	156	464,256	15T	Yes	[14]
CHI-Taxi	Taxi Demand	Chicago, USA	12 months	121	8,479,680	15T	Yes	[11]
NYC-Taxi	Taxi Demand	New York City, USA	2 months	200	1,152,000	30T	No	[11]
DC-Bike	Bike-sharing	Washington, USA	3 months	128	276,480	H	Yes	[11]
CHI-Bike	Bike-sharing	Chicago, USA	3 months	270	3,576,960	30T, H	Yes	[11]
NYC-Bike	Bike-sharing	New York City, USA	2 months	200	1,152,000	30T	No	[11]
Loop-Seattle	Vehicle Speed	Seattle, USA	12 months	207	67,857,520	5T, 10T, 15T, 30T, H	Yes	[2]
METR-LA	Vehicle Speed	Los Angeles, USA	4 months	207	14,188,600	5T, 10T, 15T, 30T, H	Yes	[6]
PEMS-BAY	Vehicle Speed	San Francisco, USA	6 months	325	33,873,732	5T, 10T, 15T, 30T, H	Yes	[6]
DiDi-CD	Traffic Index	Chengdu, China	4 months	524	9,054,720	10T	No	[9]
DiDi-SZ	Traffic Index	Shenzhen, China	4 months	627	10,834,560	10T	No	[9]
PEMS03	Vehicle Flow	California, USA	3 months	358	18,764,928	5T, 10T, 15T, 30T, H	Yes	[10]
PEMS04	Vehicle Flow	San Francisco, USA	2 months	307	10,433,088	5T, 10T, 15T, 30T, H	Yes	[4]
PEMS07	Vehicle Flow	California, USA	2 months	883	49,843,584	5T, 10T, 15T, 30T, H	Yes	[10]
PEMS08	Vehicle Flow	San Bernardino, USA	2 months	170	6,071,040	5T, 10T, 15T, 30T, H	Yes	[4]
SD	Vehicle Flow	San Diego, USA	12 months	716	25,088,640	15T	No	[8]
YD-AQ	Air Quality	Yangtze Delta, China	12 months	175	1,533,000	H	Yes	[5]
GBA-AQ	Air Quality	Great Bay Area, China	12 months	105	919,800	H	Yes	[5]
Beijing-AQI	Air Quality	Beijing, China	12 months	35	306,600	H	No	[5]
DC-Wind	Wind Speed	Washington, USA	12 months	759	13,334,112	30T	No	[3]
DC-WP	Wind Power	Washington, USA	12 months	759	13,334,112	30T	No	[3]
NYC-PVm	Solar Energy	New York City, USA	12 months	129	2,260,080	15T	No	[1]
NYC-PVh	Solar Energy	New York City, USA	12 months	129	1,130,040	H	No	[1]
TrafficHZ	Vehicle Speed	Hangzhou, China	1 month	672	1,413,888	30T, H	Yes	[12]
TrafficJN	Vehicle Speed	Jinan, China	1 month	576	1,211,904	30T, H	Yes	[12]
TrafficNJ	Vehicle Speed	Nanjing, China	1 month	768	1,615,872	30T, H	Yes	[12]
TrafficSH	Vehicle Speed	Shanghai, China	1 month	896	1,885,184	30T, H	Yes	[12]
TrafficTJ	Vehicle Speed	Tianjin, China	1 month	720	1,130,040	30T, H	Yes	[12]
TrafficZZ	Vehicle Speed	Zhengzhou, China	1 month	676	1,514,880	30T, H	Yes	[12]
TrafficCD	Vehicle Speed	Chengdu, China	1 month	728	1,531,712	30T, H	Yes	[12]

REFERENCES

- [1] Andrea Cini, Ivan Marisca, Filippo Maria Bianchi, and Cesare Alippi. 2023. Scalable spatiotemporal graph neural networks. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 37. 7218–7226.
- [2] Zhiyong Cui, Kristian Henrikson, Ruimin Ke, and Yinhai Wang. 2019. Traffic graph convolutional recurrent neural network: A deep learning framework for network-scale traffic learning and forecasting. *IEEE Transactions on Intelligent Transportation Systems* 21, 11 (2019), 4883–4894.
- [3] Caroline Draxl, Andrew Clifton, Bri-Mathias Hodge, and Jim McCaa. 2015. The wind integration national dataset (wind) toolkit. *Applied Energy* 151 (2015), 355–366.
- [4] Shengnan Guo, Youfang Lin, Ning Feng, Chao Song, and Huaiyu Wan. 2019. Attention based spatial-temporal graph convolutional networks for traffic flow forecasting. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 33. 922–929.
- [5] Jindong Han, Weijia Zhang, Hao Liu, and Hui Xiong. 2023. Machine learning for urban air quality analytics: A survey. *arXiv preprint arXiv:2310.09620* (2023).
- [6] Yaguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu. 2018. Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting. In *International Conference on Learning Representations*.
- [7] Lingbo Liu, Jingwen Chen, Hefeng Wu, Jiajie Zhen, Guanbin Li, and Liang Lin. 2020. Physical-virtual collaboration modeling for intra-and inter-station metro ridership prediction. *IEEE Transactions on Intelligent Transportation Systems* 23, 4 (2020), 3377–3391.

- [8] Xu Liu, Yutong Xia, Yuxuan Liang, Junfeng Hu, Yiwei Wang, Lei Bai, Chao Huang, Zhenguang Liu, Bryan Hooi, and Roger Zimmermann. 2024. Largest: A benchmark dataset for large-scale traffic forecasting. *Advances in Neural Information Processing Systems* 36 (2024).
- [9] Bin Lu, Xiaoying Gan, Weinan Zhang, Huaxiu Yao, Luoyi Fu, and Xinbing Wang. 2022. Spatio-temporal graph few-shot learning with cross-city knowledge transfer. In *Proceedings of the 28th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 1162–1172.
- [10] Chao Song, Youfang Lin, Shengnan Guo, and Huaiyu Wan. 2020. Spatial-temporal synchronous graph convolutional networks: A new framework for spatial-temporal network data forecasting. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 34. 914–921.
- [11] Jingyuan Wang, Jiawei Jiang, Wenjun Jiang, Chao Li, and Wayne Xin Zhao. 2021. Libcity: An open library for traffic prediction. In *Proceedings of the 29th international conference on advances in geographic information systems*. 145–148.
- [12] Yuan Yuan, Jingtao Ding, Jie Feng, Depeng Jin, and Yong Li. 2024. UniST: a prompt-empowered universal model for urban spatio-temporal prediction. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. 4095–4106.
- [13] Jinlei Zhang, Feng Chen, Zhiyong Cui, Yinan Guo, and Yadi Zhu. 2020. Deep learning architecture for short-term passenger flow forecasting in urban rail transit. *IEEE Transactions on Intelligent Transportation Systems* 22, 11 (2020), 7004–7014.
- [14] Ling Zhao, Yujiao Song, Chao Zhang, Yu Liu, Pu Wang, Tao Lin, Min Deng, and Haifeng Li. 2019. T-GCN: A temporal graph convolutional network for traffic prediction. *IEEE transactions on intelligent transportation systems* 21, 9 (2019), 3848–3858.