

1 **Spatiotemporal Traffic Forecasting: Review and Proposed Directions**

2 **Alireza Ermagun** (*Corresponding Author*)

3 Ph.D. Candidate

4 University of Minnesota

5 Department of Civil, Environmental, and Geo- Engineering

6 500 Pillsbury Drive SE, Minneapolis, MN 55455 USA

7 ermag001@umn.edu

8 **David Levinson**

9 Professor

10 University of Minnesota and University of Sydney

11 500 Pillsbury Drive SE, Minneapolis, MN 55455 USA

12 dlevinson@umn.edu

13 Paper submitted for:

14 Presentation at 96th Annual Transportation Research Board Meeting, January 2017

15 Standing Committee on Transportation Demand Forecasting (ADB40)

16 5480 words + 4 figures + 2 tables

17 July 30, 2016

1 **ABSTRACT**

2 This paper systematically reviews studies that forecast short-term traffic conditions using spatial
3 dependence between links. We synthesize 130 extracted research papers from two perspectives: (1)
4 methodological framework, and (2) approach for capturing and incorporating spatial information.
5 From the methodology side, spatial information boosts the accuracy of prediction, particularly in
6 congested traffic regimes and for longer horizons. There is a broad and longstanding agreement that
7 non-parametric methods outperform the naive statistical methods such as historical average, real
8 time profile, and exponential smoothing. However, to make an inexorable conclusion regarding
9 the performance of neural network methods against STARIMA family models, more research is
10 needed in this field. From the spatial dependency detection side, we believe that a large gulf exists
11 between the realistic spatial dependence of traffic links on a real network and the studied networks.
12 This systematic review highlights that the field is approaching its maturity, while it is still as crude
13 as it is perplexing. It is perplexing in the conceptual methodology, and it is crude in the capture of
14 spatial information.

15 **Keywords:** Traffic Forecasting; Spatial Correlation; Systematic Review; Traffic Network;
16 Life-cycle

1 INTRODUCTION

2 Short-term traffic forecasting aims to predict the number of vehicles on a link during a given
3 time slice, typically less than an hour. With the growing need to develop more adaptive traffic
4 management systems, short-term traffic forecasting has aroused the interest of traffic engineers.
5 This is a fundamental objective of advanced traffic management systems and advanced traveler
6 information systems. Approaches generally take advantage of the information that many of the
7 cars that will be on one link soon are already on the network upstream of the relevant location, and
8 of typical patterns of flow.

9 Does spatial interdependence exist between traffic links? Is embedding this dependency in
10 short-term traffic forecasting methods propitious? If so, how is this information captured? These
11 questions have been confronting researchers who seek to maximize the performance of the network
12 by anticipating traffic conditions. Two strands of research tackled these questions in two discrete
13 time spans. One benefits from the information of upstream and downstream traffic links as an
14 input of the system. The other predefines the spatial dependence structure between traffic links,
15 and embeds this structure in forecasting methods. Irrespective of which strand is chosen, the
16 success of the method heavily relies on detecting the spatial dependence structure.

17 Embedding the spatial components in traffic forecasting methods has been the focus of
18 countless research papers over the past few years. The related literature has compelling evidence
19 to support the potential of spatial components to augment traffic forecasting. Nevertheless, cou-
20 pling the spatial components with forecasting methods may act as either a catalyst or a hindrance.
21 It behaves as a catalyst when actual spatial information feeds the system, and behaves as a hin-
22 drance when misrepresented spatial information causes erroneous results. Ample of methods have
23 emerged aiming to extract spatial dependency between traffic links as accurately as possible. How-
24 ever, little is known about whether and to what extent the emerged methods represent the spatial
25 interdependence realistically.

26 This paper reviews studies that fall into the aforementioned two strands of research. Partic-
27 ularly, we delve into the existing research through the lens of a comprehensive systematic frame-
28 work. This approach comprehensively searches the literature, rather than just one part of it, and
29 thereby lowers the chance of bias. Drilling down further, we seek to answer the following questions
30 in this review:

- 31 • What are spatial components and their role in traffic forecasting?
- 32 • To what extent does spatial dependency exist between traffic links?
- 33 • How is spatial dependence captured and embedded in forecasting methods?
- 34 • Is the current knowledge exhaustive or crude?
- 35 • What are the lacuna in the current literature?
- 36 • What are directions should research take?

37 Answering these questions enables us to disclose what and how much we know about
38 the effectiveness of spatial information in traffic forecasting methods. It also sheds light on the
39 consistencies and inconsistencies of the findings across multiple studies, and leads to identifying
40 gaps in our knowledge that require further research.

1 Having this introduction, the remainder of the paper is set out as follows. First, we discuss
2 the methodology of the review that we adopted for the sake of literature synthesis. Second, we sum-
3 marize the statistics of 130 research papers extracted from the pool of studies with our systematic
4 approach. Third, we review and synthesize the extracted research papers from two perspectives:
5 (1) methodological framework of the models and (2) approach for capturing and incorporating
6 spatial information in the models. Fourth, we conclude the paper with a broad discussion on the
7 lacuna of the current literature, and propose future directions.

8 **REVIEW METHODOLOGY: A SYSTEMATIC APPROACH**

9 There is a general agreement on reviewing the literature “systematically” to avoid representing
10 islands without continents. Despite the emphasis on systematic literature review, researchers adopt
11 the following recipe sporadically (1)

12 “Take a simmering topic, extract the juice of an argument, add the essence of one filing
13 cabinet, sprinkle liberally with your own publications and sift out the work of noted detractors or
14 adversaries.”

15 To avoid this pitfall, we follow five steps in conducting a systematic review proposed by
16 Khan et al. (2):

- 17 • **Step 1:** Framing questions for a review
- 18 • **Step 2:** Identifying relevant work
- 19 • **Step 3:** Assessing the quality of studies
- 20 • **Step 4:** Summarizing the evidence
- 21 • **Step 5:** Interpreting the findings

22 To capture the potential range of published articles in the field, we identified relevant arti-
23 cles by an electronic search of Google Scholar, IEEE Xplore, and Scopus academic search engines
24 along with electronic library records. The limited coverage time of electronic sources does not
25 cause any bias in our case, as we trace back utilization of spatial information in traffic forecasting
26 methods to 1984. We hunted for studies while considering manifold and distinct search keys not
27 just simply in titles, keywords, and abstracts, but in the text of articles. Although this necessitated
28 double effort, it resulted in extracting a more comprehensive pool of research. The main search
29 keys were “traffic forecast”, “forecasting traffic”, “forecasting of traffic”, “spatial”, and “space.”
30 We searched for both “spatial” and “space” terms, as they are interchangeably used to describe
31 spatial components in the literature of traffic forecasting.

32 We summarized the study exclusion process in Figure 1. This process encompasses three
33 steps. In the first step, we searched the literature to extract all articles including the combination
34 of selected keywords as shown in Figure 1. This search assuredly led to extracting articles from
35 diverse disciplines. In the second step, we executed four distinct assessment criteria to not only
36 exclude irrelevant disciplines, but to only include articles that are germane to using spatial com-
37 ponents for traffic forecasting. Thus, we excluded literature about wireless local area networks,
38 internet traffic, railways, and groundwater, to name but a few. We also dropped articles where our
39 search keys appeared in the introduction, literature review, recommendation, and reference sec-
40 tions. Concretely speaking, we perused the pool of articles closely and excluded articles which

1 lack implementation of spatial information in traffic forecasting methods. This resulted in 113
 2 English research articles. In the third step, we systematically reviewed the lists of references from
 3 excluded articles. We then added those research papers that met the inclusion criteria in accordance
 4 with the second step. The consequence of this systematic search resulted in 130 publications in
 5 peer-reviewed journals, conference proceedings, and dissertations. A strong point of emphasis is
 6 that the literature includes mounting articles in employing spatial components on traffic forecast-
 7 ing methods in different languages. Nonetheless, we have limited the scope of this review to only
 8 English literature.

9 REVIEW STATISTICS

10 In this section, we provide a statistical overview of extracted articles. Table 1 classifies the source
 11 of the articles that embedded spatial components in traffic forecasting methods. As depicted
 12 in Table 1, 63.8% of articles were published in peer-reviewed journals. Almost 67.5% of the
 13 extracted articles appeared in Transportation Research Part C, Transportation Research Record,
 14 IEEE Transactions on Intelligent Transportation Systems, Journal of Transportation Engineering,
 15 Computer-Aided Civil and Infrastructure Engineering, IET Intelligent Transport Systems, Journal
 16 of Intelligent Transportation Systems, Transportation Research Part B, and Journal of Advanced
 17 Transportation. This statistic reveals that articles on traffic forecasting using spatial components
 18 are concentrated in emerging technology journals. It is not surprising as traffic forecasting is an
 19 integral part of intelligent transportation systems. The other 32.5% of the articles appeared in 27
 20 other journals.

TABLE 1 : Distribution of publications by source

Classification of Sources	Number of Retrievals	Percentage
<i>Article Division</i>		
Scientific Journals	83	63.8%
Dissertations	6	4.6%
Conference proceedings	41	31.6%
<i>Journal Source</i>		
Transportation Research Part C: Emerging Technologies	12	14.5%
Transportation Research Record	11	13.3%
IEEE Transactions on Intelligent Transportation Systems	11	13.3%
Journal of Transportation Engineering	6	7.2%
Computer-Aided Civil and Infrastructure Engineering	4	4.8%
IET Intelligent Transport Systems	4	4.8%
Journal of Intelligent Transportation Systems	4	4.8%
Transportation Research Part B: Methodological	2	2.4%
Journal of Advanced Transportation	2	2.4%
Other	27	32.5%

21 To give the reader a sense of the temporal evolution of the field, we drew the life-cycle
 22 graph of publications in Figure 2. This figure shows the number of publications per year over
 23 the extracted articles in this review. As shown, utilizing spatial components in traffic forecasting
 24 methods is an emerging research field. We designate 1984 as the historical starting point for
 25 earmarking spatial components as a potential input of forecasting methods. The growth phase of

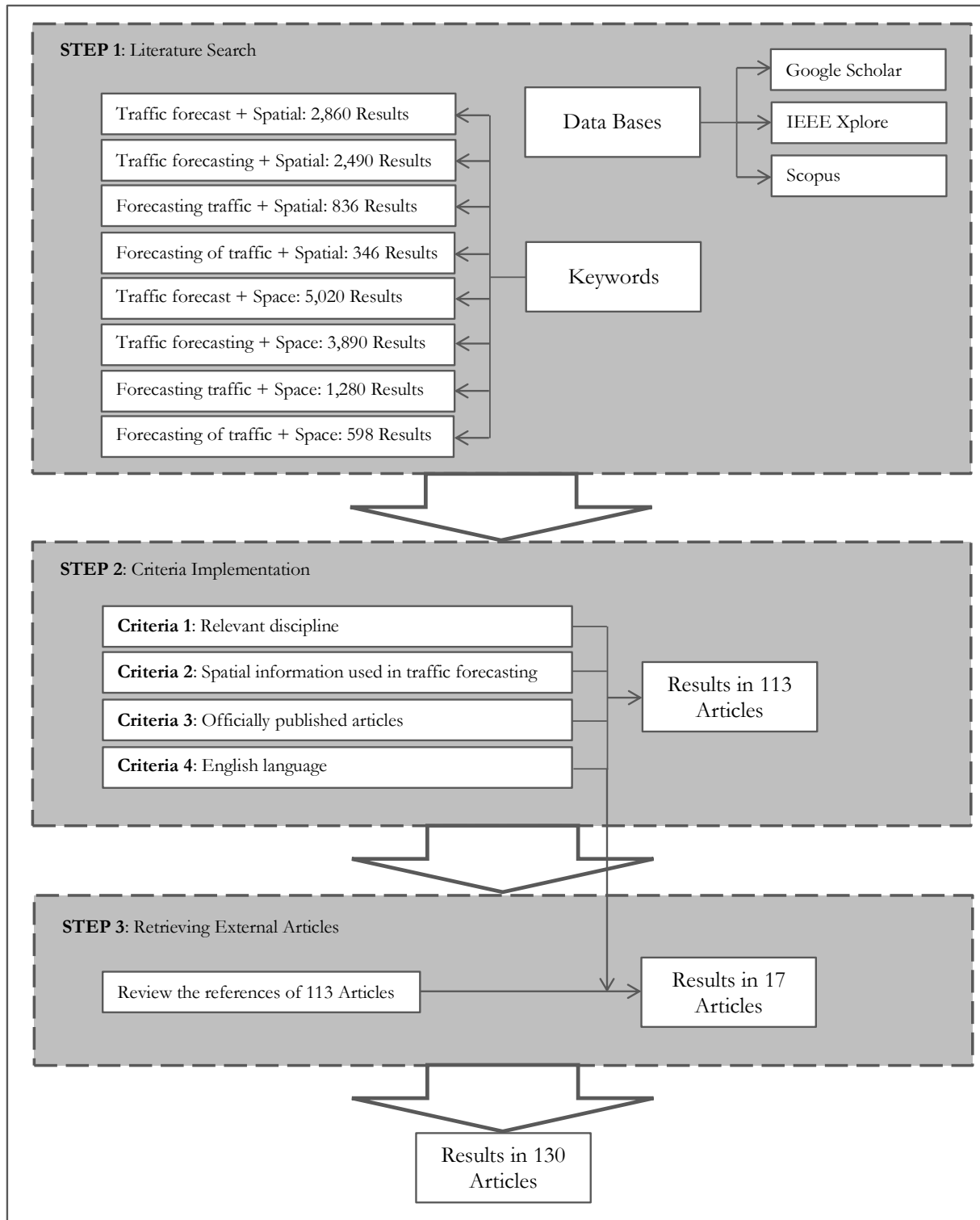


FIGURE 1 : Flowchart diagram of study inclusion process

1 this field is laid as early as 2001. As portrayed in Figure 2, the number of publications had a
 2 significant jump in the past two years. The drop in the number of publications for 2016 is due to
 3 the time of search, which was June 30th 2016. We expect the field would continue its growth, and
 4 more research is needed to reach the apex of maturity as we discuss later in detail.

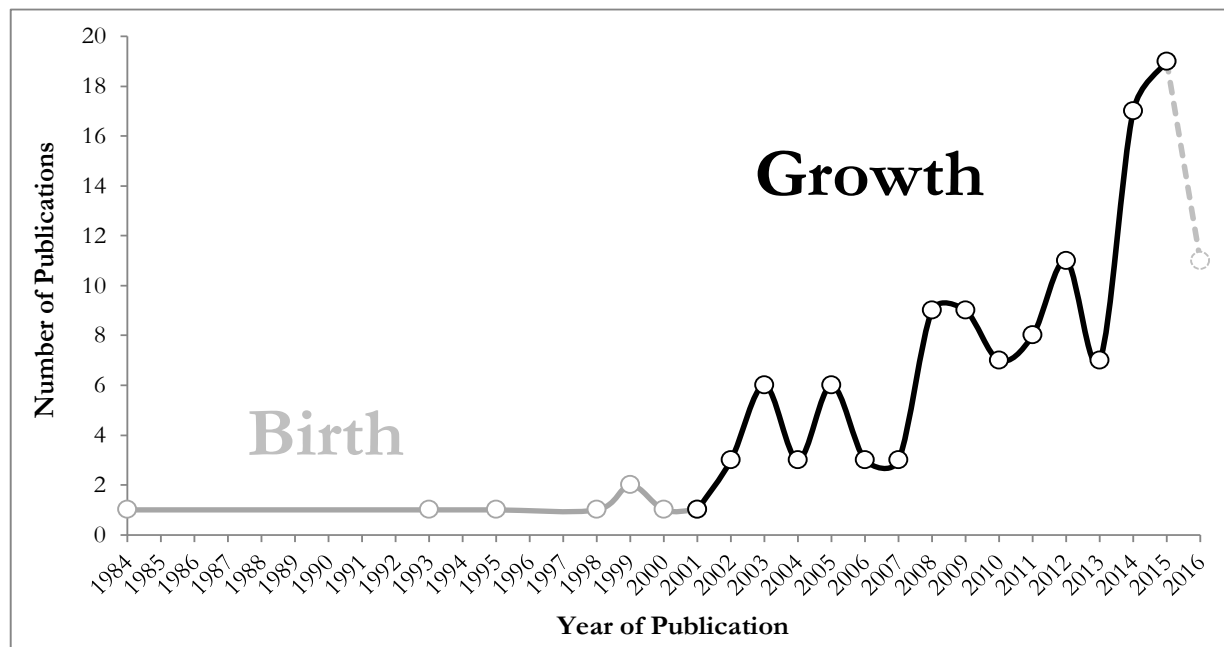


FIGURE 2 : The life-cycle diagram of the research field

5 We summarized the 130 extracted publications in Table 2 where their key characteristics
 6 are provided, such as forecasting resolution, the type of data, number of traffic links incorporated
 7 in the study, and modeling framework. The third column of Table 2 shows the implementation of
 8 traffic forecasting methods is carried out mainly in North America, followed by Europe and Asia.
 9 Only two studies were conducted in Australia. Other continents such as South America and Africa
 10 are not at all covered by this literature. The Netherlands, England, and Greece are more prevalent
 11 than other European countries in our review. This distribution stems from the language of retrieved
 12 articles, which is English in this systematic review.

13 In the subsequent sections, we review and synthesize 130 extracted publications across
 14 two principal aspects. One discusses the conceptual methodology used in publications. The other
 15 elaborates on emerging hypotheses and techniques aimed at detecting spatial components. Re-
 16 flecting on the flow of thinking that underlies the construction of spatial dependence is essential,
 17 as forecasting methods stand on the foundation of detecting the spatial dependence structure.

18 A REVIEW OF METHODS FOR PREDICTING SHORT-TERM TRAFFIC

19 In 1984, Okutani and Stephanedes (130) were the first to achieve a better traffic flow prediction
 20 on a link by taking into account the spatial information of its upstream feeder links. Twenty years
 21 later, Kamarianakis and Prastacos (115) borrowed a model, the so-called space-time autoregressive
 22 integrated moving average (STARIMA), from the regional science literature to forecast relative
 23 velocity on major arterials of Athens, Greece. Although the fundamental of STARIMA is laid as

TABLE 2 : Summary of literature

No.	First Author	Location	Road	Step (Min)	Predictor	Data	Link	Method	
								ST	ML
1	Fusco (3)	Italy	Urban	5	Speed	R	5		✓
2	Zhu (4)	Germany	Urban	5, 10, 15	Flow	S	19		✓
3	Yu (5)	China	Urban	5	Flow	R	6		✓
4	Xia (6)	China	Urban	5	Flow	R	3		✓
5	Zhang (7)	US	Highway	5	Flow	R	6	✓	✓
6	Ko (8)	Korea	Expressway	1	Flow	R	5	✓	✓
7	Zhao (9)	China	Urban	15	Flow	R	10		✓
8	Jiang (10)	China	Urban	2	Speed	R	3	✓	✓
9	Polson (11)	US	Highway	5	Speed	R	21	✓	✓
10	Salamanis (12)	Germany	Urban	5	Travel Time	R	218,576	✓	
11	Wu (13)	US	Urban	5	Flow	R	14		✓
12	Xu (14)	China	Urban	10	Flow	R	17		✓
13	Lv (15)	US	Freeway	5	Flow	R	-		✓
14	Zou (16)	US	Freeway	5	Speed	R	5		✓
15	Ma (17)	Canada	Highway	60	Flow	R	9		✓
16	Schimbinschi (18)	Australia	Freeway	15	Flow	R	4	✓	✓
17	Dong (19)	China	Freeway	2	Flow	R	12	✓	
18	Agafonov (20)	Russia	Urban	10	Travel Time	R	3,387		✓
19	Fusco (21)	Italy	Urban	5	Speed	R	7		✓
20	Zou (22)	China	Urban	5	Flow	R	3		✓
21	Reza (23)	US	Highway	1	Travel Time	R	28	✓	
22	Hou (24)	US	Freeway	15	Flow	R	8		✓
23	Shahsavari (25)	US	Highway	15	Flow	R	36		✓
24	Xing (26)	China	Highway	15	Flow	R	120	✓	
25	Ahn (27)	Korea	Expressway	1	Flow	R	4		✓
26	Yang (28)	US	Highway	10	Flow	R	3,254	✓	✓
27	Yang (29)	US	Highway	1	Speed	R	9	✓	
28	Dell'Acqua (30)	US	Freeway	15	Flow	R	-	✓	
29	Ran (31)	US	Highway	5	Speed	R	13		✓
30	Zhong (32)	US	Highway	-	Flow	R	2	✓	✓
31	Wu (33)	China	Urban	5	Flow	R	5		✓
32	Cheng (34)	England	Urban	5	Flow	R	22	✓	
33	Zhu (35)	China	Urban	15	Flow	R	3		✓
34	Chen (36)	US	Freeway	5	Speed	R	5	✓	✓
35	Niu (37)	China	Urban	15	Flow	R	64		✓
36	Daraghmi (38)	Taiwan	Urban	2	Flow	R	13		
37	Mohan (39)	Singapore	Expressway	5	Speed	R	12		✓
38	Yang (40)	US	Freeway	1	Speed	R	9	✓	
39	Dong (41)	China	Freeway	2	Flow	R	12	✓	
40	Ratrou (42)	US	Urban	15	Flow	R	4		✓
41	Dong (19)	China	Freeway	5	Flow	R	10		✓
42	Zhao (43)	US	Freeway	5	Flow	R	2	✓	
43	Fabrizi (44)	Italy	Motorway	3	Speed	R	3		✓
44	Qing (45)	China	Urban	5	Flow	S	11		✓
45	Liang (46)	Germany	Urban	0.5	Flow	S	6		✓
46	Zou (47)	US	Highway	5	Travel time	R	5	✓	
47	Haworth (48)	England	Urban	5	Flow	R	22		
48	Li (49)	US	Freeway	5	Flow	R	3	✓	
49	Pan (50)	US	Freeway	5	Flow	R	7	✓	
50	Zeng (51)	US	Freeway	5	Travel Time	R	3		✓

TABLE 2 : Summary of literature (Continue)

No.	Authors	Location	Road	Step (Min)	Predictor	Data	Link	Method	
								ST	ML
51	Fowe (52)	US	Urban	15	Flow	R	8	✓	
52	Han (53)	France	Urban	15	Flow	S	13,627		✓
53	Huang (54)	China	Urban	5	Flow	R	11		✓
54	Zheng (55)	Netherlands	Urban	1	Travel time	S	3		✓
55	Kamarianakis (56)	US	Highway	5	Speed	R	-	✓	
56	Haworth (57)	England	Urban	5	Travel Time	R	22		✓
57	Cheng (58)	England	Urban	5	Travel Time	R	22	✓	
58	Guo (59)	England	Urban	15	Flow	R	2		✓
59	Guo (60)	England	Urban	15	Flow	R	-		✓
60	Pan (61)	US	Freeway	5	Travel Time	R	3	✓	
61	Ngan (62)	China	Urban	-	Flow	R	8		✓
62	Chen (63)	-	-	0.5	Flow	R	4		✓
63	Wu (64)	US	Urban	5	Flow	R	14		✓
64	Yuan (65)	China	Urban	5	Flow	R	-		✓
65	Sun (66)	China	Urban	15	Flow	R	31		✓
66	Pascale (67)	US	Highway	15	Flow	R	11		✓
67	Djuric (68)	US	Highway	5	Speed	R	11		✓
68	Han (69)	France	Urban	15	Flow	S	13,627		✓
69	Samaranayake (70)	US	Highway	2.5	Speed	R	-		✓
70	Cheng (71)	England	Urban	5	Travel Time	R	22	✓	
71	Deng (72)	-	Urban	15	Flow	R	7	✓	
72	Min (73)	-	Urban	5	Flow	R	502		✓
73	Khostravi (74)	Australia	Freeway	15	Travel Time	R	4		✓
74	Lippi (75)	US	Freeway	15	Flow	R	7		✓
75	Min (76)	China	Urban	5	Flow	R	50		✓
76	Herring (77)	US	Urban	30	Travel Time	S	322	✓	
77	Sun (78)	China	Expressway	5	Micro-LOS	R	18		✓
78	Guo (79)	England	Urban	15	Flow	R	-		✓
79	Lee (80)	Germany	Freeway	15	Flow	R	15	✓	
80	McCrea (81)	England	Urban	-	Flow	S	6		✓
81	Min (82)	China	Urban	5	Flow	R	10	✓	
82	Chandra (83)	US	Freeway	5	Flow and Speed	R	5	✓	
83	Dong (84)	-	-	2	Flow	R	20		✓
84	Li (85)	China	Freeway	5	Flow	R	3		✓
85	Chandra (86)	US	Freeway	5	Flow and Speed	R	5	✓	
86	Ghosh (87)	Ireland	Urban	15	Flow	R	10	✓	
87	van Hinsbergen (88)	Netherlands	Motorway	5	Travel Time	R	19		✓
88	Bell (89)	England	-	3	Speed	S	8	✓	
89	Innamaa (90)	Finland	Urban	5	Travel Time	R	2		✓
90	Yue (91)	Hong Kong	Urban	-	Flow	R	7	✓	
91	Stathopoulos (92)	Greece	Urban	3	Flow	R	2		✓
92	Chandra (93)	US	Freeway	5	Speed	R	5	✓	
93	Dimitriou (94)	Greece	Urban	3	Flow	R	2		✓
94	De Fabritiis (95)	Italy	Motorway	3	Speed	R	-		✓
95	Wu (96)	US	Freeway	5	Flow	R	2		✓
96	Hu (97)	US	Freeway	5	Flow	R	4		✓
97	van Lint (98)	Netherlands	Freeway	5	Travel Time	R	14		✓
98	Ye (99)	China	Urban	5	Flow	R	8		✓
99	Vlahogianni (100)	Greece	Urban	3	Flow	R	4		✓
100	Yue (101)	Hong Kong	Urban	1	Flow	R	7	✓	

TABLE 2 : Summary of literature (Continue)

No.	Authors	Location	Road	Step (Min)	Predictor	Data	Link	Method	
								ST	ML
101	Sun (102)	China	Freeway	15	Flow	R	20		✓
102	Xie (103)	US	Freeway	5	Flow	R	4		✓
103	Van Lint (104)	Netherlands	Freeway	1	Travel time	R	26		✓
104	Wang (105)	-	Freeway	1	Flow	S	23		✓
105	Vlahogianni (106)	Greece	Urban	3	Flow	R	3		✓
106	Sun (107)	China	Freeway	15	Flow	R	31		✓
107	Kamarianakis (108)	Greece	Urban	7.5	Flow	R	25	✓	
108	van Lint (104)	Netherlands	Highway	1	Speed	S	19		✓
109	Bajwa (109)	Japan	Expressway	5	Travel time	R	5		✓
110	Innamaa (110)	Finland	Highway	1	Travel time	R	4		✓
111	Ishak (111)	US	Freeway	5	Speed	R	3		✓
112	Kamarianakis (112)	Greece	Urban	7.5	Flow	R	11	✓	
113	Alecsandru (113)	US	Freeway	5	Speed	R	-		✓
114	Vlahogianni (114)	Greece	Urban	3	Flow	R	-		✓
115	Kamarianakis (115)	Greece	Urban	7.5	Relative velocity	R	25	✓	
116	Stathopoulos (116)	Greece	Urban	3	Flow	R	5	✓	
117	Ishak (117)	US	Freeway	5	Speed	R	4		✓
118	Hu (118)	China	Urban	-	Speed	R	60		✓
119	van Lint (119)	Netherlands	Freeway	-	Travel Time	S	13		✓
120	van Lint (120)	Netherlands	Highway	-	Travel Time	S	12		✓
121	Tebaldi (121)	US	Highway	1	Flow	R	15	✓	
122	Abdulhai (122)	US	Freeway	0.5, 1, 2, 5, 15	Flow	R	3		✓
123	Williams (123)	France	Motorway	30	Flow	R	-	✓	
124	van Lint (124)	Netherlands	Motorway	1, 5, 10	Flow and Speed	R	2	✓	
125	Park (125)	US	Freeway	5	Travel Time	R	6		✓
126	Abdulhai (126)	US	Freeway	0.5	Flow	R	9		✓
127	Park (127)	US	Freeway	5	Flow	R	4		✓
128	Larry (128)	US	Urban	5	Flow	R	4	✓	
129	Clark (129)	England	Urban	5	Flow	R	3	✓	
130	Okutani (130)	Japan	Urban	5	Flow	R	4	✓	

Note. R: Real data and S: Simulation data

1 early as 1975 by Cliff and Ord (131), they were the first to test this model in a traffic forecasting
2 framework. The STARIMA family model is considered a generic form of autoregressive linear
3 models used in traffic forecasting. This model is quite distinct from the traditional autoregressive
4 integrated moving average (ARIMA) model by capturing the spatial information of neighboring
5 links for traffic forecasting. We depict the taxonomy of this family of models in Figure 3. In these
6 models, d , p , and q are non-negative integers and stand for degree of differentiation, order of the
7 autoregressive model, and order of the moving-average model, respectively. W_k is a $n \times n$ matrix
8 of spatial weights for spatial order l and temporal lag k . The terms m_i and n_i denote spatial order
9 of the i^{th} autoregressive and moving average terms, respectively. The components of the spatial
10 weight matrix regularly satisfy three major rules:

- 11 1. $W_{ij} \geq 0$,
- 12 2. $W_{ii} = 0$, and
- 13 3. $\sum_{j=1}^n W_{ij} = 1$, for all $i = 1, 2, \dots, n$. (132).

14 The studies of Okutani and Stephanedes (130) and Kamarianakis and Prastacos (115)
15 formed the essence of a methodological strand of thinking at different points in time. They
16 acknowledged embedding spatial information as the potential of enhancing traditional temporal

1 stations on I-4 in the downtown region of Orlando, Florida, Chandra and Al-Deek (93) developed
2 a univariate ARIMA time-series model and a vector autoregressive (VAR) model. Comparing both
3 models, they found VAR significantly outperforms ARIMA. This is consistent with Chandra and
4 Al-Deek (83).

5 To investigate whether the inclusion of spatial information improves the accuracy of the
6 artificial neural network (ANN) model, Zeng and Zhang (51) compared the state-space neural net-
7 work (SSNN) model with traditional ANN models. The findings expounded that the SSNN model
8 consistently outperforms other neural network models in both short and long horizons. Wu et al.
9 (33) added the spatial information in k-nearest neighbor model to enhance the accuracy of traffic
10 flow forecasting in urban roads of Guiyang, China. The performance of the improved k-nearest
11 neighbor model was also compared with the traditional historical average and neural network mod-
12 els without spatial information. The results indicated the model including both temporal and spatial
13 information reduces the error significantly in comparison with the model with only temporal in-
14 formation. The historical average model was also found the worst model among the developed
15 models.

16 To investigate the effectiveness of spatial information, Dong et al. (19) compared a spa-
17 tiotemporal model with traditional ARIMA and a linear regression model encompassing only spa-
18 tial information. The output of the models affirmed the superiority of the spatiotemporal model. It
19 was also noted that the temporal input factor provides more accurate information than the spatial
20 input factor in uncongested situations. In congested conditions, it reverses.

21 **Class 2: Modeling Performance Emphasis**

22 Studies of this class compare the performance of sundry modeling techniques to introduce the most
23 efficient method. Kamarianakis and Prastacos (108) embedded the spatial information in the tra-
24 ditional ARIMA model and compared its performance with STARIMA, where the spatial compo-
25 nents are captured with a spatial weight matrix. The performance of both models was found quite
26 close. However, a point worthy of attention is that the STARIMA model included 7 parameters
27 and a naive spatial weight matrix (first- and second-order adjacent matrix), whereas the ARIMA
28 model encompassed 75 different parameters. Sun et al. (107) employed both spatial and temporal
29 information, and compared the accuracy of random walk, Markov chain, and Bayesian network
30 methods by the root mean square error. The findings stated the Bayesian network performs better
31 than Markov chain, and the latter outperforms the random walk model. Stathopoulos et al. (92)
32 introduced a fuzzy rule-based system method, which is the combination of a Kalman filter and an
33 artificial neural network methods. This study compared the performance of the combined model
34 against the other two models using three different measures, namely mean absolute relative error,
35 mean square relative error, and normalized error. Building on the results, they concluded that the
36 neural network method generally gives more accurate results than Kalman filter method, while the
37 authors' fuzzy rule-based system method outperformed both models.

38 Min et al. (82) compared the accuracy prediction power of Dynamic STARIMA with mul-
39 tivariate adaptive regression splines (MARS). The former and STARIMA are alike in structure,
40 whereas the spatial weight matrix of the Dynamic STARIMA is derived from traffic flow infor-
41 mation of links, and not simply adjacency. It enables the model to be updated dynamically in a
42 real network. The latter is a non-parametric model. The comparison of two models indicated the
43 superiority of Dynamic STARIMA. Interestingly, Ye et al. (99) found that MARS is more accurate
44 than linear regression and neural network methods. This may result in superiority of Dynamic

1 STARIMA over ANN. (76) generalized the STARIMA model and introduced GSTARIMA model,
2 which relaxes the assumption that the autoregressive parameters and the moving average param-
3 eters are the same for all traffic locations. They noted the performance of GSTARIMA model
4 exceeded the STARIMA model.

5 **Class 3: Hybrid Emphasis**

6 Class 3 is a combination of Class 1 and Class 2. We thereupon labeled this class hybrid analysis, as
7 the studies of this class not only scrutinize the potential of spatial information, but they also com-
8 pare the modeling techniques. One comprehensive study developed four different artificial neural
9 network models and compared the accuracy of them with historical average, Kalman filtering, real-
10 time profile, and exponential smoothing (125). The four artificial network models were distinct in
11 whether they include spatial information, of which the information of upstream and downstream
12 links was selected for travel time forecasting. In general, they underlined that the neural network
13 with temporal information is superior to other models in predicting one or two steps ahead. For
14 longer horizons, however, adding spatial information of upstream and downstream traffic links
15 augments the forecasting models.

16 In a comparison of state-space neural network models, van Lint et al. (120) noted that the
17 highly nonlinear and complex characteristics of the freeway travel time necessitates a modeling
18 approach that is able to deal with this complexity. They used SSNN as the best model to capture
19 the complex nonlinear spatiotemporal relationships between traffic links, and compared various
20 version of SSNN. The partially connected SSNN model was found inferior to connected SSNN
21 and reduced SSNN models. Likewise, van Lint (104) found the excellence of SSNN in a com-
22 prehensive comparison with Kalman filter, feed-forward neural network (FNN), modular FNN,
23 regular FNN, spectral-bases FNN, linear regression, and support vector-regression.

24 Kamarianakis and Prastacos (115) compared the forecasting performance of historical aver-
25 age, ARIMA, VARMA, and STARIMA models. Comparing the root mean square error of models,
26 they found the last three models perform remarkably better than historical average, while there is
27 not a significant difference between ARIMA, VARMA, and STARIMA models. Vlahogianni et
28 al.(100) employed ARIMA, state-space, and neural network methods to forecast traffic flow of a
29 link by using its immediate upstream and downstream links. The results indicated the mean relative
30 error of the state-space model that considers the information of upstream and downstream links and
31 the ARIMA model is 12% and 18%, respectively. They concluded that the neural network method
32 outperforms both ARIMA and state-space models. It is in line with the previous studies of the
33 authors on the same data (106). They also mentioned the accuracy of the neural network method
34 depends on the prediction technique, where the modular predictor surpasses genetically optimized
35 multi-layer perceptron (MLP) and statistic MLP. Guo et al. (79) tested three distinct machine learn-
36 ing methods, namely time delay, recurrent neural networks, and the k-nearest neighbor for traffic
37 flow forecasting in the urban area of London. Comparing the models, they recommended k-nearest
38 neighbor based prediction models with error feedback for short-term traffic prediction.

39 This trajectory leads us to the following conclusions:

- 40 • Irrespective of which method is selected, spatial information inclusion in short-term traf-
41 fic forecasting models boosts the accuracy of prediction, particularly in congested traffic
42 regimes and longer time horizons.
- 43 • There is a broad and longstanding agreement that non-parametric methods outperform

1 the naive statistical methods such as historical average, real time profile, and exponential
2 smoothing. However, to make an inexorable conclusion regarding the performance of
3 neural network methods against STARIMA family models, more research is needed in
4 this field.

5 **A REVIEW OF METHODS FOR CAPTURING SPATIAL INFORMATION**

6 It has been over three decades since spatial information was first captured in a traffic corridor for
7 the sake of traffic flow prediction (130). In this section, we discuss the evolution of techniques for
8 dealing with capturing spatial information for traffic forecasting. We take a fairly narrow view of
9 analysis, and delve into the emerged approaches from two conceptual aspects. For each aspect, we
10 elaborate on the nature of spatial components used in traffic forecasting, and identify the notion
11 behind an objective evaluation of approaches.

12 **A Naive Approach**

13 Traffic conditions of a downstream section of a road are highly associated with traffic conditions
14 upstream (as those vehicles will ultimately travel to the link in question). Thereupon, spatial
15 information of upstream sections may capture the dynamics of traffic. Following the study of
16 Okutani and Stephanedes (130), Larry (128) utilized the traffic flow of detectors on the approach of
17 each upstream intersection to predict future arrivals. He noticed the longer horizons are achieved
18 when spatial information is embedded in traffic forecasting methods. In another study, Park et
19 al. (127) found the traffic flow of upstream links is highly correlated with the study link, and
20 mentioned spatial information is as informative as temporal information. (116) predicted traffic
21 flow in an urban corridor while using the spatial information of four consecutive loop detectors in
22 the upstream of the study section. Although they acknowledged spatial information as a catalyst,
23 they noticed farther links are correlated with the study link over a longer time lag. (106) used the
24 flow information of two upstream loop detectors to predict the traffic flow of the study link in an
25 urban arterial. They argued that the spatial information has the potential of enhancing the accuracy
26 of forecasting methods, particularly over a longer traffic horizon.

27 Not only is a link affected by its upstream links, but downstream links also may involve traf-
28 fic conditions of their upstream links. This is a case in congested situations, where the downstream
29 link propagates its traffic to upstream links. (122) benefited from both upstream and downstream
30 flow information to take backward propagating shockwaves into account. (117) embedded both
31 downstream and upstream information in the forecasting modeling. Studies took a step forward
32 by examining to what extent the downstream information is crucial in traffic forecasting. (120)
33 highlighted the downstream information plays a more critical role than upstream information in
34 congested situations for travel time forecasting. However, no superiority was witnessed in un-
35 congested conditions. In the congested regime, (68) also concluded that the current speed of the
36 downstream link has a greater weight than the upstream link for speed forecasting. This is also
37 confirmed by Daraghmi et al. (38), who made the same conclusion for traffic flow forecasting
38 on an arterial road. Vlahogianni et al. Zou et al. (16) used the information of two upstream and
39 two downstream links. They developed distinct models to explore the role of downstream and
40 upstream links in forecasting of traffic speed. No significant difference was found between using
41 either downstream or upstream information for various prediction horizons in both congested and
42 uncongested regimes.

1 A Modest Approach

2 Studies corroborated the hypothesis about enhancing the accuracy of forecasting methods by incor-
3 porating the information of neighboring links. Researchers, practitioners, and policymakers who
4 seek to develop intelligent transportation systems embraced this hypothesis with enthusiasm. How-
5 ever, little information was known about which and how many links is needed to be included in
6 forecasting methods. Researchers dealt properly and fairly with this complication. Consequently,
7 two criteria were introduced to select the neighboring links: (1) correlation-coefficient assessment
8 and (2) distance adjustment. The former probes deeply into the data to explore whether and to
9 what extent the information of neighboring links is correlated with the study link. The highly cor-
10 related links are then selected as an input of forecasting methods. The latter borrows from regional
11 science, and more specifically from the first law of geography. In accordance with this law, every
12 link is related with every other links, but near links are more related than distant links. Particularly
13 noticeable is the word “nearness.” Despite the existence of many alternative methods to define
14 the nearness and distance threshold in regional science, the traffic forecasting field has benefited
15 mostly from spatial information of adjacent links.

16 From the correlation-coefficient assessment side, Sun et al. (107) calculated the Pearson
17 correlation coefficient to rank the input spatial and temporal exogenous variables. They then se-
18 lected the four most correlated upstream and downstream links in different time regimes. Building
19 on their experimental results, they concluded that not only near links, but also distant links in a
20 traffic network, have high correlation coefficients. This association is needed to be employed for
21 traffic flow forecasting. Likewise, Chandra and Al-Deek (93) and Chandra and Al-Deek (83) uti-
22 lized cross correlation function and found that past values of an input series influence the future
23 values of a response series. Huet al. (97) also adopted the cross correlation function to select the
24 relative neighboring links, rather than the selection of immediate upstream and downstream links.
25 The results of the analyses showed the immediate upstream and downstream link as well as the
26 eighth link located in the upstream are the most correlated links. They also found the downstream
27 link is more effective than upstream links, and validated this by the existence of a ramp between
28 the upstream link and the study link, which reduces the correlation.

29 From the distance adjustment side, most studies using this criteria fall into the spatiotem-
30 poral methodological category, and prejudge the spatial dependency by creating a spatial weight
31 matrix. As we mentioned, two methods are adopted to identify the components of a spatial weight
32 matrix in traffic forecasting. One simply assumes just adjacent links have a spatial dependence
33 with the study links. The other takes a step forward more comprehensively measuring the spatial
34 dependency and states both adjacent and distant links are spatially correlated with the study link;
35 however, the strength of the dependency is reduced by increasing the distance. In traffic forecast-
36 ing, the ring of dependency is labeled by “order.” For example, the first-order adjacency matrix
37 shows the dependency between the study link and its immediate adjacent links. The second-order
38 adjacency matrix, however, indicates the links that are connected to the study links indirectly and
39 with having the first-order links in middle.

40 Kamarianakis et al. (112) used the first- and second-order adjacency matrix to capture spa-
41 tial dependency. Studies using the distance adjusted approach simply expect all adjacent links have
42 a similar effect on the study link. Thereupon, spatial weight matrices encompass binary elements,
43 in which zero and one values stand for spatial independence and spatial dependence, respectively.
44 These matrices are occasionally row normalized for statistical and prediction reasons that leads
45 to not binary elements. Although this normalization results in dissimilar spatial dependency, this

1 dissimilarity does not stem from a conceptual traffic theory.

2 In our best knowledge, only three studies considered dissimilar spatial dependency in cre-
3 ating spatial weight matrices. One studied the traffic flow forecasting of a link using the flow
4 information of the upstream T-junction (82). The weight of spatial dependence for each upstream
5 links equals the traffic flow ratio of each link to the sum of the flow in the T-junction. This needs
6 a dynamic update of spatial weights in real time. The second used the speed differentials over
7 space formula and defined the spatial dependency between two links as the difference between the
8 average speeds of links divided by their distance (71). Likewise, the third employed the speed
9 differentials over speed formula and defined the spatial dependency between two links as the dif-
10 ference between the average speeds of links divided by the speed of the target link (34). The
11 theoretical concept behind this calculation is a decrease in traffic speed on one link follows relative
12 decrease in traffic speed of its adjacent link.

13 **CLOSING REMARKS AND OPPORTUNITIES FOR FUTURE RESEARCH**

14 In this section, we intend to deal with the last two questions from the introduction:

- 15 • What is the lacuna in the current literature?
- 16 • What directions should research take?

17 To answer these questions, we need to dive into the types of traffic networks studied in
18 the literature. However, a preliminary knowledge of graph theory is required, which drove us to
19 provide a brief introduction here. For details the reader may refer to (135). A graph is a collection
20 of nodes that are connected by links. In accordance with graph theory, the following terminologies
21 are drawn:

- 22 • Two links are parallel if they connect the same pair of nodes.
- 23 • Two links are adjacent if they share a common node.
- 24 • A link is loop if its two nodes are the same.
- 25 • A graph is simple if it has no parallel links or loops.
- 26 • A graph is directed if its links show direction.
- 27 • A graph is connected if at least one link exists between every pair of nodes.
- 28 • A ring network is a closed path where every node has exactly two links incident with it.
- 29 • A grid network is a network topology where each node corresponds to a point in a plane.

30 Having these terminologies, a traffic network is exemplified by a graph $G = (N, L)$ encom-
31 passes N nodes and L links, which is both directed and connected. Studies have explored the spatial
32 dependency between traffic links in three distinct network topologies: (1) simple network, (2) grid
33 network, and (3) ring network. The first topology is dominant in analysis, and where one of the
34 other two topologies was analyzed, the selected test sub-graph collapsed the network to a simple
35 network. Irrespective of which topology is chosen, all studies, except one (28), have explored spa-
36 tial dependency between traffic links for the sake of traffic forecasting in a simple graph including

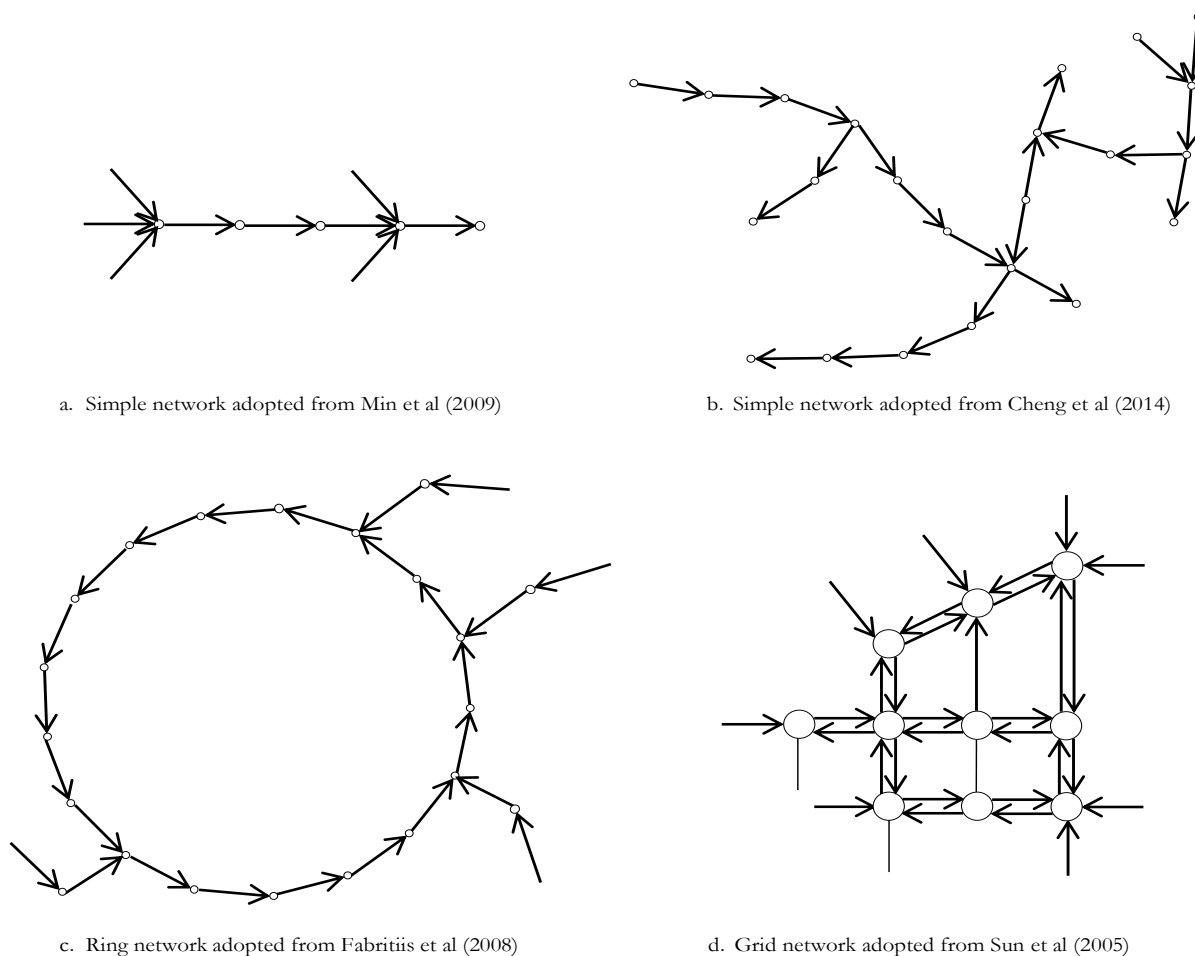


FIGURE 4 : Typical network topology used in the literature

1 upstream and downstream links. We draw the schematic of networks used in the studies in Figure
 2 4.

3 We are of the opinion that a large gulf exists between the realistic spatial dependence of
 4 traffic links on real networks and the typical sub-networks which have been studied in the research
 5 to date. We detected the following gaps in the literature, which signpost the way forward for further
 6 research.

- 7 1. As alluded to previously, studies capture spatial dependency of either adjacent or distant
 8 upstream and downstream links with the study link. We hypothesize that the spatial cor-
 9 relation between traffic links follows a more sophisticated pattern, which is not captured
 10 simply by distance rule. We now have new evidence to corroborate our hypothesis. For
 11 instance, Hu et al. (97) revealed the first- and the eighth-order upstream links, but not
 12 other upstream links, are highly correlated with the link of interest in their specific ex-
 13 ample. A comprehensive recent paper (28) investigated the correlation between traffic
 14 links in the highway network of Twin Cities, Minnesota. The results highlighted that the
 15 contributive links in forecasting models are widely distributed in the traffic network, and
 16 are not a function of distance. This leads to this conclusion that the spatial dependency

- 1 between traffic links is more complex in a whole network than what is presumed to exist
2 in a corridor.
- 3 2. The spatially relevant links are selected either by prejudgment or by correlation-coefficient
4 analysis, each of which is criticized by a drawback. In the former, researchers assume
5 neighboring links are the most spatially correlated links with the study link, and em-
6 bed their information in forecasting methods as an input. This prejudgment results in
7 increasing error, if the adjacent link has not any spatial effect on the study link, as we
8 discussed in preceding paragraph. The latter does not suffer from this shortcoming, as
9 the input information is selected according to the most highly correlated links. However,
10 a similar spatial effect is typically considered for all selected links, which may distort
11 the accuracy of models.
- 12 3. According to graph theory, two links are adjacent if they share a common node, while
13 they are parallel if they connect the same pair of nodes. All studies, except one (28),
14 have developed forecasting methods in a corridor test sample, where all links are con-
15 nected sequentially together. As a result, they studied the correlation of adjacent links
16 and assume a similarity between the behavior of both parallel and adjacent links in the
17 hope that the reader will unquestioningly accept this assumption. We do not hold this
18 assumption reasonable and present here the complementary and competitive nature of
19 traffic link to shed light on the dissimilarity of spatial correlation between parallel and
20 adjacent links. By our definition, two links are complementary, when an increase in the
21 cost of one decreases the flow of both links. Two links are competitive, when an increase
22 in the cost of one link decreases the flow of itself, but increases the flow of the other.
23 We then expect a positive and a negative spatial dependency between complementary
24 and competitive links, respectively. This nature, however, has not been captured in the
25 literature.

26 This systematic review highlighted that the field is approaching its maturity, while it is still
27 as crude as it is perplexing. It is perplexing in the conceptual methodology used, and it is crude in
28 capturing spatial information.

29 REFERENCES

- 30 [1] Andrew Booth, Anthea Sutton, and Diana Papaioannou. *Systematic approaches to a suc-*
31 *cessful literature review*. Sage, 2016.
- 32 [2] Khalid S Khan, Regina Kunz, Jos Kleijnen, and Gerd Antes. Five steps to conducting a
33 systematic review. *Journal of the Royal Society of Medicine*, 96(3):118–121, 2003.
- 34 [3] Gaetano Fusco, Chiara Colombaroni, and Natalia Isaenko. Comparative analysis of im-
35 plicit models for real-time short-term traffic predictions. *IET Intelligent Transport Systems*,
36 10(4):270–278, 2016.
- 37 [4] Zheng Zhu, Bo Peng, Chenfeng Xiong, and Lei Zhang. Short-term traffic flow prediction
38 with linear conditional gaussian bayesian network. *Journal of Advanced Transportation*,
39 2016.

- 1 [5] Bin Yu, Xiaolin Song, Feng Guan, Zhiming Yang, and Baozhen Yao. k-nearest neighbor
2 model for multiple-time-step prediction of short-term traffic condition. *Journal of Trans-*
3 *portation Engineering*, 142(6):04016018, 2016.
- 4 [6] Dawen Xia, Binfeng Wang, Huaqing Li, Yantao Li, and Zili Zhang. A distributed spatial–
5 temporal weighted model on mapreduce for short-term traffic flow forecasting. *Neurocom-*
6 *puting*, 179:246–263, 2016.
- 7 [7] Yanru Zhang and Yunlong Zhang. A comparative study of three multivariate short-term
8 freeway traffic flow forecasting methods with missing data. *Journal of Intelligent Trans-*
9 *portation Systems*, pages 1–14, 2016.
- 10 [8] Eunjeong Ko, Jinyoung Ahn, and Eun Yi Kim. 3d markov process for traffic flow prediction
11 in real-time. *Sensors*, 16(2):147, 2016.
- 12 [9] Jing Zhao and Shiliang Sun. High-order gaussian process dynamical models for traffic flow
13 prediction.
- 14 [10] Han Jiang, Yajie Zou, Shen Zhang, Jinjun Tang, and Yin Hai Wang. Short-term speed pre-
15 diction using remote microwave sensor data: Machine learning versus statistical model.
16 *Mathematical Problems in Engineering*, 2016, 2016.
- 17 [11] Nicholas Polson and Vadim Sokolov. Deep learning predictors for traffic flows. *arXiv*
18 *preprint arXiv:1604.04527*, 2016.
- 19 [12] Athanasios Salamanis, Dionysios D Kehagias, Christos K Filelis-Papadopoulos, Dimitrios
20 Tzovaras, and George A Gravvanis. Managing spatial graph dependencies in large volumes
21 of traffic data for travel-time prediction. *IEEE Transactions on Intelligent Transportation*
22 *Systems*, 17(6):1678–1687, 2016.
- 23 [13] Yao-Jan Wu, Feng Chen, Chang-Tien Lu, and Shu Yang. Urban traffic flow prediction using
24 a spatio-temporal random effects model. *Journal of Intelligent Transportation Systems*,
25 20(3):282–293, 2016.
- 26 [14] Yanyan Xu, Hui Chen, Qing-Jie Kong, Xi Zhai, and Yuncai Liu. Urban traffic flow predic-
27 tion: a spatio-temporal variable selection-based approach. *Journal of Advanced Transporta-*
28 *tion*, 2015.
- 29 [15] Yisheng Lv, Yanjie Duan, Wenwen Kang, Zhengxi Li, and Fei-Yue Wang. Traffic flow
30 prediction with big data: a deep learning approach. *IEEE Transactions on Intelligent Trans-*
31 *portation Systems*, 16(2):865–873, 2015.
- 32 [16] Tong Zou, Yuxi He, Nian Zhang, Renjie Du, and Xunfei Gao. Short-time traffic flow fore-
33 casting based on the k-nearest neighbor model. *traffic*, 1:36, 2015.
- 34 [17] Tao Ma, Zhou Zhou, and Baher Abdulhai. Nonlinear multivariate time–space threshold
35 vector error correction model for short term traffic state prediction. *Transportation Research*
36 *Part B: Methodological*, 76:27–47, 2015.

- 1 [18] Florin Schimbinschi, Xuan Vinh Nguyen, James Bailey, Chris Leckie, Hai Vu, and Rao
2 Kotagiri. Traffic forecasting in complex urban networks: Leveraging big data and machine
3 learning. In *Big Data (Big Data), 2015 IEEE International Conference on*, pages 1019–
4 1024. IEEE, 2015.
- 5 [19] Chunjiao Dong, Zhihua Xiong, Chunfu Shao, and Hui Zhang. A spatial–temporal-based
6 state space approach for freeway network traffic flow modelling and prediction. *Transport-*
7 *metrica A: Transport Science*, 11(7):547–560, 2015.
- 8 [20] Anton Agafonov and Vladislav Myasnikov. Traffic flow forecasting algorithm based on
9 combination of adaptive elementary predictors. In *International Conference on Analysis of*
10 *Images, Social Networks and Texts*, pages 163–174. Springer, 2015.
- 11 [21] Gaetano Fusco, Chiara Colombaroni, Luciano Comelli, and Natalia Isaenko. Short-term
12 traffic predictions on large urban traffic networks: applications of network-based machine
13 learning models and dynamic traffic assignment models. In *Models and Technologies for*
14 *Intelligent Transportation Systems (MT-ITS), 2015 International Conference on*, pages 93–
15 101. IEEE, 2015.
- 16 [22] Yajie Zou, Xuedong Hua, Yanru Zhang, and Yin Hai Wang. Hybrid short-term freeway speed
17 prediction methods based on periodic analysis. *Canadian Journal of Civil Engineering*,
18 42(8):570–582, 2015.
- 19 [23] RM Reza, Srinivas S Pulugurtha, and Venkata R Duddu. Arima model for forecasting short-
20 term travel time due to incidents in spatio-temporal context. In *Transportation Research*
21 *Board 94th Annual Meeting*, number 15-5553, 2015.
- 22 [24] Yi Hou, Praveen Edara, and Carlos Sun. Traffic flow forecasting for urban work zones.
23 *IEEE Transactions on Intelligent Transportation Systems*, 16(4):1761–1770, 2015.
- 24 [25] Behrooz Shahsavari and Pieter Abbeel. Short-term traffic forecasting: Modeling and learn-
25 ing spatio-temporal relations in transportation networks using graph neural networks. 2015.
- 26 [26] Xingxing Xing, Xiabing Zhou, Haikun Hong, Wenhao Huang, Kaigui Bian, and Kunqing
27 Xie. Traffic flow decomposition and prediction based on robust principal component anal-
28 ysis. In *2015 IEEE 18th International Conference on Intelligent Transportation Systems*,
29 pages 2219–2224. IEEE, 2015.
- 30 [27] Jin Young Ahn, Eunjeong Ko, and EunYi Kim. Predicting spatiotemporal traffic flow based
31 on support vector regression and bayesian classifier. In *Big Data and Cloud Computing*
32 *(BDCloud), 2015 IEEE Fifth International Conference on*, pages 125–130. IEEE, 2015.
- 33 [28] Su Yang, Shixiong Shi, Xiaobing Hu, and Minjie Wang. Spatiotemporal context awareness
34 for urban traffic modeling and prediction: sparse representation based variable selection.
35 *PloS one*, 10(10):e0141223, 2015.
- 36 [29] Jianjiang Yang. Spatio-temporal dynamics of short-term traffic. 2015.

- 1 [30] Pietro Dell'Acqua, Francesco Bellotti, Riccardo Berta, and Alessandro De Gloria. Time-
2 aware multivariate nearest neighbor regression methods for traffic flow prediction. *IEEE*
3 *Transactions on Intelligent Transportation Systems*, 16(6):3393–3402, 2015.
- 4 [31] Bin Ran, Huachun Tan, Jianshuai Feng, Ying Liu, and Wuhong Wang. Traffic speed data im-
5 putation method based on tensor completion. *Computational intelligence and neuroscience*,
6 2015:22, 2015.
- 7 [32] Jing-ting Zhong and Shuai Ling. Key factors of k-nearest neighbours nonparametric regres-
8 sion in short-time traffic flow forecasting. In *Proceedings of the 21st International Confer-*
9 *ence on Industrial Engineering and Engineering Management 2014*, pages 9–12. Springer,
10 2015.
- 11 [33] Shanhua Wu, Zhongzhen Yang, Xiaocong Zhu, and Bin Yu. Improved k-nn for short-term
12 traffic forecasting using temporal and spatial information. *Journal of Transportation Engi-*
13 *neering*, 140(7):04014026, 2014.
- 14 [34] Tao Cheng, Jiaqiu Wang, James Haworth, Benjamin Heydecker, and Andy Chow. A dy-
15 namic spatial weight matrix and localized space–time autoregressive integrated moving av-
16 erage for network modeling. *Geographical Analysis*, 46(1):75–97, 2014.
- 17 [35] Jia Zheng Zhu, Jin Xin Cao, and Yuan Zhu. Traffic volume forecasting based on radial basis
18 function neural network with the consideration of traffic flows at the adjacent intersections.
19 *Transportation Research Part C: Emerging Technologies*, 47:139–154, 2014.
- 20 [36] Xing-Yu Chen, Hsing-Kuo Pao, and Yuh-Jye Lee. Efficient traffic speed forecasting based
21 on massive heterogenous historical data. In *Big Data (Big Data), 2014 IEEE International*
22 *Conference on*, pages 10–17. IEEE, 2014.
- 23 [37] Xiaoguang Niu, Ying Zhu, and Xining Zhang. Deepsense: a novel learning mechanism for
24 traffic prediction with taxi gps traces. In *2014 IEEE Global Communications Conference*,
25 pages 2745–2750. IEEE, 2014.
- 26 [38] Yousef-Awwad Daraghmi, Chih-Wei Yi, and Tsun-Chieh Chiang. Negative binomial ad-
27 ditive models for short-term traffic flow forecasting in urban areas. *IEEE Transactions on*
28 *Intelligent Transportation Systems*, 15(2):784–793, 2014.
- 29 [39] Dhanya Menoth Mohan, Muhammad Tayyab Asif, Nikola Mitrovic, Justin Dauwels, and
30 Patrick Jaillet. Wavelets on graphs with application to transportation networks. In *17th*
31 *International IEEE Conference on Intelligent Transportation Systems (ITSC)*, pages 1707–
32 1712. IEEE, 2014.
- 33 [40] Jianjiang Yang, Lee Han, Phillip Freeze, Shih-Miao Chin, and Ho-Ling Hwang. Short-term
34 freeway speed profiling based on longitudinal spatiotemporal dynamics. *Transportation*
35 *Research Record: Journal of the Transportation Research Board*, (2467):62–72, 2014.
- 36 [41] Chunjiao Dong, Chunfu Shao, Stephen H Richards, and Lee D Han. Flow rate and time
37 mean speed predictions for the urban freeway network using state space models. *Trans-*
38 *portation Research Part C: Emerging Technologies*, 43:20–32, 2014.

- 1 [42] Nedal T Ratrou. Short-term traffic flow prediction using group method data han-
2 dling (gmdh)-based abductive networks. *Arabian Journal for Science and Engineering*,
3 39(2):631–646, 2014.
- 4 [43] Ningyu Zhao, Zhiheng Li, and Yuebiao Li. Improving the traffic data imputation accu-
5 racy using temporal and spatial information. In *Intelligent Computation Technology and*
6 *Automation (ICICTA), 2014 7th International Conference on*, pages 312–317. IEEE, 2014.
- 7 [44] V Fabrizi and R Ragona. A pattern matching approach to speed forecasting of traffic net-
8 works. *European Transport Research Review*, 6(3):333–342, 2014.
- 9 [45] Li Qing, Tao Yongqin, Han Yongguo, and Zhang Qingming. The forecast and the optimiza-
10 tion control of the complex traffic flow based on the hybrid immune intelligent algorithm.
11 *Open Electrical & Electronic Engineering Journal*, 8:245–251, 2014.
- 12 [46] Zilu Liang and Yasushi Wakahara. Real-time urban traffic amount prediction models for
13 dynamic route guidance systems. *EURASIP Journal on Wireless Communications and Net-*
14 *working*, 2014(1):1–13, 2014.
- 15 [47] Yajie Zou, Xinxin Zhu, Yunlong Zhang, and Xiaosi Zeng. A space–time diurnal method
16 for short-term freeway travel time prediction. *Transportation Research Part C: Emerging*
17 *Technologies*, 43:33–49, 2014.
- 18 [48] James Haworth. *Spatio-temporal forecasting of network data*. PhD thesis, UCL (University
19 College London), 2014.
- 20 [49] Li Li, Yuebiao Li, and Zhiheng Li. Efficient missing data imputing for traffic flow by
21 considering temporal and spatial dependence. *Transportation research part C: emerging*
22 *technologies*, 34:108–120, 2013.
- 23 [50] TL Pan, Agachai Sumalee, Ren-Xin Zhong, and Nakorn Indra-Payoong. Short-term traffic
24 state prediction based on temporal–spatial correlation. *IEEE Transactions on Intelligent*
25 *Transportation Systems*, 14(3):1242–1254, 2013.
- 26 [51] Xiaosi Zeng and Yunlong Zhang. Development of recurrent neural network considering
27 temporal-spatial input dynamics for freeway travel time modeling. *Computer-Aided Civil*
28 *and Infrastructure Engineering*, 28(5):359–371, 2013.
- 29 [52] Adeyemi J Fowe and Yupo Chan. A microstate spatial-inference model for network-traffic
30 estimation. *Transportation Research Part C: Emerging Technologies*, 36:245–260, 2013.
- 31 [53] Yufei Han and Fabien Moutarde. Statistical traffic state analysis in large-scale transporta-
32 tion networks using locality-preserving non-negative matrix factorisation. *IET Intelligent*
33 *Transport Systems*, 7(3):283–295, 2013.
- 34 [54] Xiaodan Huang and Wei Wang. Traffic prediction based on correlation of road sections.
35 *Indonesian Journal of Electrical Engineering and Computer Science*, 11(10):5523–5529,
36 2013.

- 1 [55] Fangfang Zheng and Henk Van Zuylen. Urban link travel time estimation based on sparse
2 probe vehicle data. *Transportation Research Part C: Emerging Technologies*, 31:145–157,
3 2013.
- 4 [56] Yiannis Kamarianakis, Wei Shen, and Laura Wynter. Real-time road traffic forecasting
5 using regime-switching space-time models and adaptive lasso. *Applied stochastic models in
6 business and industry*, 28(4):297–315, 2012.
- 7 [57] James Haworth and Tao Cheng. Non-parametric regression for space–time forecasting under
8 missing data. *Computers, Environment and Urban Systems*, 36(6):538–550, 2012.
- 9 [58] Tao Cheng, James Haworth, and Jiaqiu Wang. Spatio-temporal autocorrelation of road
10 network data. *Journal of Geographical Systems*, 14(4):389–413, 2012.
- 11 [59] F Guo, R Krishnan, and JW Polak. Short-term traffic prediction under normal and incident
12 conditions using singular spectrum analysis and the k-nearest neighbour method. In *Road
13 Transport Information and Control (RTIC 2012), IET and ITS Conference on*, pages 1–6.
14 IET, 2012.
- 15 [60] Fangce Guo, Rajesh Krishnan, and John W Polak. Short-term traffic prediction under nor-
16 mal and abnormal traffic conditions on urban roads. In *Transportation Research Board 91st
17 Annual Meeting*, number 12-1627, 2012.
- 18 [61] Tianlu Pan. *The stochastic dynamic journey time reliability analysis by considering the
19 spatial and temporal correlation*. PhD thesis, The Hong Kong Polytechnic University, 2012.
- 20 [62] Henry YT Ngan, Nelson HC Yung, and Anthony GO Yeh. Modeling of traffic data character-
21 istics by dirichlet process mixtures. In *2012 IEEE International Conference on Automation
22 Science and Engineering (CASE)*, pages 224–229. IEEE, 2012.
- 23 [63] Liang Chen, Qiao Ru Li, Xiao Yong Tian, Xiang Shang Chen, and Rong Xia Wang. Paratac-
24 tic spatial-temporal two dimension data fusion based on support vector machines for traffic
25 flow prediction of abnormal state. In *Advanced Materials Research*, volume 532, pages
26 1225–1229. Trans Tech Publ, 2012.
- 27 [64] Yao-Jan Wu, Feng Chen, C Lu, B Smith, and Y Chen. Traffic flow prediction for urban
28 network using spatio-temporal random effects model. In *91st Annual Meeting of the Trans-
29 portation Research Board (TRB)*, 2012.
- 30 [65] Zheng-Wu Yuan and Yuan-Hui Wang. Research on k nearest neighbor non-parametric re-
31 gression algorithm based on kd-tree and clustering analysis. In *Computational and Infor-
32 mation Sciences (ICCIS), 2012 Fourth International Conference on*, pages 298–301. IEEE,
33 2012.
- 34 [66] Shiliang Sun, Rongqing Huang, and Ya Gao. Network-scale traffic modeling and fore-
35 casting with graphical lasso and neural networks. *Journal of Transportation Engineering*,
36 138(11):1358–1367, 2012.

- 1 [67] A Pascale and M Nicoli. Adaptive bayesian network for traffic flow prediction. In *2011*
2 *IEEE Statistical Signal Processing Workshop (SSP)*, pages 177–180. IEEE, 2011.
- 3 [68] Nemanja Djuric, Vladan Radosavljevic, Vladimir Coric, and Slobodan Vucetic. Travel
4 speed forecasting by means of continuous conditional random fields. *Transportation Re-*
5 *search Record: Journal of the Transportation Research Board*, (2263):131–139, 2011.
- 6 [69] Yufei Han and Fabien Moutarde. Analysis of network-level traffic states using locality
7 preservative non-negative matrix factorization. In *2011 14th International IEEE Conference*
8 *on Intelligent Transportation Systems (ITSC)*, pages 501–506. IEEE, 2011.
- 9 [70] Samitha Samaranyake, Sébastien Blandin, and Alexandre Bayen. Learning the depen-
10 dency structure of highway networks for traffic forecast. In *2011 50th IEEE Conference on*
11 *Decision and Control and European Control Conference*, pages 5983–5988. IEEE, 2011.
- 12 [71] T Cheng, J Wang, J Haworth, BJ Heydecker, and AHF Chow. Modelling dynamic space-
13 time autocorrelations of urban transport network. In *Proceedings of the 11th International*
14 *Conference on Geocomputation 2011*, pages 215–210, 2011.
- 15 [72] Rui Deng and Lizhu Jiang. Traffic state forecast of road network based on spatial-temporal
16 data mining. In *Third International Conference on Transportation Engineering (ICTE)*,
17 2011.
- 18 [73] Wanli Min and Laura Wynter. Real-time road traffic prediction with spatio-temporal corre-
19 lations. *Transportation Research Part C: Emerging Technologies*, 19(4):606–616, 2011.
- 20 [74] Abbas Khosravi, Ehsan Mazloumi, Saeid Nahavandi, Doug Creighton, and JWC Van Lint.
21 Prediction intervals to account for uncertainties in travel time prediction. *IEEE Transactions*
22 *on Intelligent Transportation Systems*, 12(2):537–547, 2011.
- 23 [75] Marco Lippi, Matteo Bertini, and Paolo Frasconi. Collective traffic forecasting. In *Joint*
24 *European Conference on Machine Learning and Knowledge Discovery in Databases*, pages
25 259–273. Springer, 2010.
- 26 [76] Xinyu Min, Jianming Hu, and Zuo Zhang. Urban traffic network modeling and short-term
27 traffic flow forecasting based on gstarima model. In *Intelligent Transportation Systems*
28 *(ITSC), 2010 13th International IEEE Conference on*, pages 1535–1540. IEEE, 2010.
- 29 [77] Ryan Herring, Aude Hofleitner, Pieter Abbeel, and Alexandre Bayen. Estimating arterial
30 traffic conditions using sparse probe data. In *Intelligent Transportation Systems (ITSC)*,
31 *2010 13th International IEEE Conference on*, pages 929–936. IEEE, 2010.
- 32 [78] XiaoLiang Sun, LiMin Jia, HongHui Dong, Yong Qin, and Min Guo. Urban expressway
33 traffic state forecasting based on multimode maximum entropy model. *Science China Tech-*
34 *nological Sciences*, 53(10):2808–2816, 2010.
- 35 [79] Fangece Guo, John W Polak, and Rajesh Krishnan. Comparison of modelling approaches
36 for short term traffic prediction under normal and abnormal conditions. In *Intelligent Trans-*
37 *portation Systems (ITSC), 2010 13th International IEEE Conference on*, pages 1209–1214.
38 IEEE, 2010.

- 1 [80] Ming-Tsung Lee. *Short-term Freeway Traffic Flow Forecasting with ARIMAX Modeling*.
2 PhD thesis, 2010.
- 3 [81] Jennifer McCrea and Salissou Moutari. A hybrid macroscopic-based model for traffic flow
4 in road networks. *European Journal of Operational Research*, 207(2):676–684, 2010.
- 5 [82] Xinyu Min, Jianming Hu, Qi Chen, Tongshuai Zhang, and Yi Zhang. Short-term traffic flow
6 forecasting of urban network based on dynamic starima model. In *2009 12th International*
7 *IEEE Conference on Intelligent Transportation Systems*, pages 1–6. IEEE, 2009.
- 8 [83] Srinivasa Ravi Chandra and Haitham Al-Deek. Predictions of freeway traffic speeds and
9 volumes using vector autoregressive models. *Journal of Intelligent Transportation Systems*,
10 13(2):53–72, 2009.
- 11 [84] Chunjiao Dong, Chunfu Shao, and Xia Li. Short-term traffic flow forecasting of road net-
12 work based on spatial-temporal characteristics of traffic flow. In *Computer Science and*
13 *Information Engineering, 2009 WRI World Congress on*, volume 5, pages 645–650. IEEE,
14 2009.
- 15 [85] Ruimin Li and Huapu Lu. Combined neural network approach for short-term urban freeway
16 traffic flow prediction. In *International Symposium on Neural Networks*, pages 1017–1025.
17 Springer, 2009.
- 18 [86] SRINIVASA RAVI CHANDRA. *Spatio-temporal Analyses For Prediction Of Traffic Flow,*
19 *Speed And Occupancy On I-4*. PhD thesis, University of Central Florida Orlando, Florida,
20 2009.
- 21 [87] Bidisha Ghosh, Biswajit Basu, and Margaret O’Mahony. Multivariate short-term traffic
22 flow forecasting using time-series analysis. *IEEE Transactions on Intelligent Transportation*
23 *Systems*, 10(2):246–254, 2009.
- 24 [88] CPIJ van Hinsbergen, J van Lint, and H Van Zuylen. Bayesian training and committees
25 of state-space neural networks for online travel time prediction. *Transportation Research*
26 *Record: Journal of the Transportation Research Board*, (2105):118–126, 2009.
- 27 [89] J Hu I Kaparias MGH Bell. Spatial econometrics models for congestion prediction with
28 in-vehicle route guidance. 2009.
- 29 [90] S Innamaa. Self-adapting traffic flow status forecasts using clustering. *IET Intelligent Trans-*
30 *port Systems*, 3(1):67–76, 2009.
- 31 [91] Yang Yue and Anthony Gar-On Yeh. Spatiotemporal traffic-flow dependency and short-term
32 traffic forecasting. *Environment and Planning B: Planning and Design*, 35(5):762–771,
33 2008.
- 34 [92] Antony Stathopoulos, Loukas Dimitriou, and Theodore Tsekeris. Fuzzy modeling approach
35 for combined forecasting of urban traffic flow. *Computer-Aided Civil and Infrastructure*
36 *Engineering*, 23(7):521–535, 2008.

- 1 [93] Srinivasa Chandra and Haitham Al-Deek. Cross-correlation analysis and multivariate pre-
2 diction of spatial time series of freeway traffic speeds. *Transportation Research Record:
3 Journal of the Transportation Research Board*, (2061):64–76, 2008.
- 4 [94] Loukas Dimitriou, Theodore Tsekeris, and Antony Stathopoulos. Adaptive hybrid fuzzy
5 rule-based system approach for modeling and predicting urban traffic flow. *Transportation
6 Research Part C: Emerging Technologies*, 16(5):554–573, 2008.
- 7 [95] Corrado De Fabritiis, Roberto Ragona, and Gaetano Valenti. Traffic estimation and predic-
8 tion based on real time floating car data. In *2008 11th International IEEE Conference on
9 Intelligent Transportation Systems*, pages 197–203. IEEE, 2008.
- 10 [96] Tianshu Wu, Kunqing Xie, Guojie Song, and Cheng Hu. A multiple svr approach with time
11 lags for traffic flow prediction. In *2008 11th International IEEE Conference on Intelligent
12 Transportation Systems*, pages 228–233. IEEE, 2008.
- 13 [97] Cheng Hu, Kunqing Xie, Guojie Song, and Tianshu Wu. Hybrid process neural network
14 based on spatio-temporal similarities for short-term traffic flow prediction. In *2008 11th In-
15 ternational IEEE Conference on Intelligent Transportation Systems*, pages 253–258. IEEE,
16 2008.
- 17 [98] JWC Van Lint. Online learning solutions for freeway travel time prediction. *IEEE Transac-
18 tions on Intelligent Transportation Systems*, 9(1):38–47, 2008.
- 19 [99] Shengqi Ye, Yingjia He, Jianming Hu, and Zuo Zhang. Short-term traffic flow forecasting
20 based on mars. In *Fuzzy Systems and Knowledge Discovery, 2008. FSKD'08. Fifth Interna-
21 tional Conference on*, volume 5, pages 669–675. IEEE, 2008.
- 22 [100] Eleni I Vlahogianni, Matthew G Karlaftis, and John C Golias. Spatio-temporal short-term
23 urban traffic volume forecasting using genetically optimized modular networks. *Computer-
24 Aided Civil and Infrastructure Engineering*, 22(5):317–325, 2007.
- 25 [101] Yang Yue, Anthony GO Yeh, and Yan Zhuang. Prediction time horizon and effectiveness of
26 real-time data on short-term traffic predictability. In *2007 IEEE Intelligent Transportation
27 Systems Conference*, pages 962–967. IEEE, 2007.
- 28 [102] Shiliang Sun and Changshui Zhang. The selective random subspace predictor for traffic
29 flow forecasting. *IEEE Transactions on intelligent transportation systems*, 8(2):367–373,
30 2007.
- 31 [103] Yuanchang Xie and Yunlong Zhang. A wavelet network model for short-term traffic volume
32 forecasting. *Journal of Intelligent Transportation Systems*, 10(3):141–150, 2006.
- 33 [104] JW Van Lint. Reliable real-time framework for short-term freeway travel time prediction.
34 *Journal of transportation engineering*, 132(12):921–932, 2006.
- 35 [105] Yibing Wang, Markos Papageorgiou, and Albert Messmer. Renaissance—a unified macro-
36 scopic model-based approach to real-time freeway network traffic surveillance. *Transporta-
37 tion Research Part C: Emerging Technologies*, 14(3):190–212, 2006.

- 1 [106] Eleni I Vlahogianni, Matthew G Karlaftis, and John C Golias. Optimized and meta-
2 optimized neural networks for short-term traffic flow prediction: a genetic approach. *Trans-*
3 *portation Research Part C: Emerging Technologies*, 13(3):211–234, 2005.
- 4 [107] Shiliang Sun, Changshui Zhang, and Yi Zhang. Traffic flow forecasting using a spatio-
5 temporal bayesian network predictor. In *International Conference on Artificial Neural Net-*
6 *works*, pages 273–278. Springer, 2005.
- 7 [108] Yiannis Kamarianakis and Poulicos Prastacos. Space–time modeling of traffic flow. *Com-*
8 *puters & Geosciences*, 31(2):119–133, 2005.
- 9 [109] Sul I Bajwa, Edward Chung, and Masao Kuwahara. Performance evaluation of an adaptive
10 travel time prediction model. In *Proceedings. 2005 IEEE Intelligent Transportation Systems,*
11 *2005.*, pages 1000–1005. IEEE, 2005.
- 12 [110] Satu Innamaa. Short-term prediction of travel time using neural networks on an interurban
13 highway. *Transportation*, 32(6):649–669, 2005.
- 14 [111] Sherif Ishak and Ciprian Alecsandru. Optimizing traffic prediction performance of neural
15 networks under various topological, input, and traffic condition settings. *Journal of Trans-*
16 *portation Engineering*, 130(4):452–465, 2004.
- 17 [112] Yiannis Kamarianakis, Poulicos Prastacos, and D Kotzinos. Bivariate traffic relations: A
18 space-time modeling approach. *AGILE proceedings*, pages 465–474, 2004.
- 19 [113] Ciprian-Danut Alecsandru. *A hybrid model-based and memory-based short-term traffic*
20 *prediction system*. PhD thesis, Faculty of the Louisiana State University and Agricultural
21 and Mechanical College in partial fulfillment of the requirements for the degree of Master
22 of Science in Civil Engineering in The Department of Civil and Environmental Engineering
23 By Ciprian-Danut Alecsandru B. Engr., University" Politehnica" of Bucharest, 2003.
- 24 [114] EI Vlahogianni, MG Karlaftis, and JC Golias. A multivariate neural network predictor
25 for short term traffic forecasting in urban signalized arterial. In *10th IFAC Symposium on*
26 *Control in Transportation Systems*, pages 4–6, 2003.
- 27 [115] Yiannis Kamarianakis and Poulicos Prastacos. Forecasting traffic flow conditions in an
28 urban network: comparison of multivariate and univariate approaches. *Transportation Re-*
29 *search Record: Journal of the Transportation Research Board*, (1857):74–84, 2003.
- 30 [116] Anthony Stathopoulos and Matthew G Karlaftis. A multivariate state space approach for
31 urban traffic flow modeling and prediction. *Transportation Research Part C: Emerging*
32 *Technologies*, 11(2):121–135, 2003.
- 33 [117] Sherif Ishak, Prashanth Kotha, and Ciprian Alecsandru. Optimization of dynamic neural
34 network performance for short-term traffic prediction. *Transportation Research Record:*
35 *Journal of the Transportation Research Board*, (1836):45–56, 2003.

- 1 [118] Jianming Hu, Jingyan Song, Guoqiang Yu, and Yi Zhang. A novel networked traffic parameter forecasting method based on markov chain model. In *Systems, Man and Cybernetics, 2003. IEEE International Conference on*, volume 4, pages 3595–3600. IEEE, 2003.
- 2
3
- 4 [119] JWC Van Lint, SP Hoogendoorn, and Henk J van Zuylen. Toward a robust framework for
5 freeway travel time prediction: experiments with simple imputation and state-space neural
6 networks. In *TRB 82nd Annual Meeting (CD-ROM)*, 2003.
- 7 [120] J Van Lint, S Hoogendoorn, and H Van Zuylen. Freeway travel time prediction with
8 state-space neural networks: modeling state-space dynamics with recurrent neural net-
9 works. *Transportation Research Record: Journal of the Transportation Research Board*,
10 (1811):30–39, 2002.
- 11 [121] Claudia Tebaldi, Mike West, and Alan F Karr. Statistical analyses of freeway traffic flows.
12 *Journal of Forecasting*, 21(1):39–68, 2002.
- 13 [122] Baher Abdulhai, Himanshu Porwal, and Will Recker. Short-term traffic flow prediction
14 using neuro-genetic algorithms. *ITS Journal-Intelligent Transportation Systems Journal*,
15 7(1):3–41, 2002.
- 16 [123] Billy Williams. Multivariate vehicular traffic flow prediction: evaluation of arimax mod-
17 eling. *Transportation Research Record: Journal of the Transportation Research Board*,
18 (1776):194–200, 2001.
- 19 [124] Rik Van Grol, Domenico Inaudi, and Eric Kroes. On-line traffic condition forecasting us-
20 ing on-line measurements and a historical database. In *7th World Congress on Intelligent*
21 *Transport Systems*, pages 6–9, 2000.
- 22 [125] Dongjoo Park and Laurence R Rilett. Forecasting freeway link travel times with a multi-
23 layer feedforward neural network. *Computer-Aided Civil and Infrastructure Engineering*,
24 14(5):357–367, 1999.
- 25 [126] Baher Abdulhai, Himanshu Porwal, and Will Recker. Short term freeway traffic flow pre-
26 diction using genetically-optimized time-delay-based neural networks. *California Partners*
27 *for Advanced Transit and Highways (PATH)*, 1999.
- 28 [127] Byungkyu Park, Carroll Messer, and Thomas Urbanik II. Short-term freeway traffic volume
29 forecasting using radial basis function neural network. *Transportation Research Record:*
30 *Journal of the Transportation Research Board*, (1651):39–47, 1998.
- 31 [128] HEAD K LARRY. Event—based short—term traffic flow prediction model. *Transportation*
32 *Research Record*, 1510:125–143, 1995.
- 33 [129] Stepen D Clark, Mark S Dougherty, and Howard R Kirby. The use of neural networks
34 and time series models for short term traffic forecasting: a comparative study. In *TRAN-*
35 *SPORTATION PLANNING METHODS. PROCEEDINGS OF SEMINAR D HELD AT THE*
36 *PTRC EUROPEAN TRANSPORT, HIGHWAYS AND PLANNING 21ST SUMMER ANNUAL*
37 *MEETING (SEPTEMBER 13-17, 1993), UMIST. VOLUME P363*, 1993.

- 1 [130] Iwao Okutani and Yorgos J Stephanedes. Dynamic prediction of traffic volume through
2 kalman filtering theory. *Transportation Research Part B: Methodological*, 18(1):1–11, 1984.
- 3 [131] AD Cliff and John K Ord. Space-time modelling with an application to regional forecasting.
4 *Transactions of the Institute of British Geographers*, pages 119–128, 1975.
- 5 [132] Francois Bavaud. Models for spatial weights: a systematic look. *Geographical analysis*,
6 30(2):153–171, 1998.
- 7 [133] Brian L Smith, Billy M Williams, and R Keith Oswald. Comparison of parametric and non-
8 parametric models for traffic flow forecasting. *Transportation Research Part C: Emerging*
9 *Technologies*, 10(4):303–321, 2002.
- 10 [134] Eleni I Vlahogianni, John C Golias, and Matthew G Karlaftis. Short-term traffic forecasting:
11 Overview of objectives and methods. *Transport reviews*, 24(5):533–557, 2004.
- 12 [135] Jean-Paul Rodrigue, Claude Comtois, and Brian Slack. *The geography of transport systems*.
13 Routledge, 2013.