Spatiotemporal Traffic Forecasting: Review and Proposed Directions

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ABSTRACT

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

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

INTRODUCTION

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

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

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

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

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

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

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

REVIEW METHODOLOGY: A SYSTEMATIC APPROACH

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

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

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

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

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

We summarized the study exclusion process in Figure 1. This process encompasses three steps. In the first step, we searched the literature to extract all articles including the combination of selected keywords as shown in Figure 1. This search assuredly led to extracting articles from diverse disciplines. In the second step, we executed four distinct assessment criteria to not only exclude irrelevant disciplines, but to only include articles that are germane to using spatial components for traffic forecasting. Thus, we excluded literature about wireless local area networks, internet traffic, railways, and groundwater, to name but a few. We also dropped articles where our search keys appeared in the introduction, literature review, recommendation, and reference sections. Concretely speaking, we perused the pool of articles closely and excluded articles which lack implementation of spatial information in traffic forecasting methods. This resulted in 113 English research articles. In the third step, we systematically reviewed the lists of references from excluded articles. We then added those research papers that met the inclusion criteria in accordance with the second step. The consequence of this systematic search resulted in 130 publications in peer-reviewed journals, conference proceedings, and dissertations. A strong point of emphasis is that the literature includes mounting articles in employing spatial components on traffic forecasting methods in different languages. Nonetheless, we have limited the scope of this review to only English literature.

REVIEW STATISTICS

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

TABLE 1 : Distribution of publications by source

Classification of Sources	Number of Retrievals	Percentage
Article Division		
Scientific Journals	83	63.8%
Dissertations	6	4.6%
Conference proceedings	41	31.6%
Journal Source		
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%

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

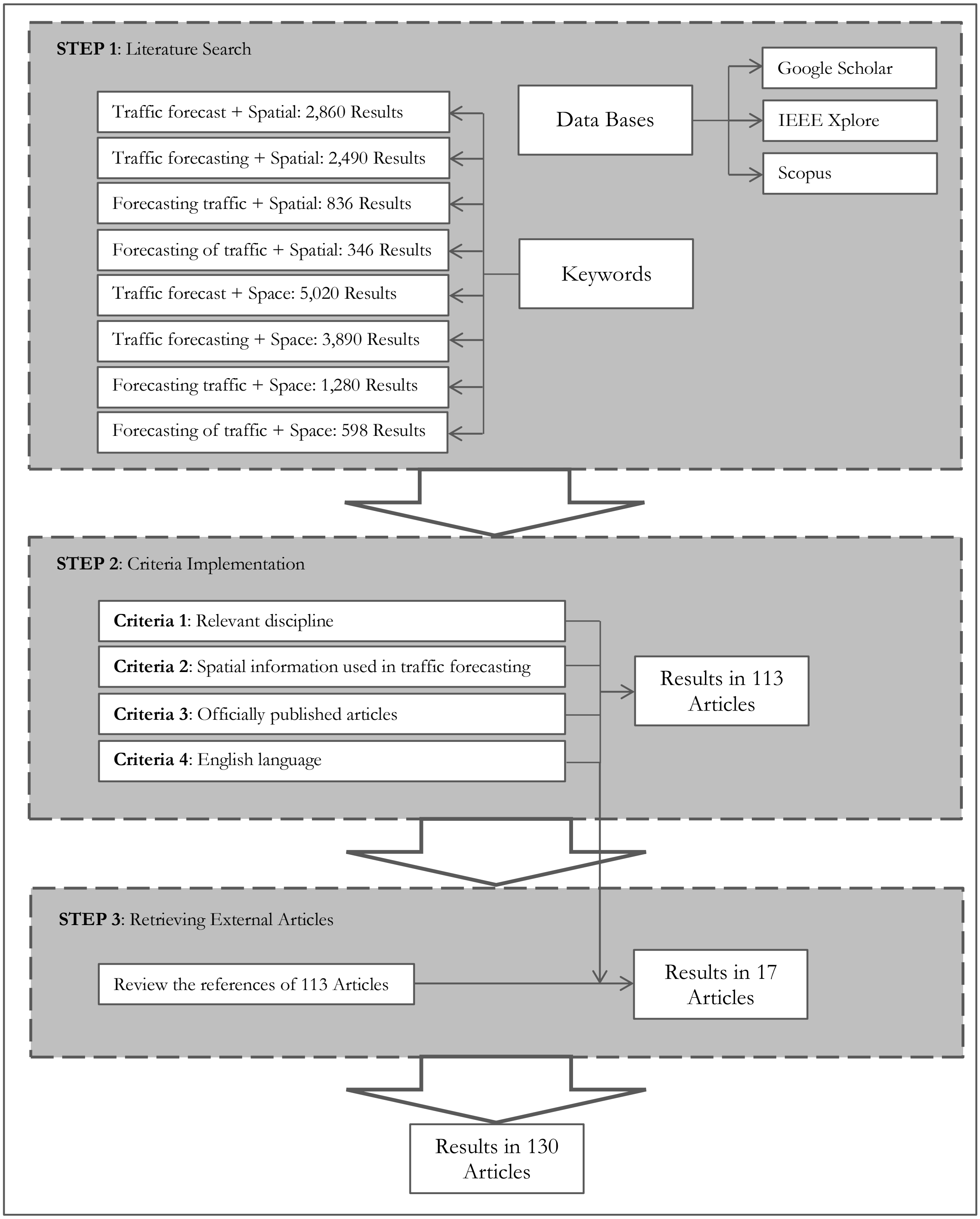


FIGURE 1 : Flowchart diagram of study inclusion process

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

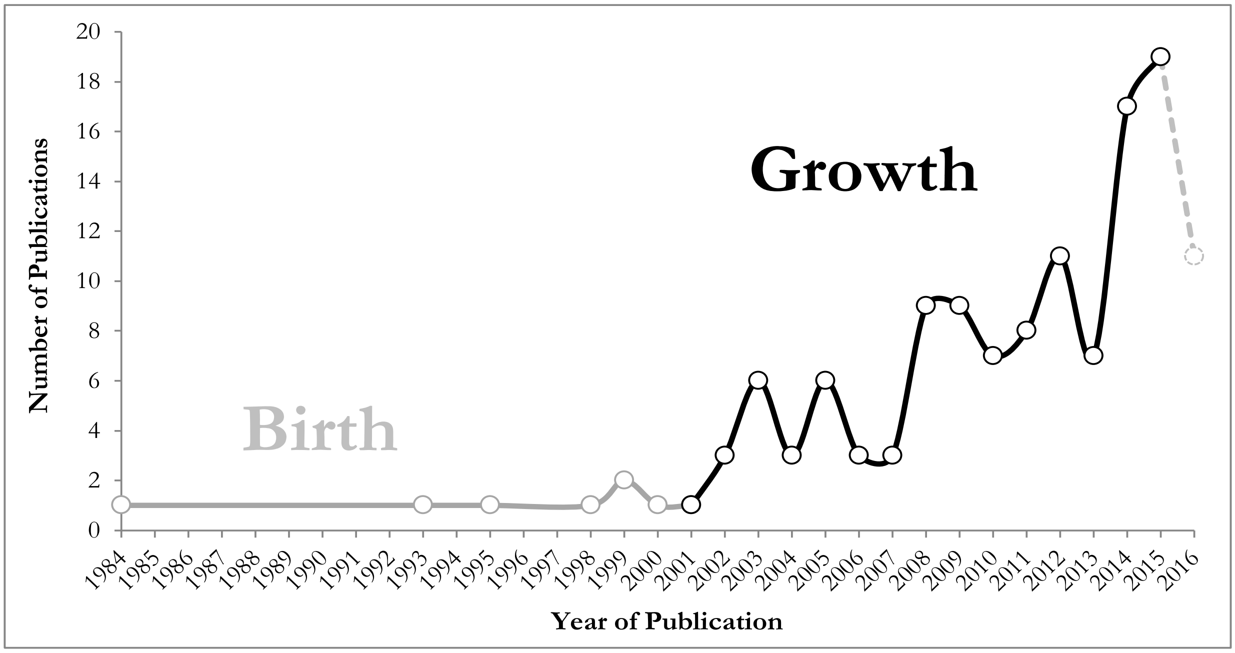


FIGURE 2 : The life-cycle diagram of the research field

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

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

A REVIEW OF METHODS FOR PREDICTING SHORT-TERM TRAFFIC

In 1984, Okutani and Stephanedes (130) were the first to achieve a better traffic flow prediction on a link by taking into account the spatial information of its upstream feeder links. Twenty years later, Kamarianakis and Prastacos (115) borrowed a model, the so-called space-time autoregressive integrated moving average (STARIMA), from the regional science literature to forecast relative 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	Method 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	Ratrout (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	Khosravi (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 I. R: Real data and S: Simulation data
Note II. ST: Statistical and ML: Machine Learning

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

1. $w_{i,j} \geq 0$,
2. $w_{i,i} = 0$, and
3. $\sum_{j=1}^{n} w_{i,j} = 1$, for all $i = 1, 2, \ldots, n$. (132).

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

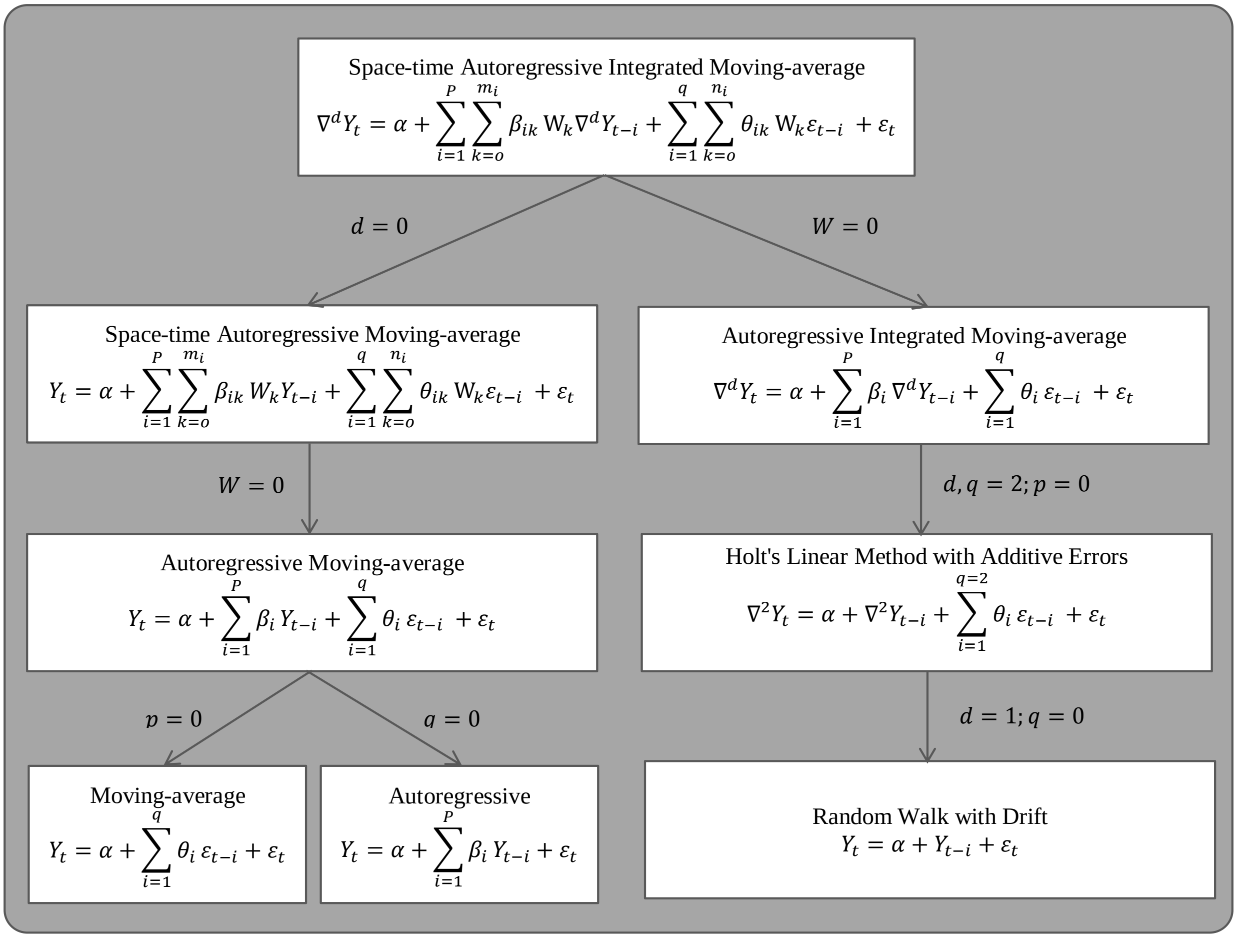


FIGURE 3 : Taxonomy of spatiotemporal family models

models. These methods have burgeoned and developed in the literature. The spatiotemporal methods stand on the foundation of traditional temporal techniques. The only refinement is benefiting from the spatial information to advance the accuracy of predictions. The literature that discusses this subject has been prolific. For instance, Smith et al. (133) classified temporal traffic forecasting models into parametric and non-parametric, and discussed their pros and cons in detail. Vlahogianni et al. (134) also broadly reviewed the short-term traffic forecasting methods, and compared the proposed models in parametric and non-parametric framework. We hence eschew digging into the performance of models and their formulations. Rather, we elaborate the results of the studies through the lens of spatial components effectiveness and modeling performance. To achieve this, we review the studies in three separate classes. The following subsections expound these categories.

Class 1: Spatial Effectiveness Emphasis

In this class, the studies aim at examining the effectiveness of spatial components by comparing models with and without spatial information. Williams' ARIMAX model (123) treats the upstream traffic flow series as transfer function inputs into the ARIMA model. Embedding the spatial factor enhanced the accuracy of traffic flow forecasting by 15.6%. To forecast the traffic speed in five stations on I-4 in the downtown region of Orlando, Florida, Chandra and Al-Deek (93) developed a univariate ARIMA time-series model and a vector autoregressive (VAR) model. Comparing both models, they found VAR significantly outperforms ARIMA. This is consistent with Chandra and Al-Deek (83).

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

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

Class 2: Modeling Performance Emphasis

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

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

Dynamic STARIMA over ANN. Min et al. (76) generalized the STARIMA model and introduced GSTARIMA model, which relaxes the assumption that the autoregressive parameters and the moving average parameters are the same for all traffic locations. They noted the performance of GSTARIMA model exceeded the STARIMA model.

Class 3: Hybrid Emphasis

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

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

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

This trajectory leads us to the following conclusions:

- Irrespective of which method is selected, spatial information inclusion in short-term traffic forecasting models boosts the accuracy of prediction, particularly in congested traffic regimes and longer time horizons.

- There is a broad and longstanding agreement that non-parametric methods outperform the naive statistical methods such as historical average, real time profile, and exponential smoothing. However, to make a conclusion regarding the performance of neural network methods against STARIMA family models, more research is needed in this field.

A REVIEW OF METHODS FOR CAPTURING SPATIAL INFORMATION

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

A Naive Approach

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

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

A Modest Approach

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

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

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

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

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

CLOSING REMARKS AND OPPORTUNITIES FOR FUTURE RESEARCH

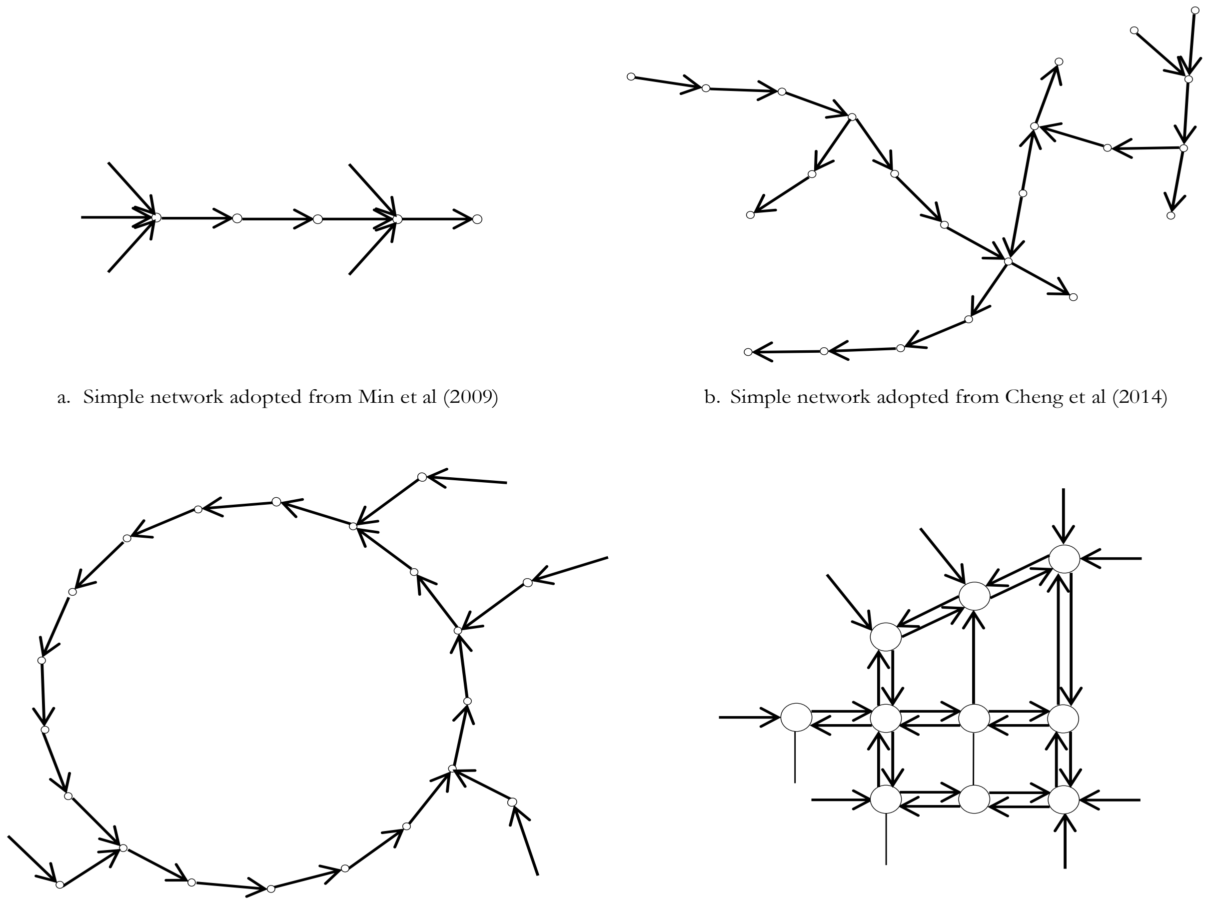
In this section, we intend to deal with the last two questions from the introduction:

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

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

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

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



a. Simple network adopted from Min et al (2009)

b. Simple network adopted from Cheng et al (2014)

c. Ring network adopted from Fabritiis et al (2008)

d. Grid network adopted from Sun et al (2005)

FIGURE 4 : Typical network topology used in the literature

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

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

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

between traffic links is more complex in a whole network than what is presumed to exist in a corridor.

2. The spatially relevant links are selected either by prejudgment or by correlation-coefficient analysis, each of which is criticized by a drawback. In the former, researchers assume neighboring links are the most spatially correlated links with the study link, and embed their information in forecasting methods as an input. This prejudgment results in increasing error, if the adjacent link has not any spatial effect on the study link, as we discussed in preceding paragraph. The latter does not suffer from this shortcoming, as the input information is selected according to the most highly correlated links. However, a similar spatial effect is typically considered for all selected links, which may distort the accuracy of models.

3. According to graph theory, two links are adjacent if they share a common node, while they are parallel if they connect the same pair of nodes. All studies, except one (28), have developed forecasting methods in a corridor test sample, where all links are connected sequentially together. As a result, they studied the correlation of adjacent links and assume a similarity between the behavior of both parallel and adjacent links. We do not hold this assumption reasonable and present here the complementary and competitive nature of traffic link to shed light on the dissimilarity of spatial correlation between parallel and adjacent links. By our definition, two links are complementary, when an increase in the cost of one decreases the flow of both links. Two links are competitive, when an increase in the cost of one link decreases the flow of itself, but increases the flow of the other. We then expect a positive and a negative spatial dependency between complementary and competitive links, respectively. This nature, however, has not been captured in the literature.

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

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