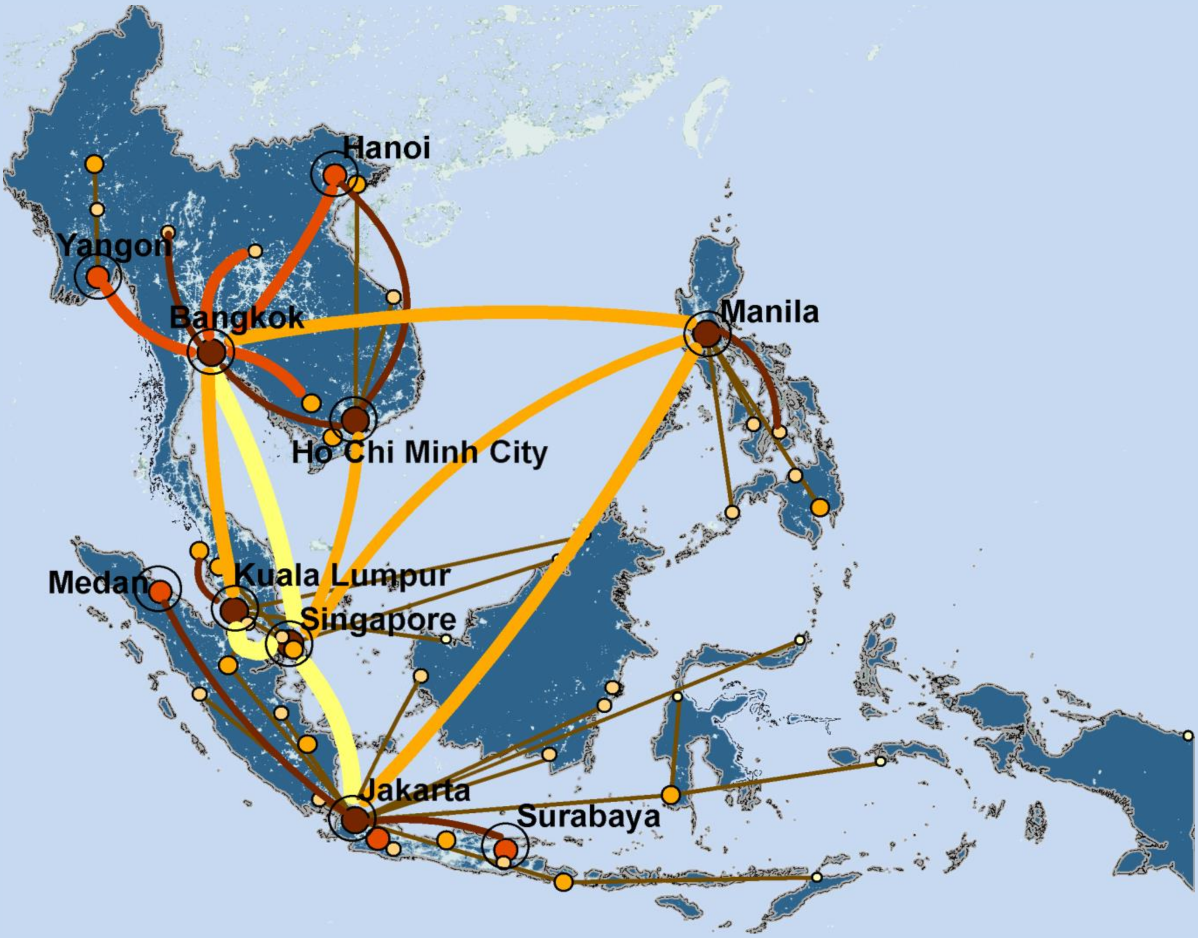
The structure, modelling and abstraction of urban networks in Southeast Asia: evidence from intercity transport networks



Liang Dai

ISBN: 978-94-6197-612-3

NUR: 755/902/904

The research reported in this book was conducted at the Social and Economic Geography research unit, Department of Geography, Faculty of Sciences, Ghent University and funded by the Flemish Fund for Scientific Research (FWO).

The structure, modelling and abstraction of urban networks in Southeast Asia: evidence from intercity transport networks

ACADEMIC THESIS
Submitted to obtain the degree of Doctor in Sciences: Geography

by
Liang Dai

Promotor:
Prof. dr. Ben Derudder

May 3rd, 2018

Promotor

Prof. dr. Ben Derudder

Department of Geography, Ghent University

Members of the Examination Committee

Prof. dr. Nico Vande Weghe (Chair)

Department of Geography, Ghent University

Prof. dr. Frank Witlox (Secretary)

Department of Geography, Ghent University

Prof. dr. Theo Notteboom

Maritime Institute, Ghent University

Prof. dr. César Ducruet

Institute for Humanities and Social Sciences，French National Centre for Scientific Research

Prof. dr. Kurt Fuellhart

Geography and Earth Science Department, Shippensburg University

Acknowledgements

This dissertation not only represents years of work behind my computer, it is also a milestone after almost five years of working at Ghent University in general and within the ‘SEG’ (Social and Economic Group) specifically. My experience here has been nothing short of amazing. During those years of studying and living in Ghent, I have transitioned from a ‘research rookie’ to a scholar who has grasped detailed knowledge about research into urban networks. The difficulties and rewards I encountered during this transition will hopefully give me the strength to face future challenges. However, this dissertation is also in large part the result of the many interactions I have had at Ghent University with dozens of amazing people, some of whom I would like to specifically acknowledge because of their importance to this work.

First and foremost, I cannot express enough my appreciation for my supervisor, Professor Ben Derudder, for his fundamental role in my doctoral program as well as for his sincere support in my personal life. It has been my honor to be guided by him in the study of urban networks in Southeast Asia. Ben has not only supported me by providing me with a scholarship, but also academically and emotionally as I tried to finish this dissertation. He has contributed immense enthusiasm, time, and patience to teaching me how to articulate innovative research questions, solve research problems, help framing research in the international literature, as well as overcoming seemingly mundane issues such as proofreading manuscripts. Indeed, I will never forget the thousands of improvements in tracked changes in all of my research proposals, manuscripts, and drafts of my dissertation. Equally, I will never forget the comforting and encouraging words he spoke to me when I felt down because of critical comments from reviewers, and his staunch defense of me to a journal editor after particularly harsh words from one reviewer – I found this particularly impressive and touching. With regard to my personal life, he always encouraged me to “enjoy life in Ghent” and never pushed me to work harder. Especially when I was pregnant, he told me not to worry about my research progress and that the most important thing was to take good care of myself and adjust to what my body required. Finally, I will never forget his kind words and emails when I got married and became a mother.

I would also like to express my sincerest thanks to Dr. Xingjian Liu and Professor Frank Witlox. It is Xingjian, who is working at the University of Hong Kong, who together with Ben offered me the opportunity to work in Ghent with due financial support. Since then, he has also provided me invaluable guidance in my doctoral research by helping me sharpen research ideas, helping me out when I faced technical difficulties, improving my written English, and so forth. Meanwhile, Frank's sense of humor and empathy, broad horizon and generous help have inspired me a lot while I was studying in such an excellent team.

This dissertation would not exist in its current form without the insightful suggestions from the other members of my examination committee, Professor César Ducruet, Professor Kurt Fuellhart, and Professor Theo Notteboom, all of whom are experts in transport networks and whose work I admire a lot. Having them as part of my examination committee is a source of pride. I would also like to thank Professor Nico Van de Weghe for taking the time to efficiently organize the entire process.

I would like to dedicate this dissertation to my family. They have provided me with what appeared to be never ending support throughout my very long study career. I truly believe that I have the best family in the world. I thank my father, Aidong Dai, for his confidence and diligence which has set a good example. I thank my mother, Meiqin Wang, for her endless care and words of wisdom that taught me how to better handle my life and study overseas. I thank my husband, Qing Zhu, for keeping me in the program, being by my side throughout everything, and for being the love of my life. I thank my little baby, Lingxi (Lindsey) Zhu, for her cuteness, giving me joy whenever I felt tired and lost.

Seven years ago, Professor Shenglu Zhou and Dr. Shaohua Wu at Nanjing University employed me as a research assistant and then as a graduate student in Land Resources Management. It was they who led me into academic research. Because of their guidance, I started this amazing academic career. I cannot find words to express how important that experience has been to this dissertation.

I wish to thank the colleagues in the Department of Geography for providing me with such an enjoyable working atmosphere. This includes many people, but some colleagues do stand out, in particular Dr. Shengrun Zhang, Dr. Weiyang Zhang, and Galuh Syahbana Indraprahasta. I also owe thanks to my Chinese friends who have made me feel at home here, with special thanks to Xinyi Zhou, Jing Liu, Zhan Cao, Rui Shao, Kunbo Shi, and Dr. Long Cheng for their everlasting help and companionship.

Finally, I sincerely acknowledge the financial support provided by the Flemish Fund for Scientific Research (FWO), which enabled me to complete my PhD in Belgium.

Liang Dai

Ghent, April 2018

Contents

List of Figures V
List of Tables VI
List of Abbreviations VII
Chapter 1 Introduction 1
1.1 Main objective of the dissertation 2
1.2 Background 3
1.2.1 Network analysis 3
1.2.2 The popularity of the urban network paradigm 5
1.2.2.1 Theoretical frameworks 5
1.2.2.2 Methodological approaches 7
1.2.3 Urban studies of Southeast Asia 15
1.2.3.1 An overview of Southeast Asia: unity-in-diversity 15
1.2.3.2 Urbanization in Southeast Asia 19
1.2.3.3 Urban network studies of Southeast Asia 21
1.3 Research questions 24
1.4 Data: intercity transport linkages 25
1.4.1 Intercity composite transport linkages 26
1.4.2 Intercity air transport linkages 26
1.5 Organization of the dissertation 27
References 30
Chapter 2 Spatial inequality in the Southeast Asian intercity transport network 38
2.1 Introduction 39
2.2 Data and methods 41
2.2.1 Data 41
2.2.2 Methods 44
2.3 Results and discussion 46
2.3.1 Centrality analysis 46
2.3.1.1 Degree centrality 50
2.3.1.2 Closeness centrality 51
2.3.1.3 Betweenness centrality 52

2.3.2 Community detection...54
2.4 Conclusions...55
References..58
Chapter 3 The evolving structure of the Southeast Asian intercity air transport network through the lens of complex networks, 1979-2012...62
3.1 Introduction..63
3.2 Literature review...65
3.2.1 A growing air transport market in the context of regional integration 65
3.2.2 Complex network analysis on air transport networks..67
3.3 Data and methods..70
3.3.1 Data 70
3.3.2 Complex network methods 71
3.3.2.1 Network representation...71
3.3.2.2 Network structure measures..71
3.3.2.3 K-core decomposition...74
3.4 Results...74
3.4.1 Statistical properties of the SAAN topological structure..74
3.4.1.1 Scale-free properties 75
3.4.1.2 Disassortative mixing..76
3.4.1.3 Small-world properties...77
3.4.2 Spatiotemporal variations of the SAAN multilayered structure 78
3.5 Conclusions...86
Reference 88
Chapter 4 Generative network models for simulating urban networks, the case of intercity transport network in Southeast Asia 92
4.1 Introduction...93
4.2 Literature review...94
4.2.1 Urban network analysis...94
4.2.2 Space and topology in the simulation of urban networks.......................................95
4.2.3 Previous approaches to the simulation of urban networks......................................96
4.3 Data and Methodologies 98
4.3.1 Data: Intercity transport networks in Southeast Asia 98

4.3.2 Model specification 104
4.3.3 Model parameter estimation 105
4.4 Results 106
4.4.1 Comparisons between the simulated and the observed networks 106
4.4.2 Analyses of each driving factor underlying network formation 109
4.5 Conclusions and avenues for further research 112
Reference 113
Chapter 5 A comparative analysis of network backbones extracted from different techniques: the case of the Southeast Asian intercity air transport network 117
5.1 Introduction 118
5.2 Existing techniques for backbone extraction 120
5.2.1 Overview 120
5.2.2 Global weight thresholding 121
5.2.3 Hierarchical topological filter 121
5.2.4 Spanning tree 122
5.2.5 Linkage analysis 122
5.2.6 Multiscale network reduction 123
5.3 Data and methods 124
5.3.1 Framework for analytical comparisons 124
5.3.2 Data: the Southeast Asian intercity air transport network 125
5.4. Results 126
5.4.1. Overview: Size of abstracted networks and their QAP correlation with SAAN 126
5.4.2. Topological properties of the abstracted networks 128
5.4.3 Spatial patterns of the abstracted networks 131
5.5 Discussion and conclusions 134
References 137
Chapter 6 Conclusions 141
6.1 Introduction 142
6.2 Overview of the main results 142
6.3 Further discussion 144
6.3.1 Structure of the Southeast Asian urban networks 144
6.3.2 Main factors shaping the network structure 145

6.3.3 Policy implications of this research 146
6.4 Avenues for future research 147
References 149
Summary 151
Samenvatting 153
Curriculum Vitae (Bibliography) 155

List of Figures

Figure 1.1 Two-mode (left) and one-mode (right) network paradigms. 8

Figure 1.2 Southeast Asia. 15

Figure 1.3 GDP and FDI of Southeast Asia, 2001-2015. 18

Figure 1.4 Urbanization level of Southeast Asia, 1960-2015. 19

Figure 1.5 Overview of the dissertation. 27

Figure 2.1 Distribution of selected cities in Southeast Asia. 42

Figure 2.2 The toy network. 46

Figure 2.3 Intercity transportation network between 47 Southeast Asian cities. 49

Figure 3.1 Growth of scheduled air passenger traffic, GDP and population of Southeast Asia, 1979-2012. 66

Figure 3.2 The SEA study area. 71

Figure 3.3 Cumulative degree distribution of the SAAN plotted using a double-logarithmic scale, 2012 75

Figure 3.4 Fitted exponents for the power-law distribution, 1979-2012. 76

Figure 3.5 Degree-degree correlation for the SAAN, 2012. 76

Figure 3.6 Disassortativity coefficients for the SAAN, 1979-2012 77

Figure 3.7 Characteristic path length (a) and average clustering coefficient (b) of the SAAN compared to those of the random network (RN) in the same size, 1979-2012. 78

Figure 3.8 The three layers of the SAAN in 1979, 1996 and 2012.. 85

Figure 4.1 Distribution of selected cities in Southeast Asia.. 100

Figure 4.2 The three layers used in the construction of the composite network. 102

Figure 4.3 Connections in the observed network of composite transport in Southeast Asia. 103

Figure 4.4 Degree distributions in the observed and the simulated networks. 107

Figure 4.5 Connections in the simulated networks. 108

Figure 4.6 Degree distributions after each removal of the different forces. 109

Figure 4.7 Simulated networks after removal of the different forces. 110

Figure 5.1 The Southeast Asian intercity air transport network (SAAN), 2012 126

Figure 5.2 Evolution of QAP correlation and density in terms of GWT thresholds. 127

Figure 5.3 The cumulative strength distribution on double-logarithmic scale for original and abstracted networks. 129

Figure 5.4 Spatial patterns of abstracted networks derived from six techniques 132

List of Tables

Table 1.1 Demography and economy of Southeast Asian countries in 2015. 16

Table 2.1 Centrality rankings for the ‘toy’ network. 45

Table 2.2 Centrality rankings for 47 Southeast Asian cities..48

Table 2.3 The 20 strongest dyads. 52

Table 3.1 Summary statistics of the SAAN in 2012 and its counterparts................................74

Table 3.2 Number of cities, connections and air passengers within and between layers to the total in the SAAN..79

Table 4.1 List of selected cities...98

Table 4.2 The 10 strongest intercity connections in different layers in Southeast Asia. 101

Table 4.3 Network metrics for the observed and the simulated networks. 107

Table 4.4 Network statistics for the simulated networks after removal of driving force. 109

Table 5.1 Size of six abstracted networks and their QAP correlation with SAAN. 126

Table 5.2 Statistical properties of the original and abstracted networks. 128

Table 5.3 Network metrics of the GWT and DFA backbones in different size.....................130

Table 5.4 Summary on strengths and weaknesses of different backbone extraction methods. 134

List of Abbreviations

AEC	ASEAN Economic Community
AFTA	ASEAN Free Trade Area
AHN	ASEAN Highway Network
ASAM	ASEAN Single Aviation Market
ASEAN	Association of Southeast Asia Nations
BC	Betweenness centrality
BIMP	Brunei Darussalam-Indonesia-Malaysia-Philippines
BKK	Bangkok
C	Average clustering coefficient
CC	Closeness centrality
CEB	Cebu
CLMV	Cambodia, Laos, Myanmar, and Vietnam
D	Degree distribution
DC	Degree centrality
DFA	Disparity filter algorithm
DM	Degree mixing
E	Global efficiency
EAGA	East ASEAN Growth Area
ERGM	Exponential random graph models
EU	European Union
EV	Energy value
FDI	Foreign Direct Investment
GaWC	Globalization and World Cities
GDP	Gross domestic product
GNM	Generative network model
GWT	Global weight thresholding
IWCNM	Interlocking world city network model
JKT	Jakarta
KCD	K-core decomposition
KUL	Kuala Lumpur
L	Average path length
M	Modularity
MLA	Multiple linkage analysis
MNL	Manila
MSC	Multimedia Super Corridor
MST	Minimum spanning tree
NIC	Newly industrializing countries

OAG	Official Airline Guide
PLA	Primary linkage analysis
QAP	Quadratic Assignment Procedures
RN	Random network
SAAN	Southeast Asian air transport network
SABM	Stochastic actor-based models
SARS	Severe acute respiratory syndrome
SEA	Southeast Asia
SIN	Singapore
SKRL	Singapore Kunming Rail Link
US	United States

Chapter 1 Introduction

1.1 Main objective of the dissertation

This dissertation has two main objectives. On the one hand, it seeks to contribute to ongoing research on the structure of urban system in Southeast Asia from a network perspective. On the other hand, it tries to integrate recent advances in network analysis that have been developed in different disciplines into the modelling and abstraction of urban networks.

As one of the world's most populous and fastest-growing economies, Southeast Asia has been experiencing both accelerated urban transformations and regional integration in the wider context of globalization processes. The region's urban transformations have been well-documented in the literature dealing with the emergence of megacities, transnational urban corridors, and sub-regional cooperations (Jones, 2002; McGee and Robinson, 1995; Yeung and Lo, 1996), but here we add to these literatures by adopting the 'urban network paradigm' to explore the structure of the urban system in this region. To date, research efforts in this paradigm have been primarily used to analyze world city networks (Derudder and Taylor, 2016), the EU (Vinciguerra, 2012), the US (Liu et al., 2012) and China (Zhao et al., 2015), and this alongside analysis of mega-city regions (Hall and Pain, 2006). As a result, there is lack of attention to the emergence of urban networks in Southeast Asia, so that the spatial organization of intra-regional interactions has remained relatively under-reported. The dissertation attempts to address this issue by systematically and empirically analyzing the characteristics of urban networks in Southeast Asia. By mapping two types of intercity transport linkages – multimodal transport linkages and air transport linkages – this dissertation aims to describe their spatial patterns and evolving structures, and analyze their underlying determinants.

When modelling urban networks, geographers mainly rely on gravity-type models to simulate intercity relations (Matsumoto, 2004) as their primary interest lays in studying spatial effects. Although topological effects have been shown to be also essential in network formation processes by physicist and sociologist, attempts to consider both spatial and topological effects in the study of urban networks have been quite scarce. As Ducruet and Beauguitte (2014) have shown, the lack of use of recent insights from network analysis in the spatial sciences is a more general feature of this field. Neal (2013b), for example, has shown that bespoke node centrality measures could be useful in this literature. This dissertation also attempts to help addressing a specific part of this gap, i.e. the lack of engagement with network de-densification methods. Overall, this dissertation then aims to model urban network by combining spatial and topological effects in a single framework, and offer a systematic comparative analysis of different techniques to abstract these urban networks.

The reminder of this introductory chapter is organized as follows. First, I present the broader background of my dissertation through a brief introduction to recent developments in network analysis in different disciplines, the increasing popularity of the urban network paradigm in theoretical and methodological terms, and urbanization in Southeast Asia. The two main research questions of this dissertation will then be put forward in light of this discussion. The subsequent section elaborates the data used in this study, after which the organization of the remainder of this dissertation is outlined in the final section.

1.2 Background

1.2.1 Network analysis

Network analysis can be found at the crossroads of various scientific disciplines, including mathematics, physics, sociology, biology, geography, etc. (Lin and Ban, 2013). With the help of graph theory, a network can be visualized and analyzed as a graph with a set of nodes (vertices) connected by edges (links). The historically notable “Königsberg Bridge problem” in mathematics, solved by Euler in 1736, is often considered as the first proof for graph theory. The problem asks whether the seven bridges of the city of Königsberg over the river Pregel can all be traversed in a single trip without doubling back, with the additional requirement that the trip ends in the same place it begins. Euler proved that the problem has no solution by representing it as an abstract network (i.e. a graph). Since then graph theory has become an important field in network science, and developed a set of topological and mathematic measures to quantify network properties. Despite the success of classical graph theory, it does not always work well in explaining real-world phenomena. One empirically observation is the fact the ‘distances’ in sparsely and mainly locally connected networks are often much smaller than expected (Stam and Reijneveld, 2007). In this respect, the later developed complex network analysis and social network analysis could offer some enlightened insights.

In the late 1990s, mostly led by physicists, the emergence of complex network theory systematically brought in an array of new concepts and methods. Situated at the intersection of graph theory and statistical mechanics, this approach has offered new insights into the structure and dynamics of large-scale networks of all kinds (Ducruet and Lugo, 2013). Arguably one of the major discoveries has been that many real-world networks display pronounced structures that are distinct from random networks, in which edges are randomly assigned between nodes. For example, a typical feature is that most networks exhibit a right-skewed distribution of nodal degree (i.e., a node’s number of adjacent neighbors), suggesting that a few nodes have many links (hubs) whereas a majority of nodes have few links (Barabási and Albert, 1999). Another common feature is that most networks have a shorter diameter (i.e., the average number of edges in the shortest path between two nodes) and higher transitivity (i.e., probability for a node to have its neighbors interconnected) than a random network (Watts and Strogatz, 1998).

In the past few years, sociologists have also started developing a systematic and standardized methodology to study networks. In social network analysis, where nodes represent individuals and edges represent social relations between them (acquaintance, scientific collaboration, etc.), researchers are mainly interested in the position of individuals and densely inter-connected parts (i.e., cliques) within a network. Furthermore, recent social network analysis provides a promising array of statistical models for explaining structural properties of social networks observed at a given moment (cross-sectional, e.g., exponential random graph models (ERGM)) (Snijders et al., 2006) or over periods (longitudinal, e.g., stochastic actor-based models (SABM)) (Snijders et al., 2010). Related to this, in biology and geography, Vértes et al. (2012) and Vinciguerra et al.(2010) have tried to explain the structure and formation of brain network and the Internet network, respectively, through different generative network models (Ducruet and Lugo, 2013).

In a nutshell, network analysis has been discussed, applied, and developed in different disciplines, with often-interesting inter-disciplinary excursions. However, the more precise focus in the field of network analysis varies across research fields, ranging from individual nodes and densely connected parts in a network to the entire network, and from the simple description of network structures to attempts at explaining these structures through network modelling. In such cases, bridging the gaps between different perspectives, integrating recent advances from different scientific fields, and constructing an overall understanding of networks, becomes increasingly difficult yet important. In this dissertation, this challenge is taken up for the case of urban network research.

1.2.2 The popularity of the urban network paradigm

Although networks analysis in geography and regional science dates back to at least the 'quantitative revolution' (Haggett and Chorley, 1969), we can observe a surge in interest since the 1990s: references to 'urban networks' have grown dramatically in the scientific literature (Neal, 2013b). This renewed interest is understandable since most networks have a spatial structure, with nodes being embedded in space and edges between them crossing a particular geographical distance (Barthélemy, 2011). This suggests that distance in urban networks takes on two related, yet distinctive forms: geographical distance and topological distance. The former simply refers to the distance between two nodes in geographical space (in miles or kilometers); and the latter, also called geodesic distance, refers to the shortest path between two nodes in a network. Hence, the analysis of urban networks should ideally combine both conventional spatial analysis and more recent developments in network analysis. This increased popularity of urban network paradigm is not only visible in a range of theoretical frameworks, but also in methodological approaches to examine urban systems.

1.2.2.1 Theoretical frameworks

"Dependence on a network rather than on the servicing of an environing region, or a wider hinterland, existed for a few exceptional cities in the past, but now it has become the general rule for the majority of substantial cities anywhere" (Gottmann, 1989: 62).

“Connections are the very raison d’etre of cities” (Castells, 1996:1).

As a textbook of theoretical geography, the well-known analytical model to interpret ‘urban system(s)’, also referred to as ‘system(s) of cities’, is central place theory developed by Christaller (1933) and Lösch (1944). Under this framework, cities are seen as “central place(s) providing goods and services for a surrounding area” (Berry and Pred, 1961: 3), after which the function and hierarchy of cities are defined by their regional and local external relations (Bunge, 1966). The organizational logic underlying is a territorial logic, emphasizing a gravity-type control of market areas and a core-hinterland structure of intercity relations.

However, Jacobs argued that “a city does not grow by trading only with a rural hinterland” (Jacobs, 1969: 35). Pred (1977) elaborates that it is not only vertical (hierarchical) relationships that are important in an urban system, but also the horizontal and cooperative linkages, while Bourne and Simmons (1978) define urban systems as a set of regionally, nationally or globally linked and interdependent urban areas. As a consequence, ‘urban network(s)’ has increasingly become the reference paradigm for ‘urban system(s)’ (Camagni, 1993), and is believed to provide “a successful theoretical framework for overcoming the limiting interpretative power of the traditional central place model” (Capello, 2000: 1928).

In its most basic guise, the urban network paradigm emphasizes the bearing of intercity relations regardless of the distance barrier and focuses on *flows between cities* rather than *characteristics of cities* in and by themselves. ‘Network thinking’ in urban studies has been fuelled by the publication of *The Global City* (Sassen, 1991) and the formalization of the concept of *space of flows* (Castells, 1996) in an era of globalization and informatization. In Sassen’s work, global cities (e.g., London, New York, Tokyo) are posited to be related to each other through “vast multinational networks” (Sassen, 1991: 173) of advanced producer service (APS) firms so that the interactions among these global cities constitute an emerging transnational urban system. For Manuel Castells (1996), global cities are “not a place but a process. A process by which centers [. . . .] are connected in a global network” (386). He thus proposes a spatial logic of “space of flows” that consists of three layers: infrastructural support for networked social practices, geographical network spaces formed by nodes and hubs, and the spatial organization of the managerial elite using these networks. Inspired by these contributions, Peter Taylor further emphasizes "the necessity to think of cities relationally, as the product of networking activities" (Taylor, 2003: 27) and introduces central flow theory to complement central place theory when analyzing external urban relational processes (Derudder and Taylor, 2017; Taylor et al., 2010)

With the intensification of globalization and the development of transportation and telecommunication infrastructures, cities can maintain close linkages with a non-neighboring city, and high-order functions can locate in small but specialized centers. As Coe et al. (2004) demonstrate, urban and regional development is becoming a globalizing phenomenon while Florida (2008) perceives globally interconnected cities as the engines of economic growth. In this context, there is a gradual transformation in theoretical frameworks for analyzing urban systems with a national, continental or worldwide scope from static, closed, and hierarchical-centered models to dynamic, open, and multi-centered network models.

Under this new spatial logic, the evolution of cities can be (partly) explained by their position in urban networks, which may involve flows of people, capital, information, services, and goods. In addition, small- and medium-sized cities can potentially internalize the benefits of larger cities by being well-positioned in these urban networks (Burger and Meijers, 2016). It is sometimes even argued that the urban network embeddedness currently is more important for urban productivity than urban size (McCann and Acs, 2011).

1.2.2.2 Methodological approaches

(1) Urban network representation

An exhaustive review of empirical studies of transnational urban networks reveals that there are two types of urban network representations. One is two-mode or bipartite networks in the form of a city-to-agent matrix. The other is one-mode or unipartite networks in the form of a city-to-city matrix. In practice, corporate networks and infrastructure networks are main examples for these two representations, respectively (Derudder, 2008). As shown in Figure 1.1, a two-mode network is characterized by connections between two separate sets of nodes (cities and agents such as firms, respectively). There is no *direct* linkage within the same set of nodes (i.e. between cities or between firms): researchers simply know which firms are in what cities, and which cities house what firms. In contrast, a one-mode network – probably the more well-known elaboration of a 'network' – consists of only one set of nodes (i.e. cities) that are directly interlinked (Liu and Derudder, 2013).

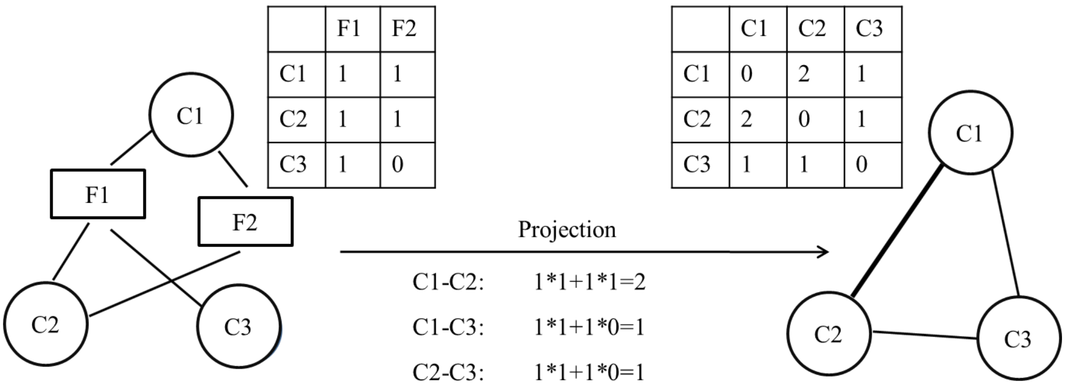


Figure 1.1 Two-mode (left) and one-mode (right) network paradigms (C: City; F: Firm).

In the corporate approach, based on Sassen's conceptualization, data on the office networks of advanced producer services firms are used to analyze the spatial organization of world city network by Peter Taylor (2001) and other colleagues from the Globalization and World Cities (GaWC, http://www.lboro.ac.uk/gawc) Research Network (Derudder et al., 2010; Liu and Derudder, 2013). And later Alderson and Beckfield (2004) try to define this network based on the ownership linkages of the world's largest multinational enterprises, such as the Fortune 500 companies. Both of them assume that people, goods, capital, and information flows between any of two branches belonging to the same company. The latter suggests that it is possible to infer one-mode networks from two-mode datasets by applying a 'projection' function (cf. Figure 1.1), which in this case essentially represents developing a guesstimate of how different parts of the company 'interact' across space (Latapy et al., 2008).

Several projection methods have been proposed from different grounds, such as the most widely used interlocking world city network model (IWCNM) devised by Taylor (2001), the 'sorting process' algorithm by Neal (2013a), an alternative algorithm combining geographic and hierarchical features by Hennemann and Derudder (2014) and its improvement by Zhao et al. (2015). However, Neal (2013c) contends that "one-mode projections contain less information than their two-mode sources" (915). Meanwhile, methods developed for the direct analysis of two-mode networks are relatively limited whereas for one-mode networks ‘‘the full range of network analytic methods are available’’ (Borgatti and Everett, 1997: 246). Therefore, scholars have great interest in utilizing more straightforward intercity relational data, which points to the second type of urban network representation.

In the infrastructure approach, the intercity connections can be expressed by virtual telecommunication flows (e.g. the Internet backbone; Zook, 1999) or physical transportation flows (e.g. airlines; Smith and Timberlake, 2001). These infrastructure networks correspond to the first layer of the space of flows and provide the “fundamental spatial configuration” for the networked society put forward by Castells (1996: 433). The underlying rationale is that “infrastructure networks are often assumed to be important determinants of the economic potential of urban agglomerations” (Bruinsma and Rietveld, 1993: 919). Meanwhile, Keeling (1995) points out that the role of transport infrastructure in the evolving world city system is both crucial and fundamental since it facilitates the dense interactions between people, goods and information, on which the commanding nodes (i.e. world cities) are based.

Due to the relative scarcity of data on the Internet traffic between particular cities (Tranos and Gillespie, 2011), most empirical studies on urban interactions are concerned with the actual connections through physical transportation flows. These transportation connections range from intercity relational data on public transport flow (Cats, 2017) at the city-region level, to railway flows (Wang et al., 2009) at the national level, to composite transport connectivity (Derudder et al., 2014) at the continental level, and to maritime (Ducruet and Notteboom, 2012) and airline flows (Matsumoto, 2007) at the global level. It is within the analysis of transport-based urban networks that the present dissertation is situated.

(2) Urban network description

Research on network description is both extensive and diverse, with most research being cross-sectional. The description can be divided into three levels: 1) local or micro level, which compares the relative position/importance of cities within the network; 2) sub-network or meso level, which highlights the densely inter-connected clusters/communities within the network; 3) global or macro level, which characterizes and analyzes the entire network.

First, the ‘importance’ of cities has been examined by calculating a range of centrality measures such as degree centrality, closeness centrality and betweenness centrality in Wang et al. (2011), eigenvector centrality in Smith and Timberlake (2001), recursive centrality in Neal (2011) as well as other centrality measures that have been specifically tailored for urban network analysis (Neal, 2013b). Because the various forms of centrality analysis produce different city hierarchies, the connectivity structure of a city and its function in the network can be revealed. For example, cities with higher degree centrality might have broader hinterlands or larger throughput; cities with higher closeness centrality are endowed with better accessibility; cities with higher betweenness centrality play a more important brokering role in the network; cities with higher eigenvector or recursive centrality may have more important neighbors. In addition, nodes with low degree centrality but high betweenness centrality reveal their role as a strategic position or intermediacy between different subgroups (i.e. a set of closely connected nodes whose intra-community connections exceed inter-community connections) (Fleming and Hayuth, 1994; Guimera et al., 2005).

Second, a network can be divided into multiple subgroups or communities, thus contributing to the analysis of the existence of functionally networked groups (Blondel et al., 2010; Liu et al., 2014). In general, algorithms for community detection fall into two broad categories: graph partition and hierarchical clustering. Graph partition aims to divide network into groups without overlapping with each other, whereas hierarchical clustering aims to construct the hierarchical structure of clusters of nodes, which can further be divided into hierarchical agglomerative and hierarchical divisive. The most widely used community detection method is arguably the modularity maximization method proposed by Newman and Girvan (2004).

Third, on the one hand, there have been analyses of statistical properties of the overall urban network. Guimera et al. (2005), for example, present a detailed analysis of the topological properties of the global air transport network, and find that it exhibits small-world characteristics (Watts and Strogatz, 1998) in that city-pairs tend to be separated by just a few links and show a high local clustering coefficient. Meanwhile, Ducruet et al. (2011) point out that both worldwide sea and air transport flows exhibit a scale-free structure (Barabási and Albert, 1999) with a power-law degree distribution (Reed, 2003) reflecting the hierarchy of cities. On the other hand, the structural equivalence and similarity of different urban networks have been assessed through the application of Quadratic Assignment Procedures (QAP; Krackardt, 1987), as in Choi et al.'s (2006) analysis of air transport and the Internet backbone connections between cities, as well as Ducruet et al.'s (2011) assessment of worldwide sea and air transport flows.

With the growing availability of coherent longitudinal datasets, scholars have also traced the spatial and structural changes of urban networks. Research in this vein draws on methodologies of network description, but aims to extend these by analyzing network characteristics from a longitudinal perspective. For instance, Smith and Timberlake (2001) examined the changing patterns of airline-based global city system in terms of centrality hierarchies and clique membership between 1977 and 1997. Ducruet (2017) and Ducruet et al. (2010) have uncovered the evolution of urban hierarchies, regional patterns, and overall structures in global maritime networks, while Wang et al. (2009; 2014) have conducted similar studies of China's evolving railway and air transport network.

Network description has predominantly focused on the analysis of a single network (i.e. a simplex network). However, there is an increasing awareness that urban networks are diverse and should be envisaged as multiplex networks (Tsiotas and Polyzos, 2017). This implies the recognition of the need of envisaging urban networks as (1) multimodal networks, networks integrating several modes of interdependent transport networks (Zhang and Peeta, 2011) and (2) multilayer networks, networks decomposed into differently structured layers (Ducruet and Zaidi, 2012). With regard to the former, there exists strong complementarity between multiple modes of transport networks in the formation of an urban network. This has been highlighted in the joint analysis of global airline and maritime networks by Ducruet et al. (2011), and also in the construction of composite network including rail, road, and air networks by Derudder et al. (2014) (see a recent review by Ducruet, 2017). With regard to the latter, it helps disentangling the complexity of urban networks and providing insights into the different layers unevenly contributing to the configuration of the network, as shown in the hierarchical core-bridge-periphery structure in China's and global air networks (Du et al., 2016; Verma et al., 2014).

(3) Urban network modelling

Complementing the description of urban networks, attention has been paid to model these networks with the specific purpose of uncovering their underlying mechanisms. This simulation and modelling mainly relies on space-based and/or topology-based techniques.

The most commonly techniques adopted by geographers are gravity-type models, in which the flows between two cities are assumed to be proportional to their 'masses' and inversely proportional to the 'distance' separating them (Matsumoto, 2007; Tobler, 1970). These gravity-type models are intuitively conceptualized and can be easily extended to include other factors with a spatial connotation. However, they are based on the premise of interdependence of nodes, while most urban networks are characterized by structural independence between cities. For example, the strength of the linkages between London, New York and Hong Kong, derives from the interdependence of their financial services complexes, a topological property resulting in important long-distance connections that might deform gravitational predictions (Van Meeteren et al., 2016).

Two recent topology-based models (i.e., the ERGM and SABM mentioned in section 1.2.1) derived from social network analysis have tackled this 'deformation' problem. On the one hand, Liu et al. (2013a) have employed the ERGM to explore regional differences in the underlying formation processes of intercity corporate network. On the other hand, Liu et al. (2013b) and Zhang et al. (2016) have drawn on SABM to investigate the different processes underlying the dynamics of the global intercity corporate network and the European air transport network, respectively. However, both models have their own limitations in the context of urban network simulation. EGRM, for instance, sometimes has the problem of computational intractability and 'degenerate' model behavior, thus being not that stable (Karwa et al., 2016). Meanwhile, SABM's need for clear-cut definition of key actors and their network-generating behavior is sometimes hard to implement and/or interpret (cf. Broekel et al., 2014).

As can be seen from these previous studies, topological and spatial effects are not mutually exclusive and they may exert overlapping (yet separate) influences in the shaping of urban networks (Pflieger and Rozenblat, 2010). To date, geographers have made all in all limited attempts to explicitly incorporate topological effects when modelling urban networks. A major exception has been Vinciguerra et al.'s (2010) simulation of the formation of the Internet backbone in Europe. They show how a combination of topological effects (a preferential attachment process whereby nodes have the tendency to connect to nodes that are already well-connected) and spatial effects (e.g. borders) help explaining the shape of this particular intercity network. Another notable generative network model incorporating topological and spatial effects was proposed by Vértes et al. (2012) in biological science to model functional human brain networks. Instead of the preferential attachment process in Vinciguerra et al (2010), Vértes et al (2012) explained the topological force by transitive process, which is arguably much more common in urban and social networks.

(4) Network backbone extraction

With the increasing availability of big data and the increasing complexity of transport networks, the visualization, description and analysis of transport-based urban networks continue to face a range of challenges (Hennemann, 2013; Radicchi et al., 2011; Vertesi, 2008), which necessities further research of backbone extraction of urban networks. This has been studied in a wide range of disciplines using slightly different terms, such as network simplification, network sparsification, network reduction and network abstraction. It aims to extract the 'backbone' of a network: a simplified version that is reduced in size – i.e., some edges and/or nodes are deleted – but retains the most 'valuable' information contained in the original network. The abstracted network can be mapped and explored with significantly less effort, and this without too much compromising the real-world remit of the network.

Several strategies have been proposed to achieve this goal in the study of urban networks. The most frequently used approach is to introduce an unconditional threshold, which keeps edges and/or nodes that have a level of connectivity above a certain value. For instance, Dennis (2005) considered air routes with at least 3 weekly non-stop services to unravel the distinct markets each European hub airport serves, while Fuellhart and O'Connor (2013) retain international routes with more than 18250 passengers per annum in their study of air services at Australian cities to reduce the original airline network to a more manageable scale.

Another well-known alternative is primary linkage analysis (Nystuen and Dacey, 1961) which keeps the most important edge for each node in the network so that the number of edges contained in the backbone is normally identical to the number of nodes. This approach has been applied to outline the backbone of complex global airline network (Grubesic et al., 2008) as well as worldwide maritime network (Ducruet, 2017). Different from the pre-determination of a single edge in primary linkage analysis, multiple linkage analysis (Haggett et al., 1977) offers a more refined determination of the number of edges for each node. This helps simplifying the original network by judiciously removing non-significant edges. Van Nuffel et al. (2010) employ the technique to extract the most significant flows in the European air transport network, while Wang and Cullinane's (2014) conduct a similar identification of traffic flows through major container ports in East Asia.

Needless to say, these methods are not unique to the study of urban networks: they have for example been discussed and applied in fields as disparate as physics (Gemmetto et al., 2017), sociology (Neal, 2014), biology (Darabos et al., 2014), and computer science (Foti et al., 2011). Nonetheless, it can be noted that oftentimes the illustrative examples put forward in these domains are infrastructure networks, reinforcing the broader relevance of urban network analysis. In spite of this, the adoption of the ideas developed in other scientific fields has been limited and uneven in urban geography itself (cf. Ducruet and Beauguitte, 2014), thus calling for a systematic comparison of the relevance of different backbone extraction techniques for urban-network research in general and for transport-network research in particular.

1.2.3 Urban studies of Southeast Asia

1.2.3.1 An overview of Southeast Asia: unity-in-diversity

Although different delineations abound, Southeast Asia (SEA) can roughly be described as the region situated east of the Indian subcontinent, south of China and north of Australia, between the Indian Ocean (in the west) and the Pacific Ocean (in the east). As shown in Figure 1.2, this region is commonly defined (cf. Rimmer and Dick, 2009) as including Cambodia, Laos, Myanmar, Vietnam (CLMV), Thailand, Malaysia, Singapore, Indonesia, Philippines, Brunei, and East Timor (formerly part of Indonesia).

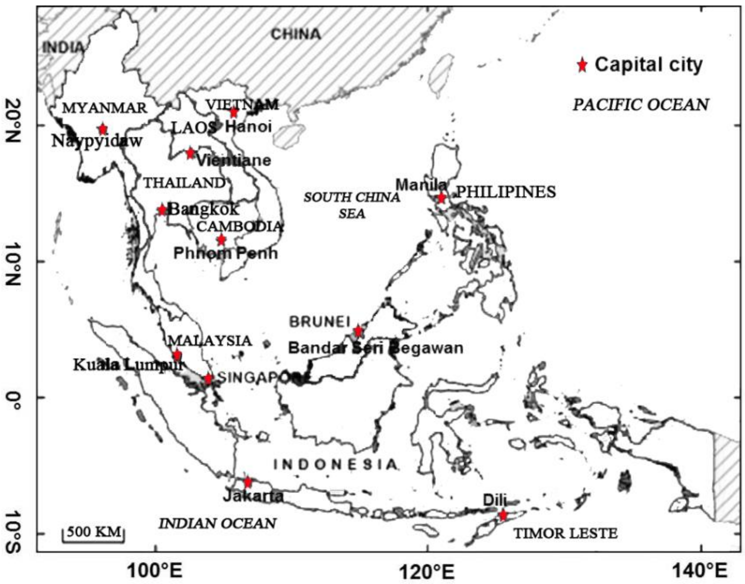


Figure 1.2 Southeast Asia.

The term “Southeast Asia” came into general use during the Second World War, especially in relation to Japan’s occupation of the area during the Pacific War. Scholars have described this region as a “unity-in-diversity” (Jönsson, 2010), in the sense that it contains divergent and overlapping features in terms of geography, history, demography and economy, socio-cultures. For example, they all have been colonized by western powers except for Thailand. Despite their relative geographic proximity, some of them are on the mainland while others to a large extent consist of archipelagos.

The population in Southeast Asian countries varies widely from tiny oil-rich nation, Brunei, to Indonesia (see Table 1.1). Furthermore, the urbanization level also exhibits great disparity. Countries with the largest levels of gross domestic product (GDP) per capita (Singapore, Brunei, and Malaysia) are highly urbanized, with an urbanization rate above 74%. In particular, the figure of Singapore reached 100% as early as 1960 (Yap and Thuzar, 2012). The middle income countries including Thailand, Indonesia, and Philippines have urbanization rates between 40% and 60%, which is approximating the world average of 53.8%. The less developed countries (CLMV and East Timor) have levels of urbanization below 40%. Apart from Singapore, Indonesia and Vietnam have recently shown remarkable Foreign Direct Investment (FDI) influxes due to their large market size and cheap labor force. Religious and ethnic diversity are also marked. The dominance of Chinese heritage in Vietnam and Singapore, the primarily Indianized culture of Myanmar, Thailand, Cambodia, and Laos, the Islam of Indonesia and Malaysia, and the Catholicism of the Philippines underwrite by intense regional variation.

Table 1.1 Demography and economy of Southeast Asian countries in 2015.

Country	Population (million)	Urbanization (%)	GDP (billion USD)	GDP per capita (USD)	FDI (billion USD)
Singapore	5.54	100.00	296.84	53630	70.58
Brunei	0.42	77.20	12.93	30968	0.17
Malaysia	30.72	74.71	296.43	9649	9.86
Indonesia	258.16	53.74	861.26	3336	19.78
Thailand	68.66	50.37	399.23	5815	8.93
Philippines	101.72	44.37	292.77	2878	5.64
Laos	6.66	38.61	14.39	2159	1.42
Myanmar	52.40	34.10	59.69	1139	4.08
Vietnam	91.71	33.59	193.24	2107	11.80
East Timor	1.24	32.77	1.61	1295	0.04
Cambodia	15.52	20.72	18.05	1163	1.70
SEA	**632.75**	**47.75**	**2446.45**	**3866**	**134.00**

Source: data.worldbank.org.

However, in spite of all this, today Southeast Asia displays more homogeneity and convergence than ever before (Acharya, 2000), and this mainly due to the increasing regional integration and globalization processes (i.e. a relatively homogenized integration into the world economy in as specified in Dick and Rimmer (1998: 2303)). During the last couple of decades, cooperation within regions has, in general, rise, among which the most successful example is the European Union (EU). In Southeast Asia, Thailand, Malaysia, Indonesia, Singapore and Philippines in 1967 formed the Association of Southeast Asia Nations (ASEAN) political and economic grouping. Membership of ASEAN has grown over the years to include another five member states, with Brunei joining in 1984, Vietnam in 1995, Laos and Myanmar in 1997, and Cambodia in 1999. Since its foundation, the ASEAN has made persistent efforts to promote regional integration. In 2015, a series of initiatives came to fruition to establish the ASEAN Economic Community (AEC). These initiatives are designed, among other things, to reduce tariff and non-tariff barriers to trade, to harmonize standards and regulations of all kinds, to develop human capital and professional standards, to facilitate movement of labor, and generally to serve to strengthen ASEAN as a homogeneous economic community, and this broadly along the lines of the early European Economic Community.

However, Southeast Asian countries have very different experiences with global and regional integration. It is well documented that regional economic integration in East Asia - including large part of its Southeast Asian component - has been preceded by fast-paced industrial development in Japan and the emergence of newly industrializing countries (NICs) - South Korea, Taiwan, Hong Kong, and Singapore - since the mid-1960s (Yap, 2014). Consecutive waves of relocating labor-intensive industries then cascaded down to next-tier NICs - Indonesia, Malaysia, Thailand - and later to the Philippines after it introduced a transition towards more liberal economic policies from the early 1980s onwards (Coclanis and Doshi, 2000). Meanwhile, the three Indochinese economies (i.e. Vietnam, Laos and Cambodia) were trapped in conflicts and isolated from the SEA regional market for more than a decade after 1975. They subsequently embarked on a trajectory of regional economic integration through a fundamental shift in development strategy from a centrally planned economy to a market economy since the late 1980s, as exemplified by Vietnam's Doi Moi reforms (Hill and Menon, 2012). By 1993, CLMV countries had all embraced market mechanisms, emphasizing export promotion, welcoming foreign investment, and promoting tourism (Thant, 2012). The flows of trade and investment to these newcomers to regional integration led to the establishment of broader regional production networks. As a consequence, regional integration in SEA has been significantly accelerating since the early 1990s: Tanaka (2009) demonstrates that the intraregional trade has almost doubled over the past two decades and now constitutes a quarter of the region's total trade.

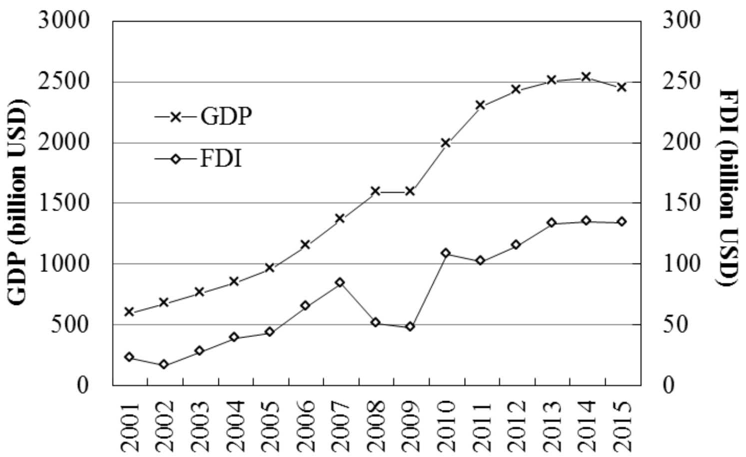


Figure 1.3 GDP and FDI of Southeast Asia, 2001-2015[1].

As a single bloc, this region has emerged as one of the most economically dynamic and strategically significant regions in the global economy (Sien, 2003). As the world third largest labor market, SEA produces a combined GDP of US$2.45 trillion in 2015, which ranks third in Asia, following China and Japan (ASEAN Secretariat, 2016a). In tandem with its economic growth, SEA remains a major destination of global investment recently and has received increasing FDI except for a short drop during 2008-2009 because of the global economic recession (Figure 1.3). In 2015, it attracted around 18% of the world's FDI into

[1] GDP and FDI data for each of the eleven Southeast Asian countries were gathered from World Bank (https://data.worldbank.org/) and then were aggregated, respectively, to represent those for the whole region of Southeast Asia.

developing economies with an inflows of US$ 134 billion (ASEAN Secretariat, 2016b), with Singapore being the biggest beneficiary (cf. Table 1.1).

1.2.3.2 Urbanization in Southeast Asia

Over the past few decades, SEA has experienced substantial urbanization, growing from less than one fifth of the population being urban dwellers in 1960 to almost half of the population living in cities in 2015 (Figure 1.4), close to the world average of 53.8% . Urbanization of individual cities in SEA also differs greatly which can date back to historical development as well as recent political systems of each country (Dutt et al., 1994). The evolution of Southeast Asian urbanization has been depicted by Dutt and Song (1996) as consisting of four phases: (1) indigenous urbanization, (2) colonial urbanization, (3) extended pre-industrial urbanization, and (4) industrial city urbanization.

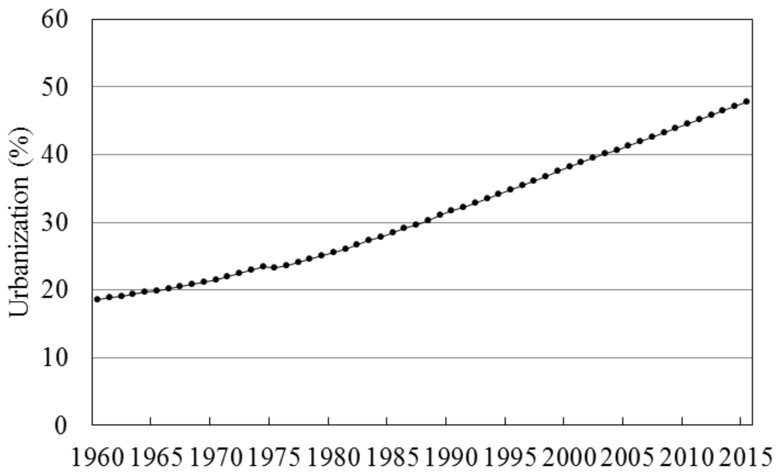


Figure 1.4 Urbanization level of Southeast Asia, 1960-2015[2].

From the third century B.C., *indigenous urbanization* developed three types of cities – administrative cities, sacred cities, and coastal cities – that exercised different functions (McGee, 1967). The administrative cities including imperial capital, provincial or vassal

[2] Urban population and total population data for each of the eleven Southeast Asian countries were gathered from World Bank (https://data.worldbank.org/) and then the urbanization level was calculated by the ratio of total urban population in Southeast Asia to its total population.

capital, and regional centers helped organizing the hierarchy of political power. The sacred cities, normally located in the interior part of the country, helped housing an elaborate religious structure and were closed societies with limited human interactions (Read, 1976). The coastal cities, developed by merchants, were to conduct trade with other regions based on free market society and technology innovation. In the stable economic conditions at that time, sacred cities seemed to be more prosperous than coastal cities.

However, during the *colonial urbanization* starting from 1511 A.D., coastal areas or at river mouths were selected to support trading activities and, later, to facilitate the export of raw materials from colonies to the European countries and America (Thailand was the only country not colonized). Therefore, these cities become the nuclei of current great cities and the urban development in this region explicitly took place within the context of a global economy. Colonialism was also accompanied by the introduction of new transport technology needed for colonial administration as well as economic activity.

Beginning with independence from colonialism, SEA entered into the third phase of *extended pre-industrial urbanization*. Counties in this region started to making efforts on postwar decolonization and nation building. Since the mid-1960s, beginning with Japan, waves of urban explosion and economic growth cascaded down first to newly industrializing countries (NICs) such South Korea, Taiwan, Hong Kong, and Singapore. With the increasing enthusiasm for new international division of labour, labour-intensive stage of production was relocated form the developed economies to the Third World for lower labour cost (Frobel et al., 1980). This trend then further spread into the so-called next-tier NICs in Southeast Asia (initially mainly Indonesia, Malaysia, and Thailand) and later to Philippine. The economies of most countries depended on export to a significant level, so coastal cities received greater impetus for development during the post-independence period.

For the *industrial city urbanization*, Singapore has entered into this phase since the 1990s when industries started to utilizing high-tech devices and producing goods out of capital-intensive enterprises. Nowadays apart from Singapore's prominence in the global economy, rapid economic growth have turned Bangkok, Kuala Lumpur, Manila, and Jakarta into progressive cities. More recently, Vietnam has emerged after economic reforms in the 1986 (Freeman, 1996). Laos, Cambodia and Myanmar embarked upon this trajectory by fundamental shift in development strategy from a planned economy to market economy. This shift leads to the rapid development of some towns which has initial advantages (ports, proximity to government policymakers, human capital), or towns where a particular industry is rapidly emerging, for example, Luang Prabang and Siem Reap as key tourist destinations in Laos and Cambodia, respectively.

1.2.3.3 Urban network studies of Southeast Asia

Urbanization in this region has been characterized by the emergence of megacities, extended metropolitan areas, mega-urban regions, and transnational urban corridors (Ginsburg, 1991; Jones, 1997; McGee and Greenberg, 1992). Among them, the most distinctive characteristic is the high degree of urban primacy (Rimmer and Dick, 2009). There is a consensus that the urbanization process in Asia has been reshaped and facilitated by globalization processes (Huff and Angeles, 2011; McGee, 2009; Shatkin, 2008; Yeung, 2011).Thereby, a 'paradigm shift' has taken place to engage cities and urbanization in the world-system perspective (Smith, 2003).

GaWC's work clearly suggests this paradigm shift, for instance, with a selection of cities with population larger than one million, the position of 25 Southeast Asian cities are analyzed in the world city network based on transnational corporate location strategies (Derudder and Taylor, 2017). Other research includes the paper by Bowen and Leinbach (2006), who explore the role of Kuala Lumpur, Metro Manila, Penang, and Singapore in the global production network. The ASEAN mega-urban regions (McGee and Robinson, 1995) are now regarded as international hubs embedded in a competitive urban network centered on Tokyo, which is linked with both London and New York. This has also been picked up by Rimmer's (1995) analysis of the nature of transport and communication interactions between world cities in Pacific Asia by using data on container movement, air freight and mail, and air passengers. In addition, Shin and Timberlake (2000) describe the changing hierarchy, cliques and connectivity patterns of Asian cities in the world system of cities by using data on airline travel between all pairs of about 100 world cities from 1975 to 1997.

The integration at the global level has been replicated at the regional level (Thant, 2012). Lo and Yeung (1996) suggest that a new spatial articulation of the global economy has emerged, rendering national boundaries far less salient than in the recent past. Some scholars see regionalism as a by-product of globalization processes, i.e. regionalism is "determined by location and specificity within the world economy or traditional production structures" (Scholte, 2000: 42). Regionalism can be described as a kind of re-territorialization. New alliances and collaboration patterns are created in order to cope with the new challenges caused by globalization, and even if the states lose some of their power, regionalism strengthens the states vis-à-vis the rest of the world (Jönsson, 2010). At the same time, a process of de-territorialization is taking place, i.e. territories are not as important as they used to be. Borders simply lose their importance through increased integration.

One can discern various trans-border cooperation patterns within Southeast Asia. Examples include the Singapore Growth Triangle (Macleod and McGee, 1996), Penang Malaysia - southern Thailand - Sumatra (Yeung and Lo, 1996), and the Greater Mekong Sub-regional cooperation (Walsh, 2010), which point to a more de-territorialized system of cities (Stærkebye, 2005). In this respect, Yeung (2001) analyzes the cross-border activities of Singapore-based manufacturing transnational corporations in Southeast Asia, and found the spatial fragmentation is rather limited in this regional production network. Li and Dawood (2017) specify the connectivity of 33 crucial Southeast Asian cities through the office network of 30 advanced producer services firms with the analogy to GaWC's immense empirical study of world city network, and then identify most dominant cities, inter-regional connections, hierarchical and regional structures in Southeast Asia. Dick (2005) also examines how Southeast Asia might be imagined from a trans-national urban perspective:

"Focused on main cities and their hinterlands, trans-national interactions in the movement of people, goods, money and information define a core region or corridor, which contrasts with dispersed trans-national peripheries in both maritime and mainland Southeast Asia. This approach offers a stimulating and realistic way to re-imagine Southeast Asia without national boundaries in the foreground." (Dick 2005: 251).

Actually, ASEAN's efforts to promote regional integration is also reflected in a range of initiatives to enhance the intra-regional infrastructure connectivity (ASEAN Secretariat, 2011). A key step in this process was the agreement on an ASEAN Free Trade Area (AFTA) in 1992. The AFTA framework carried a commitment to further enhance regional cooperation by providing safe, efficient and innovative transportation and communications networks. This then boosted a series of sub-regional cooperation and two flagship land transport infrastructure projects, namely the ASEAN Highway Network (AHN) and the Singapore Kunming Rail Link (SKRL). In addition, air transport began to be liberalized based on sub-regional agreements, such as between CLMV countries and in ASEAN's Northern Growth Triangle. Another important step was the 2008 agreement to form ASEAN Single Aviation Market by 2016, although the Open Skies policy has not been fully implemented to date. Today, cities in this region are increasingly linked by business networks, trade relationships, migration, etc., much of which is supported by intercity transport connections. The economic bloc is shifting from a mosaic of nations towards an integrated and globally competitive single market and production base.

All in all, the changing role of Southeast Asian cities and their regional organization patterns have become vital in the context of globalization. As can be seen from previous studies, cities with small populations and/or less advanced economy in Southeast Asia are usually overlooked in global and regional urban-network analysis and in a sense ‘off the map’ in public media, government reports, and academic studies. While megacities such as Bangkok, Kuala Lumpur, Jakarta, Manila are competing for the status of ‘global cities’, relatively little is known about secondary cities and other small or less developed cities in the vast Southeast Asia. In this light, regional urban networks based on airline data can provide a more detailed portray with comprehensive inclusion of airport cities and description of connections between cities (e.g. Bowen, 2000; Rimmer, 2000). However, most of them take a transport perspective rather than an urban perspective, resulting in relatively limited knowledge of the Southeast Asian urban system. Against this backdrop, analyzing the systems of Southeast Asian cities in a regional framework based on transport data is of the utmost interest to researchers and also of great value in both practice and scholarship (Thompson, 2013).

1.3 Research questions

As illustrated in the background section, the urban network paradigm has been marshalled to understand transnational urban systems in an era of heightened globalization. However, to date there have been limited efforts to investigate urban networks in Southeast Asia. To bridge the gap between state-of-art urban network research and the limited knowledge of the spatial organization of intercity linkages in this region, this dissertation offers an in-depth analysis of urban networks in Southeast Asia drawing on intercity transport linkages. Furthermore, this dissertation also explicitly positions itself as part of the methodological strands of the network analysis literature: it is argued that integrating spatial analysis with network analysis brings a new and more complete perspective to the understanding of urban/transport networks. Based on a range of analyses of the intercity transport linkages, this dissertation has both conceptual (Q1 & Q2) and methodological (Q3 & Q4) research questions.

As demonstrated before, Southeast Asia has been experiencing both accelerated urban transformations and regional integration, and the development of both countries and cities in this region is quite uneven. The structure of this regional urban system will be explored from a network perspective cross-sectionally (Chapter 2) and longitudinally (Chapter 3). Specifically, the respective research questions are specified as: Q1: *What are the spatial patterns of the urban network in Southeast Asia from the lens of composite transport linkages?* and Q2: *What is the evolving structure of the urban network in Southeast Asia from the lens of air transport linkages?* In Chapter 2, social network analysis will be used to examine these spatial patterns in 2016, focusing on cities and city communities. In Chapter 3, we will trace the dynamics of overall network structures from 1979 to 2012, both geographically and topologically, using complex network analysis.

As reviewed in previous section, urban network analysis has been fertilized by a range of scientific fields. We will pay particular attention to network modelling (Chapter 3) and network abstraction (Chapter 4) in the study of the urban networks in Southeast Asia by employing recent advances in other disciplines. Specifically, the respective research questions are specified as: Q3: *How can spatial science and network science be bridged to better model the formation of urban networks?* And Q4: *What is the relative usefulness of different methods to extract the backbone of urban networks?* These research questions will be addressed by introducing a generative network model to uncover the spatial and topological forces underlying network formation (Chapter 4) and by comparing the topological and spatial features of different backbones (Chapter 5).

1.4 Data: intercity transport linkages

In the context of the empirical studies in this dissertation, two types of data on intercity transport linkages were collected to map urban networks in Southeast Asia. The sample cities studied in both networks were slightly different.

1.4.1 Intercity composite transport linkages

The first type of data are intercity composite transport linkages, which will be used in Chapters 2 and 4. In this composite network, 47 Southeast Asian cities were selected based on two criteria: 1) all metropolises with more than half a million residents (based on citypopulation.de's data); and 2) all capital cities (e.g. Vientiane, Laos and Dili, East Timor) regardless of their population size. The units of analysis are not cities *proper*, but metropolitan areas that often aggregate cities within geographic proximity (e.g. Metro Manila is composed of the city of Manila and surrounding cities such as Quezon City).

To create a symmetric composite network, intercity road, rail, and air connectivity data were first collected in the form of nonstop weekly frequencies in February 2016 from online bus/ferry and rail ticketing systems of individual countries and SkyScanner's commercial flight search engine, respectively. The data were cross-validated with multiple sources. Then the data in each individual network were logged and normalized, ranging from 0 (no connectivity) to 1 (strongest connectivity), after which the composite transport network was produced by averaging transformed dyadic values in three individual networks.

In Chapter 4, a third criterion was added to select cities: 3) in order to produce a more balanced geographical distribution, we also included the four largest cities in the vast but sparsely populated islands of Sulawesi, Maluku and western half of New Guinea even though these cities had less than 0.5 million inhabitants. Hence, the resulting composite transport network specified the connectivity among 51 major cities in Southeast Asia.

1.4.2 Intercity air transport linkages

The second type of data are intercity air transport linkages, and are used in Chapters 3 and 5. The air transport data refers to nonstop flights and air passengers scheduled between any pair of airports within Southeast Asia, as collected from the Official Airline Guide (OAG) database. Each airport city represents a single node except for a number of aggregations related with the presence of multi-airport cities (cf. Derudder et al., 2010), i.e. a combination of Suvarnabhumi and Don Mueang into Bangkok, Kuala Lumpur International and Sultan Abdul Azziz Shah into Kalua Lumpur, Soekarno-Hatta and Halim Perdana Kusuma into Jakarta, and Changi and Seletar into Singapore.

The symmetric air network can be binary, with 1 denoting the presence of nonstop flights between two cities in one year and 0 denoting the absence, or weighted by the number of air passengers in the year under study. Chapter 3 utilizes a binary air transport network from 1979 to 2012 to explore the evolution of topological structure and also utilized weighted air transport network in 1979, 1996, and 2012 to explore the changing geography of multilayered structure. Chapter 5 used the weighted air transport network in 2012.

1.5 Organization of the dissertation

Figure 1.5 shows the structure of this dissertation, specifying how the title, research questions and chapters are related, as well as data and methodologies used in each chapter. There are six chapters, i.e. this introduction, four formative chapters that collectively answer the two research questions, and the conclusions. Chapters 2-5 correspond to papers that have been published or prepared for publication in international peer-reviewed journals.

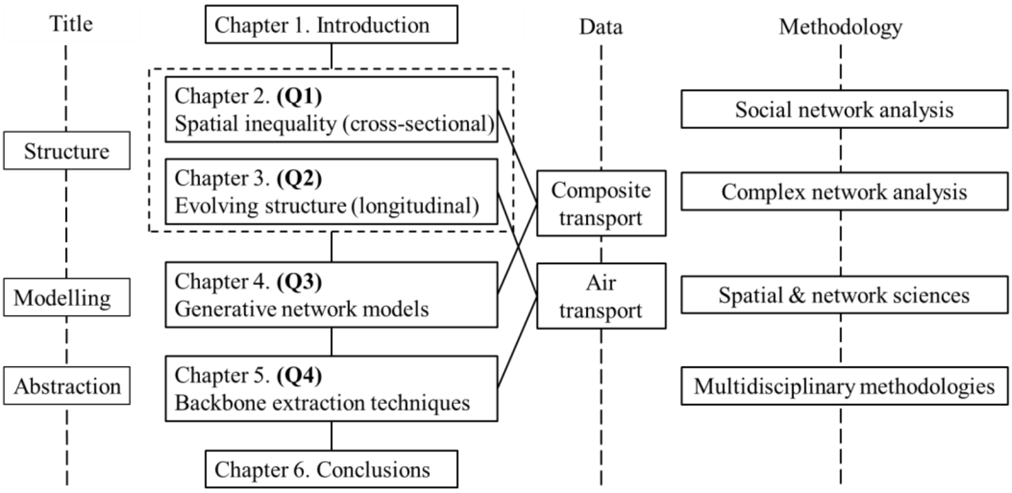


Figure 1.5 Overview of the dissertation.

Inspired by the idea of multiplex network analysis, Chapter 2 analyzes the Southeast Asian urban network created by the ensemble of intercity road, rail, and air connectivity in 2016. Using a social network analysis perspective, three different centrality (degree, closeness, and betweenness centrality) of cities are examined, and four closely interconnected communities are detected. This study takes into account the complementarity of multimodal transportation in Southeast Asia and sheds light on the spatial inequality in this region from an urban network perspective.

Chapter 3 investigates the evolving structure of the Southeast Asian urban network from 1979 to 2012 through the lens of complex network theory. To our knowledge, both the topological properties of the entire network and the multilayered structures are examined for the first time in this study. On the one hand, the study of topological properties offers insights into the common grounds the Southeast Asia urban network shares with other regions' as well as the specific features it exhibits. On the other hand, the study of multilayered structures enhances our understanding of the development of cities at different levels in Southeast Asia.

In Chapter 4, extending the work of Vinciguera et al. (2010) and Vértes et al. (2012), who incorporate both spatial and topological factors to model networks, we present a generative network model combining factors commonly analyzed through traditional spatial simulation models (e.g., gravity-type models) and topological simulation models (e.g., SABM). In our model, it is assumed that the probability of connections between cities emerges from competing forces. Stimulating factors are a measure of city size (i.e., population) and a topological rule favoring the formation of connections between cities sharing nearest neighbors (i.e., transitive effects). The hampering factors are physical distance between two cities as well as institutional distance (i.e., border effects). We discuss the model in the context of on-going engagements between urban-geographical research and the network science literature, and validate the credence of the model against empirical data on the composite transport linkages connecting 51 major cities in Southeast Asia.

In Chapter 5, we review six frequently-used methods from different scientific fields to extract network backbones, i.e. global weight thresholding, k-core decomposition, minimum spanning tree, primary linkage analysis, multiple linkage analysis, and the disparity filter algorithm. We then present a conceptual and experimental comparison of backbone extraction techniques in the context of urban networks in general and transport network in particular. In addition, we explore under which circumstances or for which research objective the different techniques are particularly useful (or less so). The Southeast Asian intercity air transport network in 2012 are used as an empirical case in this chapter.

The sixth and final chapter of this dissertation summarizes the main findings drawn from the combined conclusions of the previous chapters, and outlines some avenues for further research.

The four formative chapters are co-authored papers. I am the corresponding author for Chapter 2 and I was responsible for data collection, data analysis, as well as preliminary interpretation and discussion of the results. For Chapter 3-5 where I am the first author, I conducted the data collection and statistical analysis, and oversaw the interpretation of results manuscript preparation. My co-authors' work was mainly found in helping better framing the research, assisting with concrete technical difficulties, and improving the manuscript in terms of research objectives and language. The first and final chapter of this dissertation were entirely completed by myself.

References

Acharya, A., 2000. The Quest for Identity. International Relations of Southeast Asia. Oxford University Press, Singapore.

Alderson, A.S., Beckfield, J., 2004. Power and Position in the World City System. American Journal of sociology 109, 811-851.

ASEAN Secretariat, 2011. Master plan on ASEAN connectivity, Jakarta. Http://www.asean.org/storage/images/ASEAN_RTK_2014/4_Master_Plan_on_ASEAN_Connectivity.pdf.

ASEAN Secretariat, 2016a. ASEAN Economic Community Chartbook 2016, Jakarta. Http://www.aseanstats.org/wp-content/uploads/2016/11/AEC-Chartbook-2016-1.pdf.

ASEAN Secretariat, 2016b. ASEAN Investment Report 2016: Foreign Direct Investment and MSME Linkages, Jakarta. http://asean.org/storage/2016/09/ASEAN-Investment-Report-2016.pdf.

Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509-512.

Barthélemy, M., 2011. Spatial networks. Physics Reports 499, 1-101.

Berry, B., Pred, A., 1961. Central place studies. A bibliography of theory and applications. Regional Science Research Institute, Philadelphia.

Blondel, V., Krings, G., Thomas, I., 2010. Regions and borders of mobile telephony in Belgium and in the Brussels metropolitan zone. Brussels Studies 42, 1-12.

Borgatti, S.P., Everett, M.G., 1997. Network analysis of 2-mode data. Social Networks 19, 243-269.

Bourne, L.S., Simmons, J.W., 1978. Systems of cities: readings on structure growth and policy. Oxford University Press, New York, U.S.

Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. Journal of Transport Geography 8, 25-41.

Bowen, J., Leinbach, T.R., 2006. Competitive advantage in global production networks: air freight services and the electronics industry in Southeast Asia. Economic Geography 82, 147-166.

Broekel, T., Balland, P.A., Burger, M., Oort, F.v., 2014. Modeling knowledge networks in economic geography: A discussion of four empirical strategies. The Annals of Regional Science 53, 423-452.

Bruinsma, F., Rietveld, P., 1993. Urban agglomerations in European infrastructure networks. Urban Studies 30, 919-934.

Bunge, W., 1966. Theoretical geography. Lund studies in Geography, Royal University of Lund, Series C, No.1.

Burger, M.J., Meijers, E.J., 2016. Agglomerations and the rise of urban network externalities. Papers in Regional Science 95, 5-15.

Camagni, R., 1993. From city hierarchy to city network: reflections about an emerging paradigm, In: Lakshmanan, T.R., Nijkamp, P. (Eds.), Structural and change in the space economy. Springer, Berlin, Germany, pp. 66-87.

Capello, R., 2000. The city network paradigm: measuring urban network externalities. Urban Studies 37, 1925-1945.

Castells, M., 1996. The information age: Economy, society, and culture. Volume I: The rise of the network society. Blackwell, Oxford, UK.

Cats, O., 2017. Topological evolution of a metropolitan rail transport network: The case of Stockholm. Journal of Transport Geography 62, 172-183.

Choi, J.H., Barnett, G.A., Chon, B.-S., 2006. Comparing world city networks: A network analysis of Internet backbone and air transport intercity linkages. Global Networks 6, 81-99.

Christaller, W., 1933. Die zentralen Orte in Süddeutschland. Gustav Fischer, Jena, Germany.

Coclanis, P.A., Doshi, T., 2000. Globalization in Southeast Asia. The ANNALS of the American Academy of Political and Social Science 570, 49-64.

Coe, N.M., Hess, M., Yeung, H.W.C., Dicken, P., Henderson, J., 2004. 'Globalizing'regional development: a global production networks perspective. Transactions of the Institute of British Geographers 29, 468-484.

Darabos, C., White, M.J., Graham, B.E., Leung, D.N., Williams, S.M., Moore, J.H., 2014. The multiscale backbone of the human phenotype network based on biological pathways. BioData mining 7, 1-18.

Dennis, N., 2005. Industry consolidation and future airline network structures in Europe. Journal of Air Transport Management 11, 175-183.

Derudder, B., 2008. Mapping global urban networks: A decade of empirical world cities research. Geography Compass 2, 559-574.

Derudder, B., Devriendt, L., Witlox, F., 2010a. A spatial analysis of multiple airport cities. Journal of Transport Geography 18, 345-353.

Derudder, B., Liu, X., Kunaka, C., Roberts, M., 2014. The connectivity of South Asian cities in infrastructure networks. Journal of Maps 10, 47-52.

Derudder, B., Taylor, P., 2016. Change in the world city network, 2000–2012. The Professional Geographer 68, 624-637.

Derudder, B., Taylor, P.J., 2017. Central flow theory: comparative connectivities in the world-city network. Regional studies, 1-14.

Derudder, B., Taylor, P.J., 2017. Classification of cities 2016. GaWC Research Project 98, Retrived on 31 March, from website http://www.lboro.ac.uk/gawc/world2016.html.

Derudder, B., Timberlake, M., Witlox, F., Taylor, P., Ni, P., De Vos, A., Hoyler, M., Hanssens, H., Bassens, D., 2010b. Pathways of change: Shifting connectivities in the world city network, 2000-08. Urban Studies 47, 1861-1877.

Dick, H., 2005. Southeast Asia as an Open System:Geo-politics and Economic Geography, In: Kratoska, P.H., Raben, R., Nordholt, H.S. (Eds.), Locating Southeast Asia. Geographies of knowledge and politics of space. Singapore University Press, Singapore, pp. 250-274.

Dick, H.W., Rimmer, P.J., 1998. Beyond the third world city: the new urban geography of South-east Asia. Urban Studies 35, 2303-2321.

Du, W.-B., Zhou, X.-L., Lordan, O., Wang, Z., Zhao, C., Zhu, Y.-B., 2016. Analysis of the Chinese Airline Network as multi-layer networks. Transportation Research Part E: Logistics and Transportation Review 89, 108-116.

Ducruet, C., 2017. Multilayer dynamics of complex spatial networks: The case of global maritime flows (1977-2008). Journal of Transport Geography 60, 47-58.

Ducruet, C., Beauguitte, L., 2014. Spatial Science and Network Science: Review and Outcomes of a Complex Relationship. Networks and Spatial Economics 14, 297-316.

Ducruet, C., Ietri, D., Rozenblat, C., 2011. Cities in worldwide air and sea flows: a multiple networks analysis. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 528, posted March 531, 2011.

Ducruet, C., Lugo, I., 2013. Structure and dynamics of transportation networks: Models, methods and applications, In: Rodrigue, J.-P., Notteboom, T., Shaw, J. (Eds.), The SAGE handbook of transport studies. SAGE, pp. 347-364.

Ducruet, C., Notteboom, T., 2012. The worldwide maritime network of container shipping: Spatial structure and regional dynamics. Global Networks 12, 395-423.

Ducruet, C., Rozenblat, C., Zaidi, F., 2010. Ports in multi-level maritime networks: Evidence from the Atlantic (1996–2006). Journal of Transport Geography 18, 508-518.

Ducruet, C., Zaidi, F., 2012. Maritime constellations: a complex network approach to shipping and ports. Maritime Policy & Management 39, 151-168.

Dutt, A.K., Costa, F.J., Aggarwal, S., Noble, A., 1994. The Asian City: Processes of Development, Characteristics and Planning. Kluwer Academic Publishers, Dordrecht, the Netherlands.

Dutt, A.K., Song, N., 1996. Urbanization in Southeast Asia, In: Dutt, A.K. (Ed.), Southeast Asia: A Ten Nation Region. Kluwer Academic Publishers, Dordrecht, the Netherlands, pp. 95-116.

Fleming, D.K., Hayuth, Y., 1994. Spatial characteristics of transportation hubs: centrality and intermediacy. Journal of Transport Geography 2, 3-18.

Florida, R., 2008. Who's Your City? How the Creative Economy in Making Where to Live the most Important Decision of Your Life. Basic Books, New York, U.S.

Foti, N.J., Hughes, J.M., Rockmore, D.N., 2011. Nonparametric sparsification of complex multiscale networks. PloS one 6, e16431.

Freeman, D.B., 1996. Doi Moi policy and the small-enterprise boom in Ho Chi Minh City, Vietnam. Geographical Review 86, 178-197.

Frobel, F., Heinrichs, J., Kreye, O., 1980. The new international division of labour: structural unemployment in industrialised countries and industrialisation in developing countries. Cambridge University Press, Cambridge, UK.

Fuellhart, K., O'Connor, K., 2013. Air Services at Australian Cities: Change and Inertia 2005-2010. Geographical Research 51, 37-48.

Gemmetto, V., Cardillo, A., Garlaschelli, D., 2017. Irreducible network backbones: unbiased graph filtering via maximum entropy. Https://arxiv.org/abs/1706.00230.

Ginsburg, N., 1991. Extended metropolitan regions in Asia: a new spatial paradigm, In: Ginsburg, N., Koppel, B., MCgee, T.G. (Eds.), The extended metropolis: Settlement transition in Asia. University of Hawaii press, Honolulu.

Gottmann, J., 1989. What are cities becoming the centers of? Sorting out the possibilities, In: Knight, R.V., Gappert, G. (Eds.), Cities in a Global Society. Sage, Newbury Park, CA, pp. 58-67.

Grubesic, T.H., Matisziw, T.C., Zook, M.A., 2008. Global airline networks and nodal regions. Geojournal 71, 53-66.

Guimera, R., Mossa, S., Turtschi, A., Amaral, L.A.N., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. Proceedings of the National Academy of Sciences 102, 7794-7799.

Haggett, P., Chorley, R.J., 1969. Network analysis in geography. Edward Arnold, London, UK.

Haggett, P., Cliff, A.D., Frey, A., 1977. Locational analysis in human geography. Edward Arnold, London.

Hall, P.G., Pain, K., 2006. The polycentric metropolis: learning from mega-city regions in Europe. Routledge.

Hennemann, S., 2013. Information-rich visualisation of dense geographical networks. Journal of Maps 9, 68-75.

Hennemann, S., Derudder, B., 2014. An alternative approach to the calculation and analysis of connectivity in the world city network. Environment and Planning B 41, 392-412.

Hill, H., Menon, J., 2012. ASEAN economic integration: Driven by markets, bureaucrats, or both?, In: Kreinin, M.E., Plummer, M.G. (Eds.), The Oxford Handbook of International Commercial Policy. Oxford University Press, Oxford, UK, pp. 357-386.

Huff, G., Angeles, L., 2011. Globalization, industrialization and urbanization in Pre-World War II Southeast Asia. Explorations in Economic History 48, 20-36.

Jacobs, J., 1969. The economy of cities. Vintage Books, New York.

Jones, G.W., 1997. The throughgoing urbanisation of East and Southeast Asia. Asia Pacific Viewpoint 38, 237-249.

Jones, G.W., 2002. Southeast Asian urbanization and the growth of mega-urban regions. Journal of Population Research 19, 119-136.

Jönsson, K., 2010. Unity-in-Diversity? Regional Identity-building in Southeast Asia. Journal of Current Southeast Asian Affairs 29, 41-72.

Karwa, V., Petrović, S., Bajić, D., 2016. DERGMs: Degeneracy-restricted exponential random graph models. arXiv preprint arXiv:1612.03054.

Keeling, D.J., 1995. Transport and the world city paradigm, In: Knox, P.L., Taylor, P.J. (Eds.), World cities in a world-system. Cambridge University Press, Cambridge, UK, pp. 115-131.

Krackardt, D., 1987. QAP partialling as a test of spuriousness. Social Networks 9, 171-186.

Latapy, M., Magnien, C., Del Vecchio, N., 2008. Basic notions for the analysis of large two-mode networks. Social Networks 30, 31-48.

Li, Z., Dawood, S.R.S., 2017. Examining Inter-city connections in Southeast Asia based upon interlocking city network model. International Journal of Advanced and Applied Sciences 4, 110-115.

Lin, J., Ban, Y., 2013. Complex network topology of transportation systems. Transport Reviews 33, 658-685.

Liu, X., Derudder, B., 2013. Analyzing urban networks through the lens of corporate networks: A critical review. Cities 31, 430-437.

Liu, X., Derudder, B., Liu, Y., 2013a. Regional geographies of intercity corporate networks: The use of exponential random graph models to assess regional network-formation. Papers in Regional Science.

Liu, X., Derudder, B., Liu, Y., Witlox, F., Shen, W., 2013b. A stochastic actor-based modelling of the evolution of an intercity corporate network. Environment and Planning A 45, 947-966.

Liu, X., Derudder, B., Taylor, P., 2014. Mapping the evolution of hierarchical and regional tendencies in the world city network, 2000–2010. Computers, Environment and Urban Systems 43, 51-66.

Liu, X., Neal, Z., Derudder, B., 2012. City networks in the United States: a comparison of four models. Environment and Planning A 44, 255-256.

Lo, F.C., Yeung, Y.M., 1996. Emerging World Cities in Pacific-Asia. United Nations University Press, Tokyo.

Lösch, A., 1944. Die Räumliche Ordnung der Wirtschaft. Gustav Fischer, Jena, Germany.

Macleod, S., McGee, T.G., 1996. The Singapore-Johore-Riau growth triangle: an emerging extended metropolitan region, In: Lo, F.C., Yeung, Y.M. (Eds.), Emerging World Cities in Pacific-Asia. United Nations University Press, Tokyo, pp. 417-464.

Matsumoto, H., 2004. International urban systems and air passenger and cargo flows: some calculations. Journal of Air Transport Management 10, 239-247.

Matsumoto, H., 2007. International air network structures and air traffic density of world cities. Transportation Research Part E: Logistics and Transportation Review 43, 269-282.

McCann, P., Acs, Z.J., 2011. Globalization: countries, cities and multinationals. Regional studies 45, 17-32.

McGee, T.G., 1967. The Southeast Asian city: a social geography of the primate cities of Southeast Asia. S. Bell and Sons, London, UK.

McGee, T., 2009. The spatiality of urbanization: the policy challenges of mega-urban and Desakota Regions of Southeast Asia. UNU-IAS Working Paper No. 161. United Nations University-Institute for Advance Studies, Yokohama, Japan.

McGee, T., Greenberg, C., 1992. The emergence of extended metropolitan regions in ASEAN: towards the year 2000. ASEAN Economic Bulletin, 22-44.

McGee, T.G., Robinson, I.M., 1995. The Mega-urban Regions of Southeast Asia. University of British Columbia Press, Vancouver.

Neal, Z., 2011. Differentiating Centrality and Power in the World City Network. Urban Studies 48, 2733-2748.

Neal, Z., 2013a. Brute force and sorting processes: two perspectives on world city network formation. Urban Studies 50, 1277-1291.

Neal, Z., 2013b. Does world city network research need eigenvectors? Urban Studies 50, 1648-1659.

Neal, Z., 2013c. Identifying statistically significant edges in one-mode projections. Social Network Analysis and Mining 3, 915-924.

Neal, Z., 2014. The backbone of bipartite projections: Inferring relationships from co-authorship, co-sponsorship, co-attendance and other co-behaviors. Social Networks 39, 84-97.

Newman, M., Girvan, M., 2004. Finding and evaluating community structure in networks. Physical Review E 69, 026113.

Nystuen, J.D., Dacey, M.F., 1961. A graph theory interpretation of nodal regions. Papers of the Regional Science Association 7, 29-42.

Pflieger, G., Rozenblat, C., 2010. Urban networks and network theory: the city as the connector of multiple networks. Urban Studies 47, 2723-2735.

Pred, A., 1977. City-systems in advanced economies. Hutchinson, London, UK.

Radicchi, F., Ramasco, J.J., Fortunato, S., 2011. Information filtering in complex weighted networks. Physical review E 83, 046101.

Reed, R.R., 1976. Indigenous urbanism in Southeast Asian cities, In: Yeung, Y.M. (Ed.), Changing Southeast Asian Cities Oxford University Press, Oxford, UK, pp. 20-21.

Reed, W.J., 2003. The Pareto law of incomes-an explanation and an extension. Physica A: Statistical Mechanics and its Applications 319, 469-486.

Rimmer, P.J., 1995. Moving goods, people, and information: putting the ASEAN mega-urban regions in context, In: McGee, T.G., Robinson, I.M. (Eds.), The Mega-urban Regions of Southeast Asia. University of British Columbia Press, Vancouver, pp. 150-175.

Rimmer, P.J., 2000. Effects of the Asian Crisis on the geography of Southeast Asia's air traffic. Journal of Transport Geography 8, 83-97.

Rimmer, P.J., Dick, H.W., 2009. The city in Southeast Asia: Patterns, processes and policy. NUS Press, Singapore.

Sassen, S., 1991. The Global City: New York, London, Tokyo. Princeton University Press, Princeton NJ, U.S.

Scholte, J.A., 2000. Globalization, a Critical Introduction. Palgrave Macmillan, London.

Shatkin, G., 2008. The city and the bottom line: urban megaprojects and the privatization of planning in Southeast Asia. Environment and Planning A 40, 383-401.

Shin, K.-H., Timberlake, M., 2000. World cities in Asia: cliques, centrality and connectedness. Urban Studies 37, 2257-2285.

Sien, C.L., 2003. Southeast Asia transformed: a geography of change. Institute of Southeast Asian Studies, Singapore.

Smith, D., 2003. Rediscovering Cities and Urbanization in the 21st Century World-System, In: Dunaway, W.A. (Ed.), Emerging Issues in the 21st Century World-system: New theoretical directions for the 21st century world-system. Greenwood Publishing Group, Westport, CT, pp. 111-129.

Smith, D.A., Timberlake, M.F., 2001. World City Networks and Hierarchies, 1977-1997: An Empirical Analysis of Global Air Travel Links. American Behavioral Scientist 44, 1656-1678.

Snijders, T.A., Van de Bunt, G.G., Steglich, C.E., 2010. Introduction to stochastic actor-based models for network dynamics. Social Networks 32, 44-60.

Snijders, T.A.B., Pattison, P.E., Robins, G.L., Handcock, M.S., 2006. New specifications for exponential random graph models. Sociological Methodology 35, 99-153.

Stam, C.J., Reijneveld, J.C., 2007. Graph theoretical analysis of complex networks in the brain. Nonlinear biomedical physics 1, 3.

Stærkebye, J.O.F., 2005. Regional integration in Southeast Asia: Indonesia's and Malaysia's approach to ASEAN analysed with regard to AFTA and the Myanmar crisis. University of Oslo, oslo, Norway.

Tanaka, K., 2009. Regional Integration in Southeast Asia: Better Macroeconomic Co-operation Can Mitigate Risks. OECD Development Centre Policy Insights 90, OECD Publishing.

Taylor, P.J., 2001. Specification of the world city network. Geographical Analysis 33, 181-194.

Taylor, P.J., 2003. World city network: A global urban analysis. Routledge, London.

Taylor, P.J., Hoyler, M., Verbruggen, R., 2010. External urban relational process: introducing central flow theory to complement central place theory. Urban Studies 47, 2803-2818.

Thant, M., 2012. Regional cooperation and the changing urban landscape of Southeast Asia, In: Sheng, Y.K., Thuzar, M. (Eds.), Urbanization in Southeast Asia: Issues & impacts. Institute of Southeast Asian Studies, Singapore, pp. 154-171.

Thompson, E.C., 2013. In Defence of Southeast Asia: A Case for Methodological Regionalism. TRaNS: Trans-Regional and-National Studies of Southeast Asia 1, 281-302.

Tobler, W.R., 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography 46, 234-240.

Tranos, E., Gillespie, A., 2011. The urban geography of Internet backbone networks in Europe: roles and relations. Journal of Urban Technology 18, 35-50.

Tsiotas, D., Polyzos, S., 2017. The Complexity in the Study of Spatial Networks: an Epistemological Approach. Networks and Spatial Economics, 1-32.

Van Meeteren, M., Neal, Z., Derudder, B., 2016. Disentangling agglomeration and network externalities: A conceptual typology. Papers in Regional Science 95, 61-80.

Van Nuffel, N., Derudder, B., Witlox, F., 2010. Even important connections are not always meaningful: on the use of a polarisation measure in a typology of European cities in air transport networks. Tijdschrift voor economische en sociale geografie 101, 333-348.

Verma, T., Araújo, N.A., Herrmann, H.J., 2014. Revealing the structure of the world airline network. Scientific reports 4, 5638.

Vértes, P.E., Alexander-Bloch, A.F., Gogtay, N., Giedd, J.N., Rapoport, J.L., Bullmore, E.T., 2012. Simple models of human brain functional networks. Proceedings of the National Academy of Sciences 109, 5868-5873.

Vertesi, J., 2008. Mind the gap the london underground map and users' representations of urban space. Social Studies of Science 38, 7-33.

Vinciguerra, S., 2012. The Geography, Structure and Evolution of Infrastructure Networks in Europe. Utrecht University, Utrecht, the Netherlands.

Vinciguerra, S., Frenken, K., Valente, M., 2010. The geography of Internet infrastructure: An evolutionary simulation approach based on preferential attachment. Urban Studies 47, 1969-1984.

Walsh, J.C., 2010. Land transportation network development in the Greater Mekong Sub-region. Journal of Management 8, 17-29.

Wang, J., Jin, F., Mo, H., Wang, F., 2009. Spatiotemporal evolution of China's railway network in the 20th century: An accessibility approach. Transportation Research Part A: Policy and Practice 43, 765-778.

Wang, J., Mo, H., Wang, F., 2014. Evolution of air transport network of China 1930-2012. Journal of Transport Geography 40, 145-158.

Wang, J., Mo, H., Wang, F., Jin, F., 2011. Exploring the network structure and nodal centrality of China's air transport network: A complex network approach. Journal of Transport Geography 19, 712-721.

Wang, Y., Cullinane, K., 2014. Traffic consolidation in East Asian container ports: a network flow analysis. Transportation Research Part A: Policy and Practice 61, 152-163.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of 'small-world'networks. Nature 393, 440-442.

Yap, J.T., 2014. Addressing Inequality in Southeast Asia through Regional Economic Integration. Institute of Developing Economies, Tokyo, Japan. Retrieved from website: http://www.ide.go.jp/English/Publish/Download/Brc/pdf/14_01.pdf.

Yap, K.S., Thuzar, M., 2012. Urbanization in Southeast Asia: Issues & Impacts. ISEAS Publishing, Singapore.

Yeung, H.W.-c., 2001. Organising regional production networks in Southeast Asia: implications for production fragmentation, trade, and rules of origin. Journal of Economic Geography 1, 299-321.

Yeung, Y.-m., 2011. Rethinking Asian cities and urbanization: Four transformations in four decades. Asian Geographer 28, 65-83.

Yeung, Y.M., Lo, F.C., 1996. Global restructuring and emerging urban corridors in Pacific Asia, In: Lo, F.C., Yeung, Y.M. (Eds.), Emerging World Cities in Pacific-Asia. United Nations University Press, Tokyo, pp. 17-47.

Zhang, P., Peeta, S., 2011. A generalized modeling framework to analyze interdependencies among infrastructure systems. Transportation Research Part B: Methodological 45, 553-579.

Zhang, S., Derudder, B., Witlox, F., 2016. Dynamics in the European air transport network, 2003-9: an explanatory framework drawing on stochastic actor-based modeling. Networks and Spatial Economics 16, 643-663.

Zhao, M., Liu, X., Derudder, B., Zhong, Y., Shen, W., 2015a. Mapping producer services networks in mainland Chinese cities. Urban Studies 52, 3018-3034.

Zhao, M., Wu, K., Liu, X., Derudder, B., 2015b. A novel method for approximating intercity networks: An empirical comparison for validating the city networks in two Chinese city-regions. Journal of Geographical Sciences 25, 337-354.

Zook, M.A., 1999. Old hierarchies or new networks of centrality? The global geography of the internet content market. American Behavioral Scientist 44, 1679-1696.

Chapter 2 Spatial inequality in the Southeast Asian intercity transport network

Liu, X., Dai, L.*, Derudder, B., 2017. Spatial inequality in the Southeast Asian intercity transport network. Geographical Review 107, 317-335.

Abstract

Spatial inequality in transport access is both the driver and outcome of rising economic inequality in Southeast Asia. Unlike many regional disparity studies that focus on national economic indicators, this paper takes an urban network approach to assess the spatial inequality in Southeast Asian intercity transport network. We analyze urban connectivity in intercity road, rail, and air networks for a total of 47 Southeast Asian cities. Spatial inequality at the city and network level is revealed via centrality measures and community detection, respectively. Gini coefficients for individual centrality rankings point to a hierarchical degree distribution, a rather even distribution of closeness centrality, and a highly concentrated distribution of betweenness centrality. Four network communities are identified, reflecting the influences of entrenched uneven development, fragmented geography, and economic and political policies.

2.1 Introduction

Economic inequality has been rising in Southeast Asia in the past few decades (Yap, 2014). Spatial inequality in transport access is both the driver and outcome of rising economic inequality. On the one hand, economic development in Southeast Asia has long been constrained by its ‘tyranny of geography’ (Armstrong and Read, 2006). The fragmented and tropical geography has inhibited efficient transportation and the formation of an integrated market (Hooper, 2005). Areas with better physical infrastructure and transport access would benefit from lower transaction costs, larger market size, and higher chances of attracting foreign direct investment (Munnell, 1992; Fujimura, 2004; Walsh, 2010). On the other hand, existing spatial inequality in transport access is conditioned on uneven economic growth, as improving physical connectivity requires substantial public investments.

Therefore, spatial inequality in transport access has always been high on regional and national agendas. For example, developing efficient and extensive transportation networks is highlighted in various Association of Southeast Asian Nations (ASEAN) initiatives (Goh, 2008; Bhattacharyay, 2009). More recently, Asian Development Bank and Asian Infrastructure Investment Bank are actively seeking to help Southeast Asian countries develop infrastructure networks. Flagship projects include Singapore to Kunming, China railroads and high speed rail networks in Thailand. National imperatives also feature predominantly in this process. Beyond economic functions, the development of transportation networks has been instrumental in social and political changes of ASEAN countries (Kuroda, 2008), ranging from promoting national unification and integration (Kissling, 1989; Raguraman, 1997), to boosting (labor) migration (Pye et al. 2012), and to minimizing rural-urban inequalities (Sabandar, 2007).

Rather than examining Southeast Asia as comprised of national political units and based on national statistics, this paper will employ a network approach to explore the spatial inequality of transportation connections between Southeast Asian cities. Bunnell (2013) suggests that this network approach would present an alternative geography of Southeast Asia as comprised of a network of cities and thus challenges the ‘methodological nationalism’ in area studies. Meanwhile, employing a network approach is consistent with the new network paradigm in the ‘urban system’ literature (e.g., Camagni, 1993; Castells, 2001). The network paradigm departs from some of the ‘conventional’ approaches of studying urban hierarchies in that the focus is no longer on the ‘characteristics’ or ‘attributes’ of cities in and by themselves (e.g. population size and number of companies; e.g., Tonts and Taylor 2010). Using data on intercity connections has thereupon become an increasingly popular way to examine urban hierarchies (Grubesic et al., 2011). Still, we acknowledge the danger of upscaling ‘methodological nationalism’ to ‘methodological regionalism’ by conceptualizing Southeast Asia through the lens of transnational urban networks (Bunnell, 2013). For example, intercity flows of capital, information, and goods are not confined within regional boundaries, thus problematizing the very regional framings such as ‘Southeast Asia’ and ‘ASEAN’. Nevertheless, Thompson (2013) argues that regional entities such as ‘Southeast Asia’ remain valuable in both practices and scholarship.

Using an urban network perspective, our exploratory analysis focuses on the spatial inequality of transportation connections in two levels. First, we look into how well individual cities are connected in transportation networks, i.e., inequality of network connections at the nodal level. This enables us to reveal the hierarchical geography of transportation connections produced by the layered economic, political and social processes in Southeast Asia. For example, Pacific Rim cities such as Kuala Lumpur and Singapore are emerging as well-connected world cities (Perry et al., 1997; Taylor et al., 2000; Bunnell et al., 2002), while cities like Phnom Penh are in dire need of adequate road infrastructure (Motomura, 1996). Second, our analysis will identify groups of cities that are more densely connected to each other, i.e., inequality of transportation connections at the network level. In the context of urban networks, groups of densely connected cities form network ‘clusters’, where intra-cluster connections are stronger than inter-cluster linkages (Derudder et al., 2003). These clusters correspond to network-based regions in economic geography and reflect functional (economic) integration across cities (Liu et al. 2015). Regional integration policies (e.g., Brunei Darussalam-Indonesia-Malaysia-Philippines East ASEAN Growth Area (BIMP-EAGA) are deemed important for reducing economic inequality in Southeast Asia (Yap, 2014), generating intercity traffic flows and fostering network-based city-regions.

Although several studies have examined individual cities' positions with Southeast Asian transportation networks, especially airline networks, they often (1) analyse a limited set of cities (e.g., O'Connor, 1995); (2) focus on one transportation mode (Bowen, 2000); and/or (3) are limited to one network indicator such as degree centrality (Taylor et al., 2000). Thus, the overall pattern of the connectivity of cities in transportation networks remains unclear (Yap and Thuzar, 2012). Against this backdrop, we measure how major cities in Southeast Asian are connected in the ensemble of road, air, and rail transportation networks. More specifically, we will explore the inequality of transportation connectivity across cities and look into (1) which cities are important in Southeast Asian transportation networks based on a set of network centrality measures (i.e., inequality of transport access at the city level); and (2) which groups of cities are more connected to each other, forming densely connected network-based sub-regions (i.e., inequality of transport access at the network level).

In the next section, we report the construction of a composite measure of urban infrastructural connectivity as well as details the centrality measures and community detection algorithms employed to reveal network-based regions. The paper concludes with a discussion of major network patterns of intercity transportation networks in Southeast Asia, and points to avenues for future research.

2.2 Data and methods

2.2.1 Data

We analyze urban connectivity in intercity road, rail and air networks for a total of 47 Southeast Asian cities (Figure 2.1). Countries under investigation include Brunei, Cambodia, East Timor, Indonesia, Laos, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam (i.e., all ten members of ASEAN plus East Timor, which has submitted its bid to join). Cities are selected based on the following criteria: (1) all metropolises with more than half a million residents (based on citypopulation.de's data); and (2) all capital cities (e.g., Vientiane, Laos and Dili, East Timor) are included regardless of their population size. The units of analysis are not cities *proper*, but metropolitan areas that often aggregate cities within geographic proximity (e.g., Metro Manila is composed of the city of Manila and surrounding municipalities). We adopt this working definition of cities as many nearby cities are functionally connected and share infrastructures.

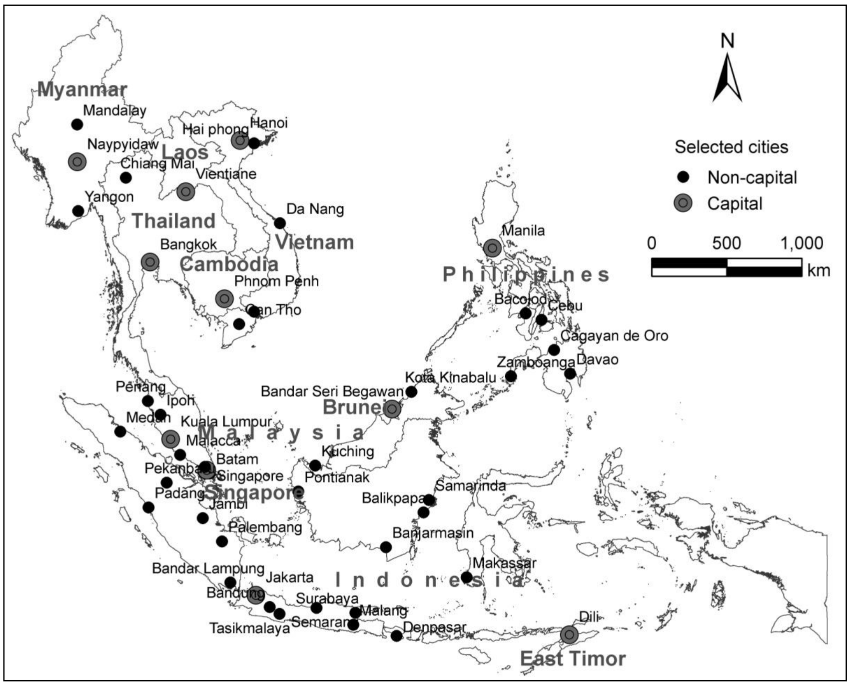


Figure 2.1 Distribution of selected cities in Southeast Asia.

The data collection process thus creates a 47-by-47 matrix, capturing intercity transportation links for passenger flows between the selected 47 cities. The intercity transportation network is constructed as a composite network of three different layers, i.e., rail, road, and air connections. Each of the three layers contains 47 x (47-1) = 2162 valued dyads. Individual layers and the composite network are treated as symmetric by averaging the values of dyads between city-pairs. Dyadic values reveal the connectivity of Southeast Asian cities, i.e., the strength of connections between individual cities. A higher dyadic value corresponds to more connections, and vice versa. Individual transportation network data are then gathered, transformed and aggregated into a composite network. The collection of individual network layers follows Liu et al. (2015) and is summarized in what follows.

Intercity connectivity in the road network is approximated by the frequency of bus and ferry services. The intercity bus schedule is manually recorded from online ticketing systems of individual countries and cross-referenced with multiple sources. Ferry capacity is estimated and converted to bus-equivalent. The two busiest bus routes are between Kuala Lumpur-Johor Bahru (1673 weekly buses) and Singapore-Johor Bahru (1099).

Data about weekly trains are obtained from websites of railroad agencies and national railroad administrations for individual countries. The strongest rail connections are Kuala Lumpur-Ipoh, Kuala Lumpur-Penang, Kuala Lumpur-Johor Bahru (147, 119 and 63 weekly trains, respectively) in the densely connected Malay Peninsula, followed by Bangkok-Chiang Mai(56) in Thailand, Kuala Lumpur-Johor Bahru-Singapore (49), Jakarta-Semarang (49) in central Java, Indonesia, and Yangon-Mandalay (49) in Myanmar. We note that, due to the region's fragmented and tropical landscape, many cities in Laos, Philippines, and eastern Indonesia are not served by railroads (Nathan, 2002).

The intercity airline network is estimated by the number of direct weekly flights based on SkyScanner's commercial flight search engine (http://www.skyscanner.com). SkyScanner provides information about both traditional and budget airline services. Charter flights are not included due to their rather idiosyncratic nature. Weekly flights data are also cross-referenced with other databases such as Openflights.org. The strongest aviation connection is between Kuala Lumpur-Singapore (582 weekly flights), followed by Ho Chi Min City-Hanoi (522), and Jakarta-Surabaya (465).

All data are collected in the first week of February, 2016. Information about the three individual transport networks is combined to produce a composite network. Applying the following equation thereupon normalized the logged dyadic values in each of the three layers: (original-min)/(max-min), where *max* and *min* denote maximum and minimum dyadic values in individual networks, respectively. All three networks therefore have dyadic values ranging from 0 (no connectivity) to 1 (strongest connectivity). Links in the composite network are produced by averaging transformed dyadic values in individual networks. The end product of the data collection process is an intercity transportation network, which characterizes the connectivity among 47 major cities in Southeast Asia.

In comparison with previous studies of Southeast Asia cities (e.g., O'Connor 1995; Bowen, 2000; Bhattacharyay, 2009; Walsh, 2010; Yap and Thuzar, 2012), our data collection process (1) measures multiple transportation networks and includes a larger array of cities; (2) features a greater geographic coverage by including major cities from all ASEAN countries;

and (3) adopts a systematic approach, thus allowing for replication and longitudinal comparisons.

We acknowledge that our analysis of passenger flows represents a specific instance among multiple urban networks (Burger et al., 2014). Empirical studies of other urban networks (e.g. cargo flows; Lee and Ducruet 2009) may or may not arrive at similar conclusions. Nevertheless, a composite measure of three passenger transportation networks is closely related to amongst other things labor mobility and external investment, thus providing a pertinent reflection of the uneven transport connectivity (Derudder et al., 2014).

2.2.2 Methods

We assess the network hierarchy of individual cities with three network centrality measures: degree, closeness and betweenness. We also perform a network clustering analysis to reveal network-based city clusters. Centrality and community analyses examine the uneven distribution of transportation connections at the city and network level, respectively.

Following Alderson et al., (2010), we illustrate the implications of these centrality measurements and the community detection algorithm with a 'toy' network (Figure 2.2). To ease interpretation, the toy network will be binary and all centrality scores will not be normalized. We note that in the result section, centrality scores will be reported in a normalized fashion (i.e., taking values between 0 and 1; Borgatti and Everett, 2006), to (1) make results independent of network size; and (2) incorporate network weights (different connectivity levels as detailed in the data construction section). Or, put differently: edges are treated as equal in the toy network, while in the real empirical setting they are weighted and represent different levels of connectivity. Our toy network depicts a hypothetical transport network among 11 Southeast Asian cities, whose degree, closeness, and betweenness centrality rankings are presented in Table 2.1.

Degree centrality reflects individual cities' direct connections to other cities. A city is more connected if it has more direct linkages with others. For example, in our toy example, Jakarta and Singapore are more connected with 5 linkages, and smaller Philippines cities Cebu and Davao attain only 2 connections.

Table 2.1 Centrality rankings for the ‘toy’ network.

Rank	City	Degree	City	Closeness	City	Betweenness
1	Singapore	5	Singapore	0.063	Jakarta	23
2	Jakarta	5	Jakarta	0.063	Singapore	21
3	Kuala Lumpur	3	Manila	0.059	Manila	16
4	Bangkok	3	Kuala Lumpur	0.043	Cebu	9
5	Yangon	3	Bangkok	0.043	Kuala Lumpur	0
6	Manila	3	Yangon	0.043	Bangkok	0
7	Surabaya	2	Surabaya	0.042	Yangon	0
8	Bandung	2	Bandung	0.042	Surabaya	0
9	Cebu	2	Cebu	0.042	Bandung	0
10	Palembang	1	Palembang	0.040	Palembang	0
11	Davao	1	Davao	0.030	Davao	0

Closeness centrality measures the overall difficulty for a city to connect with all other cities in the network. Closeness centrality is operationalized by looking at individual cities’ inverse (network) distances to all other nodes. In our toy example, Jakarta and Singapore have higher closeness centrality not only because they have the largest number of direct linkages but also because all other cities are only three ‘steps’ or ‘links’ away. While degree centrality measures the absolute number of connections, closeness centrality partly reflects the overall quality of connections, i.e., whether cities have the *right* connections to access the network at large. For example, while Palembang, Indonesia and Davao, the Philippines both have one connection in our toy network, Palembang has a higher closeness centrality and is therefore more integrated into the regional system. This is because Palembang’s sole connection is with Jakarta, which has many connections and opens doors for Palembang to connect/be connected with other cities. In comparison, Davao’s only direct linkage is with the less well-connected Cebu.

Betweenness centrality captures cities’ brokerage function in the network, i.e., their capability of controlling connections between others. In the toy network, all connections between Davao and other 9 cities (except itself and Cebu) need to go through Cebu, thus giving Cebu a betweenness centrality of 9 as it controls flows in and out of Davao. Within the larger regional context, Jakarta, Singapore, and Manila occupy similar brokerage positions for Indonesian cities, cities in the Indochina Peninsula, and the Philippine cities, respectively.

Connections between cities are not random – cities with social, economic, and geographic proximity are more likely to be connected and form network clusters. Similar to the concept of 'functional regions' in economic geography (Anderson, 2012), a network cluster or community refers to a set of closely connected cities whose within-cluster connections exceed inter-cluster connections. Community detection algorithms build upon the connections between cities and partition the original network into relatively self-contained sub-components. For example, in our toy example, most community detection algorithms would produce three communities (Figure 2.2): a community of cities on the Indochina Peninsula anchored by the city-state of Singapore; a Philippine community consists of Manila, Cebu, and Davao; and a group of Indonesian cities centred on Jakarta. We have tested a number of community detection methods on our composite network and they produce largely consistent results. Therefore, we report community detection results from the 'fast greedy modularity optimization method' (Clauset at al., 2004). All data visualization and analyses are performed on the R platform (Csardi and Nepusz, 2006).

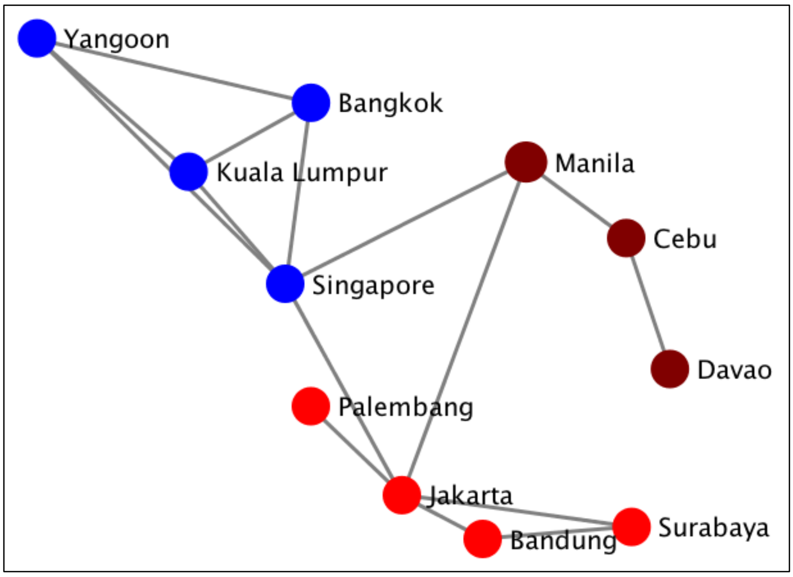


Figure 2.2 The toy network. Cities are colour-coded to represent their community affiliation.

2.3 Results and discussion

2.3.1 Centrality analysis

Centrality analysis reveals the inequality of transport access at the city level in Southeast Asia. Table 2.2 summarizes the three centrality rankings for the 47 Southeast Asian cities. Figure

2.3 visualizes the composite transportation network, where thickness of network links corresponds to connection strength, node sizes denote degree centrality, and node colours are based on community affiliation.

We discern two initial observations from Table 2.2. First, network centralities differ significantly across cities. Singapore, Kuala Lumpur, Jakarta, and Bangkok rank consistently in the top 5 of all rankings (Bowen, 2000). Unsurprisingly, cities in the sparsely populated fringe Indonesian and Philippine provinces occupy bottom spots in all rankings (Santosa and Joewono, 2005). Second, although the ranks of cities point to a general theme (connectivity), there are sizable differences. Gini coefficients for individual centrality rankings point to a rather hierarchical distribution of degree centrality (With a Gini coefficient of 0.390), a relatively evenly distributed closeness centrality (0.118), and a highly hierarchical ranking of betweenness centrality (0.874).

Rather than examining the trajectories of individual cities, several major sets of processes underlying the uneven connectivity are identified: The uneven development which dates back to the colonial times; the region's fragmented and tropical geography; and more recent socioeconomic and political strategies.

First, the spatial inequality of transport connectivity dates back to the colonial era, when different western powers coordinated development within their respective colonies (Dick and Rimmer, 2003). In order to consolidate territorial control and facilitate the extraction of natural resources, colonial governments built transportation networks around strategically important cities (Saueressig-Schreu, 1986; Sien, 2003; Lange, 2004). For example, the British linked cities along the Malay Peninsula with railroads (Nathan, 2002), while tracks were laid by the French to connect Hanoi, Vietnam with Kunming, China.

Second, individual cities' connectivity is affected by the region's 'tyranny of geography', including the mountainous terrain, insularity, remoteness within the global context, as well as many archipelago countries (Armstrong and Read, 2006). This is most evidenced by the Philippine island cities in our analysis. The lack of rail and bus linkages has further 'penalizes' these cities when being compared at the regional level.

Third, intercity transport connections are oftentimes related to economic and political projects. For example, Singapore's drive to development high value-added services is supported by the city-state's reliable transportation connections (Lo and Yeung, 1996; Yeung, 2008) and the overprovision of air transportation capacity (Phang, 2003). For the large archipelagic countries such as Indonesia and the Philippines, national airlines help incorporate cities in remote areas into national development (Kissling, 1989). Similarly, national policies also help shape connections around major cities in Vietnam (Doi Moi, 1986; Durand and Anh, 1996).

Table 2.2 Centrality rankings for 47 Southeast Asian cities. DC: Degree centrality; CC: Closeness centrality; BC: Betweenness centrality.

Rank	City	DC	City	CC	City	BC
1	Singapore	1.000	Singapore	0.186	Jakarta	1.000
2	Kuala Lumpur	0.991	Kuala Lumpur	0.179	Manila	0.436
3	Jakarta	0.909	Jakarta	0.174	Singapore	0.399
4	Surabaya	0.677	Bangkok	0.167	Bangkok	0.362
5	Bangkok	0.632	Penang	0.152	Kuala Lumpur	0.355
6	Ho Chi Minh City	0.518	Johor Bahru	0.152	Ho Chi Minh City	0.281
7	Penang	0.494	Surabaya	0.151	Yangon	0.182
8	Bandung	0.483	Ipoh	0.150	Balikpapan	0.093
9	Johor Bahru	0.482	Denpasar	0.144	Surabaya	0.050
10	Semarang	0.426	Semarang	0.142	Denpasar	0.045
11	Manila	0.403	Malacca	0.140	Medan	0.010
12	Denpasar	0.400	Chiang Mai	0.139	Hanoi	0.008
13	Hanoi	0.389	Malang	0.134	Bandung	0.002
14	Medan	0.367	Phnom Penh	0.132	Palembang	0.002
15	Ipoh	0.353	Bandung	0.131	Penang	0.000
16	Malacca	0.309	Medan	0.129	Johor Bahru	0.000
17	Da Nang	0.303	Manila	0.128	Semarang	0.000
18	Batam	0.289	Ho Chi Minh City	0.127	Ipoh	0.000
19	Yangon	0.284	Batam	0.124	Malacca	0.000
20	Palembang	0.280	Pontianak	0.119	Da Nang	0.000
21	Chiang Mai	0.254	Bandar Lampung	0.117	Batam	0.000
22	Bandar Lampung	0.251	Vientiane	0.114	Chiang Mai	0.000
23	Balikpapan	0.248	Makassar	0.114	Bandar Lampung	0.000
24	Pekanbaru	0.246	Kota Kinabalu	0.113	Pekanbaru	0.000
25	Malang	0.233	Balikpapan	0.113	Malang	0.000
26	Makassar	0.210	Palembang	0.113	Makassar	0.000
27	Cebu	0.201	Hanoi	0.111	Cebu	0.000

28	Hai phong	0.195	Kuching	0.111	Hai phong	0.000
29	Phnom Penh	0.192	Yangon	0.111	Phnom Penh	0.000
30	Mandalay	0.181	Pekanbaru	0.110	Mandalay	0.000
31	Kota Kinabalu	0.170	Da Nang	0.109	Kota Kinabalu	0.000
32	Pontianak	0.164	Padang	0.109	Pontianak	0.000
33	Vientiane	0.151	Hai phong	0.106	Vientiane	0.000
34	Jambi	0.151	Banjarmasin	0.104	Jambi	0.000
35	Bandar Seri Begawan	0.151	Jambi	0.103	Bandar Seri Begawan	0.000
36	Naypyidaw	0.146	Cebu	0.101	Naypyidaw	0.000
37	Davao	0.135	Bandar Seri Begawan	0.100	Davao	0.000
38	Padang	0.133	Cagayan de Oro	0.099	Padang	0.000
39	Kuching	0.124	Davao	0.098	Kuching	0.000
40	Banjarmasin	0.118	Bacolod	0.097	Banjarmasin	0.000
41	Cagayan de Oro	0.104	Mandalay	0.096	Cagayan de Oro	0.000
42	Can Tho	0.092	Tasikmalaya	0.095	Can Tho	0.000
43	Zamboanga	0.092	Naypyidaw	0.095	Zamboanga	0.000
44	Bacolod	0.085	Zamboanga	0.092	Bacolod	0.000
45	Tasikmalaya	0.077	Can Tho	0.087	Tasikmalaya	0.000
46	Dili	0.031	Dili	0.077	Dili	0.000
47	Samarinda	0.024	Samarinda	0.073	Samarinda	0.000
	Gini coefficient	**0.390**		**0.118**		**0.874**

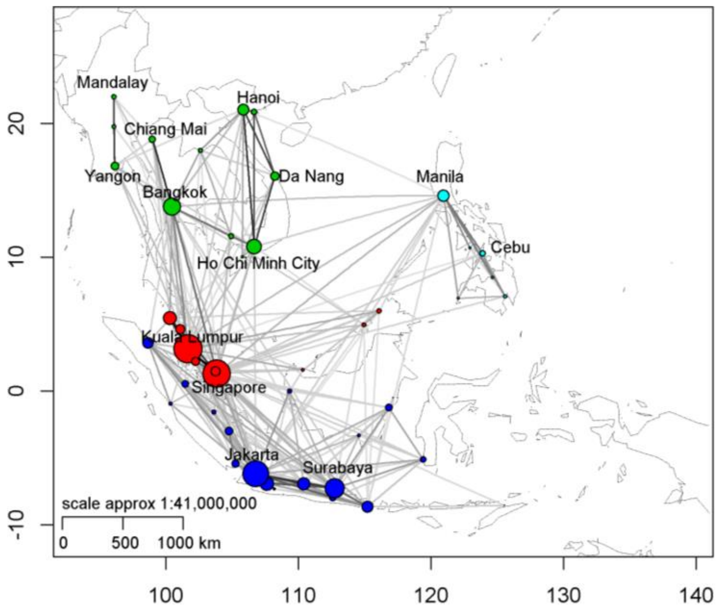


Figure 2.3 Intercity transportation network between 47 Southeast Asian cities. The circle size reflects cities' degree centrality; link width and colour are proportional to linkage strength; and the circle colour corresponds to individual network communities.

2.3.1.1 Degree centrality

Degree centrality summarizes a city's total connections with all others cities in the network. Having served as the region's gateway for a long time, Singapore attains the highest degree centrality. In addition to its role as an international air hub, Singapore's leading position benefits from its rail and road connections with mainland Southeast Asia. Facilitated by the city-state 'Open Skies' policy and the emergence of low-cost airlines in recent years, Singapore has been increasingly connected with secondary cities in other countries e.g., Surabaya and Denpasar in Indonesia, Penang in Malaysia, Chiang Mai in Thailand and Cebu in the Philippines; Bowen, 2000). These new connections could help cement Singapore's position as the region's gateway city.

Oftentimes recognized as another world city in Southeast Asia (Gugler, 2004), Kuala Lumpur ranked second in degree centrality. On the one hand, the government has strengthened East Malay's air connections to Kuala Lumpur to promote East Malay's economy and foster integration between the country's two halves. On the other hand, the Malaysian government has been aggressively redefining Kuala Lumpur's as a global hub for knowledge, trade, and foreign direct investment, thus putting forth transportation infrastructures and communications projects (Rimmer and Dick, 2009).

As the largest country in terms of both population and land size in ASEAN and with a relatively high urbanization level, Indonesia has the most cities selected in the study. Indeed, in addition to Jakarta, large Indonesian cities such as Surabaya, Bandung and Semarang also rank in the top ten in terms of degree centrality. The leading positions of Indonesian cities could be ascribed to the large number of domestic connections, as evidenced by the dense rail, road and air connections on Java Island. Similarly, the high ranks in degree centrality for Penang (ranked 7th) and Johor Bahru (ranked 9th) in Malaysia are due to dense domestic connections on the Malay Pennisula.

As a textbook example of a primate city (McGee, 1995; Sternstein, 1984), Bangkok accumulates almost a third of Thailand's urban population as well as the nation's most transportation infrastructures (Douglass, 2000). Bangkok ranks fifth in the degree centrality ranking. Though not well connected with secondary cities in Indonesia and the Philippines, Bangkok's more northerly location makes it well-situated to connect the Mekong river basin with other parts of Southeast Asia.

Having been Vietnam's commercial centre since the 1800s, Ho Chi Minh City enjoys a higher rank (6th) in degree centrality than the nation's capital Hanoi (13th). Manila does not stand out in the degree centrality ranking, which could partly be explained by Philippines' island geography. Furthermore, Manila is increasingly integrated with Northeast Asia and has intense interactions in trade and investment with Japan, South Korea and Taiwan (Rimmer, 2000).

2.3.1.2 Closeness centrality

The closeness centrality ranking adds another dimension to the connectivity analysis by scrutinizing how 'easy' it is to reach – via direct and indirect links – the other cities in the network. Given that most cities are fairly closely connected to one or more major gateways, the ranking is relatively 'flat' (Table 2.2). This also resonates with the growth of low-cost carriers (i.e., budget airlines), which improve the connectivity of small and medium cities and increase of the overall 'closeness' scores for these cities (Hooper, 2005; Zhang et al., 2008). In addition to close connections with gateway cities, cities in several countries also form dense sub-regional networks (Jones, 2002), which is associated with their geographic proximity and economic development. For instance, 9 out of the 20 strongest connections (Table 2.3) concentrate along the western seaboard of the Malay Peninsula, and this dense sub-regional network covers roughly the areas of the 'Straits of Malacca Economic Corridor' and the 'Indonesia-Malaysia-Thailand Growth Triangle'. Another case is the intensive connections along the Irrawaddy River in Myanmar (Figure 2.3), linking the country's largest port (Yangon) and its major inland administrative centre (Mandalay).

In addition, the formation of some densely connected urban regions is driven by political integration strategies (Raguraman, 1997), as many Southeast Asian countries purposely pursued economic nationalism after their independence in the 1950s. For example, attempting to promote national unification, North-South transportation was improved in Vietnam to connect the socialist North around Hanoi and the formerly capitalist South around Ho Chi

Minh City. Furthermore, extensive highways were constructed in central Malay Peninsula (Bunnel et al., 2002), aiming to connect Kuala Lumpur with its satellite cities as well as facilitate transportation within major industrial regions (e.g., the Multimedia Super Corridor; MSC). As for Indonesia, while national airlines were established for national integration on sprawling islands (Kissling, 1989), the government has strived to promote the connections of secondary cities in recent years (Bunnell and Miller, 2011). For instance, there are 11 direct flights every week between Balikpapan on the Borneo Island and Singapore (Silas and Setijanti, 1996). Similarly, we see closer economic and transportation connections between Surabaya and Bangkok (Bowen, 2000; Rimmer, 2000).

Table 2.3 The 20 strongest dyads.

Rank	Dyad	Connectivity (Max=1)
1	Kuala Lumpur - Singapore	0.900
2	Kuala Lumpur - Johor Bahru	0.896
3	Singapore - Johor Bahru	0.875
4	Kuala Lumpur - Penang	0.847
5	Bangkok - Chiang Mai	0.797
6	Ho Chi Minh City - Hanoi	0.748
7	Ho Chi Minh City - Da Nang	0.728
8	Jakarta - Surabaya	0.712
9	Jakarta - Semarang	0.709
10	Yangon - Mandalay	0.706
11	Hanoi - Da Nang	0.688
12	Ipoh - Singapore	0.683
13	Penang - Singapore	0.655
14	Yangon - Naypyidaw	0.633
15	Ho Chi Minh City - Hai phong	0.626
16	Kuala Lumpur - Ipoh	0.608
17	Ipoh - Johor Bahru	0.603
18	Semarang - Surabaya	0.599
19	Bandung - Surabaya	0.568
20	Penang - Johor Bahru	0.564

2.3.1.3 Betweenness centrality

Betweenness centrality highlights cities' brokerage functions for the interconnection of cities that are not directly linked. This ranking is much more hierarchical (Table 2.2). Notwithstanding an overall well-connected transport network, a few cities are still privileged with 'gateway' functions and high betweenness centrality. Most notable examples include Jakarta, Manila, Singapore, Bangkok and Kuala Lumpur.

Capital cities (i.e., Jakarta, Manila, Kuala Lumpur, Bangkok and Ho Chi Minh City) tend to serve as gateways in their respective countries as Southeast Asian urban system has long been characterized as a high degree of primacy since the colonial era. With the region's four most populous countries as their hinterlands, Jakarta, Manila, Kuala Lumpur and Ho Chi Minh City serve as major gateways for Indonesian, the Philippine, Malaysian and Vietnamese cities, respectively (Morshidi, 2000; Bunnell et al., 2002). For example, many cities in Sumatra 'use' Jakarta to connect to the wider network, making Jakarta a critical gateway for articulating Indonesian cities into the ASEAN economy (Bowen, 2000). Although in recent years the Indonesian government has been actively developing decentralization schemes (Bunnell and Miller, 2011), encouraging the development of low-cost budget airlines, and promoting international gateways other than Jakarta such as Surabaya and Denpasar, Jakarta international airport still accounts for the largest shares of passengers and cargos within Indonesia.

Relatedly, although Bandar Seri Begawan, Brunei is geographically closer to Cebu than to Manila, air travels between Bandar Seri Begawan and Cebu may well involve layovers in Manila, which thus acts as the Philippine gateway city.

In comparison, even without a large national hinterland, the city-state of Singapore emerges as a truly ASEAN transportation hub. This is consistent with Singaporean development strategies of projecting economic and political influence over the city-state's territorial neighbours (Yeung and Olds, 1998; Rodrigue, 2006), as well as achieving growth through translocal economic activities (e.g., international trade; Rodrigue, 1994; Taylor et al., 2000). For example, later mimicked by many other countries in the region (Forsyth et al., 2006), Singapore has long adopted policies such as 'Open Skies' to proliferate the city's aviation connections (Oum, 1998; Rodrigue et al., 2013) and geared its soft (e.g., management and amenities) and hard (e.g., new airport terminals) infrastructures (Phang, 2003) towards attracting layover passengers during long-haul inter-continental flights (Lohmann et al., 2009). In addition, the planned Singapore-Kunming Railway Link and the ASEAN Highway Network could further boost the city-state's role as the gateway city.

2.3.2 Community detection

The community detection algorithm identifies four network communities within the Southeast Asian intercity transportation network. These communities represent stronger intra-community connections and characterize the spatial inequality of transport connectivity at the network level. Our community detection analysis identifies a Greater-Mekong community that anchored by Hanoi, Yangon, Bangkok and Ho Chi Minh City; a Greater Malaysian community incorporating Singapore and Brunei; an Indonesian community organized around Jakarta, and a community of the Philippine cities. Among the four communities, the Greater Malaysian community has the highest average degree centrality of 0.430, suggesting a most connected sub-region in Southeast Asia. It is followed by the Indonesian community (0.292) and the Greater-Mekong community (0.281), while the Philippine community only has an average degree centrality of 0.175. The delineation of these communities largely reflects the archipelago geography of the region (Armstrong and Read, 2006), boundary effects (Grundy-Warr et al., 1999), as well as the legacy of national integration programs (Raguraman, 1997).

Based on socioeconomic development and environmental conditions, Southeast Asia has normally been divided into continental (e.g., Thailand and Myanmar) and insular sub-regions (e.g., Indonesia and Philippines). While Singapore and Malaysia are oftentimes treated as part of the insular Southeast Asia, our analysis suggests otherwise in the transportation network, as Singaporean and Malaysian cities form a network community with their counterparts in the continental Southeast Asia.

Economic-wise, the Greater Malaysian community is comprised of three countries with the highest GDP in the region (Singapore, Brunei, Malaysia). The GDP per capita in 2010 in these three countries is about fifteen times higher than that in the region's lagged behind countries (e.g., Cambodia, Laos, Myanmar and Vietnam, CLMV). The three strongest dyads in our analysis are among Singapore, Johor Bahru and Kuala Lumpur, thanks to geographical proximity and economic complementarity. Despite the fact the Bandar Seri Begawan has direct flight connections with leading cities in other communities (e.g., Bangkok and Ho Chi

Minh City in the Mekong sub-region, Manila in the Philippines, Jakarta, Surabaya and Denpasar in Indonesia, Kuala Lumpur and Kota Kinabalu in Malaysia and Singapore), Brunei's capital city has far more links with Malaysian and Singaporean cities. Furthermore, the dense connections within this network community could be ascribed to Malaysia's national policies to integrate East and West Malaysia.

As discussed previously, the formation of Indonesian and the Philippine communities can be ascribed to the dense domestic connections with capital cities as major gateway cities, reflecting the primate urban systems in these countries (Bowen, 2004; Huff, 2011). The Greater-Mekong network community consists of Thailand and other four least developed countries in our analysis (i.e., CLMV). Except for Thailand being one of the five original ASEAN members, CLMV joined ASEAN after 1995. Recently, Thailand has played an increasingly critical role in reducing regional inequality through strengthening links and promoting sub-regional integration (Walsh, 2010). More specifically, Thailand has actively promoted cross-border trade with neighbouring countries, importing raw material and primary products, exporting manufactured goods, and becoming a major investor in CLMV. Thailand has provided much financial and technical assistance for basic infrastructure development in neighbouring countries (e.g., the construction of road, bridge, dam and power plant) to support a long-term economic development (Fujimura, 2006).

2.4 Conclusions

According to neo-classical growth theory, urban connectivity in transportation networks is an important harbinger of economic development as well as a facilitator of social and political cohesion (Bhattacharyay, 2009). The development of intercity transportation networks in Southeast Asia has undergone several major phases, each of which is driven by different rationales, emphasizes different modes of transportation (e.g., airline networks in post-war era) and focuses on different geographic regions (e.g., the concentration of infrastructures around leading cities during colonial times as well as post-independence territorial integration targeting at remote areas). Over time, transportation networks in Southeast Asia become more integrated and cities are often able to form relationship with others nearby and afar. The co-existence of these local and trans-local linkages calls for a network approach towards understanding the urban system in the ASEAN region: these overlapping developmental patterns create a complex and uneven geography of intercity transportation networks, requiring a network-explicit examination that covers multiple transportation modes and extensive geographic areas.

In this exploratory analysis, we create a composite intercity transportation network between 47 major Southeast Asian cities by integrating information about rail, road and air transportation. Spatial inequality of transport connectivity at both the city and network levels is examined through the lens of centrality analysis and community detection. Gini coefficients for individual centrality rankings point to a hierarchical degree distribution, a rather even distribution of closeness centrality, and a highly concentrated distribution of betweenness centrality. With regard to accessibility at the city level, Singapore, Kuala Lumpur and Jakarta are identified as the most dominant nodes in terms of all three centralities in Southeast Asia transportation network. Cities in the sparsely populated peripheral regions rank at the bottom. With regard to accessibility at the network level, four network communities are detected to have denser intra-cluster connections: a Greater-Mekong community surrounded around Bangkok, a Malaysia community together with Singapore and Brunei with Kuala Lumpur and Singapore as gateways, an Indonesian community articulated into the wider region by Jakarta, and a Philippine community cantered on Manila. Our analysis also highlights important geographic, economic, political and social processes underlying the spatial inequality of transport access within Southeast Asia.

Our analysis points to several future research avenues: Firstly, future analyses would account for capacity of individual vehicles, airplanes, and trains (Yap and Thuzar, 2012). Secondly, this paper focuses infrastructure networks that transport people, and a next step would involve measuring the movement of cargos and information (Bowen and Leinbach, 2006). Thirdly, future studies would require a multi-scale approach. For example, Bangkok is the only Thai city that exceeds the 0.5 million resident selection threshold, and future analyses would incorporate smaller Thai cities by looking at both domestic (Bangkok and other parts of the Thailand) and international connections. Lastly, our analysis suggests the transportation network of Southeast Asia is controlled by a handful of leading cities. However, national governments are pursuing strategies to increase domestic equality of connectivity as well as compete internationally for more strategic positions within the global transport network. The region's leading transportation hubs are also facing external competitions. For example, Singapore is competing Hong Kong and Dubai for stopovers of long-haul routes between Asia-Pacific and Europe (Lohmann et al., 2009). Therefore, we anticipate substantive changes would emerge in terms of centrality ranking and network communities, all pointing to the need of a longitudinal study.

References

Alderson, A.S., Beckfield, J., Sprague-Jones, J., 2010. Intercity Relations and Globalisation: The Evolution of the Global Urban Hierarchy, 1981-2007. Urban Studies 47, 1899-1923.

Anderson, W.P., 2012. Economic Geography. Routledge, London, U.K.

Armstrong, H., Read, R., 2006. Geographical 'handicaps' and small states: Some implications for the Pacific from a global perspective. Asia Pacific Viewpoint 47, 79-92.

Bhattacharyay, B.N., 2009. Infrastructure development for ASEAN economic integration (AD BI Working Paper No. 138). Asian Development Bank Institute. Retrieved from website: http: //www.adbi.org/workingpaper/2009/05/27/3011.infrastructure.dev.asean.economic/. Tokyo, J apan.

Borgatti, S.P., Everett, M.G., 2006. A graph-theoretic perspective on centrality. Social Networks 28, 466-484.

Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. Journal of Transport Geography 8, 25-41.

Bowen Jr, J.T., Leinbach, T.R., 2006. Competitive advantage in global production networks: air freight services and the electronics industry in Southeast Asia. Economic Geography 82, 147-166.

Bowen, J.T., 2004. The geography of freighter aircraft operations in the Pacific Basin. Journal of Transport Geography 12, 1-11.

Bunnell, T., 2013. City Networks as Alternative Geographies of Southeast Asia. TRaNS: Trans-Regional and-National Studies of Southeast Asia 1, 27-43.

Bunnell, T., Ann Miller, M., 2011. Jakarta in post-Suharto Indonesia: decentralisation, neo-liberalism and global city aspiration. Space and Polity 15, 35-48.

Bunnell, T., Barter, P.A., Morshidi, S., 2002. Kuala Lumpur metropolitan area: A globalizing city-region. Cities 19, 357-370.

Burger, M.J., Van der Knaap, B., Wall, R.S., 2014. Polycentricity and the multiplexity of urban networks. European Planning Studies 22, 816-840.

Camagni, R.P., Salone, C., 1993. Network urban structures in northern Italy: Elements for a theoretical framework. Urban Studies 30, 1053-1064.

Castells, M., 2011. The rise of the network society (2nd Edition): The information age: Economy, society, and culture, Volume 1. John Wiley & Sons, Chichester, U.K.

Clauset, A., Newman, M.E., Moore, C., 2004. Finding community structure in very large networks. Physical review E 70, 066111.

Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. InterJournal, Complex Systems 1695, 1-9.

Derudder, Witlox, Catalano, 2003. Hierarchical tendencies and regional patterns in the world city network: a global urban analysis of 234 cities. Regional studies 37, 875-886.

Derudder, B., Liu, X., Kunaka, C., Roberts, M., 2014. The connectivity of South Asian cities in infrastructure networks. Journal of Maps 10, 47-52.

Dick, H., Rimmer, P.J., 2003. Cities, transport and communications: The integration of Southeast Asia since 1850. Palgrave Macmillan, New York, U.S.

Douglass, M., 2000. Mega-urban regions and world city formation: globalisation, the economic crisis and urban policy issues in Pacific Asia. Urban Studies 37, 2315-2335.

Durand, F.B., Anh, L.V., 1996. Case study of Can Tho city, Vietnam, The management of secondary cities in Southeast Asia. UN-Habit, Nairobi, Kenya, pp. 60-86.

Forsyth, P., King, J., Lyn Rodolfo, C., 2006. Open Skies in ASEAN. Journal of Air Transport Management 12, 143-152.

Fujimura, M., 2006. Cross-border Transport Infrastructure, Regional Integration, and Development: Implications for the Greater Mekong Subregion. Journal of Greater Mekong Subregion Development Studies 3, 48-62.

Goh, C.Y., 2008. ASEAN Infrastructure Financing Mechanism: concepts and progress, ASEAN Infrastructure Financing Mechanism Conference, Kuala Lumpur, Malaysia.

Grubesic, T.H., Matisziw, T.C., 2011. A spatial analysis of air transport access and the essential air service program in the United States. Journal of Transport Geography 19, 93-105.

Grundy-Warr, C., Peachey, K., Perry, M., 1999. Fragmented Integration in the Singapore-Indonesian Border Zone: Southeast Asia's 'Growth Triangle'Against the Global Economy. International Journal of Urban and Regional Research 23, 304-328.

Guimera, R., Mossa, S., Turtschi, A., Amaral, L.N., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. Proceedings of the National Academy of Sciences 102, 7794-7799.

Gugler, J., 2004. World Cities Beyond the West: Globalization, Development, and Inequality. Cambridge University Press, Cambridge, UK.

Hooper, P., 2005. The environment for Southeast Asia's new and evolving airlines. Journal of Air Transport Management 11, 335-347.

Huff, G., Angeles, L., 2011. Globalization, industrialization and urbanization in Pre-World War II Southeast Asia. Explorations in Economic History 48, 20-36.

Jones, G.W., 2002. Southeast Asian urbanization and the growth of mega-urban regions. Journal of Population Research 19, 119-136.

Kissling, C., 1989. International tourism and civil aviation in the South Pacific: issues and innovations. Geojournal 19, 309-315.

Kuroda, H., Kawai, M., Nangia, R., 2008. Infrastructure and regional cooperation, In: Bourgu ignon, F., Pleskovic, B. (Eds.), Annual World Bank Conference on Development Economics - Global 2007: Rethinking infrastructure for development. World Bank Publications, Tokyo, Ja pan, pp. 235-260.

Lange, MK., 2004. British colonial legacies and political development. World Development 32, 905-922.

Lee, S.-W., Ducruet, C., 2009. Spatial glocalization in Asia-Pacific hub port cities: a comparison of Hong Kong and Singapore. Urban Geography 30, 162-184.

Liu, X., Derudder, B., Wu, K., 2015. Measuring Polycentric Urban Development in China: A n Intercity Transportation Network Perspective. Regional studies, DOI:10.1080/00343404.20 15.1004535.

Lohmann, G., Albers, S., Koch, B., Pavlovich, K., 2009. From hub to tourist destination: An explorative study of Singapore and Dubai's aviation-based transformation. Journal of Air Transport Management 15, 205-211.

McGee, T.G., Robinson, I.M., 1995. The mega-urban regions of Southeast Asia. UBC Press, Vancouver, Canada.

Morshidi, S., 2000. Globalising Kuala Lumpur and the strategic role of the producer services sector. Urban Studies 37, 2217-2240.

Motomura, Y., 1996. Transportation development in Indochina. Transportation Research Record: Journal of the Transportation Research Board 1563, 41-47.

Munnell, A.H., 1992. Policy watch: Infrastructure investment and economic growth. The Journal of Economic Perspectives 6, 189-198.

Nathan, K., 2002. Malaysia-Singapore Relations: Retrospect and Prospect. Contemporary Southeast Asia 24, 385-410.

O'Connor, K., 1995. Airport development in southeast Asia. Journal of Transport Geography 3, 269-279.

Oum, T.H., 1998. Overview of regulatory changes in international air transport and Asian strategies towards the US open skies initiatives. Journal of Air Transport Management 4, 127-134.

Perry, M., Kong, L., Yeoh, B.S.A., 1997. Singapore: A developmental city state. Wiley, Chichester, U.K.

Phang, S.-Y., 2003. Strategic development of airport and rail infrastructure: The case of Singapore. Transport Policy 10, 27-33.

Pye, O., Daud, R., Harmono, Y., 2012. Precarious lives: Transnational biographies of migrant oil palm workers. Asia Pacific Viewpoint 53, 330-342.

Raguraman, K., 1997. Airlines as instruments for nation building and national identity: case study of Malaysia and Singapore. Journal of Transport Geography 5, 239-256.

Rimmer, P.J., 2000. Effects of the Asian Crisis on the geography of Southeast Asia’s air traffic. Journal of Transport Geography 8, 83-97.

Rimmer, P.J., Dick, H.W., 2009. The city in Southeast Asia: Patterns, processes and policy. NUS Press, Singapore.

Rodrigue, J.-P., 1994. Transportation and territorial development in the Singapore extended metropolitan region. Singapore Journal of Tropical Geography 15, 56-74.

Rodrigue, J.-P., 2006. Transportation and the geographical and functional integration of global production networks. Growth and Change 37, 510-525.

Rodrigue, J.-P., Comtois, C., Slack, B., 2013. The geography of transport systems. Routledge, London, U.K.

Sabandar, W., 2007. Transport and the rural economy: Institutions and institutional change in Ambeso Village, Indonesia. Asia Pacific Viewpoint 48, 200-218.

Santosa, W., Joewono, T.B., 2005. An Evaluation Of Road Network Performance In Indonesia. Proceedings of the Eastern Asia Society for Transportation Studies 5, 2418-2433.

Saueressig-Schreuder, Y., 1986. The impact of British colonial rule on the urban hierarchy of Burma. Review (Fernand Braudel Center) 10, 245-277.

Sien, C.L., 2003. Southeast Asia transformed: a geography of change. Institute of Southeast Asian Studies, Singapore.

Silas, J., Setijanti, P., 1996. Case study of Balikpapan, Indonesia, The management of secondary cities in Southeast Asia. UN-Habit, Nairobi, Kenya, pp. 135-153.

Sternstein, L., 1984. The growth of the population of the world's pre-eminent “primate city”: Bangkok at its bicentenary. Journal of Southeast Asian Studies 15, 43-68.

Taylor, P.J., Doel, M., Hoyler, M., Walker, D.R., Beaverstock, J.V., 2000. World cities in the Pacific Rim: a new global test of regional coherence. Singapore Journal of Tropical Geography 21, 233-245.

Thompson, E.C., 2013. In Defence of Southeast Asia: A Case for Methodological Regionalism. TRaNS: Trans-Regional and-National Studies of Southeast Asia 1, 281-302.

Tonts, M., Taylor, M., 2010. Corporate location, concentration and performance: Large company headquarters in the Australian urban system. Urban Studies 47, 2641-2664.

Walsh, J.C., 2010. Land transportation network development in the Greater Mekong Sub. Journal of Management 8, 17-29.

Yap, J.T., 2014. Addressing Inequality in Southeast Asia through Regional Economic Integration. Institute of Developing Economies. Retrieved from website: http://www.ide.go.jp/English/Publish/Download/Brc/pdf/14_01.pdf., Tokyo, Japan.

Yap, K.S., Thuzar, M., 2012. Urbanization in Southeast Asia: Issues & Impacts. ISEAS Publishing, Singapore.

Yeung, H.W.-c., 2008. Industrial Clusters and Production Networks in Southeast Asia: A Global Production Networks Approach, In: Kuroiwa, I., Heng, T.M. (Eds.), Production Networks and Industrial Clusters: Integrating Economies in Southeast Asia. ISEAS Publishing, Singapore, pp. 83-120.

Yeung, H.W.-c., Olds, K., 1998. Singapore's global reach: situating the city-state in the global economy. International Journal of Urban Sciences 2, 24-47.

Zhang, A., Hanaoka, S., Inamura, H., Ishikura, T., 2008. Low-cost carriers in Asia: Deregulation, regional liberalization and secondary airports. Research in Transportation Economics 24, 36-50.

Chapter 3 The evolving structure of the Southeast Asian intercity air transport network through the lens of complex networks, 1979-2012

Dai, L., Derudder, B., Liu, X., 2018. The evolving structure of the Southeast Asian air transport network through the lens of complex networks, 1979-2012. Journal of Transport Geography 68, 67-77.

Abstract

This paper presents a novel approach to investigate and understand the evolving structure of the Southeast Asian air transport network (SAAN) over the period 1979-2012. Our approach captures the main topological and spatial changes in the network from the perspective of complex network theory. We find that the SAAN combines a relatively stable topological structure with a changing multilayered geographical structure. Statistical analysis indicates that the SAAN is a scale-free network with increasing number of cities functioning as hubs, and has been characterized by small-world properties since 1996. Furthermore, the SAAN exhibits a recently intensified disassortative mixing pattern, suggesting an increasing dependence of small cities on hub-and-spoke configuration for better accessibility. A decomposition analysis is used to disaggregate the SAAN into three layers. The core layer consists of capital cities, the most economic vibrant secondary cities, and tourist destinations, and is densely interconnected with its center of gravity moving towards the western part of Southeast Asia. The periphery layer, comprised of cities in remote areas, sustains a low significance with declining internal connectivity despite a rising number of cities being connected. The bridge layer lies in between both extremes, and is characterized by a high volatility over time. The connections and passengers between different layers increase, especially those between core and bridge after 1996. In our discussion, we trace these changes back to a series of socio-economic and politico-institutional dynamics in Southeast Asia.

3.1 Introduction

Air transportation has emerged as a key facilitator of economic development and social change as it greatly enables the flow of people, goods, capital, and information across space. This is particularly true for Southeast Asia (SEA), one of the most economically dynamic and strategically significant regions in the global economy (Sien, 2003). In 2015, SEA, which is commonly defined as including Cambodia, Laos, Myanmar, Vietnam (CLMV), Thailand, Malaysia, Singapore, Indonesia, Philippines, Brunei, and East Timor (formerly part of Indonesia) (cf. Rimmer and Dick, 2009), ranked third in Asia both in terms of its population of 633 million inhabitants (following China and India) and in terms of its economic size with a combined gross domestic product (GDP) of US$2.45 trillion (following China and Japan) (ASEAN Secretariat, 2016). Important from the perspective of air transport, the region is much more geographically fragmented than, say, the European Union (EU) and North America. The archipelagic geography, further complicated by often-difficult terrain to cross in climatic and physiographic terms, endows air transportation with competitive advantages over road, rail, and water transportation (Zhang et al., 2008). Or, as O'Connor (1995: 270) has pointed out: "air transportation is the only effective means for intercity links" in this region. For example, an express coach covering the 250km trip from Ho Chi Minh City to Phnom Penh takes at least 5.5 hours, whereas the flying time is only 45 minutes. Meanwhile, travelling by rail from Bangkok to Kuala Lumpur takes about 24 hours compared to a 2-hour flight. Similarly, a ferry trip between Singapore and Jakarta via Batam can last 26 hours while a flight takes less than 2 hours. As a consequence, the importance of developing efficient and extensive air transport networks has been highlighted in various regional and national policy agendas (ASEAN Secretariat, 2011).

After several decades of fast-paced development, the Southeast Asian air transportation system has evolved into a complex network with mixed structures and large heterogeneities in capacity and intensity of connections. However, to date there has been no effort to engage in systematic complex-network analysis of the Southeast Asian air transport network (SAAN). Such a complex network approach has been shown to provide new insights into air transport systems at national (e.g., China; Wang et al., 2011), macro-regional (e.g., the EU; Zanin and Lillo, 2013), and global (e.g., Guimera et al., 2005) scales. An analysis of the SAAN may or may not reach similar conclusions, as it entails very different sets of underlying geographic, institutional, and socioeconomic factors (Lordan et al., 2014). To help filling this gap, in this paper we explore the structural evolution of the SAAN during 1979-2012 from a complex network perspective.

When examining a supra-national region such as the SEA region, one obviously risks falling into the ‘territorial trap’ (Agnew, 1994; Bunnell, 2013): it can be argued that the crux of the geographies of SEA’s air transport connections are not simply confined to the SEA region, thus challenging the *a priori* framings such as SEA and ASEAN (cf. Taylor et al., 2013). Indeed, the ‘openness’ of SEA is clearly visible in the possible extension of the system to Hong Kong (Dick, 2005), or in the identified functional airline region by including neighboring China and Japan (Guimera et al., 2005). However, there has been no consensus on how closed a transport or urban system should be to make a regional framing tenable (Kratoska et al., 2005), while the liberalization/deregulation geography as circumscribed by the move towards open skies in the context of ASEAN Economic Community (AEC) and ASEAN Single Aviation Market (ASAM) does lend the region a certain coherence in this context (Liu et al., 2017; Thompson, 2013). Our analysis will therefore focus on airline connections originating and terminating within SEA.

The main contributions of our study are twofold. First, we conduct a statistical analysis to characterize the evolving topological structure of the SAAN over this 34-year period and compare the network metrics with some other major regional blocs. Second, a decomposition technique is employed to unveil the multilayered structure of the SAAN for the years 1979, 1996 and 2012, respectively. By doing so, we shed light on how the topological and geospatial architecture of the SAAN changes over time. To this end, the remainder of this paper is organized as follows: section 2 reviews the literature, focusing on the application of complex network theory in the study of the geography of air transport networks. This is followed by a discussion of our methodological framework and data in Section 3. Section 4, then, presents the results of the complex network analysis of SAAN, after which the paper is concluded with an overview of our major findings, the limitations of our approach, and some avenues for further research.

3.2 Literature review

3.2.1 A growing air transport market in the context of regional integration

Southeast Asian countries have very different experiences with regional integration. It is well documented that regional economic integration in East Asia - including a large part of its Southeast Asian component - has been preceded by fast-paced industrial development in Japan and the emergence of newly industrializing countries (NICs) - South Korea, Taiwan, Hong Kong, and Singapore - since the mid-1960s (Yap, 2014). Consecutive waves of relocating labour-intensive industries then cascaded down to next-tier NICs - Indonesia, Malaysia, Thailand - and later to the Philippines after it introduced a transition towards more liberal economic policies from the early 1980s onwards (Coclanis and Doshi, 2000). Meanwhile, the three Indochinese economies (i.e. Vietnam, Laos and Cambodia) were trapped in conflicts and isolated from the SEA regional market for more than a decade after 1975. They subsequently embarked on a trajectory of regional economic integration through a fundamental shift in development strategy from a centrally planned economy to a market economy since the late 1980s, as exemplified by Vietnam's *Doi Moi* reforms (Hill and Menon, 2012). By 1993, CLMV countries had all embraced market mechanisms, emphasizing export promotion, welcoming foreign investment, and promoting tourism (Thant, 2012). The flows of trade and investment to these newcomers to regional integration led to the establishment of broader regional production networks. As a consequence, regional integration in SEA has been significantly accelerating since the early 1990s: Tanaka (2009) demonstrates that the intraregional trade has almost doubled over the past two decades and now constitutes a quarter of the region's total trade.

Enhanced intercity airline connectivity has been part and parcel of SEA's evolution towards greater regional integration and the development of a single economic market. Since the Association of Southeast Asian Nations (ASEAN) was founded in 1967, it has facilitated both improved regional economic integration and air transport connectivity, seeing both as being fundamentally intertwined. A key step was the agreement on an ASEAN Free Trade Area (AFTA) in 1992. The AFTA framework carried a commitment to further enhance regional cooperation by providing safe, efficient and innovative transportation and communications infrastructure networks. This boosted a series of sub-regional air liberalization initiatives, such as a joint agreement by Indonesia, Malaysia, and Thailand in 1994 to promote the development of air transport in ASEAN's Northern Growth Triangle. The agreement was later broadened to include the Philippines and Brunei, and was supplemented with a similar CLMV cooperation in 1998, which liberalized air transport between the four countries. Another important step was the 2003 agreement to building the AEC by 2015 in order to move SEA towards an integrated and globally competitive single market and production base. Under this umbrella, Southeast Asian governments have been engaged in concerted efforts to work out an open skies policy similar to the one realized in the EU, namely the ASAM. Against this background, the airline industry in SEA has been evolving from an assortment of individual and highly-protected companies into an increasingly integrated and liberalized system of regional business organizations.

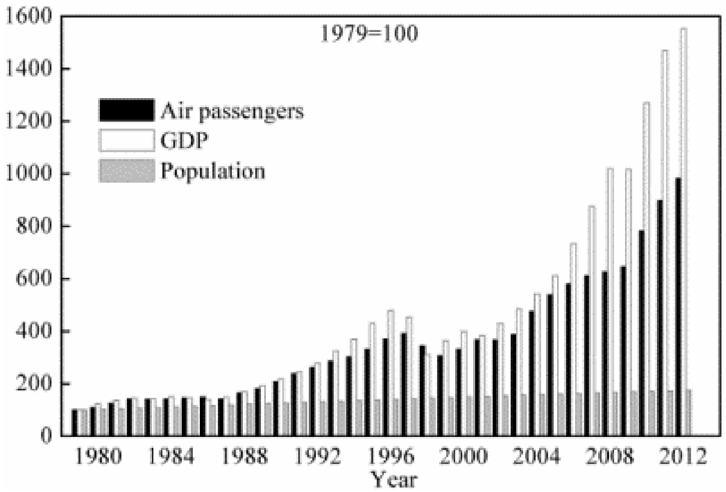


Figure 3.1 Growth of scheduled air passenger traffic, GDP and population of Southeast Asia, 1979-2012[3]. The data in 1979 were standardized as 100 and those in other years were scaled according to this benchmark.

According to data from the Official Airline Guide (OAG) database (http://analytics.oag.com), SEA has witnessed substantial expansion in its regional air transport network over the past thr ee decades. More than 60 new airports have been constructed and/or come into operation duri ng the 1979-2012 period, while the number of direct intra-SEA air connections has nearly dou bled from 330 to 602. In line with booming regional economic output and surpassing overall p

[3] Scheduled air passenger traffic from 1979 to 2012 was compiled from the OAG database. GDP and population data for each of the eleven Southeast Asian countries were gathered from World Bank (https://data.worldbank.org/). Since the World Bank GDP data of CLMV countries were incomplete, they were crosschecked and supplemented by data from http://ivanstat.com. Data from both sources were counted in current U.S. dollars (at 2015 prices). There was no GDP information for East Timor before 1999, since it was part of Indonesia. This confirmed the necessity to include it in our longitudinal study to keep geographic and statistical consistency although it has not become a formal ASEAN member yet.

opulation growth, the total volume of scheduled air passenger traffic within SEA has increase d dramatically from 23.9 million in 1979 to 234.9 million in 2012 (Figure 3.1).

These evolutions have drawn considerable attention from air transport geographers. One the one hand, transport geographers have been interested in the positionality of cities and the (geo)spatial patterns of linkages between them, as well as their complex associations with economy, tourism, state policies, etc. For example, Bowen (2000) examined the changes in nodal accessibility of Southeast Asian hubs during 1979-1997 and assessed how different state policies and strategies shaped the development of air transport networks. Rimmer (2000) analyzed the impacts of the Asian Crisis on the geography of ex/intra-SEA air traffic with particular attention to changes in city-pair routes. On the other hand, researchers have discussed the mixed blessings of deregulation/privatization trends and emerging open skies policies for the Southeast Asian aviation market with regard to airports/cities, carriers, and air routes (Forsyth et al., 2006; Hooper, 2005).

Taken together, these studies offer insight into the changing geographies of the SAAN in light of a series of socio-economic and politico-institutional dynamics in SEA. However, there is relatively limited insight into the structural changes of and in the network. An exception is O'Connor’s (1995) elaboration of a four-stage model of the historical development of the SAAN. He states that the network begins with “major destinations and trunk route stops” due to colonialism; then bypassing some places to exhibit “new intermediate conditions” with the development of national/regional economies and the advancement of aircraft technology; then entering into the “international hub development and proximity” stage by concentration of feeder connections from small cities; followed by the final “principal axis shift” from the traditional west-east to a north-south orientation with an increased vitality of southern cities. Complementing O'Connor’s classical spatial analysis, here we attempt to uncover the evolution of overall SAAN structures through complex network analysis, which could provide insights into the network topological structure and multilayered geographical structure.

3.2.2 Complex network analysis on air transport networks

Situated at the intersection of graph theory and statistical mechanics, complex network theory offers an array of useful tools to analyze network structures, dynamics and their underlying mechanisms (Ducruet and Lugo, 2013). This has resulted in a bourgeoning literature (re)examining various transportation networks, such as urban public transport (Cats, 2017), road (Xie and Levinson, 2009), railway (Wang et al., 2009), maritime (Ducruet and Notteboom, 2012), and airline networks (Lin, 2012).

Air transport networks, in which airports/cities represent nodes and flights represent edges connecting these nodes can be conceptualized as either binary or weighted networks. Obviously, air transport networks are neither simply random or regular. Therefore, a complex network analysis of their structures starts with topological characterization and pattern recognition, with particular reference to scale-free and small-world networks. A scale-free network is characterized by a power-law distribution of nodal degree (i.e., a node's number of adjacent neighbors), showing that a few large degree nodes dominate a large number of less connected nodes (Barabási and Albert, 1999). In comparison, a small-world network has a larger density of edges because of a shorter average/characteristic path length (i.e., the average number of edges in the shortest path between two nodes) and higher transitivity (i.e., probability for a node to have its neighbors interconnected) than a random network of the same size (Watts and Strogatz, 1998).

These concepts and models have been tested in a number of air transportation networks, including the entire world (Guimera et al., 2005), the EU (Lordan et al., 2015), the United States (US; Xu and Harriss, 2008), China (Wang et al., 2011), India (Bagler, 2008), and Italy (Guida and Maria, 2007). In general, these studies examine overall network structures as well as indices for individual nodes, after which the implications of the network analysis results are explored. The presence of scale-free properties is related to the existing literature on hub-and-spoke configurations (O'Kelly, 1998). Nonetheless, the degree distribution can be very distinct in different air transportation systems, as can the shape of the distribution ranging from (stretched) exponential to power law (with or without cutoff), to two-regime/double power law (cf. Reed, 2003). Against the backdrop of this diversity, Paleari et al. (2010) compared the structure of air transport networks in the US, EU and China. The results showed that all three airport systems are characterized by a double Pareto-law (i.e. a two-regime power law) degree distribution, but with the distribution declining more rapidly in the EU. Overall, 'small-worldiness' is more universal in non-planar networks (i.e. networks that allow links to cross without creating a node at the intersection) due to the existence of communities, a set of nodes sharing denser connections with each other than with the rest of the network.

It can be noted that the above-discussed analyses are cross-sectional. However, with the growing availability of coherent longitudinal datasets, several studies focus on the historical evolution of air transport networks. For instance, Wandelt and Sun’s (2015) analysis of international air transport networks from 2002 to 2013 indicated that the scale-free and small-world properties were stable and the network shifted towards symmetric, transitive closure due to the increasing interconnection between each country’s neighbors. Burghouwt and Hakfoort (2001) explored the evolution of the European aviation network during 1990-1998, and demonstrated the development of hub-and-spoke structures notwithstanding there being no evidence for concentration of intra-European traffic on the primary hubs. Lin and Ban (2014) studied both topological and spatial characteristics of the US airline network during 1990-2010, finding stability in topology and an increasing importance of distance in the development of new routes. That is, more and more short- and medium-length (less than 700km) routes have been created, and passengers increasingly need one or more transfers to realize a long-distance connection due to network structure optimization and integration. The evolution of the Chinese air transport network since 1930 was examined in Wang et al. (2014), indicating a significant improvement of connectivity and a gradual expansion of a core network along with the development of China’s economy (cf. Liu et al., 2016). Rocha (2009) discovered a relatively high and stable clustering coefficient and a slightly declining average path length for the Brazilian airport network, as well as a shrinkage of network routes in spite of a more than doubling of air traffic between 1995 and 2006.

Apart from conventional topological analysis in cross-sectional and longitudinal studies alike, multilayer/multilevel analysis has become prevalent within the framework of complex network theory (Tsiotas and Polyzos, 2017). Recent major contributions in this light are Verma et al. (2014), Du et al. (2016) and Lordan and Sallan (2017). These authors employ the *k*-core decomposition method to uncover the multilevel structure of the worldwide, Chinese, and European air transport networks, respectively. *K*-core decomposition is a technique to hierarchically identify particular subsets of a complex network, called *k*-cores, in which the degree of every node is larger than or equal to *k*. Each subset is obtained by recursively removing all nodes with degree smaller than a certain threshold *k* (Ducruet and Zaidi, 2012). This approach progressively disentangles the complexity of airline networks, thus providing insight into the different layers unevenly contributing to the configuration of the network. Because, as we will see, the SAAN exhibits both high complexity and spatial inequality, such a multilayer analysis is of the utmost interest to help grasping the geographies of the network.

This literature review leads us to three major observations in the context of this paper. First, air transport networks have been widely analyzed in terms of the statistical properties of the network structure. However, these studies have primarily focused on the US, European countries, China, and India: the SAAN thus appears under-researched from this perspective. Second, most studies examine the static state of the network in a single year through the lens of complex network theory: longitudinal analysis could help revealing underlying geographic, political and economic factors in the structuration of the network. Third, multilayer/multilevel analysis has evolved into a prominent approach to discover hidden information and extract hierarchical structures from complex networks. However, this approach has not yet been widely adopted in research on air transport networks. Against this backdrop, this paper examines the evolving structure of the SAAN from 1979 to 2012 by means of multilevel complex network analysis, and discusses these with key social and economic changes in the region. In the next section, we will elaborate on the methodology and data used in this study.

3.3 Data and methods

3.3.1 Data

All our data refer to nonstop flights and air passengers scheduled between any pair of airports within Southeast Asia (Figure 3.2), as detailed in the aforementioned OAG database (see Derudder and Witlox (2008) for a discussion of data limitations). Our empirical study was conducted between 1979 and 2012 on a yearly basis: 1979 was taken as a starting point as it can be seen as a benchmark in that it marks the onset of ASEAN air transport liberalization, while 2012 was determined by data availability. During this period, the region has seen rapid air traffic growth, a wide range of industrial transformations, economic fluctuations and a tourism boom, thus providing us with a diverse background for a longitudinal study of the evolution of topological and spatial properties of the SAAN.

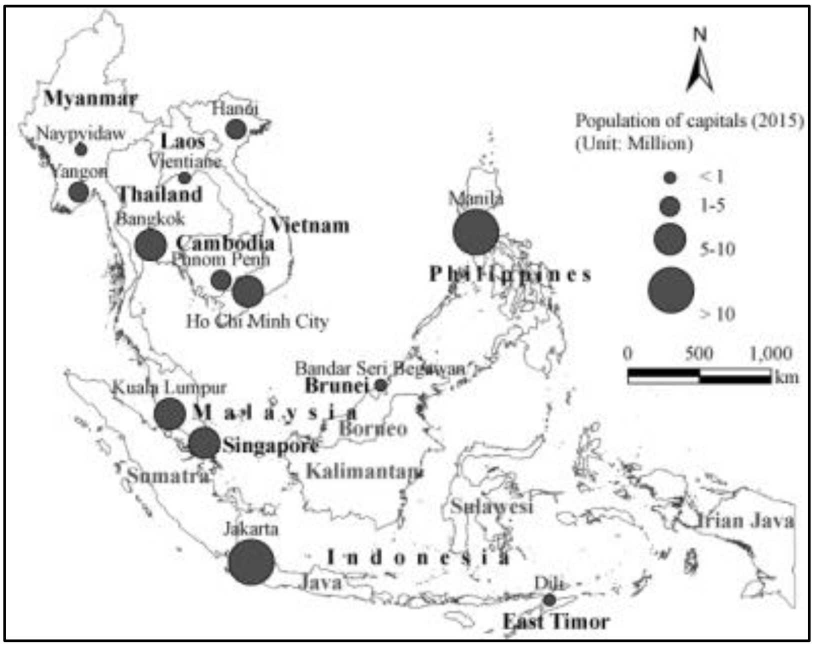


Figure 3.2 The SEA study area[4].

3.3.2 Complex network methods

3.3.2.1 Network representation

The SAAN takes the form of a symmetric adjacency matrix ***A*** wherein a_{ij}=1 if there are scheduled flights between airport city *i* and city *j* in the studied year and a_{ij}=0 of otherwise. Each airport city represents a single node except for a number of aggregations related with the presence of multi-airport cities (cf. Derudder et al., 2010), i.e. a combination of Suvarnabhumi and Don Mueang into Bangkok, Kuala Lumpur International and Sultan Abdul Azziz Shah into Kalua Lumpur, Soekarno-Hatta and Halim Perdana Kusuma into Jakarta, and Changi and Seletar into Singapore. The number of nodes in the SAAN ranges from 177 in 1979 to 237 in 2012. Given our focus on connections/passengers within SEA, we use the term 'domestic' or 'internal' to refer to connections/passengers between cities in the same country while 'international' or 'external' is used to refer to connections/passengers between cities in different SEA countries.

3.3.2.2 Network structure measures

The starting point for evaluating network structures is to introduce a set of fundamental network metrics, such as degree, degree distribution, degree-degree correlation, characteristic

[4] Population of capital cities in 2015 was derived from https://aseanup.com/infographic-top-cities-urbanization-asean/. Yangon and Ho Chi Minh City were dotted in the map since they were formerly capitals of Myanmar and Vietnam, respectively.

path length and average clustering coefficient. Degree is the most basic index to measure the centrality of nodes in a network, while the degree distribution helps exploring the underlying processes by which the network has come into existence. Degree-degree correlation reflects a node's connection preference and reveals the mixing pattern of an observed network. Characteristic path length is a global property that is essential to the topology and communication efficiency of networks, while the average clustering coefficient allows quantifying the degree of clustering of a network. Below we formally specify each of these measures.

(1) Degree and degree distribution

The degree k_i of node *i* is defined as the number of nodes it is directly connected to, and is given by:

$$k_i = \sum_{j \in V(i)} a_{ij} \tag{3-1}$$

Where *V(i)* denotes the neighbor set of node *i*.
For a scale-free network which is generated by a preferential attachment rule, the degree distribution *p(k)* follows a power law, given by:

$$P(k) \sim k^{-\gamma} \tag{3-2}$$

Where γ is the fitted power-law exponent.
We compute the cumulative degree distribution *P(>k)*, as it paints a more accurate picture of the shape of the distribution in relatively small and noisy datasets (Lordan et al., 2015). The cumulative degree distribution *P(>k)* expresses the probability of nodes with degree equal to or greater than *k* and is given by:

$$P(>k) = \sum_{k'=k}^{\infty} p(k') \tag{3-3}$$

Whose scaling exponent γ_{cum} is related to that of *P(k)* by $\gamma=\gamma_{cum}+1$.

(2) Degree-degree correlation

This refers to the correlation between degree *k* and the average degree of their neighbors $\overline{K(k)}$:

$$K(i) = \frac{1}{k_i}\sum_{j \in V(i)} k_j \tag{3-4}$$

Where *K(i)* is the average degree of the neighbors of node *i*. For *N(k)* nodes with degree *k*, $\overline{K(k)}$ is defined as:

$$\overline{K(k)} = \frac{1}{N(k)}\sum_{k_i = k} K(i) \tag{3-5}$$

A positive coefficient indicates a correlation between nodes of similar degree, termed ‘assortativity’. A negative value indicates relationships between nodes of different degree, termed as ‘disassortativity’ (Newman, 2003).

(3) Characteristic path length

The characteristic path length *L* is defined as the average number of edges along the shortest paths for all possible node-pairs in the network:

$$L = \frac{1}{N(N-1)}\sum_{i,j=1}^{N} d_{ij} \quad (i \neq j) \tag{3-6}$$

Where d_{ij} is the number of edges for the shortest path from node *i* to *j*.

(4) Average clustering coefficient

The clustering coefficient C_i is defined as the probability that two nodes are connected to each other given that both of them are connected to node *i*, written as:

$$C_i = \frac{2E_i}{k_i(k_i-1)} \tag{3-7}$$

Where E_i indicates the actual number of edges between the neighbors of node *i*. The average clustering coefficient *C* is the mean value of *Ci* of all *N* nodes in the network:

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i \tag{3-8}$$

The characteristic path length and average clustering coefficient are two basic indices that allow testing whether a network exhibits small-world properties: a network in which most nodes are not neighbors of one another, but in which the neighbors of any given node are likely to be neighbors of each other and most nodes can be reached from every other node by a small number of connections. If a network has a higher C and a shorter L than those in an identical-size random network, it suggests the presence of small-worldiness.

3.3.2.3 K-core decomposition

In addition to the metrics discussed in 3.2.2, we will also explore the SAAN's multilayer structure by drawing on the *k*-core decomposition method. A network can theoretically be decomposed into 1, 2, 3, …, k_{max} layers. However, it is not very informative to present all layers separately. Rather, and as highlighted in Verma et al. (2014), nodes in the air transport network can be categorized into three distinct layers: core, bridge and periphery. The core layer contains the nodes belonging to the k_{max}-core while the periphery layer includes the nodes in the 1-core; the remainder of the network forms the bridge layer. We employ this classification to decompose the SAAN into a hierarchical core-bridge-periphery structure.

3.4 Results

3.4.1 Statistical properties of the SAAN topological structure

We begin our analysis by looking at the network architecture in 2012 and then tracing the changes over the period 1979-2012. Table 3.1 summarizes the basic network metrics of the SAAN, and compares these results to those for other regions as reported in the literature.

Table 3.1 Summary statistics of the SAAN in 2012 and its counterparts. V: number of nodes; E: number of edges; P(>k): cumulative degree distribution; L: characteristic path length; C: average clustering coefficient.

Scale	Network	Reference	V	E	P(>k)	L	C
Macro-regional	Southeast Asia		237	602	Power law	3.12	0.21
Global	Worldwide	Guimera et al., 2005	3663	27051	Truncated power law	4.40	0.62
Macro-regional	EU	Lordan et al., 2015	661	8104	Double Pareto law	2.71	0.55
National	US	Xu and Harriss, 2008	272	6566	Truncated power law	1.90	0.73
	China	Wang et al., 2011	144	1018	Exponential	2.23	0.69
	India	Bagler, 2008	79	228	Power law	2.26	0.66
	Italy	Guida and Maria, 2007	42	310	Double Pareto law	1.98	0.10
	Austria	Han et al., 2007	136	1296	Power law	2.38	0.21
	Greece	Tsiotas and Polyzos, 2015	41	154	Exponential	2.09	0.42
	Brazil	Rocha, 2009	142	2601	Streched exponential	2.34	0.63

3.4.1.1 Scale-free properties

As can be seen in Figure 3.3, the SAAN's P(>k) fits a power-law function with a scaling exponent of γ_{cum} =1.42 in 2012. Therefore, the corresponding exponent γ for P(k) is 1+1.42=2.42. Given that this is in the range of 2<γ< 3, this characterizes the SAAN as a scale-free network as previously observed for India and Austria as well as, to a lesser extent, for the global level and the US, the EU and Italy (cf. Table 3.1).

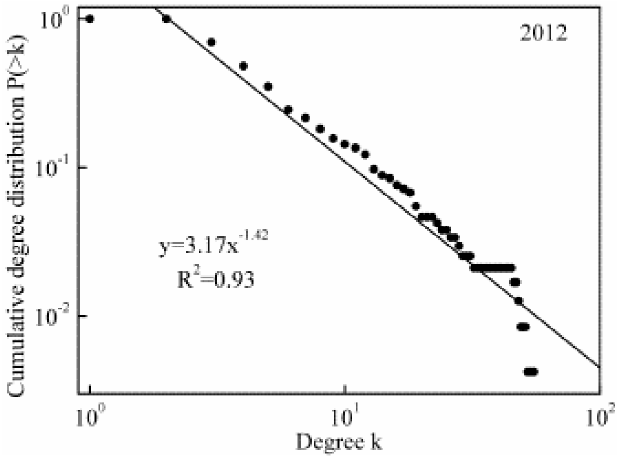


Figure 3.3 Cumulative degree distribution of the SAAN plotted using a double-logarithmic scale, 2012.

This pattern reflects the dominance of a few well-connected cities (hubs) in SEA with a large number of air passenger routes while the majority of cities (spokes) only have a limited number of connections (cf. Bowen, 2000). The shape of the distribution remains roughly similar between 1979 and 2012, meaning that even with strong rewiring at the micro level (see section 4.2), the overall characteristics of the network have remained roughly the same. Nevertheless, the slope of the degree distribution generally decreased (Figure 3.4), meaning that there are relatively more cities with a large degree (Rocha, 2017). This is above all the result of the recent emergence of capital cities in CLMV, a feature that will be elaborated upon in the discussion of the spatiotemporal variations of core cities in section 4.2. The minor deviations in some of the years may be attributed to the sensitivity of air transport to sudden events, such as the outbreak of economic crisis in 1997 and the severe acute respiratory syndrome (SARS) in 2003 (Bowen and Laroe, 2006; Rimmer, 2000).

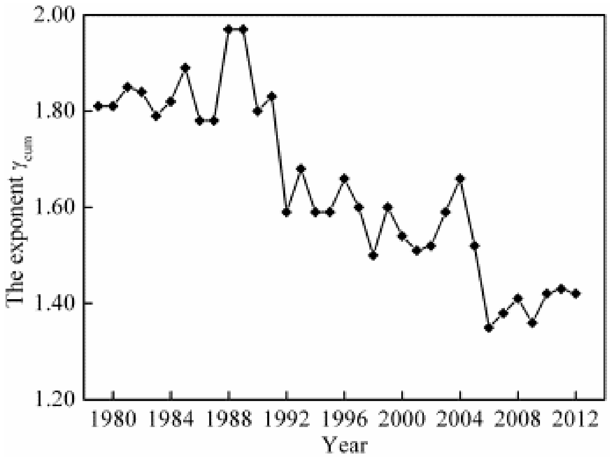


Figure 3.4 Fitted exponents for the power-law distribution, 1979-2012.

3.4.1.2 Disassortative mixing

Figure 3.5 demonstrates the presence of a negative correlation between a city's degree and the average degree of its neighboring cities for the SAAN in 2012. This points to a disassortative mixing pattern in which high-degree cities such as Singapore, Kuala Lumpur, Bangkok, Jakarta and Manila on average have relatively low-degree neighbors.

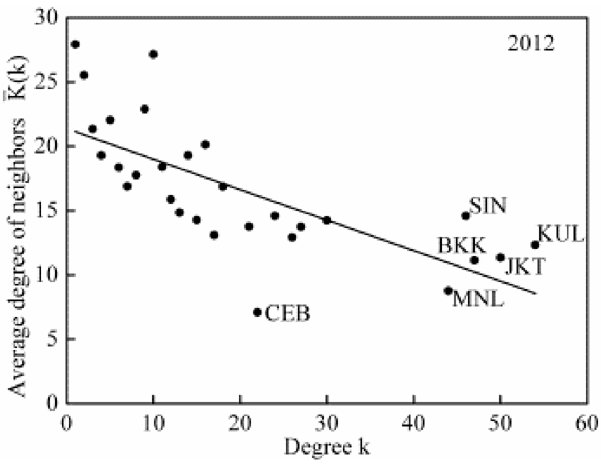


Figure 3.5 Degree-degree correlation for the SAAN, 2012 (SIN: Singapore; KUL: Kuala Lumpur; BKK: Bangkok; JKT: Jakarta; MNL: Manila; CEB: Cebu).

However, Cebu is an outlier here in that, as a medium-sized city, its average neighbor degree is less than half of the expected value. This can be ascribed to a 'shadow effect' (cf. O'Connor, 1995) of its major hub, Manila, which confines Cebu's connections to domestic small cities instead of major cities in other countries. On the other hand, Singapore neighbors' average degree is higher than expected. This suggests that it is directly connected to many key hubs and secondary cities in other countries, compensating for the relatively smaller number of connections with low-degree cities.

Figure 3.6 shows disassortativity to be slowly declining from -0.14 in 1979 to -0.01 in 1995 (pointing to an almost neutral mixing pattern). Since 1995, however, disassortativity has again roughly intensified, although the mixing pattern in 2012 is still not very strong. The two stages identified here are the joint result of a changing diversity of pairs of connected cities and the partial hierarchical structure (Ru and Xu, 2005). The growing importance of air transport and the integration of more remote local cities into the national and regional development process had implied that small cities increasingly rely on hub-and-spoke configurations to attain better accessibility in SEA (Lin, 2012).

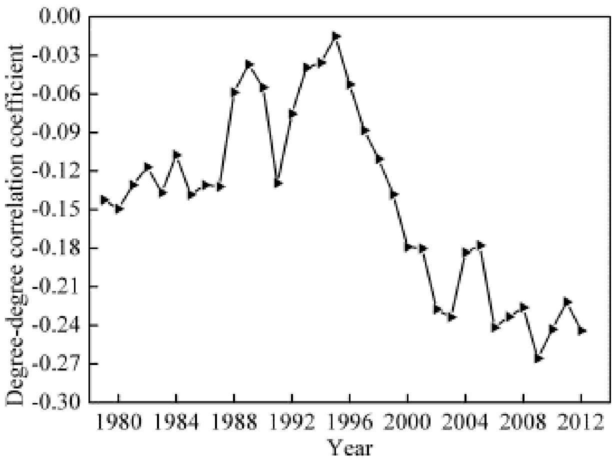


Figure 3.6 Disassortativity coefficients for the SAAN, 1979-2012.

3.4.1.3 Small-world properties

Figure 3.7 presents the characteristic path length and average clustering coefficient of the SAAN and a comparable network (i.e. with the same number of edges and nodes) with a random distribution. In the case of the SAAN, *L* is very close to that of a random network with a turning point in 1996 when the random network's *L* starts surpassing that of the SAAN. The clustering coefficient is nevertheless continuously significantly higher than that of a comparable random network. Hence, the SAAN exhibits small-world properties from 1996 onwards. One possible explanation for this is that major low-cost carriers came into focus after 1996, such as Cebu Pacific, Lion Air, AirAsia, Jetstar Asia (Zhang et al., 2008), which has greatly densified the overall intercity air transport network and improved the accessibility of many secondary cities in this region.

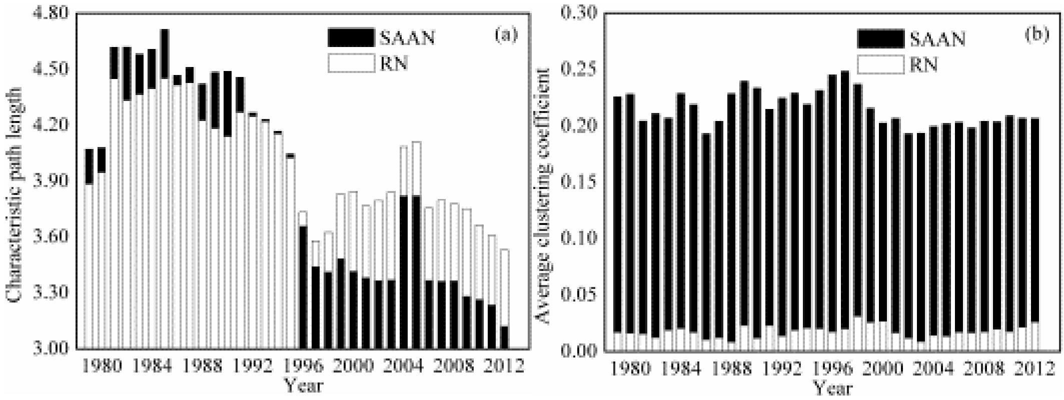


Figure 3.7 Characteristic path length (a) and average clustering coefficient (b) of the SAAN compared to those of the random network (RN) in the same size, 1979-2012.

From 1979 to 2012, *L* decreased from 4.07 to 3.12, conforming to an average decline of one step for cities to reach other cities in the SAAN. *C* remained stable around 0.2, which suggests a trade-off between efficiency and economic considerations (Xie et al., 2015). Compared with other regions in Table 3.1, the SAAN has a large characteristic path length of 3.12 whereas the worldwide network has a larger value at 4.4. It can of course be hypothesized that *L* will increase with the scale of the networks because distance and border effects still matter in air transport networks (Matsumoto, 2007). As a result, the level of *L* at the national level is usually smaller than that at the macro-regional level, which is in turn also smaller than that at the global level.

However, the EU network does possess a shorter characteristic path length of 2.71 and a larger average clustering coefficient of 0.55 compared to the SAAN, implying that SEA, as a single bloc, remains at a less-developed stage in air transportation with much room to improve the efficiency of the connectivity structure of its air transport network (Wang et al., 2011): in an increasingly liberalized economic environment, the SAAN is still far from an integrated and mature market. Compared to the extensive multilateral agreements and low-cost connections across countries as in the EU (Dobruszkes, 2006), current liberalizing processes in SEA still largely rely on bilateral air service agreements in which a substantial number of routes are exposed to government regulations (Hanaoka et al., 2014).

3.4.2 Spatiotemporal variations of the SAAN multilayered structure

In this section, we present a more detailed morphology of the SAAN's multilayered structure and discuss its changes by taking multiple snapshots at different time points. Figure 3.8 displays the hierarchical core-bridge-periphery structure of the SAAN in 1979, 1996, 2012, respectively, and Table 3.2 reports the number of cities, connections and air passengers within and between layers.

Table 3.2 Number of cities, connections and air passengers within and between layers to the total in the SAAN.

Type	Cities			Connections			Passengers (Million)		
	1979	1996	2012	1979	1996	2012	1979	1996	2012
Core	23	12	18	68	45	87	13.85	30.46	85.13
Core-Bridge	-	-	-	92	162	251	5.88	44.74	114.29
Core-Periphery	-	-	-	25	22	40	1.16	1.14	8.61
Bridge	101	168	147	117	283	192	2.69	11.46	24.99
Bridge-Periphery	-	-	-	21	29	32	0.25	0.57	1.67
Periphery	53	56	72	7	5	0	0.06	0.03	0.00
Sum	177	236	237	330	546	602	23.89	88.39	234.69

The SAAN has changed markedly by growing from 177 cities linked through 330 connections in 1979 to 237 cities linked through 602 connections in 2012. At the same time, the number of air passengers soared to 234.69 million from a relative small base of 23.89 million. Prior to the outbreak of the 1997 financial crisis, the SAAN enjoyed faster growth in the number of cities, connections and passengers by 33.33%, 65.45% and 270.07%, respectively, than those in the subsequent period (0.42%, 10.26% and 165.50%, respectively). In terms of the multilayer structure, the three layers (i.e., core, bridge, and periphery) exhibit heterogeneous patterns over space and time, in which several major changes can be identified.

First, there is a minor drop in the number of cities in the core layer, but at the same time there has been a substantial gain in the intensity of the connections. As can be seen in Figure 3.8, the core layer has evolved into a well-developed and tightly connected backbone and the gravitational center of this layer explicitly moves towards the northern part of. This tendency is in line with O'Connor's (1995) "principal axis shift". In 1979, the 23 core cities were capital cities of economically developed countries alongside a number of large cities in archipelagic countries (i.e. Indonesia, Philippines, Malaysia). The core layer had 68 connections connecting 13.85 million passengers. However, the number of core cities in 1996 was almost halved, while the connections between them also decreased to 45 whereas the number of air passengers more than doubled. Cities that remained in the core layer were capital cities of economically developed countries, provincial capitals of East Malay (Kuching and Kota Kinabalu), as well as the second largest city (Surabaya), the most well-developed tourist destination (Denpasar) and the busy domestic hub of Makassar in Indonesia. After a further 17 years, the core layer witnessed a moderate growth in size (18 cities and 87 connections) and a drastic rise in the number of passengers (85.13 million). The layer includes all capital cities of the ASEAN region except for Vientiane, a number of critical secondary cities and international gateways (i.e., Penang, Surabaya, Medan), as well as the region's important tourist destinations (i.e., Phuket, Siem Reap and Denpasar).

Second, the bridge layer has gone through a mixed growth pattern, above all exhibiting high volatility during 1979-2012. Initially, the connections between bridge cities were relatively sparse. Air passenger flows were concentrated in the remote parts of East Indonesia around Makassar on the one hand, and a Northwest Burmese group around Yangon on the other hand. The layer mushroomed in 1996 with connections and traffic more than doubling and quadrupling respectively. This is largely due to the emergence of Vietnamese cities as well as a number of Indonesian and Philippine cities that were downgraded from the core layer. In 2012, the number of cities and connections respectively shrank by 12.5% and 32.2%. It is noteworthy that Chiang Mai and Da Nang became prominent bridge cities in the Greater-Mekong sub-region (GMS) in the face of the rise of Ho Chi Minh City, Hanoi and Yangon to the core layer. Besides, Makassar reappeared in this layer after 1996's temporary upgrade into a core city, with the connections between the divided parts of Malaysia being much denser in 2012.

Third, the periphery layer has a consistent low significance in the SAAN with a gradually rising number of cities located at the margins of their national systems and rarely being inter-connected as expected. However, these cities are increasingly connected to cities in core and bridge layers. This phenomenon has also been observed in the spatial organization of freight flows between French urban areas, featuring only a few exchanges between small urban areas, but more with other levels in the urban hierarchy (Guerrero and Proulhac, 2014). In a similar vein, the connections between bridge and core layers ascended drastically from 92 to 251, with a parallel growth in air traffic from 5.88 to 114.29 million. This of course leads to the disassortative mixing of degrees discussed in the previous section.

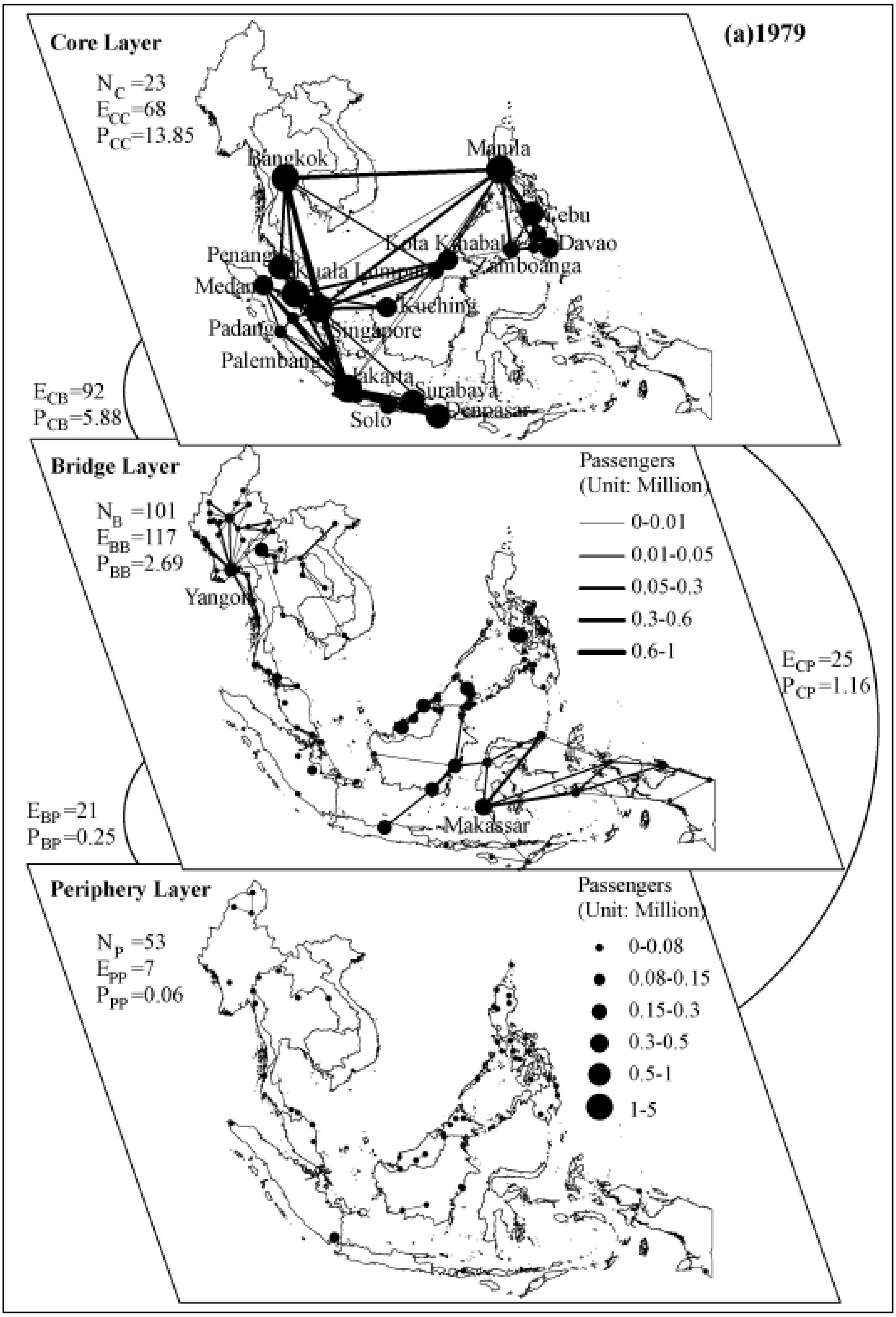
The dynamics of the multilayer structure in the SAAN can easily be associated with the geographic peculiarities of, and socio-economic and politico-institutional changes in Southeast Asia (Liu et al., 2017). First and foremost, the region's fragmented geographical nature continues shaping the spatial and topological patterns of the SAAN. For instance, especially for remote areas with small population and economic output, Makassar acts as a local hub in Indonesia to handle frequent air links from densely-populated Java to Sulawesi and Irian Java. Given that the Malaysian communities on Borneo are both relatively less developed and isolated from the Malay Peninsula, intense air connections are established to numerous cities in East Malaysia (often through Kuching and Kota Kinabalu). This geographical dispersion of archipelagic countries has placed an unusual dependence on air services as a unifying force to keep the national development project on track (Kissling, 1989).

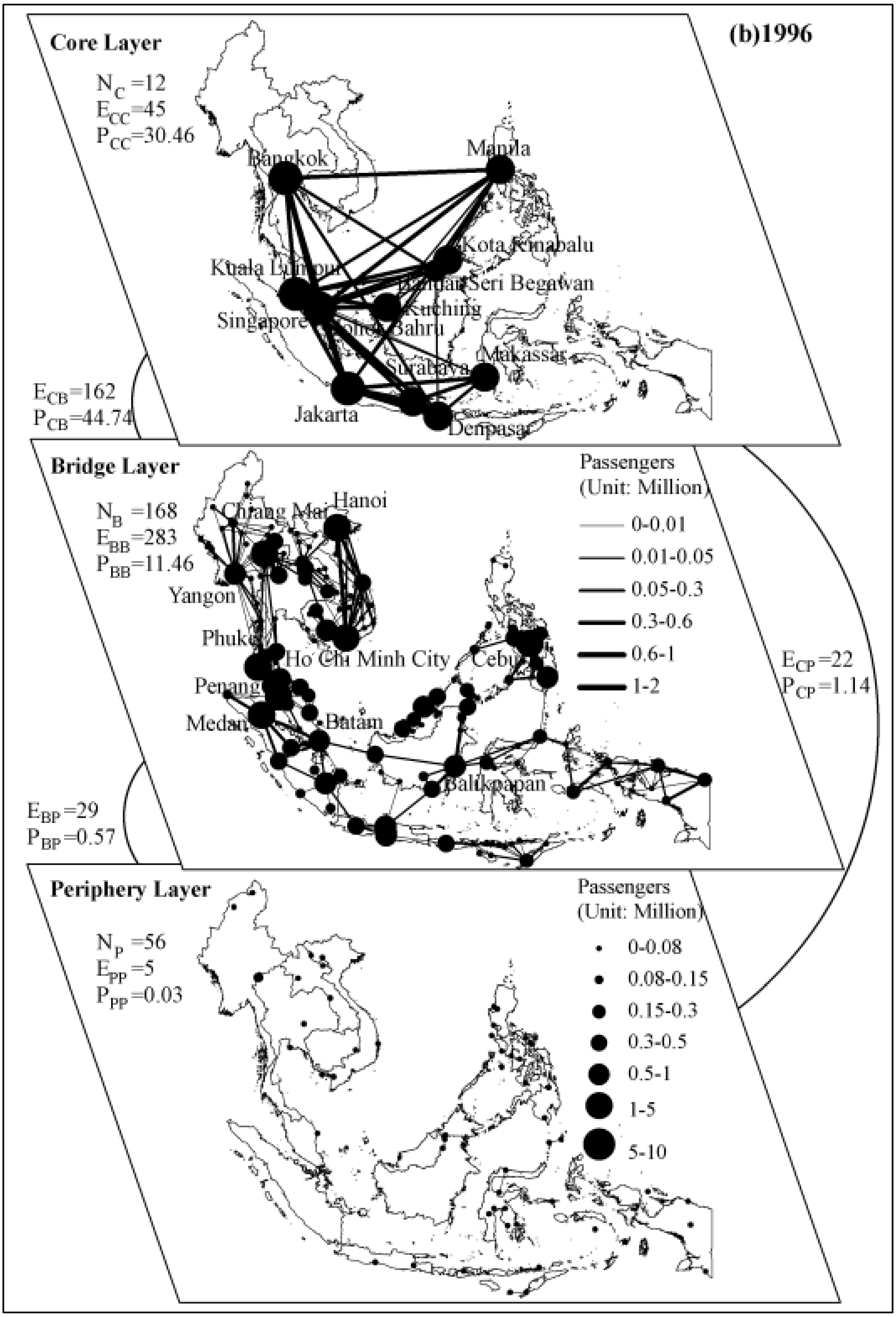
Furthermore, the evolving multilayered geography of the SAAN is heavily influenced by underlying disparities in national development and regional integration as reviewed in section 2.1. One the one hand, the early NICs, being export-oriented, started to integrate into the global economy, thus reinforcing the significance of their respective international hubs by synergies of soft (e.g. information, telecommunication) and hard (e.g. airport, port, rail and road) infrastructures (Airriess, 2001; Rimmer, 1999; Robinson, 2006). For instance, with the development of high tech and value-added manufacturing and business services, Singapore has become one of the major investors in other Southeast Asian countries. Therefore, it has geared its soft (e.g. management and amenities) and hard (e.g. new airport terminals) infrastructures (Phang, 2003) towards attracting layover passengers during long-haul inter-continental flights. On the other hand, the lagging CLMV got involved into the regional production network by economic reforms from the late 1980s and joined ASEAN later on (Vietnam in 1995, Laos and Myanmar in 1997, and Cambodia in 1999). In Vietnam, Ho Chi Minh City, Hanoi and Da Nang were designated as three development poles and have enjoyed rapid economic growth from a small base, which spurs investment in air transport connections to external economies. In addition, the CLMV sub-regional cooperation in air transport since 1998 contributes to an improved competitiveness and gradual participation in the international air transport market (Hien, 2003), ultimately bolstering the capital cities of CLMV in the core layer in 2012. An equally important contributor has been the growing volumes in tourism (Van De Vijver et al., 2014). This shift leads to mushrooming air connections to Siem Reap (the world heritage site of Angkor Wat), and Phuket and Denpasar (resort islands), all of which are also included in the core layer in 2012.

Finally, government policies play a vital role in the SAAN evolution (Bowen, 2000). Before the 1990s, air services were overwhelmingly state-regulated or even state-operated in SEA.

National carriers played an instrumental role the processes of nation-building, serving to integrate various parts of a country on the one hand and reinforcing the positionality of the national capital/primary cities on the other hand (Raguraman, 1997; Bowen, 2000). Partly in order to cope with the rapid growth of air transport demand, most SEA countries started to permit the entry of private corporations into the aviation industry (Hooper, 2005), while flagship carriers shifted towards regional and international cooperation and competition. The gradual deregulation of domestic markets promoted joint-venture Low Cost Carriers (LCCs), such as Malaysia’s AirAsia which is perceived to be a pan-ASEAN carrier (Zhang et al., 2008). The connections provided by these carriers greatly enhanced the nodality of most economically vibrant secondary cities and tourism destinations in the region as pronounced in the core layers of 1996 and 2012.

The impact of air transport liberalization can also be detected from the presence of Johor Bahru and Clark in 2012 as bridge cities with dense connections. The emergence of Johor Bahru in the SAAN can be ascribed to the ‘spillover effect’ of Singapore owing to geographic proximity (Ooi, 1995) as well as its potential to be the secondary airport of Singapore with convenient ground transportation between both places. A similar observation can be made for Clark, an airport city 80 kilometers away from Manila, which is increasingly well connected by its attraction of connectivity from congested Manila airport (Hanaoka et al., 2014). In our empirical framework, we initially opted to aggregate these airports into ‘city nodes’, but these findings suggest that a more nuanced reading of connectivity in a city-regional context would have been warranted. This is, of course, in line with Addie’s (2014) coining of the concept of aero-regionalism to enhance and reshape our understanding of the relations between aviation infrastructures and their surrounding regional spaces.


Core Layer
(a)1979
N_C =23
E_CC=68
P_CC=13.85
Bangkok
Manila
Cebu
Davao
Kota Kinabalu
Zamboanga
Penang
Kuala Lumpur
Medan
Kuching
Padang
Singapore
Palembang
Jakarta
Surabaya
Solo
Denpasar
E_CB=92
P_CB=5.88
Bridge Layer
N_B =101
E_BB=117
P_BB=2.69
Yangon
Passengers
(Unit: Million)
0-0.01
0.01-0.05
0.05-0.3
0.3-0.6
0.6-1
E_CP=25
P_CP=1.16
Makassar
E_BP=21
P_BP=0.25
Periphery Layer
N_P =53
E_PP=7
P_PP=0.06
Passengers
(Unit: Million)
0-0.08
0.08-0.15
0.15-0.3
0.3-0.5
0.5-1
1-5



(b)1996
Core Layer
N_C =12
E_{CC}=45
P_{CC}=30.46
Bangkok
Manila
Kota Kinabalu
Kuala Lumpur
Bandar Seri Begawan
Kuching
Singapore
Johor Bahru
Surabaya
Makassar
Jakarta
Denpasar
E_{CB}=162
P_{CB}=44.74
Bridge Layer
N_B =168
E_{BB}=283
P_{BB}=11.46
Chiang Mai
Hanoi
Yangon
Phuket
Ho Chi Minh City
Cebu
Penang
Medan
Batam
Balikpapan
Passengers
(Unit: Million)
0-0.01
0.01-0.05
0.05-0.3
0.3-0.6
0.6-1
1-2
E_{CP}=22
P_{CP}=1.14
E_{BP}=29
P_{BP}=0.57
Periphery Layer
N_P =56
E_{PP} =5
P_{PP} =0.03
Passengers
(Unit: Million)
0-0.08
0.08-0.15
0.15-0.3
0.3-0.5
0.5-1
1-5
5-10

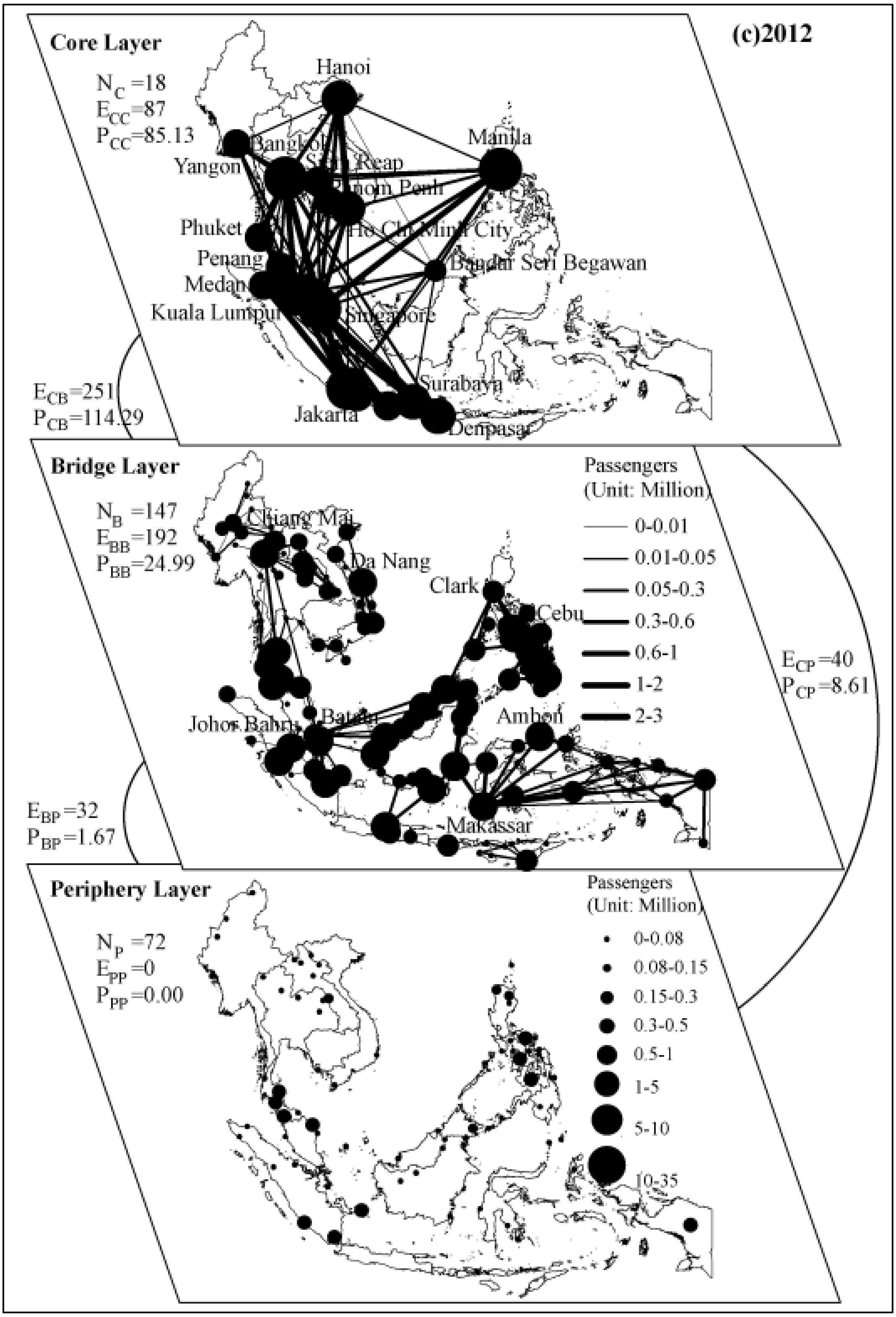


Figure 3.8 The three layers of the SAAN in 1979, 1996 and 2012. E denotes the number of connections within (Ecc, Ebb, and Epp) or between (Ecb, Ecp, and Ebc) layers; P denotes the passengers within (Pcc, Pbb, and Ppp) or between (Pcb, Pcp, and Pbc) layers; and N denotes the number of nodes in each layer (Nc, Nb, and Np).

3.5 Conclusions

In this paper, we examined the evolving SAAN using tools developed in the context of complex network theory. Both topological features and spatial patterns were taken into account. Starting from the longstanding focus of air transport geographers on changing positions of cities and connections in air transport networks, we have aimed to contribute to the literature by exploring the topology and multilayer structure of the SAAN, and tracing its evolution over the period 1979-2012.

The topological structure of the SAAN has exhibited relative stability over the past 34 years. It follows a power-law degree distribution, suggesting scale-free properties as previously observed for air transport networks in India, Austria and, to a lesser extent, in the global, US, EU and Italian networks. The slope of the degree distribution generally decreased, indicating more cities now having a large degree. This is largely due to the emerging hubs in CLMV countries. Meanwhile, the SAAN has been characterized by small-world properties since 1996 when its characteristic path length and average clustering coefficient were both above values of a comparable random network. Furthermore, the SAAN exhibits an intensified disassortativity, showing an increasing dependence of small cities on a hub-and-spoke configuration to access the entire network. However, compared to its EU macro-regional counterpart, the SAAN is far from mature and integrated.

The multilayer structure of the SAAN has changed over time and space, which can be traced back to a range of socio-economic and politico-institutional dynamics. The tourism boom has resulted in the entry of Phuket, Siem Reap and Denpasar into the core layer. And because of the more recent economic development of CLMV, the core layer is now shifting towards the western half of Southeast Asia, leading to a relative marginality of Philippine cities. Our analysis shows a prominent increase in connections and traffic between the core and other layers. Although more remote cities are integrated into the SAAN, connections between peripheral cities remain almost non-existent, which again suggests an increasing dependence of small cities on hub-and-spoke configuration to access the network.

There are, of course, a number of limitations associated with our approach. Our binary (as opposed to a weighted) specification of connections implies that we have focused on the major topological features of the SAAN, but this may result in losing sight on some of the nuances engendered in the edges being unevenly weighted. In addition, our study sheds light on the evolving structure of the SAAN from the perspective of air transport capacity/supply; it would also be interesting to conduct empirical studies from a demand dimension. Our analysis also has its data limitations. First, the network we analyzed is an aggregated one that does not differentiate between types of carriers (i.e., Full Service Carrier and Low Cost Carrier) and airline companies (e.g., Tiger Airways, AirAsia, Jetstar). Second, the rise and fall of cities in these networks may mesh with changes in other modes of transportation, such as port and railway development, which cannot be identified in our study. With more refined and multiplex data, an improvement in these aspects would provide a more accurate understanding of the structural evolution in terms of development strategies and policies for cities and the air transport industry. And finally, our all-too-straightforward definition of what constitutes a node could be conceptually enriched by triangulating it with research on the diversity of the meaning of airport-cities and airport-regions as per Addie (2014) and Derudder et al. (2010).

Reference

Addie, J.-P.D., 2014. Flying high (in the competitive sky): Conceptualizing the role of airports in global city-regions through “aero-regionalism”. Geoforum 55, 87-99.

Agnew, J., 1994. The territorial trap: the geographical assumptions of international relations theory. Review of international political economy 1, 53-80.

Airriess, C., 2001. Regional production, information–communication technology, and the developmental state: The rise of Singapore as a global container hub. Geoforum 32, 235-254.

ASEAN Secretariat, 2011. Master plan on ASEAN connectivity, Jakarta. Http://www.asean.org/storage/images/ASEAN_RTK_2014/4_Master_Plan_on_ASEAN_Connectivity.pdf.

ASEAN Secretariat, 2016. ASEAN Economic Community Chartbook 2016, Jakarta. Http://www.aseanstats.org/wp-content/uploads/2016/11/AEC-Chartbook-2016-1.pdf.

Bagler, G., 2008. Analysis of the airport network of India as a complex weighted network. Physica A: Statistical Mechanics and its Applications 387, 2972-2980.

Barabási, A.-L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509-512.

Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. Journal of Transport Geography 8, 25-41.

Bowen, J.T., Laroe, C., 2006. Airline networks and the international diffusion of severe acute respiratory syndrome (SARS). The Geographical Journal 172, 130-144.

Bunnell, T., 2013. City Networks as Alternative Geographies of Southeast Asia. TRaNS: Trans-Regional and-National Studies of Southeast Asia 1, 27-43.

Burghouwt, G., Hakfoort, J., 2001. The evolution of the European aviation network, 1990-1998. Journal of Air Transport Management 7, 311-318.

Cats, O., 2017. Topological evolution of a metropolitan rail transport network: The case of Stockholm. Journal of Transport Geography 62, 172-183.

Coclanis, P.A., Doshi, T., 2000. Globalization in Southeast Asia. The Annals of the American Academy of Political and Social Science 570, 49-64.

Derudder, B., Witlox, F. 2008. Mapping world city networks through airline flows: context, relevance, and problems. Journal of Transport Geography 16, 305-312.

Derudder, B., Devriendt, L & Witlox, F. 2010. A spatial analysis of multiple airport cities. Journal of Transport Geography 18, 345-353.

Dick, H., 2005. Southeast Asia as an open system:Geo-politics and economic geography, In: Kratoska, P.H., Raben, R., Nordholt, H.S. (Eds.), Locating Southeast Asia. Geographies of knowledge and politics of space. Singapore University Press, Singapore, pp. 250-274.

Dobruszkes, F., 2006. An analysis of European low-cost airlines and their networks. Journal of Transport Geography 14, 249-264.

Du, W.-B., Zhou, X.-L., Lordan, O., Wang, Z., Zhao, C., Zhu, Y.-B., 2016. Analysis of the Chinese airline network as multi-layer networks. Transportation Research Part E: Logistics and Transportation Review 89, 108-116.

Ducruet, C., Lugo, I., 2013. Structure and dynamics of transportation networks: Models, methods and applications, In: Rodrigue, J.-P., Notteboom, T., Shaw, J. (Eds.), The SAGE handbook of transport studies. SAGE, pp. 347-364.

Ducruet, C., Notteboom, T., 2012. The worldwide maritime network of container shipping: Spatial structure and regional dynamics. Global Networks 12, 395-423.

Ducruet, C., Zaidi, F., 2012. Maritime constellations: a complex network approach to shipping and ports. Maritime Policy & Management 39, 151-168.

Forsyth, P., King, J., Lyn Rodolfo, C., 2006. Open skies in ASEAN. Journal of Air Transport Management 12, 143-152.

Guerrero, D., Proulhac, L., 2014. Freight flows and urban hierarchy. Research in Transportation Business & Management 11, 105-115.

Guida, M., Maria, F., 2007. Topology of the Italian airport network: A scale-free small-world network with a fractal structure? Chaos, Solitons & Fractals 31, 527-536.

Guimera, R., Mossa, S., Turtschi, A., Amaral, L.A.N., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. Proceedings of the National Academy of Sciences 102, 7794-7799.

Hanaoka, S., Takebayashi, M., Ishikura, T., Saraswati, B., 2014. Low-cost carriers versus full service carriers in ASEAN: The impact of liberalization policy on competition. Journal of Air Transport Management 40, 96-105.

Hien, P.V., 2003. Sub-regional cooperation on air transport among Cambodia, Lao PDR, Mya nmar and Vietnam, Fifth Worldwide Air Transport Conference. International Civil Aviation Organization, Montreal. Https://www.icao.int/Meetings/ATConf5/Documents/PhanVuHien.p df.

Hill, H., Menon, J., 2012. ASEAN economic integration: Driven by markets, bureaucrats, or both?, In: Kreinin, M.E., Plummer, M.G. (Eds.), The Oxford Handbook of International Commercial Policy. Oxford University Press, Oxford, UK, pp. 357-386.

Hooper, P., 2005. The environment for Southeast Asia's new and evolving airlines. Journal of Air Transport Management 11, 335-347.

Kissling, C., 1989. International tourism and civil aviation in the South Pacific: issues and innovations. Geojournal 19, 309-315.

Kratoska, P.H., Raben, R., Nordholt, H.S., 2005. Locating southeast Asia, In: Kratoska, P.H., Raben, R., Nordholt, H.S. (Eds.), Locating Southeast Asia. Geographies of knowledge and politics of space. Singapore University Press, Singapore, pp. 1-19.

Lin, J., 2012. Network analysis of China’s aviation system, statistical and spatial structure. Journal of Transport Geography 22, 109-117.

Lin, J., Ban, Y., 2014. The evolving network structure of US airline system during 1990-2010. Physica A: Statistical Mechanics and its Applications 410, 302-312.

Liu, X., Dai, L., Derudder, B., 2017. Spatial Inequality in the Southeast Asian Intercity Transport Network. Geographical Review 107, 317-335.

Liu, X., Derudder, B., García, C.G., 2013. Exploring the co-evolution of the geographies of air transport aviation and corporate networks. Journal of Transport Geography 30, 26-36.

Liu, X., Derudder, B., Taylor, P., 2014. Mapping the evolution of hierarchical and regional tendencies in the world city network, 2000–2010. Computers, Environment and Urban Systems 43, 51-66.

Liu, X., Derudder, B., Wu, K., 2016. Measuring polycentric urban development in China: An intercity transportation network perspective. Regional Studies 50, 1302-1315.

Lordan, O., Florido, J., Sallan, J.M., Fernandez, V., Simo, P., Gonzalez-Prieto, D., 2015. Study of the robustness of the European air routes network, In: Zhang, Z., Shen, Z., Zhang, J., Zhang, R. (Eds.), LISS 2014. Springer, pp. 195-200.

Lordan, O., Sallan, J.M., 2017. Analyzing the multilevel structure of the European airport network. Chinese Journal of Aeronautics 30, 554-560.

Lordan, O., Sallan, J.M., Simo, P., 2014. Study of the topology and robustness of airline route networks from the complex network approach: a survey and research agenda. Journal of Transport Geography 37, 112-120.

Matsumoto, H., 2007. International air network structures and air traffic density of world cities. Transportation Research Part E: Logistics and Transportation Review 43, 269-282.

Newman, M.E., 2003. The structure and function of complex networks. SIAM review 45, 167-256.

O'Connor, K., 1995. Airport development in southeast Asia. Journal of Transport Geography 3, 269-279.

O'Kelly, M.E., 1998. A geographer's analysis of hub-and-spoke networks. Journal of Transport Geography 6, 171-186.

Ooi, G.-L., 1995. The Indonesia-Malaysia-Singapore Growth Triangle: Sub-Regional Economic Cooperation and Integration. Geojournal 36, 337-344.

Paleari, S., Redondi, R., Malighetti, P., 2010. A comparative study of airport connectivity in China, Europe and US: Which network provides the best service to passengers? Transportation Research Part E: Logistics and Transportation Review 46, 198-210.

Raguraman, K., 1997. Airlines as instruments for nation building and national identity: case study of Malaysia and Singapore. Journal of Transport Geography 5, 239-256.

Reed, W.J., 2003. The Pareto law of incomes-an explanation and an extension. Physica A: Statistical Mechanics and its Applications 319, 469-486.

Rimmer, P.J., 1999. The Asia-Pacific Rim's transport and telecommunications systems: spatial structure and corporate control since the mid-1980s. Geojournal 48, 43-65.

Rimmer, P.J., 2000. Effects of the Asian Crisis on the geography of Southeast Asia's air traffic. Journal of Transport Geography 8, 83-97.

Rimmer, P.J., Dick, H.W., 2009. The city in Southeast Asia: Patterns, processes and policy. NUS Press, Singapore.

Robinson, R., 2006. Port-oriented landside logistics in Australian ports: a strategic framework. Maritime Economics & Logistics 8, 40-59.

Rocha, L.E.D., 2009. Structural evolution of the Brazilian airport network. Journal of Statistical Mechanics: Theory and Experiment 2009, P04020.

Ru, W., Xu, C., 2005. Hierarchical structure, disassortativity and information measures of the US flight network. Chinese Physics Letters 22, 2715-2718.

Sien, C.L., 2003. Southeast Asia transformed: a geography of change. Institute of Southeast Asian Studies, Singapore.

Tanaka, K., 2009. Regional Integration in Southeast Asia: Better Macroeconomic Co-operation Can Mitigate Risks. OECD Development Centre Policy Insights 90, OECD Publishing.

Taylor, P.J., Derudder, B., Hoyler, M., Ni, P., 2013. New regional geographies of the world as practised by leading advanced producer service firms in 2010. Transactions of the Institute of British Geographers 38, 497-511.

Thant, M., 2012. Regional cooperation and the changing urban landscape of Southeast Asia, In: Sheng, Y.K., Thuzar, M. (Eds.), Urbanization in Southeast Asia: Issues & impacts. Institute of Southeast Asian Studies, Singapore, pp. 154-171.

Thompson, E.C., 2013. In Defence of Southeast Asia: A Case for Methodological Regionalism. TRaNS: Trans-Regional and-National Studies of Southeast Asia 1, 281-302.

Tsiotas, D., Polyzos, S., 2017. The Complexity in the Study of Spatial Networks: an Epistemological Approach. Networks and Spatial Economics, 1-32.

Van De Vijver, E., Derudder, B., Witlox, F., 2014. Exploring causality in trade and air passenger travel relationships: the case of Asia-Pacific, 1980-2010. Journal of Transport Geography 34, 142-150.

Verma, T., Araújo, N.A., Herrmann, H.J., 2014. Revealing the structure of the world airline network. Scientific reports 4, 5638.

Wandelt, S., Sun, X., 2015. Evolution of the international air transportation country network from 2002 to 2013. Transportation Research Part E: Logistics and Transportation Review 82, 55-78.

Wang, J., Jin, F., Mo, H., Wang, F., 2009. Spatiotemporal evolution of China’s railway network in the 20th century: An accessibility approach. Transportation Research Part A: Policy and Practice 43, 765-778.

Wang, J., Mo, H., Wang, F., 2014. Evolution of air transport network of China 1930-2012. Journal of Transport Geography 40, 145-158.

Wang, J., Mo, H., Wang, F., Jin, F., 2011. Exploring the network structure and nodal centrality of China’s air transport network: A complex network approach. Journal of Transport Geography 19, 712-721.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of'small-world'networks. Nature 393, 440-442.

Xie, F., Levinson, D., 2009. Modeling the growth of transportation networks: a comprehensive review. Networks and Spatial Economics 9, 291-307.

Xie, F., Lin, J., Cui, W., 2015. Exploring express delivery networks in China based on complex network theory. Complexity 21, 166-179.

Xu, Z., Harriss, R., 2008. Exploring the structure of the US intercity passenger air transportation network: a weighted complex network approach. Geojournal 73, 87-102.

Yap, J.T., 2014. Addressing Inequality in Southeast Asia through Regional Economic Integration. Institute of Developing Economies, Tokyo, Japan. Retrieved from website: http://www.ide.go.jp/English/Publish/Download/Brc/pdf/14_01.pdf.

Zanin, M., Lillo, F., 2013. Modelling the air transport with complex networks: A short review. The European Physical Journal Special Topics 215, 5-21.

Zhang, A., Hanaoka, S., Inamura, H., Ishikura, T., 2008. Low-cost carriers in Asia: Deregulation, regional liberalization and secondary airports. Research in Transportation Economics 24, 36-50.

Chapter 4 Generative network models for simulating urban networks, the case of intercity transport network in Southeast Asia

Dai, L., Derudder, B., Liu, X., 2016. Generative network models for simulating urban networks, the case of intercity transport network in Southeast Asia. Cybergeo: European Journal of Geography, DOI:10.4000/cybergeo.27734.

Abstract

This paper examines the driving forces of urban network formation through the simulation of intercity transport networks in Southeast Asia. We present a generative network model (GNM) considering geographical and topological effects, thus combining factors commonly analysed through traditional spatial simulation models (e.g., gravity models) and topological simulation models (e.g., actor-oriented stochastic models)in a single framework. In our GNM, it is assumed that the probability of connections between cities emerges from competing forces. Stimulating factors are a measure of city size (e.g., population) and a topological rule favouring the formation of connections between cities sharing nearest neighbours (i.e., transitive effects). The hampering factors are physical distance between two cities as well as institutional distance (e.g., border effects). We discuss the model in the context of on-going engagements between urban-geographical research and the network science literature, and validate the credence of the model against empirical data on the transport networks connecting 51 major cities in Southeast Asia. Our results show that (1) the generated networks approximate the observed ones in terms of average path length, clustering, modularity, efficiency and quadratic assignment procedure (QAP) correlation between the observed composite network and the generated one, and that (2) GNM performs best when topographical and topological factors are considered simultaneously. Each factor contributes differently to network formation, with transitive effects playing the most important role.

4.1 Introduction

Network perspectives have (re)gained increasing attentions in urban geography. This increased popularity is not only visible in a range of theoretical frameworks (e.g., Sassen, 2002; Taylor and Derudder, 2015), but also in matching methodological approaches in which 'network thinking' is invoked to understand the position of cities in urban systems (e.g., Decoupigny and Passel, 2014; Hennemann and Derudder, 2014; Rozenblat and Melançon, 2013). When adopting a network perspective, urban geographers study cities through their insertion in various immaterial and material flows (e.g., finance, investment, transportation and information) at various scales (cf. Bretagnolle and Pumain, 2010): the spatial outline of urban systems is envisaged as the spatial distribution of edges (intercity linkages) connecting nodes (cities).As corollary, this emerging urban network paradigm emphasizes the importance of the external relations of cities rather than their relations with a hinterland (cf. Camagni and Salone, 1993). Taking a broader perspective, this development can be understood as an example of the recent forging of closer relationships between geographical science and network science (e.g., Barthélemy, et al., 2005; Pasta, et al., 2014).

In spite of the increased popularity of network-scientific methods, the adoption of some of the more advanced methods has recently been described as comparatively 'limited and dispersed' in spatial sciences in general and urban geography in particular (Ducruet and Beaugitte, 2014, p. 1). The purpose of this paper is to help contribute to further cross-fertilizations by explaining and exploring the potential of a new approach for simulating networks that have an explicitly spatial dimension. More specifically, drawing on Vértes et al. (2012), we propose a generative network model (GNM) for approximating urban networks. The GNM approach takes both spatial and topological processes into consideration, and here we examine the remit of hypothesized network-generating processes through a case study of intercity transportation networks in Southeast Asia.

The remainder of this paper is organized as follows. In the next section, we review network-analytical strategies used by urban geographers, with a particular focus on urban network modeling and simulation. We use this discussion to posit the potential of GNM. We then propose our analytical framework, summarize the datasets, and elaborate the model specification and parameter estimation procedure. The model is operationalized and validated in the subsequent section by comparing simulated and observed networks from different perspective and exploring how transitivity, distance, borders and population influence network formation. The final section summarizes the main implications of our analysis and outlines some avenues for further research.

4.2 Literature review

4.2.1 Urban network analysis

Network theory is concerned with the study of graphs as representations of relations between discrete objects. Although thinking of cities as discrete and bounded objects has its conceptual problems (Saey, 2007; Brenner and Schmid, 2013), examining urban systems as the outcome and representation of intercity relations has been shown to make sense in analytical terms (Rozenblat and Pumain, 2007; Ducruet et al., 2010; Neal, 2012). Especially fertilized by other disciplines ranging from sociology and information science to physics and biology, network analysis in urban geography has thus tried to shed new light on hierarchical and regional structures of urban systems, as well as the mechanisms by which intercity connections develop over time.

A considerable number of studies have sought to describe the structure of urban systems using a series of network metrics. First, the 'importance' of cities has been examined by calculating a range of centrality such as degree centrality and betweenness centrality in Krätke (2014), eigenvector centrality in Smith and Timberlake (2001) as well as other centrality measures that have been specifically tailored for urban network analysis (Neal, 2013b). Second, spatial structures within and of urban networks have been explored by applying community detection methods (Liu et al., 2014; Blondel et al., 2010). Third, the structural equivalence of different urban networks has been assessed through the application of Quadratic Assignment Procedures (QAP) as in Choi et al.'s (2006) analysis of air transport and Internet backbone connections between cities, as well as Ducruet et al.'s (2011) assessment of worldwide sea and air transport flows. Fourth, there have been analyses of the topological properties of urban networks. Guimera et al. (2005), for example, present a detailed analysis of the topological properties of the global air transport network, and find that it exhibits small-world characteristics (Watts and Strogatz, 1998) in that city-pairs tend to be separated by just a few links and show a high local clustering coefficient. Meanwhile, Ducruet et al. (2011) point out that both worldwide sea and air transport flows exhibit a scale-free structure (Barabási and Albert, 1999) with a power-law degree distribution reflecting the hierarchy of cities.

Importantly, thinking about the nature of the hierarchical structure of cities' positions in urban networks has also proven to deliver new insights in established thinking in urban geography on the rank-size rule (Pumain et al., 2015).

Pumain et al.'s (2015) paper points to another family of potential network analysis applications in urban geography, i.e. *modelling and simulation approaches*. In their analysis, urban growth processes are compared at the macro-scale for seven large countries. Crucially, they emphasize that a few common principles such as Gibrat's Law can explain the diversity of trajectories of cities within urban systems. This then aids in the simulation of urban systems as put forward in Pumain et al. (2006), who point out that regularities in cities' centralities in urban systems can be expressed in the form of scaling laws previously recognized as revealing specific constraints on the structure and evolution of complex systems in physics and biology. In such simulation models, the focus tends to be on the outcome at the level of nodes (cities) rather than edges (intercity connections). The structure of the latter remains somewhat implicit in the operational model. That is, although it is posited that scaling laws emerge from intercity relations of competition and cooperation in interdependent networks, the focus is ultimately on that scaling of nodes rather than the distribution and spatial outline of cities' interactions. The latter can, however, also be modelled, and herein particular a number of recent advances in network sciences have opened up new opportunities for urban network research.

4.2.2 Space and topology in the simulation of urban networks

Simulating the driving forces underlying the formation of urban networks is bound to be complex for a number of reasons. For one thing, it has been pointed out that urban network evolution is rarely linear (Barrat, et al., 2004; Hazir, 2013; Taylor and Walker, 2001).In addition, effects may play out at the level of nodes and dyads. At the level of nodes, it has been demonstrated that city size (in demographic or economic terms) and different sets of policies may affect spatial interactions between cities. For instance, metropolitan areas tend to produce more connections because they are supported by larger local demand as well as having stronger abilities to satisfy these demands (Dobruszkes et al., 2011). Meanwhile, provision of air transport links can be the result of decades of aggressive policies and strategies as the example of Singapore clearly shows (Phang, 2003; Ducruet and Lee, 2006; Lee et al., 2008). At the dyadic level, factors such as physical distance and institutional distance (e.g., border effects) have been shown to impinge on intercity relation interactions.

Transaction costs and friction increase with distance, making it is easier to forge connections among cities with a shorter distance or within the same country (Mun and Nakagawa, 2010). Meanwhile, colonial legacies as specific examples of institutional facilitators of intercity connections have been shown to be pertinent in the shaping of airline networks (e.g. the London-Nairobi dyad as, see Pirie, 2010), just as tight regulation on specific routes can hinder the development of connections as has been shown in the past for the Singapore-Kuala Lumpur link (Ng, 2009).

There is one further feature of spatial networks that requires closer attention when thinking through how a simulation of urban networks might look like. One conspicuous empirical feature of Pumain et al.'s (2015) thought-provoking maps is that there are regional densities of cities (e.g. regionalized clusters of cities in China). This is due to the strong localization component in almost all underlying economic and social networks, which collectively lead to a higher probability of short-range connections than of geographically distant connections (cf. Tobler 1970, Barthelémy 2011, Hennemann et al., 2012).

4.2.3 Previous approaches to the simulation of urban networks

The most frequently adopted strategy for modelling urban networks is to emphasize the analogies with Newton's law of gravity (Ravenstein, 1885; Reilly, 1931; Enault, 2012; Josselin and Nicot, 2003). From this perspective, the flow and interaction intensity between pairs of cities is assumed to be proportional to their 'masses' and inversely proportional to the distance separating them. This approach has been validated for a wide range of urban networks, including for international trade, migration, tourism, foreign direct investment, etc. In addition to its intuitive conceptual appeal and straightforward operationalization, the popularity of the gravity-type models resides in the fact that it can be easily extended to include other factors with a spatial connotation. For instance, researchers have added political barriers (Cattan and Grasland, 1993), remoteness variables (Head and Mayer, 2000), heterogeneous coefficients (Behrens et al., 2012) to provide a richer and more accurate estimation and interpretation of the spatial characteristics of the urban network. However, in spite of these elaborations, the strong assumptions of structural independence amongst nodes loom large. From a network perspective, it is precisely the lack of independence of nodes - i.e. the *interdependence of nodes* - that defines a network. The strength of the linkages between London, New York and Hong Kong, for example, derives from the interdependence of their financial services complexes, a topological property resulting in important long-distance connections that might deform gravitational predictions (Lambiotte et al., 2008).

To date, geographers have made limited attempts to explicitly incorporate topological effects when simulating urban networks. A major exception has been Vinciguerra et al.'s (2010) simulation of the formation of the European intercity Internet backbone network. They show how a combination of topological effects (a preferential attachment process whereby nodes have the tendency to connect to nodes that are already well-connected) and spatial effects (e.g., borders) help explaining the shape of this particular intercity network.

Two recent approaches from the network analysis literature that may be applied for modelling urban networks can be found in the work of Liu et al. (2013a, 2013b). Both papers apply stochastic models, i.e. Exponential Random Graph Models (ERGM, Liu et al., 2013) and Stochastic Actor-Based Models (SABM, Liu et al., 2013). Both types of models have been developed in the social sciences to examine how different kinds of structural interdependencies between pairs of nodes at the local scale give rise to the empirically observed network patterns at the global scale (Robins et al., 2007; Snijders et al., 2010). In addition, both types of models aim to generate a hypothesized network that closely parallels an observed network, thus revealing the underlying topological forces that drive the network formation. These processes are, however, much more complicated and difficult to interpret than gravity-type models. In addition, both approaches have their drawbacks in the context of urban network simulation. EGRMs, for instance, is prone to degeneracy problems (i.e., failure to converge and hence become unstable) and at present confined to modelling binary edges. Meanwhile, while SABM clearly has potential for simulating urban networks that are produced by well-defined agents (e.g. firms), this need for clear-cut definition of key actors and their network-generating behaviour is sometimes hard to implement(cf. Broekel et al., 2014).

We also note that topological and spatial effects are not mutually exclusive, as they may exert overlapping (yet separate) influences in the shaping of urban networks (Pflieger and Rozenblat, 2010). This is because city-dyads characterized by topological proximity (e.g. two nodes that have a strong, direct connection) are often also located near each other (cf. the China example in Pumain et al., 2015). Or, put differently: interdependent cities are also often close to each other in Euclidean space. However, this need not be the case: intercity air transport connections are much less bound by distance decay effects than say, rail networks.

In our paper, we extend Vinciguera et al. (2010)'s network modelling approach, which incorporates both spatial and topological factors. Here we apply Vértes et al.'s (2012) generative network modelling approach (GNM), which was initially developed for studying functional human brain networks. In their paper, the authors successfully modelled this brain network as the outcome of trade-offs between a limited number of plausible generative forces: a constraint on connection distance and a tendency for transitive process, resulting in spatial and functional clustering of connections between brain cells.

4.3 Data and Methodologies

4.3.1 Data: Intercity transport networks in Southeast Asia

Our analysis draws upon a undirected and weighted network reflecting the strength of the transport connections between 51 major Southeast Asian cities. Tie strength is based on the strength of intercity connections in different transportation networks.

Cities were selected based on the following set of criteria: (1) all metropolises with more than 0.5 million residents; (2) all capital cities (e.g., Vientiane, Laos and Dili, East Timor) regardless of their population size; and (3) in order to produce a more balanced geographical distribution also the four largest cities in vast but sparsely populated islands of Sulawesi, Maluku and western half of New Guinea even though these cities had less than 0.5 million inhabitants. Table 4.1 and Figure 4.1 list and map the 51 cities.

Table 4.1 List of selected cities.

No.	Country	City	Abbreviation	Population	Notes
1	Malaysia	Kuala Lumpur	KUL	6279556	Greater Kuala Lumpur
2	Malaysia	Penang	PEN	708127	Greater Penang Conurbation
3	Malaysia	Johor Bahru	JHB	1026141	
4	Malaysia	Malacca	MKZ	788706	
5	Malaysia	Ipoh	IPH	657892	
6	Malaysia	Kota Kinabalu	BKI	628725	Greater Kota Kinabalu
7	Malaysia	Kuching	KCH	598617	
8	Indonesia	Jakarta	JKT	17720485	Greater Jakarta
9	Indonesia	Bandung	BDO	2936050	Combined with Cimahi (share airport)
10	Indonesia	Surabaya	SUB	2765487	
11	Indonesia	Medan	MES	2097610	

12	Indonesia	Semarang	SRG	1520481	
13	Indonesia	Palembang	PLM	1440678	
14	Indonesia	Makassar	UPG	1331391	
15	Indonesia	Batam	BTH	917998	
16	Indonesia	Pekanbaru	PKU	882045	
17	Indonesia	Bandar Lampung	TKG	873007	
18	Indonesia	Malang	MLG	820243	
19	Indonesia	Padang	PDG	799750	
20	Indonesia	Denpasar	DPS	788589	
21	Indonesia	Samarinda	SRI	685859	
22	Indonesia	Banjarmasin	BDJ	612849	
23	Indonesia	Tasikmalaya	TKL	578046	
24	Indonesia	Pontianak	PNK	554764	
25	Indonesia	Balikpapan	BPN	526508	
26	Indonesia	Jambi	DJB	515901	
27	Indonesia	Manado	MDC	394683	Provincial capital of North Sulawesi
28	Indonesia	Palu	PLW	310168	Provincial capital of Central Sulawesi
29	Indonesia	Ambon	AMQ	305984	Provincial capital of Maluku
30	Indonesia	Jayapura	DJJ	233859	Provincial capital of Papua
31	Singapore	Singapore	SIN	5076700	
32	Philippines	Manila	MNL	11236045	Metropolitan Manila + Antipolo, Dasmarinas, Bacoor (share airport)
33	Philippines	Davao	DVO	1176586	
34	Philippines	Cebu	CEB	866171	
35	Philippines	Zamboanga	ZAM	643557	
36	Philippines	Cagayan de Oro	CGY	602088	
37	Philippines	Bacolod	BCD	511820	
38	East Timor	Dili	DIL	192652	
39	Brunei	Bandar Seri Begawan	BWN	279924	
40	Vietnam	Ho Chi Minh City	SGN	6533261	Metropolitan Ho Chi Minh City
41	Vietnam	Hanoi	HAN	2316772	Metropolitan Hanoi + Thai Nguyen (share airport)
42	Vietnam	Da Nang	DAD	770911	
43	Vietnam	Hai phong	HPH	769739	
44	Vietnam	CanTho	VCA	731545	
45	Laos	Vientiane	VTE	754000	
46	Myanmar	Yangon	RGN	4090000	
47	Myanmar	Mandalay	MDL	960000	
48	Myanmar	Naypyidaw	NPD	418000	
49	Cambodia	Phnom Penh	PNH	1242992	
50	Thailand	Bangkok	BKK	8280925	Greater Bangkok
51	Thailand	Chiang Mai	CNX	1000000	Metropolitan Chiang Mai

Note: Majority population data are from citypopulation.de in the year 2010 except that 1) population of Malaysian cities in 2010 are derived from Department of Statistics Malaysia (web) and 2) population data of Lao and Vietnamese cities are obtained from citypopulation.de in the year 2009 while that of Bruneian city is in 2011.

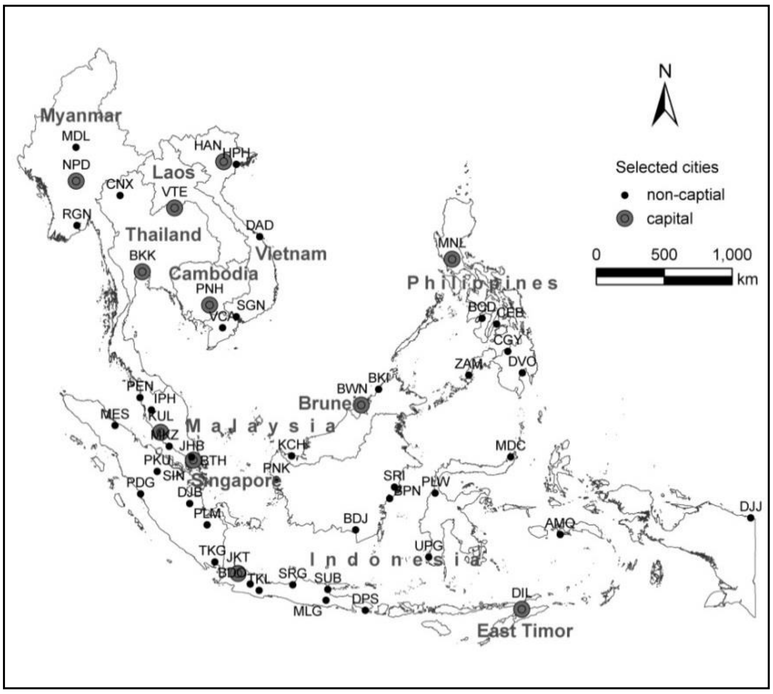


Figure 4.1 Distribution of selected cities in Southeast Asia. City abbreviations used in the figure are given in Table 4.1, hereafter.

Our composite transport network provides a surrogate measure of three individual transport networks: road, rail, and air transport. Based on the 51 selected cities, intercity connectivity in each transport network is measured through the number of weekly direct buses (including ferries), direct trains and non-stop flights in the first week of November, 2015, respectively. Intercity bus and ferry connections were acquired from national and international online-bus/ferry websites of each country[5]; for train connections we consulted websites of railway agencies and national railway administrations for individual countries[6]; and for air transport connections, data were collected through the SkyScanner web crawling service. It is worth mentioning that, as small differences in the direction of the link had no conceptual bearing, the three transport networks have been symmetrized by averaging the value from city A to city B and that from city B to city A (with all diagonal cells set at zero).

[5]Source: www.busonlineticket.com; myanmarbusticket.com; www.vietnambustickets.com; www.buso nlineticket.co.th; www.camboticket.com; www.kramatdjati.co.id; www.indonesiaferry.co.id; travel.2g o.com.ph.
[6]Source: vietnam-railway.com; www.gahanoi.com.vn; www.thairailways.com; www.ktmb.com.my; w ww.myanmarmtetours.com; www.pnr.gov.ph; tiket.kereta-api.co.id.

To combine the different networks into a single network of connectivity, we first logged measures in each layer to alleviate the skewness in the distributions, after which we normalized data through:

$$x_{ij} = \frac{x_{ij} - Min(x_{ij})}{Max(x_{ij}) - Min(x_{ij})} \quad (4\text{-}1)$$

Where x_{ij} denotes the frequencies of weekly bus/ferry, rail links, flights between city i and j in each of the three networks.

All three data layers thus have a distribution between 0 (minimum connectivity) and 1 (maximum connectivity), after which edges in the composite network were derived by taking the average score of the logged and normalized values in each of the different layers.

Table 4.2 The 10 strongest intercity connections in different layers in Southeast Asia.

Rank	Intercity connection	Road	Intercity connection	Rail
1	Kuala Lumpur-Singapore	1190	Kuala Lumpur-Ipoh	119
2	Kuala Lumpur-Johor Bahru	1190	Jakarta-Semarang	49
3	Kuala Lumpur-Penang	861	Yangon-Mandalay	49
4	Malacca-Singapore	735	Bangkok-Chiang Mai	42
5	Kuala Lumpur-Ipoh	448	Hanoi-Da Nang	42
6	Ho Chi Minh City-Can Tho	336	Singapore-Johor Bahru	42
7	Kuala Lumpur-Malacca	322	Yangon-Naypyidaw	42
8	Phnom Penh-Ho Chi Minh City	273	Bandung-Jakarta	42
9	Malacca-Johor Bahru	252	Jakarta-Surabaya	35
10	Hanoi-Hai phong	238	Ho Chi Minh City-Hanoi	35
Rank	**Intercity connection**	**Air**	**Intercity connection**	**Composite**
1	Jakarta-Surabaya	406	Kuala Lumpur-Singapore	0.857
2	Manila-Cebu	337	Kuala Lumpur-Johor Bahru	0.792
3	Denpasar-Jakarta	275	Bangkok-Chiang Mai	0.762
4	Kuala Lumpur-Singapore	257	Ho Chi Minh City-Hanoi	0.759
5	Ho Chi Minh City-Hanoi	240	Jakarta-Semarang	0.737
6	Jakarta-Medan	235	Ho Chi Minh City-Da Nang	0.716
7	Jakarta-Singapore	217	Hanoi-Da Nang	0.695
8	Kuala Lumpur-KotaKinabalu	203	Jakarta-Surabaya	0.681
9	Manila-Davao	197	Kuala Lumpur-Ipoh	0.621
10	Jakarta-Palembang	182	Kuala Lumpur-Penang	0.595

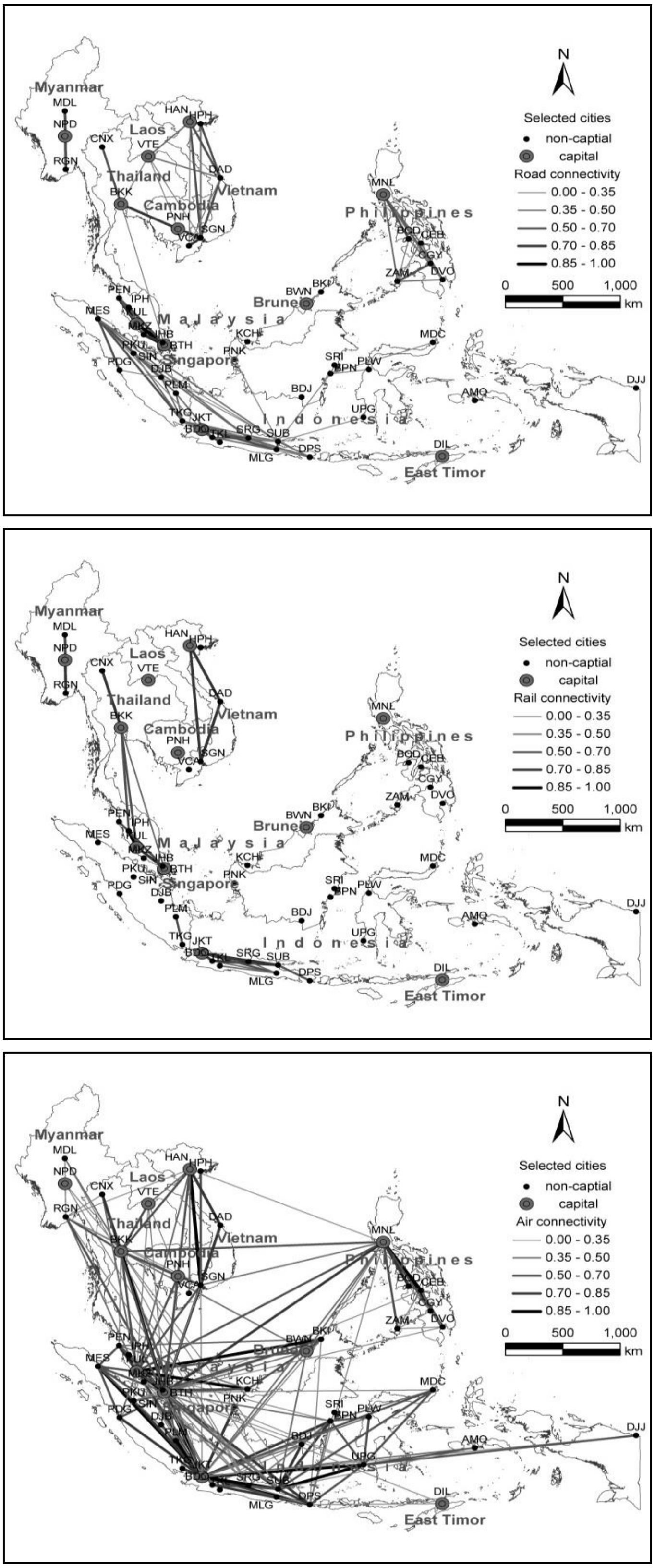


Figure 4.2 The three layers used in the construction of the composite network.

The connections in each of the three layers are shown in Figure 4.2, while the 10 strongest connections are presented in Table 4.2. It is clear that he three layers are quite different in structure. The road and rail networks are sparsely connected, and exhibit strong localization tendencies, while the air network is relatively strongly connected. Largely due to the region's mountainous terrain, tropical land covers and archipelagic geography, the three modes of transportation are complementary in providing intercity accessibility. The strongest intercity connections in the road network are Kuala Lumpur-Singapore and Kuala Lumpur-Johor Bahru with 1190 weekly direct buses along the Malaysian North-South highway.. The strongest rail connection is between Kuala Lumpur and Ipoh (119 weekly direct trains) in the densely connected Malay Peninsula, followed by Jakarta-Semarang (49) in central Java, Indonesia, and Yangon-Mandalay (49) in Myanmar. The strongest air transport connection is Jakarta-Surabaya (406 weekly non-stop flights), followed by Manila-Cebu (337), and Denpasar-Jakarta (275). Except for the strongest Kuala Lumpur-Singapore linkage, the rest of the top-10 linkages in the composite network are dominated by domestic connections such as the Straits of Malacca Corridor in West Malaysia and the North-South Economic Corridor in Vietnam and Thailand.

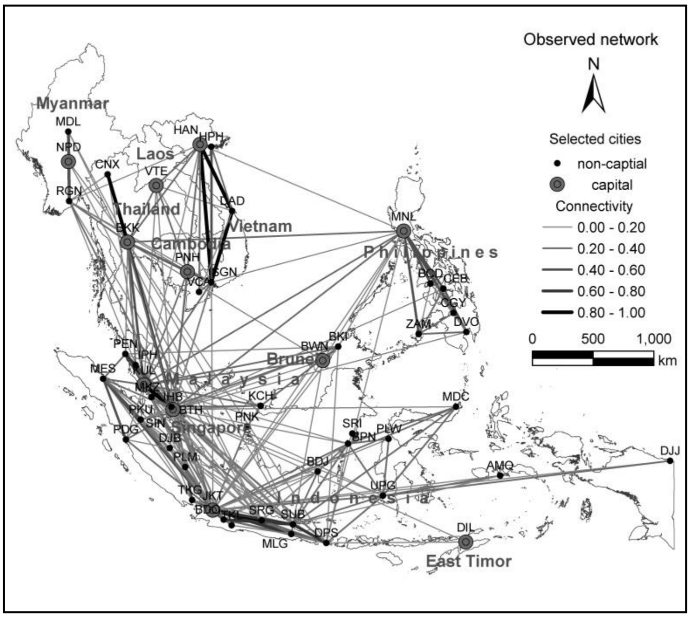


Figure 4.3 Connections in the observed network of composite transport in Southeast Asia.

In the observed network of composite network displayed in Figure 4.3, it is obvious that flows are mostly centred on capital cities (e.g., Jakarta, Kuala Lumpur, Manila) and other important cities with large population (e.g., Bandung and Semarang) in each country. Furthermore, five communities of strongly interconnected nodes can be detected through the application of a community detection method (here we employed the 'fast greedy modularity optimization method' developed in Clauset et al., 2004). The communities consist of an geographically extensive Indonesian community organized around Jakarta and Surabaya, a Philippine community centred on Manila, an integrated Malaysian community including Singapore and Brunei, a relatively isolated Burmese community and a transnational community in the north comprised by cities in Thailand, Laos, Cambodia and Vietnam together. This pattern suggests a combination of border effects and geographical proximity. Therefore, these forces alongside topological transitivity are simultaneously considered in the following simulation.

4.3.2 Model specification

In our urban network-implementation of GNM, it is assumed that the probability of a connection between two cities is adversely proportional to the distance and border between them whereas is proportional to the product of their population and a topological tendency towards transitivity. Transitivity states that when there is an edge between node A and B, and also between B and C, then there is also an edge between node B and C (Weimann, 1983). This structural property is commonly observed in social networks that friends of my friends are my friends. Here in our weighted urban networks, the manifestation of transitivity can, for instance, be linked with the presence of transport corridors such as major rail or road links. It helps additionally assessing to what degree intercity connectivity is consolidated between nodes having nearest neighbours in common. The resulting specification can be written as:

$$\mathrm{P}_{ij} \propto \frac{(\mathrm{pop}_i \cdot \mathrm{pop}_j)^{\alpha}}{\mathrm{d}_{ij}{}^{\beta}} \cdot \frac{1}{\theta} \cdot \mathrm{k}_{ij}{}^{\gamma} \tag{4-2}$$

where P_{ij} is the probability of a connection between cities i and j with (logged) populations pop_i and pop_j and separated by an Euclidean distance d_{ij}; and k_{ij} is the number of first-order neighbours that city i and j have in common. α, β, γ and θ are the model parameters: α and γ refer to strength of the facilitating impact of population and transitivity; while β is an impedance factor reflecting the friction of distance. And finally, θ is a parameter assessing the impact of border effects in intercity connections. If $0<\theta<1$, then borders stimulate intercity connections (an unlikely scenario); if $\theta=1$, borders, then have no effect; and and if $\theta>1$, then borders have an adverse effect on intercity connections.

In practice, it is intuitive how variables of population, distance, border work in the process of simulation. In case of topological properties, we consider Transitivity k_{ij} based on existing total edges. For each newly added edge (which initially will have zero connections), its location is determined by a stochastic sampling in which sampling probability is the normalized number of shared neighbours between two nodes. In the weighted network, the number of shared neighbours can be calculated as:

$$\mathrm{SN}_{ij} = \sum_{k=1}^{n} x_{ik} \cdot x_{kj} \qquad (4\text{-}3)$$

Where SN_{ij} is the number of shared neighbours node *i* and *j*; n is the total number of nodes in the simulated network; x_{ik} and x_{kj} are the weights of $dyad_{i\text{-}k}$ and $dyad_{k\text{-}j}$.

4.3.3 Model parameter estimation

Although the overall logic underlying Vértes et al.'s (2012) GNM is straightforward, its major force lays in its potential to reveal which configuration of what set of generative factors best explains the geographical and topological structure of an observed network. After modelling factors and their configurations are specified, the modelling exercise entails finding the 'optimal' combination of α, β, γ and θ that generates a network that most closely resembles the structures of the observed network. As generative network models produce probabilities, a common research strategy is to re-run models after which mean values are used for comparing the generated and the observed network.

For reasons of computational ease, we did not employ the simulated annealing method in Vértes et al.'s (2012) to seek optimal parameters. Rather, we applied a 'brute force' approach in which parameter combinations are tested by varying the four parameters from 0 to 4 in steps of +0.5 (excluding 0 for θ), resulting in 9*9*9*8=5832 model versions. For each version, we generated 100 networks with corresponding parameters. We then compare the 'mean' properties of these 100 generated networks and the observed network. An optimal combination of parameters would be identified when generated and observed networks are considered most 'similar'.

The assessment of the 'similarity' of the generated and observed networks is relatively non-trivial. Following Vértes et al.'s (2012) approach, the comparison between generated and observed networks considers four key topological features: (1) modularity (M), a measure of how the network can be decomposed into a set of sparsely interconnected modules, each comprising several densely interconnected nodes; (2) average clustering coefficient (C), a measure of cliquish interconnections between topologically neighbouring nodes; (3) global efficiency (E), a measure of network integration inversely related to path length; (4) degree distribution (D), a measure of the probability distribution of degree or number of edges per node. Two networks are considered similar if there is no statistical difference between their four topological features.

The differences between the generated and observed networks in terms of these four metrics are combined into an energy value (EV; Vértes et al.'s 2012) and the optimal parameter combination corresponds to the minimum EV. The energy value is calculated as:

$$\mathrm{EV} = \frac{1}{pM \cdot pC \cdot pE \cdot pD} \tag{4-4}$$

where *pM*, *pC* and *pE* is the *p* value associated with the *t* test for a difference in the mean modularity, mean clustering coefficients and mean global efficiency of 100 simulated networks vs. corresponding values calculated from the observed network, respectively. Similarly, *pD* is the *p* value of the Kolmogorov-Smirnoff test between the degree distributions estimated from the simulated and observed networks. The larger the *p*-values, the less likely there is a statistical difference between the metrics of the observed and the generated networks, and the lower the energy value.

4.4 Results

4.4.1 Comparisons between the simulated and the observed networks

The model fit with the lowest energy value among the 5832 versions was obtained for the following set of parameters: α=2, β=3.5, θ=2 and γ=1. This implies that the probability of a link emerging between any pair of cities is best described by:

$$\mathrm{P}_{ij} \propto \frac{\left(\mathrm{pop}_i \cdot \mathrm{pop}_j\right)^2 \cdot \left(\frac{1}{\mathrm{d}_{ij}{}^{3.5}}\right) \cdot \mathrm{k}_{ij}}{\text{if i and j are located in the same country} = 1, \text{else} = 2}$$

Table 4.3 and Figure 4.4 compares the values of the network metrics for the observed and the simulated networks. The spatial patterns of the simulated networks are shown in Figure 4.5.

Topologically, both networks are very similar, especially in terms of average clustering coefficient, global efficiency and degree distribution.

Table 4.3 Network metrics for the observed and the simulated networks.

Network	M	C	E	D	QAP (Sig.)	EV
Observed	0.481	0.496	0.534	Figure 4.4	0.309(0.001)	4.2E+73
Simulated	0.345	0.453	0.510			

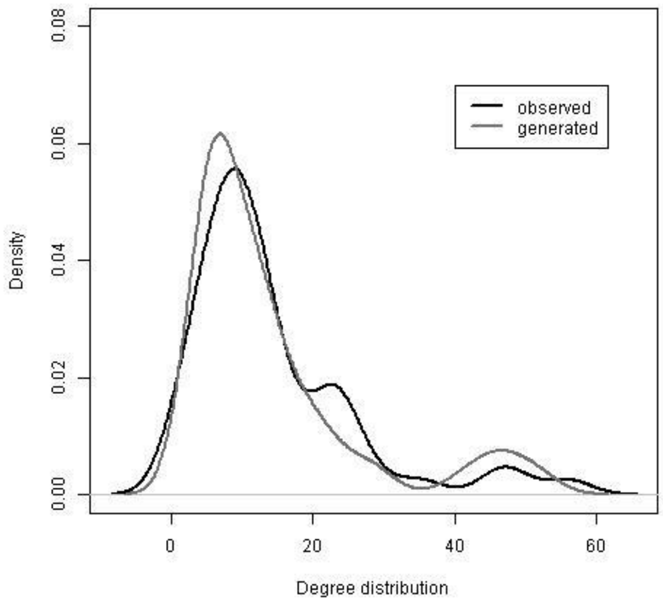


Figure 4.4 Degree distributions in the observed and the simulated networks.

The mean QAP correlation between the two networks is 0.309, statistically significant at the 1% level. A QAP correlation of 0.309 is acceptable given that our random network generation process is governed by only four simple parameters and applied to a large geographical regional with great cultural, economic, and socio diversities. In addition, the size of QAP correlation in our case is comparable with those reported in Vinciguerra et al. (2010). Furthermore, as our 'brute force' approach does not search for the entire parameter space, our model may well reach a local 'optimal' instead of the global 'optimal', implying that higher QAP values and better model fits may be achieved with other parameter specifications. A joint interpretation of these network metrics suggests that the four chosen processes explain the formation of the transport networks connecting cities in Southeast Asia reasonably well.

The simulated network picks up (1) the formation of the Indonesian and Philippine communities by the dense domestic connections with the capital cities of Manila and Jakarta functioning as major gateways; (2) the leading position of Jakarta, Singapore, and Kuala Lumpur; (3) some of the major transport corridors such as the Straits of Malacca Corridor in

West Malaysia and the North-South Economic Corridor in Vietnam and Thailand; (4) and the relatively weak connections among the rest of Southeast Asia by cities in the sparsely populated peripheral regions (such as Dili, East Timor and Jayapura, Indonesia).

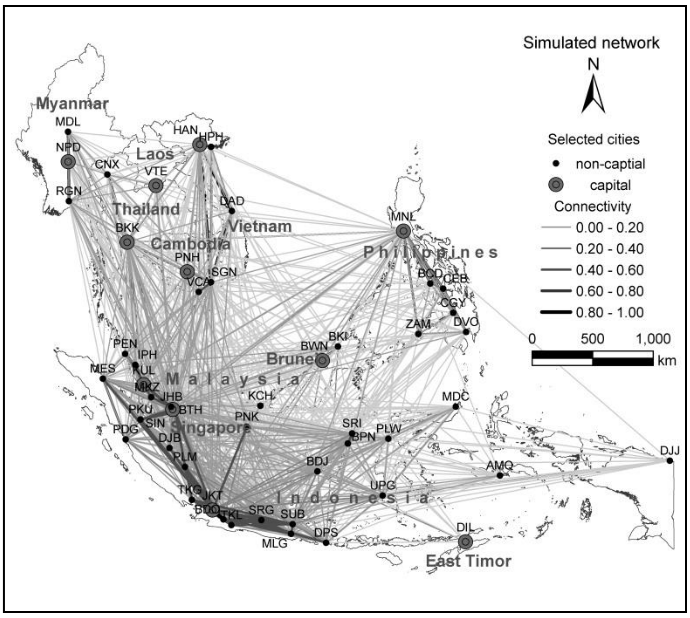


Figure 4.5 Connections in the simulated networks.

At the same time, there are some discrepancies between the simulated and the observed networks. The most notable differences are, first, the underestimation of the connectivity between cities in the north of mainland Southeast Asia as well as, second, Bangkok's pivotal hub position in linking the northern community to West Malaysia. Although the critical corridors such as Hanoi-Ho Chi Minh City, Mandalay-Yangon and Chiang Mai-Bangkok-Kuala Lumpur-Singapore are properly simulated, the strength of those connections is underestimated in comparison with the strong Indonesian domestic links centred on Jakarta. This may point to an empirical weakness of the model in that the relatively large(r) number of Indonesian cities defines a subnetwork that can be more properly modelled to the detriment of sparser parts of the network. As a consequence, major Indochinese cities tend to be more strongly integrated in the region’s transport network than predicted by the model.

In addition, stronger relations between Singapore and cities in Sumatra, Indonesia are to be expected in reality (Charras, 2014). Although the Euclidean distance from Singapore to central Sumatra averages around 400 km, it takes almost 51 hours to make this connection in the road network by using a ferry via Medan and the direct ferries and buses between them are still limited. This greatly weakens the desired connections and our analysis suggests that in reality this is not alleviated by relatively higher flight frequencies.

4.4.2 Analyses of each driving factor underlying network formation

To measure the relative effect of each of the four driving forces, we remodelled the networks by consecutively setting the parameters to 0 while retaining the original values for the other parameters (note, however, that for border effects this implies setting the value of θ to 1 rather than 0). Table 4.4 and Figure 4.6 shows the simulated models for each of these three-parameter scenarios and reveals how the topology of simulated model changes after different factors are removed. Meanwhile, Figure 4.7 displays the spatial patterns of the four networks.

Table 4.4 Network statistics for the simulated networks after removal of driving force.

Force removed	α	β	θ	γ	M	C	E	D	QAP (Sig.)	EV
Population	0	3.5	2	1	0.326	0.432	0.536	Figure 4.6	0.260 (0.001)	3.6E+90
Distance	2	0	2	1	0.247	0.378	0.586		0.161 (0.005)	2.3E+248
Border	2	3.5	1	1	0.350	0.460	0.493		0.166 (0.004)	∞
Transitivity	2	3.5	2	0	0.259	0.268	0.601		0.190 (0.000)	∞

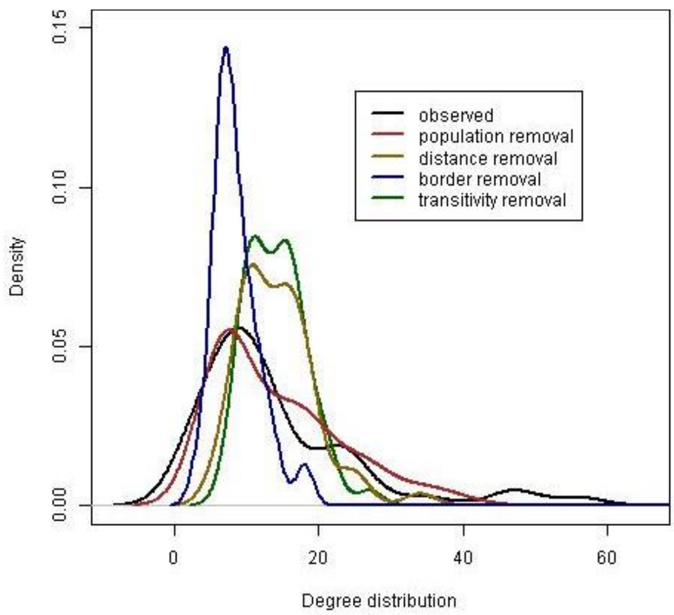


Figure 4.6 Degree distributions after each removal of the different forces.

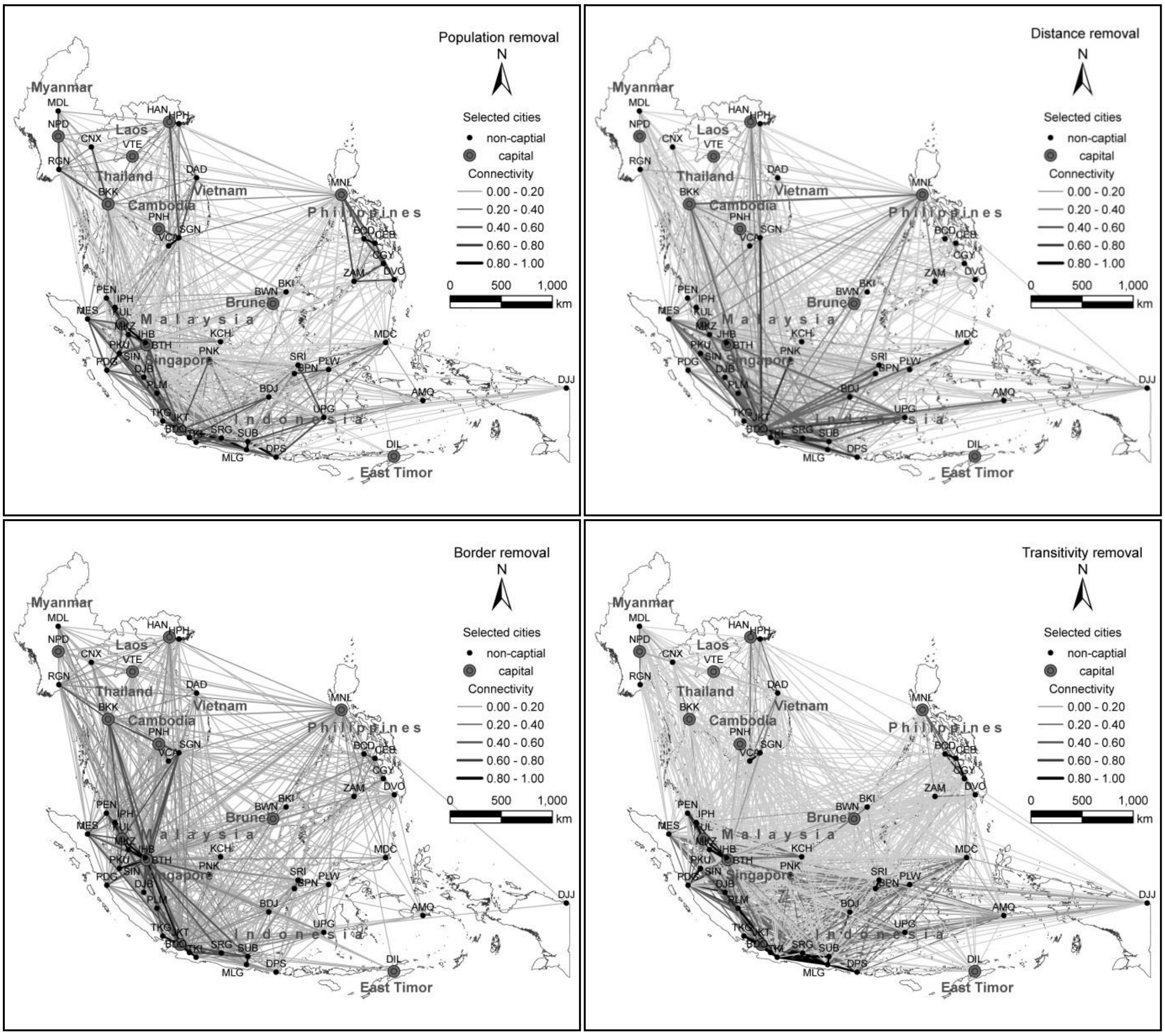


Figure 4.7 Simulated networks after removal of the different forces.

The first thing to note is that although the simulation continues to produce statistically significant results in each of the four models, parallels between the simulated and the observed network become less strong: each of the topological characteristics is further removed from the original network in terms of each tested p values and the respective energy value, and the QAP correlation – although remaining significant – declines.

When Transitivity is removed in our simulation, p values of tested for the four topological properties are really trivial, suggesting a significant difference between the generated network and the observed network. Although the energy value in the scenario of removing border effects also tends to be infinite, p values in that scenario are all much bigger, suggesting a relatively smaller difference. Therefore, the results suggest that the transitivity effect matters most in the intercity transport networks in Southeast Asia. Interestingly, this is exactly the kind of topological feature that would not be picked up in classical gravity modelling: when transitivity effects are removed from the network-generating effects, we miss out on a key force generating the transportation network. This is also shown from the fact that above all the average clustering coefficient deviates from that of the observed network: the disappearance of triadic closure configurations leads to the erroneous suggestion of there being more direct point-to-point connections than in the observed network, thus resulting in a smaller average path length and higher global efficiency. This finding is in keeping with previous findings that growth models for analysing the formation of complex systems can be more successful by including an additional topological term in the connection probability function (Yook et al., 2002).

The border effect is another main force in this region to shape the intercity transport networks. In the real transport network, The corridor Penang-Kuala Lumpur-Johor Bahru-Singapore comes much more to the fore and Malacca Strait separates the Malaysian and Indonesian communities. When borders are removed, Singapore’s vital hub function is much more expressed as it is suggested to connect two communities to integrate the western part of Southeast Asia, which is consistent with ASEAN's effort to facilitate the cooperation and development of Northern Growth Triangle including Indonesia, Malaysia and Thailand (Henderson, 2001). In addition, in this scenario, Ho Chi Min City is also upgraded and included in the hub-and-spoke network of Singapore instead of being relegated to the northern local community. However, the strength of connections between Bangkok, Ho Chi Min City and Kuala Lumpur, Singapore is in reality impaired by the lower frequencies of direct buses and trains than expected. That is also why ASEAN (Association of Southeast Asian Nations) has started investing in two flagship land transport infrastructure projects: the ASEAN Highway Network and the Singapore Kunming Rail Link (ASEAN Secretariat, 2011).

The model also shows the relevance of distance decay. The energy value increases a lot when distance is removed, indicating that the difference between the simulated and the observed networks becomes bigger. he simulated network is relatively far removed from the observed network in terms of its modularity, clustering coefficients and degree distribution. Disregarding distance yields more connections between remote cities that in reality belong to different communities.

Amongst the four driving factors, population has least influence on the network topology. When population is removed, the observed five communities remain almost unaltered, especially the Indonesian community. Again, this can probably be attributed to the relatively large number of cities in a single country. Meanwhile, due to the long-dispersed shape as well as a score of archipelagos, the Indonesian government has invested many resources into the development of domestic intercity shuttles, high speed rail networks and flights to reinforce national connectivity (Saraswati and Hanaoka, 2013; Soehodho et al., 2003), which in turn somewhat exaggerates the transitive effects in this region. The same rationale can be observed in the marked ties in the communities of the Philippines, Vietnam and Myanmar.

4.5 Conclusions and avenues for further research

In this paper, we have explored the potential of recent advances in network modelling for urban network research. To this end, we re-specified Vértes et al.'s (2012) economical clustering model to propose a generative network model (GNM) for simulating urban networks. To show the practical merit of this approach, we applied our approach to a case study of a composite intercity transport network in Southeast Asia. Overall, results confirm the potential of the proposed method, with as a major finding that the inclusion of topological effects (transitivity) alongside geographical effects as archetypically captured in (extended) gravity modelling helps understanding how urban networks are being shaped. This is further underscored by our finding that, when removing the different network-generating effects, transitivity is found to be the most important force in shaping the structure of the network.

We emphasize that the prime purpose of this paper has been methodological. This is because in our particular example results also reflect our operational choices. Both our selection of transport modes and their relative importance (they were all equally weighted), as well as how these networks were consecutively measured, transformed, and combined have an impact on our results. For instance, we have observed that the large number of cities on Java probably results in a subset of cities whose clearly defined interconnections imply that the simulation converges on this subnetwork. Although this is essentially a proper finding in the sense that it shows that regional integration through urban network-formation falls short of national network integration (further accentuated by the archipelago nature of Indonesia), it does beg the question of how the modelling exercise can be improved. However, that said, we would argue that these issues relate to the data specification rather than the simulation approach per se. Possible improvements include recognizing physical borders alongside national borders (e.g. accounting for weaker connections on Borneo and the Philippines) as well as socio-cultural issues.

Reference

ASEAN Secretariat, 2011. Master plan on ASEAN connectivity, Jakarta.

Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509-512.

Barrat, A., Barthélemy, M., Vespignani, A., 2004. Modeling the evolution of weighted networks. Physical Review E 70, 066149.

Barthélemy, M., 2011. Spatial networks. Physics Reports 499, 1-101.

Barthélemy, M., Barrat, A., Pastor-Satorras, R., Vespignani, A., 2005. Characterization and modeling of weighted networks. Physica A: Statistical Mechanics and its Applications 346, 34-43.

Behrens, K., Ertur, C., Koch, W., 2012. 'Dual'gravity: Using spatial econometrics to control for multilateral resistance. Journal of Applied Econometrics 27, 773-794.

Blondel, V., Krings, G., Thomas, I., 2010. Regions and borders of mobile telephony in Belgium and in the Brussels metropolitan zone. Brussels Studies 42, 1-12.

Brenner, N., Schmid, C., 2014. The 'Urban Age' in Question. International Journal of Urban and Regional Research 38, 731-755.

Bretagnolle, A., Pumain, D., 2010. Simulating urban networks through multiscalar space-time dynamics: Europe and the united states, 17th-20th centuries. Urban Studies 47, 2819-2839.

Broekel, T., Balland, P.A., Burger, M., Oort, F.v., 2014. Modeling knowledge networks in economic geography: A discussion of four empirical strategies. The Annals of Regional Science 53, 423-452.

Cattan, N., Grasland, C., 1993. Migratization of population in Czechoslovakia: A comparison of political and spatial determinants of migration and the measurement of barriers, Trinity Papers in Geography, pp. 221-238.

Charras, M., 2014. Sumatra transnational prospect beyond indonesian integration, In: Fau, N., Khonthapane, S., Taillard, C. (Eds.), Transnational Dynamics in Southeast Asia: The Greater Mekong subregion and Malacca straits economic corridors. Institute of Southeast Asian Studies, Singapore, pp. 221-250.

Choi, J.H., Barnett, G.A., Chon, B.-S., 2006. Comparing world city networks: A network analysis of Internet backbone and air transport intercity linkages. Global Networks 6, 81-99.

Clauset, A., Newman, M.E., Moore, C., 2004. Finding community structure in very large networks. Physical review E 70, 066111.

Decoupigny, F., Passel, S., 2014. Réseaux de villes et détermination des pressions urbaines. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 683, posted July 625, 2014.

Dobruszkes, F., Lennert, M., Van Hamme, G., 2011. An analysis of the determinants of air traffic volume for European metropolitan areas. Journal of Transport Geography 19, 755-762.

Ducruet, C., Beauguitte, L., 2014. Spatial Science and Network Science: Review and Outcomes of a Complex Relationship. Networks and Spatial Economics 14, 297-316.

Ducruet, C., Ietri, D., Rozenblat, C., 2011. Cities in worldwide air and sea flows: a multiple networks analysis. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 528, posted March 531, 2011.

Ducruet, C., Lee, S.-W., 2006. Frontline soldiers of globalisation: Port–city evolution and regional competition. Geojournal 67, 107-122.

Ducruet, C., Notteboom, T., 2012. The worldwide maritime network of container shipping: Spatial structure and regional dynamics. Global Networks 12, 395-423.

Ducruet, C., Rozenblat, C., Zaidi, F., 2010. Ports in multi-level maritime networks: Evidence from the Atlantic (1996–2006). Journal of Transport Geography 18, 508-518.

Enault, C., 2012. Simulation de l'étalement urbain de Dijon en 2030: approche systémique de la dynamique gravitaire ville-transport. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 592, posted February 515, 2012.

Guimera, R., Mossa, S., Turtschi, A., Amaral, L.N., 2005. The worldwide air transportation network: Anomalous centrality, community structure, and cities' global roles. Proceedings of the National Academy of Sciences 102, 7794-7799.

Hazir, Ç., 2013. Multilateral R&D Collaboration: An ERGM Application on Biotechnology, In: Scherngell, T. (Ed.), The Geography of Networks and R&D Collaborations. Springer International Publishing, pp. 221-237.

Head, K., Mayer, T., 2000. Non-Europe: the magnitude and causes of market fragmentation in the EU. Review of World Economics 136, 285-314.

Henderson, J.C., 2001. Regionlisation and tourism: The Indonesia-Malaysia-Singapore growth triangle. Current Issues in Tourism 4, 78-93.

Hennemann, S., Derudder, B., 2014. An alternative approach to the calculation and analysis of connectivity in the world city network. Environment and Planning B 41, 392-412.

Hennemann, S., Rybski, D., Liefner, I., 2012. The myth of global science collaboration: Collaboration patterns in epistemic communities. Journal of Informetrics 6, 217-225.

Josselin, D., Nicot, B., 2003. Un modèle gravitaire géoéconomique des échanges commerciaux entre les pays de l'U.E., les PECO et les PTM. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 237, posted March 212, 2003.

Krätke, S., 2014. How manufacturing industries connect cities across the world: extending research on 'multiple globalizations'. Global Networks 14, 121-147.

Lambiotte, R., Blondel, V.D., de Kerchove, C., Huens, E., Prieur, C., Smoreda, Z., Van Dooren, P., 2008. Geographical dispersal of mobile communication networks. Physica A: Statistical Mechanics and its Applications 387, 5317-5325.

Lee, S.-W., Song, D.-W., Ducruet, C., 2008. A tale of Asia's world ports: The spatial evolution in global hub port cities. Geoforum 39, 372-385.

Liu, X., Derudder, B., Liu, Y., 2013a. Regional geographies of intercity corporate networks: The use of exponential random graph models to assess regional network-formation. Papers in Regional Science, doi:10.1111/pirs.12060.

Liu, X., Derudder, B., Liu, Y., Witlox, F., Shen, W., 2013b. A stochastic actor-based modelling of the evolution of an intercity corporate network. Environment and Planning A 45, 947-966.

Liu, X., Derudder, B., Taylor, P., 2014. Mapping the evolution of hierarchical and regional tendencies in the world city network, 2000–2010. Computers, Environment and Urban Systems 43, 51-66.

Mun, S., Nakagawa, S., 2010. Pricing and investment of cross-border transport infrastructure. Regional Science and Urban Economics 40, 228-240.

Neal, Z., 2012. The connected city: How networks are shaping the modern metropolis. Blackwell, New York, U.S.

Neal, Z., 2013. Does world city network research need eigenvectors? Urban Studies 50, 1648-1659.

Ng, J., 2009. The impact on airports in Southeast Asia: What deregulation means. Working paper, Available at http://ardent.mit.edu.

Pasta, M.Q., Zaidi, F., Rozenblat, C., 2014. Generating online social networks based on socio-demographic attributes. Journal of Complex Networks 2, 475-494.

Pflieger, G., Rozenblat, C., 2010. Urban networks and network theory: the city as the connector of multiple networks. Urban Studies 47, 2723-2735.

Phang, S.-Y., 2003. Strategic development of airport and rail infrastructure: The case of Singapore. Transport Policy 10, 27-33.

Pirie, G., 2010. Trajectories of North-South City Inter-relations: Johannesburg and Cape Town, 1994-2007. Urban Studies 47, 1985-2002.

Pumain, D., Paulus, F., Vacchiani-Marcuzzo, C., Lobo, J., 2006. An evolutionary theory for interpreting urban scaling laws. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 343, posted July 305, 2014.

Pumain, D., Swerts, E., Cottineau, C., Vacchiani-Marcuzzo, C., Ignazzi, A., Bretagnolle, A., Delisle, F., Cura, R., Lizzi, L., Baffi, S., 2015. Multilevel comparison of large urban systems. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 706, posted January 715, 2015.

Ravenstein, E.G., 1885. The laws of migration. Journal of the Statistical Society of London 48, 167-235.

Reilly, W.J., 1931. The law of retail gravitation. William J. Reilly, New York, U.S.

Robins, G., Pattison, P., Kalish, Y., Lusher, D., 2007. An introduction to exponential random graph (p*) models for social networks. Social Networks 29, 173-191.

Rozenblat, C., Melançon, G., 2013. Methods for Multilevel Analysis and Visualisation of Geographical Networks. Springer, Neatherlands.

Rozenblat, C., Pumain, D., 2007. Firm linkages, innovation and the evolution of urban systems, In: Taylor, P., Derudder, B., Saey, P., Witlox, F. (Eds.), Cities in globalization: practices, policies and theories. Routledge, New York, U.S., pp. 130-156.

Saey, P., 2007. How cities scientifically (do not) exist: Methodological appraisal of research on globalizing processes of intercity networking, In: Taylor, P., Derudder, B., Saey, P., Witlox, F. (Eds.), Cities in globalization: practices, policies and theories. Routledge, New York, U.S., pp. 298-313.

Sassen, S., 2002. Global networks, linked cities. Routledge, New York, U.S.

Smith, D.A., Timberlake, M.F., 2001. World City Networks and Hierarchies, 1977-1997: An Empirical Analysis of Global Air Travel Links. American Behavioral Scientist 44, 1656-1678.

Snijders, T.A.B., Doreian, P., 2010. Introduction to the special issue on network dynamics. Social Networks 32, 1-3.

Soehodho, S., Burhan, H., Anwar, J., 2011. A Study on Intercity Transportation Mode Choice on Two Corridors in Java Island. Proceedings of the Eastern Asia Society for Transportation Studies 8, 19.

Taylor, P.J., Derudder, B., 2015. World City Network: A Global Urban Analysis. Routledge, London, U.K.

Taylor, P.J., Walker, D., 2001. World cities: a first multivariate analysis of their service complexes. Urban Studies 38, 23-47.

Tobler, W.R., 1970. A Computer Movie Simulating Urban Growth in the Detroit Region. Economic Geography 46, 234-240.

Vértes, P.E., Alexander-Bloch, A.F., Gogtay, N., Giedd, J.N., Rapoport, J.L., Bullmore, E.T., 2012. Simple models of human brain functional networks. Proceedings of the National Academy of Sciences 109, 5868-5873.

Vinciguerra, S., Frenken, K., Valente, M., 2010. The geography of Internet infrastructure: An evolutionary simulation approach based on preferential attachment. Urban Studies 47, 1969-1984.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of ‘small-world’networks. Nature 393, 440-442.

Weimann, G., 1983. The strength of weak conversational ties in the flow of information and influence. Social Networks 5, 245-267.

Yook, S.H., Jeong, H., Barabási, A.L., 2002. Modeling the Internet's large-scale topology. Proceedings of the National Academy of Sciences 99, 13382-13386.

Chapter 5 A comparative analysis of network backbones extracted from different techniques: the case of the Southeast Asian intercity air transport network

Dai, L., Derudder, B., Liu, X., 2018. A comparative analysis of backbone extraction techniques for urban networks, the case of intercity air transport network in Southeast Asia. Journal of Transport Geography, under review.

Abstract

Network backbone extraction techniques reduce the size of networks while trying to preserve their key topological and spatial features. Various backbone extraction algorithms have been proposed in different scientific fields. Although of clear interest to transport geographers, backbone extraction techniques have been adopted unevenly and in an ad hoc fashion in transport geography research. In this paper we therefore present a conceptual and experimental comparison of backbone extraction techniques in a transport-geographical context, and explore under which circumstances or for which research objective the different techniques are particularly useful (or less so). We review six frequently-used methods, i.e. global weight thresholding (GWT), k-core decomposition (KCD), minimum spanning tree (MST) analysis, primary linkage analysis (PLA), multiple linkage analysis (MLA), and the disparity filter algorithm (DFA), and expose and compare their analytical essence by applying them to a real-world transport geography example. To this end, we extract the backbone of the intercity air transport network in Southeast Asia. The abstracted networks are compared in terms of their topological properties and spatial patterns using the initial network as a benchmark. This comparison is then used to discuss the different techniques' potential and drawbacks in light of transport geography research.

5.1 Introduction

In recent decades, there has been burgeoning interest in the topological analysis of transport *networks* of different types and at various scales (e.g. Dobruszkes, 2006; Ducruet and Notteboom, 2012; Wang et al., 2014; Liu et al., 2017). In these networks, nodes commonly represent spatial units such as cities, airports, ports, stations, etc., while edges identify transport-related interactions between the nodes. In addition, the edges are typically weighted by capacity, frequency, distance, or the time it takes to 'travel' between nodes. In theory, the application of the ever-expanding suite of network analysis techniques allows examining complex transport systems at the level of nodes and dyads as well as the network in its entirety (Barthélemy, 2011; Tsiotas and Polyzos, 2017). To date, network-focused research efforts in transport geography have primarily focused on four areas of enquiry: (1) the representation of non-planar and planar transportation systems through networks (Lin and Ban, 2013); (2) the analysis of the topographical and topological features of transport networks (Lin, 2012); (3) tracing the spatial and structural evolution/dynamics of these networks over time (Ducruet, 2017); (4) and modelling transport networks with the specific purpose of uncovering their underlying mechanisms (Zhang et al., 2016).

The visualization, description and analysis of transport networks continue to face a range of challenges. For example, the fact that transport networks are *spatial* networks where nodes are preferably visualized in their exact geographical location makes producing transport flow maps a complex proposition (Vertesi, 2008). Dense networks with locally/regionally clustered edges in particular pose challenges when trying to explicitly convey the overall structure (Hennemann, 2013). Furthermore, analytically trivial edges in a network may give rise to biases in the measurement and interpretation of network topologies (Radicchi et al., 2011). For these and a number of related reasons, it is often useful to extract the 'backbone' of a network: a simplified version that is reduced in size – i.e., some edges and/or nodes are deleted – but retains the most 'valuable' information contained in the original network. The abstracted network can be mapped and explored with significantly less effort, and this without too much compromising the real-world remit of the network.

To achieve this goal, a large number of methods have been developed. These methods aim to de-densify networks by extracting their 'backbone(s)', and range from simple thresholding (Derudder and Taylor, 2005) to more statistically-grounded methods such as disparity filter algorithms (Serrano et al., 2009). Needless to say, these methods are not unique to transport geography: they have for example been discussed and applied in fields as disparate as physics (Gemmetto et al., 2017), sociology (Neal, 2014), biology (Darabos et al., 2014), and computer science (Foti et al., 2011). Nonetheless, it can be noted that oftentimes the illustrative examples put forward in these domains are transport and infrastructure networks, reinforcing the broader relevance of the transport geography/network analysis-nexus. In spite of this, the adoption of the ideas developed in other scientific fields has been limited and uneven in transport geography itself (cf. Ducruet and Beauguitte, 2014).

As a result, to date there has been no systematic comparison of the relevance of different backbone extraction techniques for transport geography-related research. A few comparative studies have been conducted by physicists to compare simplification methods for real-world networks (e.g. Blagus et al., 2014) and by sociologists to compare extraction approaches of statistically significant edges for social networks (e.g. Neal, 2013c). In these analyses, the assessment of the relevance of techniques is based on methods' ability to either preserve topological properties or capture germane clique structures. However, as transport networks sit at the intersection of the study of complex systems (with an emphasis on topology) and geography (which is concerned with spatial relations) (Rodrigue et al., 2006), both aspects need to be considered in an evaluation framework.

In this paper, we therefore present a comparative analysis of key network backbone extraction techniques, discussing their practical usefulness by means of an empirical study of the Southeast Asian intercity air transport network. This implies, of course, the potential problem of using a very specific example to derive generic claims about the usefulness of techniques. However, we believe our findings are broadly robust in the sense that this network shares common characteristics with many other transport networks (e.g. a small-world outline, a combination of point-to-point and hub-and-spoke configurations, etc.). In our assessment, we focus on the topology, geometry and spatial structure of the extracted backbones vis-à-vis the original network. Note that our interest is not so much in analyzing this particular network *per se* as in Bowen (2000), but more in assessing the pros and cons of the different techniques for de-densifying such a network in light of the transport geography research question at hand. More specifically, we aim to provide a nuanced analysis of which technique can best be used under what circumstances and/or for what research objective.

The reminder part of this paper is organized as follows. In the next section, we review backbone extraction techniques in various domains, with a particular focus on six approaches that are highly relevant to de-densify transport networks. This is followed by a brief description in section 3 of the data and analytical framework used in our paper. Section 4 presents the empirical results, discusses the performance of different methods in terms of topological properties and spatial patterns, and points out their advantages and disadvantages in light of transport-geographical applications. The paper is concluded with an overview of our major findings, some limitations of our study, and some avenues for further research.

5.2 Existing techniques for backbone extraction

5.2.1 Overview

Network backbone extraction has been studied in a wide range of disciplines under different names, such as network simplification (Blagus et al., 2014), sparsification (Mathioudakis et al., 2011), abstraction (Zhou et al., 2012), and reduction (Kim et al., 2011). Given that most transport networks are one-mode networks which consist of only one set of inter-connected nodes (Scott and Carrington, 2011), we will review backbone extraction techniques for one-mode networks thus excluding techniques for two-mode projections where the original networks feature connections between two different sets of nodes (Liebig and Rao, 2016).

In general, network backbone extraction techniques fall into two broad categories: 'coarse-graining' and 'edge removal' methods. Coarse-graining methods merge nodes sharing common attributes together and replace them by a single, new coarse-grained unit in the abstracted network (Itzkovitz et al., 2005). The differences between approaches within this overarching logic ultimately relate to the adopted 'compression' technique, i.e., the algorithm to identify communities and the rules of transformation. However, as most transport geography related research questions require retaining original nodes and edges, coarse-graining methods tend to be less appealing.

Edge-removing techniques focus on *removing* rather than *transforming* nodes and edges; they single out the most 'relevant' nodes and edges and subsequently eliminate the least significant ones. This can be achieved by edge sampling for binary networks (Blagus et al., 2014) and edge filtering/pruning for weighted networks (Bu et al., 2014). For binary networks in which 0 and 1 respectively denote the absence and presence of an edge, the abstracted network is represented by a random sample of the raw data based on its goodness of fit to original topologies such as degree distribution, average path length, clustering coefficient, assortativity (Newman, 2003). The edge sampling methods range from random node/link selection to snowball sampling, random walk, forest fire, and so forth (Lee et al., 2006). Although useful in several contexts, they are not considered in this paper since most geographical research has a vested interested in weighted networks that often combine both structural and functional aspects (Chawla et al., 2016).

In light of this, in this paper we focus specifically on the filtering/pruning techniques to extract the backbone of one-mode weighted networks. This class of methods typically employs a bottom-up strategy: they start by defining a criterion for a nodewise or edgewise examination of their 'importance' or 'relevance' to the network, after which the redundant edges/nodes are removed in a stepwise procedure. Different criteria result in more or less different backbones, and here we explore the nature of those differences and their impact on how we understand the original network.

5.2.2 Global weight thresholding

The most common and straightforward method is (variations to) global weight thresholding (GWT), a technique that only retains edges whose weights exceed a predefined threshold. The threshold can be defined as an absolute value, but also as a certain proportion of the maximum observed edge weight or the mean weight (Neal, 2013c). GWT has been extensively used since it works efficiently and produces networks that are clearly much sparser. However, most real-world networks have their edge weights unevenly distributed at multiple scales, thus making this method suffer from arbitrariness, structural bias and uniscalarity (Neal, 2014). To lessen the arbitrariness, Derudder et al. (2014) and Dai et al. (2016) propose to identify an optimal value in that the smallest network density associated with the highest resemblance with the original network is sought.

5.2.3 Hierarchical topological filter

A second option is to introduce a hierarchical topological filter, albeit that this is often not termed this way. The k-core decomposition (KCD) method is a typical example with a filtering rule that acts on the connectivity of nodes (Serrano et al., 2009). The KCD extract particular subsets of the network, called k-cores (Seidman, 1983), in which each subset is obtained by consecutively deleting all nodes with a degree of less than k (Alvarez-Hamelin et al., 2006). Hence, this method does not work in the case of a fully connected network. It tends to focus on the most globally connected part of the network, although this can also generate scalar biases and neglect nodes with a specific local importance.

5.2.4 Spanning tree

Another well-known method is the extraction of the minimum spanning tree (MST) in which all nodes are connected through the shortest total distances (Kruskal, 1956). Kim et al. (2004) use the MST approach to represent a communication kernel of real-world networks such as Internet and co-authorship networks, while Wu et al. (2006) implement it to reveal the superhighways dominating road transport networks. It is also possible to define a maximum spanning tree in which edges with larger weights are assumed to indicate a ‘shorter distance’ between two nodes. The resulting backbone keeps all nodes connected no matter the scale of edges, but does destroy the local cycles.

5.2.5 Linkage analysis

Linkage analysis refers to both primary linkage analysis (PLA) (Nystuen and Dacey, 1961) and multiple linkage analysis (MLA) (Haggett et al., 1977). The former only preserves the edge with largest weight for each node in the network, thus greatly reducing the size of the network and putatively identifying the network’s basic skeleton. Similar to MST, it is nonetheless confronted with problems such as the omission of cyclic structures and over-simplification. Furthermore, it is difficult to make a meaningful distinction in significance between edges for one node with roughly similar weights (Puebla, 1987).

In response to this, MLA has been proposed. The technique engages in nodewise comparisons of the actual distribution of edge weights with a series of hypothetical distributions in which those weights are evenly distributed among 1, 2, …, n, neighbors (Haggett et al., 1977). Each comparison between the observed and hypothetical distributions produce a goodness of fit that can be measured by way of a correlation coefficient (Van Nuffel et al., 2010). The number of edges preserved for each node corresponds to the number that produces the highest coefficient. In doing so, MLA offers a reasonable way to remove redundant edges (as in GWT and KCD), yet at the same time retaining the most important edges at the local level (as in MST and PLA). Furthermore, it allows geometrical features such as cycles to be retained so that communities remain intact.

5.2.6 Multiscale network reduction

Comparable to MLA, multiscale network reduction also considers local distributions of edge weights and preserves edges with statistically significance in a local sense. Techniques in this family include parametric algorithms such as the bistochastic filter proposed by Slater (2010), the disparity filter by Serrano et al. (2009), the global statistical significance filter by Radicchi et al. (2011) and a nonparametric approach called locally adaptive network sparsification by Foti et al. (2011). The first method aims to derive a single scale of importance by rescaling the edge weights through an iterative proportional fitting procedure, after which a backbone is created through an incremental addition of edges until a stopping criterion is met. However, the iteration sometimes fails to converge. The latter three assess an edge's importance by comparing observed edge weights to expectations from a local null model (or sometimes from global null model) or empirical distributions, respectively.

In our analysis, we will focus on the disparity filter algorithm (DFA) due to its strong relevance to transport-network research as well as proven performance in backbone extraction of different complex systems such as herb networks (Du et al., 2011), human phenotype networks (Darabos et al., 2014), world trade networks (García-Pérez et al., 2016), and metabolic networks (Güell et al., 2017). It takes advantages of local heterogeneities present in weight distributions to single out edges whose weights are statistically higher than those of the null hypothesis, wherein the normalized edge weights are assigned at random according to a uniform distribution.

Based on this brief review, six methods (GWT, KCD, MST, PLA, MLA, DFA) are chosen to conduct our comparative study, and this because they either have been widely adopted (e.g. primary linkage analysis) or seem to hold specific potential (e.g. the disparity filter algorithm) in geographical research in general, and transport-geographical research in particular. For detailed expressions for each approach, readers are referred to the original publications. For the implementation of GWT, KCD, MST, and DFA, free packages in R program are available. Meanwhile, PLA and MLA can be processed in ArcGIS or Excel. In the next section, we will elaborate on the data and methods used in our comparative study.

5.3 Data and methods

5.3.1 Framework for analytical comparisons

In order to compare the different methods, several network metrics will be computed for the six abstracted networks, using the original network as a benchmark. The selection of these metrics is supported by their common use in the analysis of the structure and dynamics of transport networks (Ducruet and Lugo, 2013).

First, we will calculate the quadratic assignment procedure (QAP) correlation to evaluate the structural similarity between the original and abstracted networks (Choi et al., 2006). QAP is often used to measure the extent to which two networks are correlated or have a similar pattern of connections, as it can control for the non-independence of dyadic data through a permutation test (Krackardt, 1987).

Second, in terms of topological properties, we then focus on five measurements (Li et al., 2005; Newman, 2003): (1) the cumulative strength distribution $P(>s)$, the probability of nodes with strength larger than s; (2) degree mixing DM, a measure of high-degree nodes' preference to connect to other high-degree (assortativity, positive value) or low-degree nodes (disassortativity, negative value); (3) average path length L, a measure of the number of steps needed to reach other nodes; (4) average clustering coefficient C (also called transitivity), a measure of cliquish interconnections between neighbouring nodes; (5) modularity M, a measure of how the network can be decomposed into a set of sparsely interconnected modules, each comprising several densely interconnected nodes. We compare values for extracted backbones on each of these measures to the values for the original network.

Third, in terms of spatial patterns, we compare the hierarchy and clusters of nodes at the micro and meso scopes between the original and abstracted networks. The micro scope is assessed through the lens of degree centrality, which refers to total edge weights/strengths of a node in a weighted network. The meso scope, in turn, is revealed by communities detected by the 'fast greedy modularity optimization method' (Clauset et al., 2004), which refers to a set of closely connected nodes whose within-community connections exceed inter-community connections. All calculations and visualizations are performed on the R platform.

5.3.2 Data: the Southeast Asian intercity air transport network

To test the performance of six backbone extraction methods, we apply them to the Southeast Asian intercity air transport network (SAAN; see Dai et al., 2018). The SAAN is constructed by including all flights between Southeast Asian airports for the year 2012 as derived from the Official Airline Guides (OAG) database. Most cities are associated with a single airport, but in some cases airports are collapsed into a single urban node, i.e. the combination of Suvarnabhumi and Don Mueang into Bangkok, Kuala Lumpur International and Sultan Abdul Azziz Shah into Kalua Lumpur, Soekarno-Hatta and Halim Perdana Kusuma into Jakarta, and Changi and Seletar into Singapore. Edges in the SAAN are symmetrized and weighted by averaging flows (scheduled seats) in both directions, producing a 237x237 inter-city matrix connected by 602 links.

As demonstrated in Dai et al. (2018), the SAAN has a scale-free (Barabási and Albert, 1999), small-world (Watts and Strogatz, 1998), and modular community structure (Girvan and Newman, 2002). In the SAAN, the flows range from 152 scheduled seats between Nay Pyi Taw and Vientiane (the capitals of Myanmar and Laos) to 5651314 scheduled seats between Singapore and Jakarta in 2012. The strengths vary over five orders of magnitude, presenting a highly heterogeneous distribution that confirms to a double Pareto law (Reed, 2003) (see Table 5.2). Moreover, on average it takes three steps for any city in SAAN to reach others with an overall transitivity of 0.207 and modularity of 0.553. Figure 5.1 visualizes the spatial structure of the SAAN, in which the size of nodes is proportional to a city's degree centrality; only the top 20 cities are labelled. The colors of nodes denote their community affiliations. The darkness and thickness of edges are proportional to the strength of intercity flows. In the SAAN, flows are concentrated on cities like Jakarta, Kuala Lumpur, Bangkok, Manila and Singapore (cf. Bowen, 2000). The overall network can be partitioned into six communities: a Vietnamese community centered on Hanoi, Da Nang, and Ho Chi Minh City; a Greater Mekong community surrounding centered on Bangkok; a Malay community centered on Kuala Lumpur and Singapore; a major Indonesian community and a Philippine community with their respective capitals as centers; and finally a less significant eastern Indonesian community in Sulawesi and Irian Java centered on Jayapura. These communities are primarily connected by inter-capital flows.

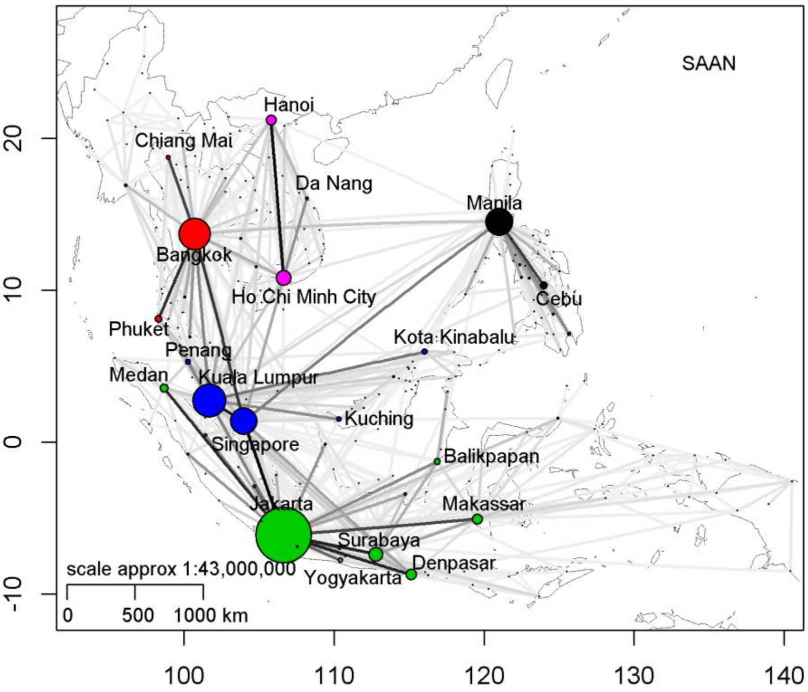


Figure 5.1 The Southeast Asian intercity air transport network (SAAN), 2012 (source: OAG data). The size of nodes is proportional to a city's degree centrality; only the top 20 cities are labelled. The colors of nodes denote their community affiliations. The darkness and thickness of edges are proportional to the strength of intercity flows, hereafter.

5.4. Results

5.4.1. Overview: Size of abstracted networks and their QAP correlation with SAAN

In this section, the six methods are applied to extract the backbone of SAAN. Table 5.1 reports the size of different abstracted networks in terms of the number of nodes (Nt), edges (Et), weights (Wt) and the corresponding percentages %Nt, %Et, %Wt as well as their QAP correlation with the original network.

Table 5.1 Size of six abstracted networks and their QAP correlation with SAAN. Nt, Et, Wt denote the number of nodes, edges, weights, respectively and %Nt, %Et, %Wt are the corresponding percentages, hereafter.

Network	Nt	Et	Wt	%Nt	%Et	%Wt	QAP
GWT	45	52	133941626	18.99	8.64	57.07	0.945
KCD	18	87	85130499	7.59	14.45	36,27	0.745
MST	237	236	163907364	100.00	38.54	66.06	0.941
PLA	237	232	155043553	100.00	39.20	69.84	0.907
MLA	237	303	183160125	100.00	50.33	78.04	0.964
DFA	149	245	193530486	62.87	40.70	82.46	0.986

The GWT method retains the 52 strongest flows between 45 cities at a cutoff of 606311, which is 21.45% of the strongest dyad of Singapore-Jakarta. Figure 5.2 plots the evolution of the density of abstracted networks and their QAP correlation with the SAAN with the increasing of thresholds. At the value of 636011, the extracted backbone has a sharply reduced density (0.085) whilst keeping a relatively high similarity to the original network (QAP=0.945). The KCD extracts a 7-core (the maximal core) sub-network from SAAN with 18 cities connected by 87 flows. Despite the larger number of connections, the backbone extracted by KCD has fewer total weights than that of GWT and bears the least resemblance (with a QAP of 0.745) to the original network.

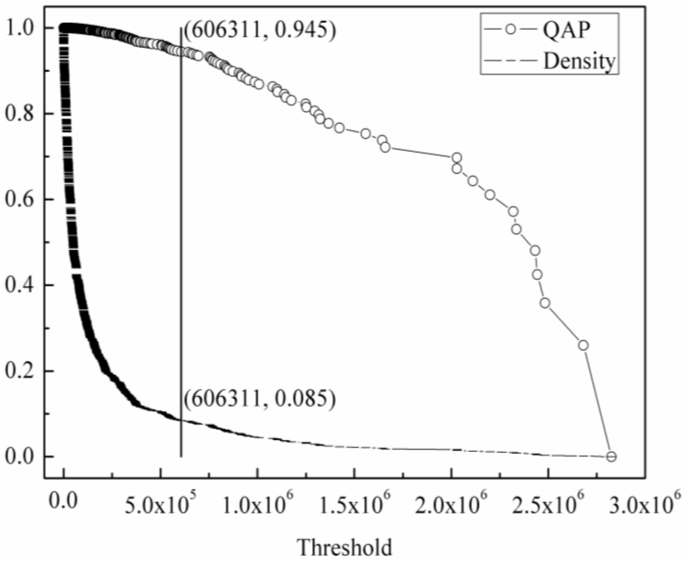


Figure 5.2 Evolution of QAP correlation and density in terms of GWT thresholds.

The MST, PLA and MLA conserve all 237 cities in their backbones. The number of connections in MST is the number of cities minus one (236), while in the PLA it (logically) equals the number of cities (237). Hence, MST and PLA produce backbones of similar size. The abstracted network of the PLA has 232 connections, as five of them are present twice and thus deleted in the undirected network. MLA keeps the most connections and PLA can be regarded as an extreme case of MLA in which every city's flows are heavily polarized on only one of their destinations. In addition, the MLA backbone has the second highest QAP correlation (QAP=0.964) with the SAAN.

In DFA, the majority of air connections are pruned at the significance level of 0.01 whereas the extracted backbone includes more than 60% cities and over 80% air traffic, retaining the largest similarity (QAP=0.986) to the SAAN. Note that the DFA generates two independent probability values α_{ij} and α_{ji} based on the two cities connected by a single flow. So two alternatives exist to determine whether the flow should be preserved: the 'OR' rule ($\alpha_{ij} < \alpha$ OR $\alpha_{ji} < \alpha$) and the 'AND' rule ($\alpha_{ij} < \alpha$ AND $\alpha_{ji} < \alpha$). Different from Serrano et al. (2009), we employ a stricter 'AND' rule by applying an α cutoff of 0.01 to avoid outliers. Adjusting the significance level allows the abstracted network to include more (a larger α) or fewer (a smaller α) intercity connections. Since the DFA is rooted in probability theory, the parameter offers a precise interpretation: there is less than 1% chance that the flows retained in the backbone are created by random fluctuations (Neal, 2014).

It is difficult to tell which technique works 'best' based on this alone as each of them simplifies networks and pinpoints the main information based on different principles. Therefore, we take both topological and spatial characteristics into account and compare different methods' capabilities of presenting or highlighting these characteristics.

5.4.2. Topological properties of the abstracted networks

Figure 5.3 plots the cumulative strength distribution on a double-logarithmic scale for the original and abstracted networks, while Table 5.2 summarizes the basic statistics of these networks' structures.

Table 5.2 Statistical properties of the original and abstracted networks. *P(>s)*: the cumulative strength distribution; (γ_1, γ_2) or γ: the fitted exponent of (double) power-law function; *DM*: degree mixing; *L*: average path length; *C*: average clustering coefficient; *M*: modularity, hereafter. The number in bold deviates least from that in the original network.

Network	P(>s) (($\boldsymbol{\gamma_1, \gamma_2}$) $\boldsymbol{or\ \gamma}$)	DM	L	C	M
SAAN	(0.058, 0.398)	-0.244	3.121	0.207	0.553
GWT	0.948	-0.559	**3.030**	0.078	**0.551**
KCD	0.761	**-0.258**	1.431	0.688	0.285
MST	(0.055, 0.424)	-0.432	4.642	0.000	0.663
PLA	(0.054, 0.422)	-0.439	3.760	0.000	0.706
MLA	**(0.061, 0.413)**	-0.405	4.404	0.058	0.643
DFA	(0.102, 0.674)	-0.044	4.352	**0.247**	0.556

It is evident that the *P(>s)* of the SAAN follows a double Pareto law distribution with two different exponents, i.e., for low strength levels $P(>s) \sim \mathrm{s}^{-\gamma_1}$ and γ_1=0.058; for high strength levels, $P(>s){\sim}\mathrm{s}^{-\gamma_2}$ and γ_2=0.398. Both GWT and KCD overlook a dozen of weak dyads as shown in Figure 5.3(a), so the cumulative strength distributions of their backbones are better fitted by a Pareto law *P(>s)* $\sim \mathrm{s}^{-\gamma}$, with γ=0.948 for GWT and γ=0.761 for KCD. A larger exponent for GWT demonstrates a more rapid distribution decay (Paleari et al., 2010), suggesting a higher concentration of air flows on a handful of cities in the GWT backbone than that in the KCD. The backbones extracted by MST, PLA, MLA and DFA are all able to capture the two-regime power-law strength distribution in SAAN. Among them, MST and PLA produce quite similar distributions in which MLA performs best in terms of the fitted exponents, partially due to its preservation of most air connections. The DFA backbone has the highest values of γ_1 and γ_2 since its deletion of almost 40% cities makes the fitting scale different from the other three as well as the original network.

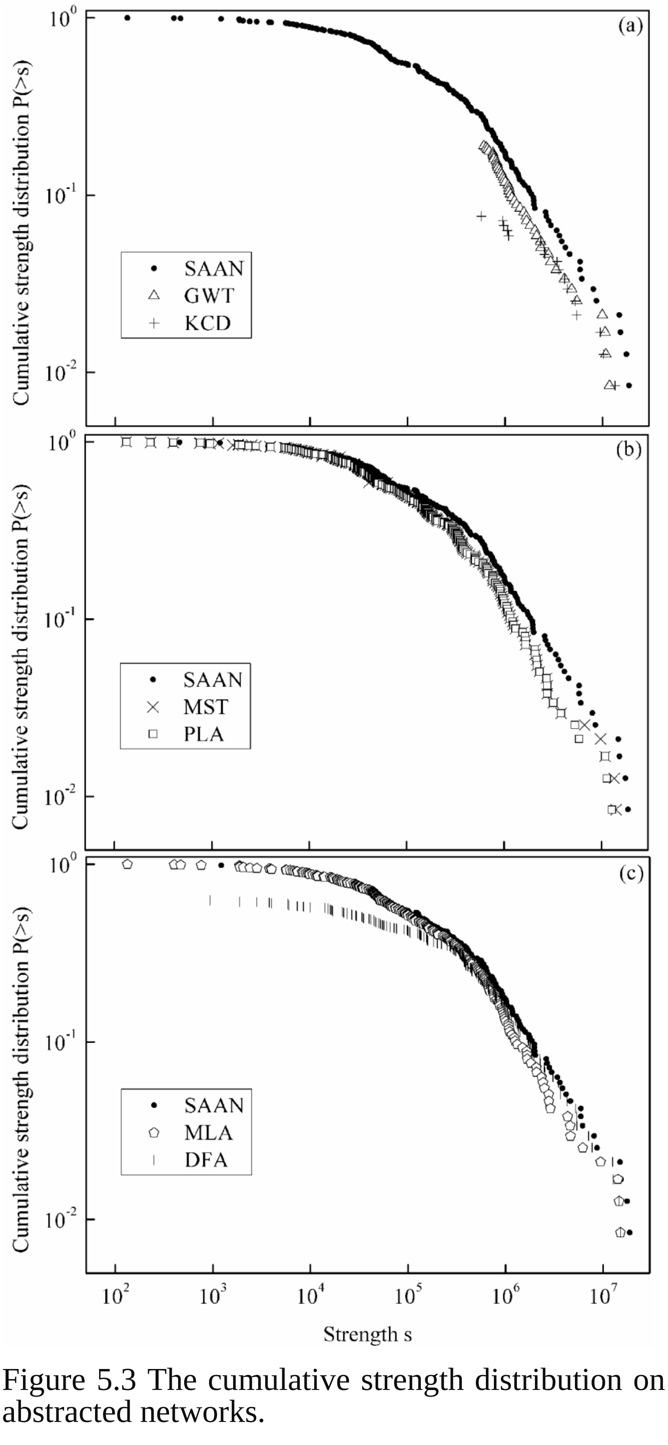


Figure 5.3 The cumulative strength distribution on double-logarithmic scale for original and abstracted networks.

Since the size of the DFA and GWT backbones is flexible, we also compute their network metrics with the same number of edges as retained in the other methods as summarized in

Table 5.3. With respect to degree mixing, all backbones present disassortativity, i.e., a preference of high-degree cities to connect to low-degree cities. This is intuitive in air transport networks with the adoption and intensification of hub-and-spoke configurations (Lin, 2012; Wang and Jin, 2007). As observed in Table 5.2, KCD proves best for preserving the slightly disassortative mixing pattern in the original network, whereas DFA shows the worst performance, which is robust at different significance levels in Table 5.3.

Table 5.3 Network metrics of the GWT and DFA backbones in different size.

Network	Counterpart	Et	Nt	D	L	C	M
DFA (α=2E-9)	GWT	52	73	-0.126	2.242	0.182	0.687
DFA (α=3E-7)	KCD	87	94	0.264	2.966	0.307	0.619
DFA (α=0.007)	PLA	232	145	-0.024	4.531	0.252	0.563
DFA (α=0.0075)	MST	236	147	-0.036	4.494	0.248	0.561
DFA (α=0.062)	MLA	303	161	-0.078	4.162	0.261	0.551
GWT (threshold=336144)	KCD	87	66	-0.588	3.074	0.123	0.542
GWT (threshold=83025)	PLA	232	125	-0.393	3.097	0.178	0.558
GWT (threshold=80974)	MST	236	126	-0.397	3.096	0.178	0.558
GWT (threshold=76484)	DFA	245	127	-0.374	2.983	0.183	0.558
GWT (threshold=43951)	MLA	303	144	-0.356	2.995	0.194	0.555

In terms of average path length and modularity, GWT outperforms the other methods. Nevertheless, the average path length is always investigated together with average clustering coefficient to test whether a network has small-world properties. In this light, DFA works best as it replicates the average clustering coefficient and simultaneously makes the backbone possess an average path length relatively close to that of the original network. With the variation of significance level, it has the ability to preserve a *L* and *C* similar to the SAAN and therefore identify the original network's small-worldiness. Meanwhile, due to the fact that the MST and PLA backbones are by construction acyclic, average clustering coefficients for them are zero, which directly leads to their highest modularity – 0.663 and 0.706, respectively. It is not surprising the KCD backbone has the smallest modularity because it is the most inter-connected component of the original network.

In a nutshell, the GWT backbone produces average path length and modularity closest to the original network at the optimal threshold, while the KCD backbone can best replicate the disassortative degree mixing pattern. Both of them entail a scalar bias with truncating the majority of nodes/edges small connectivities, making them unsuitable for the topological analysis of transport networks with edge weights that are unevenly distributed across nodes at multiple scales. In addition, KCD does not work in a fully connected network. MST and PLA can be applied to any transport network and are able to extract backbones in a much more simplified form but with topological features much paralleled to the original network except for transitivity. MLA and DFA basically capture all the key characteristics with MLA's particular strength in preserving double power-law strength distribution and DFA's particular strength in preserving transitivity. However, they both have other limitations for the analysis of the *spatialities* of transport networks that will be revealed in the next section.

5.4.3 Spatial patterns of the abstracted networks

Figure 5.4 maps the geographical outline of the six abstracted networks. These methods substantially preserve the top-20 cities of SAAN in their backbones except for the KCD. The KCD backbone highlights a couple of cities that have more regional connections but are not necessarily well connected as shown by the appearance of Yangon, Siem Reap and Phnom Penh; meanwhile, the absence of Kota Kinabalu, Kuching, Makassar and Balikpapan from the abstracted network is noticeable. With the removal of (semi)peripheral cities (some of which are local hubs) and the corresponding intercity flows, communities detected in the KCD backbone exhibit the largest deviation from the SAAN, i.e., the three separate Greater Mekong community, Malay community, and Philippine community are merged together, with Singapore's centrality becoming even more pronounced. This approach is effective to 'peel off' the network backbone at different hierarchical levels, and probes into the properties of network regions of largest centrality, as shown by Wang et al.'s (2014) analysis of the expansion of the core structure in China's air transport network from 1930 to 2012. Still, the method has been applied to extract the core layer of the worldwide and the European air networks in Verma et al. (2014) and Lordan and Sallan (2017), respectively.

The GWT does not conserve any geometry and neglects the eastern Indonesian community around Jayapura in the original network. In the abstracted network, the strongest flows are retained and the relationships between key cities and connections are highlighted. Therefore the abstracted network would best fit network research which pays attention to spatial pattern of major transport hubs and busy transport routes, but has little interest in the topological features of the transport networks (cf. Dennis, 2005; Fuellhart and O'Connor, 2013).

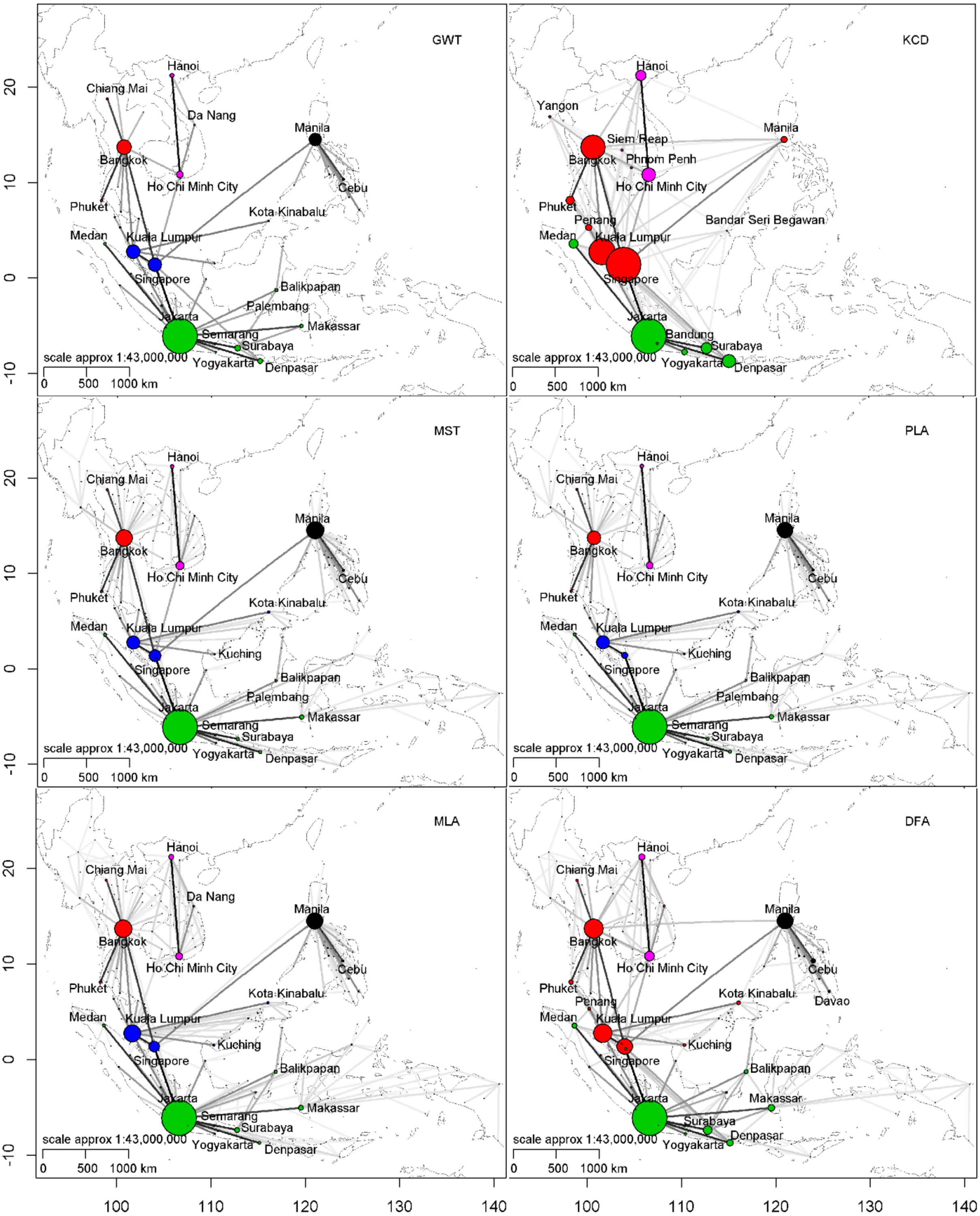


Figure 5.4 Spatial patterns of abstracted networks derived from six techniques, i.e. global weight thresholding (GWT), k-core decomposition (KCD), minimum spanning tree (MST), primary linkage analysis (PLA), multiple linkage analysis (MLA), and disparity filter algorithm (DFA).

The backbones derived from MST, PLA and MLA keep the six communities of SAAN in different geometric patterns. The PLA backbone is outlined by six seemingly isolated star-like city clusters centered on Ho Chi Minh City, Bangkok, Kuala Lumpur, Jakarta, Manila and

Jayapura, revealing the hierarchical and regional nature of the SAAN. This backbone is therefore useful to analyze nodal regions in a hierarchically organized network (Grubesic et al., 2008), to visualize the relationship between center places and their hinterlands (Ducruet and Notteboom, 2012), and to map the unfolding hub-and-spoke configurations in transport networks (Wang and Jin, 2007).

In the SAAN, MST is actually defined as maximum-flow spanning tree, so that the MST backbone is similar to that produced by PLA but retaining four additional links to connect the six communities (Singapore-Bangkok, Singapore-Ho Chi Minh City, Singapore-Manila, and Ambon-Kaimana). In this abstracted network, all cities are reachable via the shortest path while carrying most traffic flows. This backbone is particularly useful for network design and transportation planning, such as satisfying the largest transport demand for all cities with lowest costs, locating a central facility in a network with minimal distance (Alumur et al., 2009). In addition, the overlay analysis of the PLA and MST backbones jointly reveals the key inter-community connections, which could contribute to route selection and optimization.
The MLA backbone is an extension to the PLA backbone by considering other equally significant flows in addition to the strongest ones, thereby more or less losing the simplicity of the abstracted network. As shown in Figure 5.4, the backbone highlights the star-like city communities similar to PLA and the most critical inter-community flows as in MST, and meanwhile keeps some important local geometry such as the triadic configuration. However, as the number of connections preserved in the MLA backbone is fixed and often much more than the number of nodes in the original network, it might fail to achieve the desired simplification objective. Therefore, this method seems more apt in the context of a transport network with high density (even a fully connected one) but with a small number of nodes. In practice, the backbone can shed light on functional regions in commuting networks (Salas-Olmedo and Nogués, 2012), competing destinations for a certain origin in transport networks (Wang and Cullinane, 2014) as well as the degree of polarization of the spatial structure for each city (Van Nuffel et al., 2010).

Different from the emphasis on a star geometry in MST, PLA, and to a lesser extent MLA, the DFA makes the triadic geometry prominent in the backbone. This is evidenced by the preservation of the Bangkok-Manila, Singapore-Ho Chi Minh City, Singapore-Denpasar, Ho Chi Minh City-Bangkok, Ho Chi Minh City-Kuala Lumpur, Hanoi-Bangkok flows instead of the stronger connections from Kuala Lumpur to most domestic cities in East Malaysia. This is because the DFA aims to retain multiscalar heterogeneous flows against a random assignment, while a local cycle is one of the basic indicators to distinguish a city's connectivity profile from this randomness. In this respect, this method cannot work effectively in a fully connected or homogenously weighted network. In addition, the removal of stronger connections between cities in the bifurcated part of Malaysia renders the Malay community integrated into the Greater Mekong community, which deviates from the original community structure that is roughly bounded by national borders.

5.5 Discussion and conclusions

Network backbone extraction is potentially a key tool for the geographical analysis of large transport networks: it allows for faster analysis, clearer visualization, and helps quickly distilling key topological and spatial features of the network. For these reasons, a systematic comparison of the 'performance' of different backbone extraction techniques, focused on understanding the similarities between the original and abstracted networks, can help transport geographers choosing the most relevant technique if and when the need arises in their research. Based on the application of six pertinent methods derived from various disciplines to the Southeast Asian intercity air transport network, this paper has engaged in a conceptual and empirical comparison of backbone extraction techniques in a transport-geographical context. Our comparison takes both topological and spatial perspectives into account and offers insights into the circumstances in which the different methods are particularly useful.

The QAP correlations between the original and the abstracted networks are all statistically significant, but the backbone extracted from KCD bears the least structural similarity with the SAAN at the network level (QAP=0.745) whereas the DFA performs best (QAP=0.986). However, it would be incorrect to simply state that DFA outperforms others with regard to the topology, geometry and spatial structure: a careful investigation of topological properties and spatial patterns sheds a more detailed light on the different methods' pros/cons. Table 5.4 uses this broader background to summarize their potential in transport geography research.

Table 5.4 Summary on strengths and weaknesses of different backbone extraction methods.

Method	Strengths	Weaknesses	Recommendations
GWT	simplicity; replicates average path length and modularity	ignores less-connected cities and communities; inaccurate depiction of key topological characteristics	analysis of major transport, connections and major network communities
KCD	replicates degree mixing pattern;	ignores (semi)peripheral cities ; useless in	analysis of the best-connected core

	highlights central component	fully connected networks	for multilayered/multiplex networks
MST	highlights star geometry and inter-community connections; preserve community structure	omits local cycles	analysis of the optimal path to connect all cities and critical inter-community connections
PLA	highlights star geometry; preserves community structure	omits local cycles	analysis of hub-and-spoke structures and functional/nodal regions
MLA	preserves all information with better performance in replicating strength distribution	may be quite complex in the case of networks with numerous nodes; useless in networks with more or less even weight distributions	analysis of the detailed topological and spatial information for each city in the network
DFA	preserves all information with particular better performance in transitivity; adjustable size	distorts community structures; useless in networks with more or less even weight distributions	analysis of the overall topological and spatial information for large-scale networks

The GWT approach cannot give convincing topological information regarding strength distribution, degree mixing pattern and clustering coefficient but conserves the strongest flows and the most important communities. Moreover, it is the simplest method that allows preserving a relatively high structural similarity with good replication of average path length and modularity. This makes the technique above all useful for network research where the focus is on the spatial pattern of major transport nodes and the busiest transport routes without much regard for the topological features of the transport networks *per se*. The KCD retains the central component and captures the degree mixing pattern of the original network, which makes it useful for extracting the core from multilayered and/or multiplex networks. As both GWT and KCD engender scalar biases, they are useless when the goal is to preserve the key components of the multiscalar nature of the network; moreover, KCD makes no sense in the analysis of fully connected networks.

MST and PLA neglect local cycles and do not perform particularly well in terms of the conservation of topological features but highlight the network's major hierarchical features through star-like configurations. Both of them substantially preserve hierarchies and communities in the original network. PLA outlines the complex network through distinct star-shape communities which might be isolated from each other. It performs best for explicitly identifying functional regions or nodal regions as well as sketching key hub-and-spoke structures in transport networks. The MST integrates different star-like communities in PLA by including critical inter-community connections, which makes all nodes connected through a shortest path. This backbone is particularly useful in the context of transport network design and optimization, transportation planning, as well as transport resource allocation.

On the one hand, MLA outperforms others in capturing the multiscalar strengths. Furthermore, it conserves most star configurations and several triadic configurations in different communities. It can give insight into detailed topological and spatial information such as the functional region and competitive destinations for each city, as well as the degree of polarization for its connectivity profile.. Despite excellent performance in both aspects, this approach might suffer from the lack of simplicity as the size of backbone is by construction dependent on the number of cities in the original network. Hence, it best fits networks with large density (even fully connected) but with a small number of nodes. Last but not the least, the DFA extracts a multiscalar backbone bearing the highest resemblance with the original network and shows its effectiveness in the preservation of all important properties except degree mixing pattern and somewhat distorting the community structure. Moreover, the size of the abstracted network is flexible with a precise statistical interpretation in terms of significance levels. It is especially suitable for large-scale networks with local and global heterogeneities and to uncover the regularities in complex transport systems.

In this paper, we have used the example of the Asian intercity air transport network. Since the SAAN shares common characteristics of many other transport networks, we believe our findings are robust in the sense that the recommendations summarized in Table 5.4 hold for the geographical analysis of many other transport networks. Nonetheless, there are obviously some shortcomings to our study, which in turn requires future research. First, our current analysis focuses on the comparison across methods, whereas future analysis may explore how sensitive individual methods are to specific parameterizations. For instance, there is no clear rationale for which filtering cutoff to choose in the DFA backbone extraction. In a practical application of DFA, sufficient information should be given about the changes of network metrics over varying values of α to identify the critical turning point at a certain cutoff as in Serrano et al. (2009) and Darabos et al. (2014). Second, our comparison does not address the issue of the computational efficiency of the six methods in our study – they have been processed in different softwares. This requires the development of a single package to include all backbone extraction methods, which would also be useful for a range of other reasons. Third and relatedly, the need for assessing computational efficiency is more pronounced in light of the emergence of big data about transport geography. For example, smart transit card systems in individual cities are recording human trajectories at unprecedented spatial and temporal granularity (Liu et al., 2015). Testing how the backbone extraction methods fare against these emerging big urban data points to another avenue for future research.

References

Alumur, S.A., Kara, B.Y., Karasan, O.E., 2009. The design of single allocation incomplete hub networks. Transportation Research Part B: Methodological 43, 936-951.

Alvarez-Hamelin, J.I., Dall'Asta, L., Barrat, A., Vespignani, A., 2006. Large scale networks fingerprinting and visualization using the k-core decomposition. Advances in neural information processing systems 18, 41-50.

Barabási, A.-L., Albert, R., 1999. Emergence of scaling in random networks. Science 286, 509-512.

Barthélemy, M., 2011. Spatial networks. Physics Reports 499, 1-101.

Blagus, N., Šubelj, L., Bajec, M., 2014. Assessing the effectiveness of real-world network simplification. Physica A: Statistical Mechanics and its Applications 413, 134-146.

Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. Journal of Transport Geography 8, 25-41.

Bu, Z., Wu, Z., Qian, L., Cao, J., Xu, G., 2014. A backbone extraction method with Local Search for complex weighted networks, IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, Beijing, China, pp. 85-88.

Chawla, S., Garimella, K., Gionis, A., Tsang, D., 2016. Backbone discovery in traffic networks. International Journal of Data Science and Analytics 1, 215-227.

Choi, J.H., Barnett, G.A., Chon, B.-S., 2006. Comparing world city networks: A network analysis of Internet backbone and air transport intercity linkages. Global Networks 6, 81-99.

Clauset, A., Newman, M.E., Moore, C., 2004. Finding community structure in very large networks. Physical review E 70, 066111.

Dai, L., Derudder, B., Liu, X., 2016. Generative network models for simulating urban networks, the case of inter-city transport network in Southeast Asia. Cybergeo: European Journal of Geography, DOI:10.4000/cybergeo.27734.

Dai, L., Derudder, B., Liu, X., 2018. The evolving structure of the Southeast Asian inter-city air transport network through the lens of complex networks, 1979-2012. Journal of Transport Geography, forthcoming.

Darabos, C., White, M.J., Graham, B.E., Leung, D.N., Williams, S.M., Moore, J.H., 2014. The multiscale backbone of the human phenotype network based on biological pathways. BioData mining 7, 1-18.

Dennis, N., 2005. Industry consolidation and future airline network structures in Europe. Journal of Air Transport Management 11, 175-183.

Derudder, B., Liu, X., Kunaka, C., Roberts, M., 2014. The connectivity of South Asian cities in infrastructure networks. Journal of Maps 10, 47-52.

Derudder, B., Taylor, P., 2005. The cliquishness of world cities. Global Networks 5, 71-91.

Dobruszkes, F., 2006. An analysis of European low-cost airlines and their networks. Journal of Transport Geography 14, 249-264.

Du, N., Zhou, X., Zhang, R., Jia, C., Yu, J., Liu, B., 2011. Multiscale backbone based network comparison algorithm for effective herbal interaction analysis, Biomedical Engineering and Informatics (BMEI), 2011 4th International Conference on. IEEE, pp. 1757-1762.

Ducruet, C., 2017. Multilayer dynamics of complex spatial networks: The case of global maritime flows (1977-2008). Journal of Transport Geography 60, 47-58.

Ducruet, C., Beauguitte, L., 2014. Spatial Science and Network Science: Review and Outcomes of a Complex Relationship. Networks and Spatial Economics 14, 297-316.

Ducruet, C., Lugo, I., 2013. Structure and dynamics of transportation networks: Models, methods and applications, in: Rodrigue, J.-P., Notteboom, T., Shaw, J. (Eds.), The SAGE handbook of transport studies. SAGE, pp. 347-364.

Ducruet, C., Notteboom, T., 2012. The worldwide maritime network of container shipping: Spatial structure and regional dynamics. Global Networks 12, 395-423.

Foti, N.J., Hughes, J.M., Rockmore, D.N., 2011. Nonparametric sparsification of complex multiscale networks. PloS one 6, e16431.

Fuellhart, K., O'Connor, K., 2013. Air Services at Australian Cities: Change and Inertia 2005-2010. Geographical Research 51, 37-48.

García-Pérez, G., Boguñá, M., Allard, A., Serrano, M.Á., 2016. The hidden hyperbolic geometry of international trade: World Trade Atlas 1870-2013. Scientific reports 6, 33441.

Gemmetto, V., Cardillo, A., Garlaschelli, D., 2017. Irreducible network backbones: unbiased graph filtering via maximum entropy. Https://arxiv.org/abs/1706.00230.

Girvan, M., Newman, M.E., 2002. Community structure in social and biological networks. Proceedings of the National Academy of Sciences 99, 7821-7826.

Grubesic, T.H., Matisziw, T.C., Zook, M.A., 2008. Global airline networks and nodal regions. Geojournal 71, 53-66.

Güell, O., Sagués, F., Serrano, M., 2017. Detecting the Significant Flux Backbone of Escherichia coli metabolism. FEBS letters 591, 1437-1451.

Haggett, P., Cliff, A.D., Frey, A., 1977. Locational analysis in human geography. Edward Arnold, London.

Hennemann, S., 2013. Information-rich visualisation of dense geographical networks. Journal of Maps 9, 68-75.

Itzkovitz, S., Levitt, R., Kashtan, N., Milo, R., Itzkovitz, M., Alon, U., 2005. Coarse-graining and self-dissimilarity of complex networks. Physical review E 71, 016127.

Kim, D.-H., Noh, J.D., Jeong, H., 2004. Scale-free trees: The skeletons of complex networks. Physical review E 70, 046126.

Kim, J.-R., Kim, J., Kwon, Y.-K., Lee, H.-Y., Heslop-Harrison, P., Cho, K.-H., 2011. Reduction of complex signaling networks to a representative kernel. Science Signaling 4, ra35.

Krackardt, D., 1987. QAP partialling as a test of spuriousness. Social Networks 9, 171-186.

Kruskal, J.B., 1956. On the shortest spanning subtree of a graph and the traveling salesman problem. Proceedings of the American Mathematical society 7, 48-50.

Lee, S.H., Kim, P.-J., Jeong, H., 2006. Statistical properties of sampled networks. Physical review E 73, 016102.

Li, M., Fan, Y., Chen, J., Gao, L., Di, Z., Wu, J., 2005. Weighted networks of scientific communication: the measurement and topological role of weight. Physica A: Statistical Mechanics and its Applications 350, 643-656.

Liebig, J., Rao, A., 2016. Fast extraction of the backbone of projected bipartite networks to aid community detection. EPL (Europhysics Letters) 113, 28003.

Lin, J., 2012. Network analysis of China’s aviation system, statistical and spatial structure. Journal of Transport Geography 22, 109-117.

Lin, J., Ban, Y., 2013. Complex network topology of transportation systems. Transport Reviews 33, 658-685.

Liu, X., Dai, L., Derudder, B., 2017. Spatial Inequality in the Southeast Asian Intercity Transport Network. Geographical Review 107, 317-335.

Liu, X., Song, Y., Wu, K., Wang, J., Li, D., Long, Y. 2015. Understanding urban China with open data. Cities, 47, 53-61.

Lordan, O., Sallan, J.M., 2017. Analyzing the multilevel structure of the European airport network. Chinese Journal of Aeronautics 30, 554-560.

Mathioudakis, M., Bonchi, F., Castillo, C., Gionis, A., Ukkonen, A., 2011. Sparsification of influence networks, Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, pp. 529-537.

Neal, Z., 2013. Identifying statistically significant edges in one-mode projections. Social Network Analysis and Mining 3, 915-924.

Neal, Z., 2014. The backbone of bipartite projections: Inferring relationships from co-authorship, co-sponsorship, co-attendance and other co-behaviors. Social Networks 39, 84-97.

Newman, M.E., 2003. The structure and function of complex networks. SIAM review 45, 167-256.

Nystuen, J.D., Dacey, M.F., 1961. A graph theory interpretation of nodal regions. Papers of the Regional Science Association 7, 29-42.

Paleari, S., Redondi, R., Malighetti, P., 2010. A comparative study of airport connectivity in China, Europe and US: Which network provides the best service to passengers? Transportation Research Part E: Logistics and Transportation Review 46, 198-210.

Puebla, J.G., 1987. Spatial structures of network flows: A graph theoretical approach. Transportation Research Part B: Methodological 21, 489-502.

Radicchi, F., Ramasco, J.J., Fortunato, S., 2011. Information filtering in complex weighted networks. Physical review E 83, 046101.

Reed, W.J., 2003. The Pareto law of incomes-an explanation and an extension. Physica A: Statistical Mechanics and its Applications 319, 469-486.

Rodrigue, J.-P., Comtois, C., Slack, B., 2006. The geography of transport systems. Routledge, London and New York.

Salas-Olmedo, M.H., Nogués, S., 2012. Analysis of commuting needs using graph theory and census data: A comparison between two medium-sized cities in the UK. Applied Geography 35, 132-141.

Scott, J., Carrington, P.J., 2011. The SAGE handbook of social network analysis. Sage, London.

Seidman, S.B., 1983. Network structure and minimum degree. Social Networks 5, 269-287.

Serrano, M.Á., Boguñá, M., Vespignani, A., 2009. Extracting the multiscale backbone of complex weighted networks. Proceedings of the National Academy of Sciences 106, 6483-6488.

Slater, P.B., 2010. Multiscale Network Reduction Methodologies: Bistochastic and Disparity Filtering of Human Migration Flows between 3,000+ US Counties. Https://arxiv.org/abs/0907.2393.

Tsiotas, D., Polyzos, S., 2017. The Complexity in the Study of Spatial Networks: an Epistemological Approach. Networks and Spatial Economics, 1-32.

Van Nuffel, N., Derudder, B., Witlox, F., 2010. Even important connections are not always meaningful: on the use of a polarisation measure in a typology of European cities in air transport networks. Tijdschrift voor economische en sociale geografie 101, 333-348.

Verma, T., Araújo, N.A., Herrmann, H.J., 2014. Revealing the structure of the world airline network. Scientific reports 4, 5638.

Vertesi, J., 2008. Mind the gap the london underground map and users' representations of urban space. Social Studies of Science 38, 7-33.

Wang, J., Jin, F., 2007. China's air passenger transport: An analysis of recent trends. Eurasian Geography and Economics 48, 469-480.

Wang, J., Mo, H., Wang, F., 2014. Evolution of air transport network of China 1930–2012. Journal of Transport Geography 40, 145-158.

Wang, Y., Cullinane, K., 2014. Traffic consolidation in East Asian container ports: a network flow analysis. Transportation Research Part A: Policy and Practice 61, 152-163.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of'small-world'networks. Nature 393, 440-442.

Wu, Z., Braunstein, L.A., Havlin, S., Stanley, H.E., 2006. Transport in weighted networks: partition into superhighways and roads. Physical Review Letters 96, 148702.

Zhang, S., Derudder, B., Witlox, F., 2016. Dynamics in the European air transport network, 2003-9: an explanatory framework drawing on stochastic actor-based modeling. Networks and Spatial Economics 16, 643-663.

Zhou, F., Mahler, S., Toivonen, H., 2012. Review of bisonet abstraction techniques, in: Berthold, M.R. (Ed.), Bisociative Knowledge Discovery: An Introduction to Concept, Algorithms, Tools, and Applications. Springer, Berlin, Heidelberg, pp. 166-178.

Chapter 6 Conclusions

6.1 Introduction

The starting point of this dissertation was the identification of two significant gaps in the literature on urban networks. First, although Southeast Asia has witnessed accelerated urban transformations and regional integration in the context of globalization, there has been a relative lack of analyses of the urban networks in this region. As a result, the structure of the Southeast Asian urban system and its evolution from a network perspective is an almost uncharted territory. Second, while the analysis of urban networks has been fertilized by various theories and methodologies, recent advances from other disciplines in terms of modelling networks are still insufficiently explored in urban network studies.

This dissertation has addressed both issues by putting forward four research questions, which are: (1) What are the spatial patterns of the urban network in Southeast Asia from the lens of composite transport linkages? (2) What is the evolving structure of the urban network in Southeast Asia from the lens of air transport linkages? (3) How can spatial science and network science be bridged to better model the formation of urban networks? (4) What is the usefulness of different methods to extract the backbone of urban networks (using the case of Southeast Asia as an example)? We have answered these research questions in four different chapters. The purpose of this concluding chapter is to summarize and discuss the main findings, and to point out the limitations of this dissertation which in turn helps specifying avenues for further research.

6.2 Overview of the main results

In chapter 2, a composite transport network integrating road/ferry, rail, and air connectivity is created to explore the spatial patterns between 47 major Southeast Asian cities. Spatial inequality of transport connectivity in both micro and meso scales is observed through the lens of centrality analysis and community detection. Gini coefficients for individual centrality rankings point to a hierarchical degree distribution, a rather even distribution of closeness centrality, and a highly concentrated distribution of betweenness centrality. With regard to accessibility at the city level, Singapore, Kuala Lumpur and Jakarta are identified as the most dominant cities in terms of all three centralities in Southeast Asia. With regard to accessibility at the subgraph level, four network communities are detected to have denser intra-cluster connections: a Greater-Mekong community surrounded around Bangkok, a Malaysia community together with Singapore and Brunei with Kuala Lumpur and Singapore as gateways, an Indonesian community articulated into the wider region by Jakarta, and a Philippine community cantered on Manila.

In chapter 3, given the availability of coherent longitudinal dataset, the intercity air transport networks are utilized to explore the evolving structure of the Southeast Asian urban networks at a macro scale. In the context of multilayer complex network approach, both topological features and spatial patterns are investigated over the period 1979-2012. The topological structure has scale-free, small-world properties and disassortive mixing patterns and these features are relatively stable over the past 34 years. The slope of the degree distribution slightly decreased, indicating more cities now having a large degree. Meanwhile, the disassortativity become intensified recently, showing an increasing dependence of small cities on a hub-and-spoke configuration to access the entire network. However, compared to its EU macro-regional counterpart, the urban network in Southeast Asia is far from mature and integrated. In contrast, the multilayer structure has changed over time and space. The core layer is now shifting towards the western half of Southeast Asia, leading to a relative marginality of Philippine cities. Our analysis shows a prominent increase in air linkages between the core and other layers. Although more remote cities are integrated into this region by air connections, the connections between these peripheral cities remain almost non-existent, which again suggests an increasing dependence of small cities on hub-and-spoke configuration to access the network.

In chapter 4, the potential of recent advances in network modelling for urban network has been explored. To this end, we re-specified Vértes et al.'s (2012) economical clustering model to propose a generative network model (GNM) for simulating urban networks. To show the practical merit of this approach, we applied our approach to a case study of a composite intercity transport network in Southeast Asia. Overall, results confirm the potential of the proposed method, with as a major finding that the inclusion of topological effects (transitivity) alongside geographical effects as archetypically captured in (extended) gravity modelling helps understanding how urban networks are being shaped. This is further underscored by our finding that, when removing the different network-generating effects, transitivity is found to be the most important force in shaping the structure of the network.

In chapter 5, the potential of six pertinent methods derived from various disciplines has been explored for extracting the backbone of urban networks in general and transport networks in particular. To this end, we constructed a framework for analytical comparisons of different abstracted networks, benchmarked by the original network in terms of QAP correlation, topological properties, and spatial patterns. To show their practical merit, we applied each approach to a case study of a intercity air transport network in Southeast Asia. Overall, while the QAP correlations between the original and abstracted networks are all statistically significant, the backbone extracted from k-core decomposition bears the least structural similarity to the original network whereas the disparity filter algorithm performs best. A detailed comparison of topological properties and spatial patterns help illustrating the pros and cons of each method and thus points out their potential in different circumstance or for different research objectives. The results show that the global weight thresholding method is useful for urban network research where the focus is on the spatial pattern of major cities and the strongest connections without regard to the topological features of the networks *per se*. The k-core decomposition method can best be applied to extract the core from multilayered and/or multiplex urban networks that are not fully connected. Primary linkage analysis performs best for explicitly identifying functional regions or nodal regions in urban systems as well as sketching key hub-and-spoke structures in transport networks. And the minimum spanning tree method allows for identifying important inter-community connections in urban systems and is particularly suitable to transport network design and optimization, transportation planning, as well as transport resource allocation. Multiple linkages analysis best fits urban networks with large density (even fully connected) but with a small number of nodes while the disparity filter algorithm is especially suitable for large-scale urban networks with local and global heterogeneities.

6.3 Further discussion

6.3.1 Structure of the Southeast Asian urban networks

The Southeast Asian urban networks are characterized by obvious hierarchical tendencies. A handful of cities are well-developed in terms of economy and are dominant in intercity connections and flows, whereas some cities in the sparsely populated regions are hardly interconnected. This is evidenced in the centrality rankings in Chapter 2 and the 'core-bridge-periphery' geographies in Chapter 3, and confirmed by the scale-free properties of the network topology in Chapter 3.

However, different types of intercity linkages reveal a relatively different pattern. For multimodal transport linkages, the border effect is visible since many of well-connected city-dyads are domestic, usually from capital city to its secondary cities (Chapter 2). The community detection suggests that there is a mixed effect of sub-regional cooperations (Walsh, 2010) (i.e. Greater-Mekong community and Greater-Malaysia community) and border effects that are mainly derived from the island geography (i.e. Philippine community and Indonesia community). For air transport linkages, almost all capital cities and important secondary cities as well as tourist destinations are densely interconnected, forming a trans-border core network (Chapter 3). This points to the distinction between planar transport networks (i.e. rail, road) and nonplanar transport networks (i.e. airline) as well as the multiplexity of urban networks (Burger et al., 2014). In both networks, the marginality of Philippine cities and the emergence of Vietnamese cities are pronounced. Although being a latecomer in ASEAN, Vietnamese connections to cities in other Southeast Asian countries are more pronounced than for cities in the Philippines, which may result from the Philippines relatively more active integration into Northeast Asia (Bowen, 2000). This reflects that the rates of convergence among Southeast Asian countries are all in all still low (Lee, 2015) compared to other macro-regions (e.g. the European Union), which is also be confirmed by the topological comparisons of different regions and nations in Chapter 3.

Based on this observations, this dissertation enriches the conceptual debate on the coexistence of ‘networks’ and ‘territories’ in the (re)production of regions (Bunnell, 2013). This research has shown that the regional integration is bound through ‘networking’ activities, while the network structures are products of underlying physical, economic, cultural and administrative spaces.

6.3.2 Main factors shaping the network structure

The structure of Southeast Asian urban networks is influenced by historical development, the region’s fragmented and tropical geography, and a series of socioeconomic and political strategies. For instance, today’s patterns of urban primacy (Bowen, 2004; Huff and Angeles, 2011) date back to the strategical focus of major cities (e.g. capital or costal cities) in the colonial era and is later reinforced by post-independent development (Sien, 2003). The region’s ‘tyranny of geography’ (Armstrong and Read, 2006) is most evident in the Philippine island cities in our analysis. The lack of rail and bus linkages further ‘penalizes’ these cities when comparing them to other cities at the regional level. In addition, the more recent economic development of CLMV (Freeman, 1996) and tourism boom (Page, 2001) have, respectively, resulted in strong connections of Ho Chi Minh City and Denpasar to other well-connected cities. However, there are still some observations that cannot be explained by such general geographical spatial patterns .

In such cases, a topological approach enriches our understanding. Of course, spatial and topological effects are not mutually exclusive but may exert overlapping influences on the formation of urban networks (Pflieger and Rozenblat, 2010). This is because city-dyads characterized by topological proximity (e.g. two nodes that have a strong, direct connection) are often also located near each other (cf. the China example in Pumain et al., 2015). Or, put differently: interdependent cities are also often close to each other in Euclidean space. However, this need not be the case: intercity air transport connections are much less bound by distance decay effects than say, rail networks. As a consequence, both spatial and topological effects are worth considering when modelling (Chapter 4) and abstracting (Chapter 5) urban networks in general and Southeast Asian urban networks in particular. The results highlight the necessity for further bridging spatial science with network science as well as cross-disciplinary collaborations (Ducruet and Beauguitte, 2014; Reggiani, 2011).

6.3.3 Policy implications of this research

Other than examining the structures of the Southeast Asian urban networks from different perspectives and unfolding the underlying driving factors, this research may offer some general policy implications for regional integration.

Despite notable progress, the integration of Southeast Asia is still at a low level compared to other parts of the world. The rail and road networks are to a large extent bounded by physical geography: the completion of SKRL and AHN may greatly enhance the connectivity of cities in Mainland Southeast Asia, but will contribute little to include unconnected parts due to the presence of maritime borders. Due to the path dependence and Cebu’s ‘shadow effect’ from Manila to connect cities in Southeast Asia, there is a high probability for the Philippines to be more marginalized in this region if no other mode of connectivity is improved. Therefore, extended airline networks are especially important and moving towards the open skies in a deeper and broader way would be effective to achieve better regional integration. Meanwhile, with the increase of small cities’ reliance on hub-and-spoke configuration to get better accessibility, there is a potential danger that the urban primacy in capital cities will be heightened. So it is necessary to open up more cities with point-to-point routes as in the EU. In the context of the Belt and Road Initiative, this region will become more connected to China through enhanced transport connectivity and trade, and is more likely to integrate into a broader East Asian region than to achieve better self-integration.

6.4 Avenues for future research

This dissertation has attempted to broaden our understanding of the structure of urban networks in Southeast Asia both conceptually and methodologically, showing how recent advances from other scientific fields can be borrowed to model and abstract urban networks. It also points to a number of blind spots, which need to be taken up for future research.

Firstly, the notion ‘urban network’ is an abstract concept which can be represented in diverse forms of intercity linkages. As Burger et al. (2014) point out, different types of linkages do not necessarily have the same spatial structure and geographical scope, and cities in urban networks constructed by different types of linkages do not necessarily play the same role. This dissertation focuses on infrastructure networks that transport people, and an obvious next step would involve measuring the movement of cargos and information (Bowen and Leinbach, 2006). In addition, if accessibility to other dataset would be possible, urban network analysis could also include maritime flows (Ducruet and Notteboom, 2012), Internet backbones (Tranos and Gillespie, 2011), knowledge exchange (Li and Phelps, 2016), social networks based on big data mining from Facebook or twitter (Lewis et al., 2008), and so forth. In addition, the intercity air transport networks in this dissertation focus on nonstop connections/flows rather than origin-destination network, which might underestimate some cities on the end of trunk lines and overestimate hub cities. A separate and additional analysis focusing on these elements would be a welcome complement to this analysis.

Secondly, future studies could adopt a multi-scalar perspective in line with Neal’s (2012) conceptualization of a multi-scalar urban network research agenda. For instance, Southeast Asia, which was the empirical focus of this dissertation, is a regional entity which is constituted by regional gateway cities like Singapore, Kuala Lumpur, Bangkok, Jakarta, Manila, etc. as well as a great number of small cities that primarily function locally. At the same time, from a global perspective, Singapore can be understood as a pivotal hub between Asia Pacific and the global economy, with other cities constituting its hinterland and supporting its role as a ‘global city’. This dissertation focuses on urban networks within a macro-region at the continental scale without considering this region’s connections with the rest of the world, so that a logical next step would be extend this analysis to a broader global scale or zoom out to examine the individual national scale in a more detailed manner. This would undoubtedly contribute to a better understanding of the position, function and development strategies of cities.

Thirdly, this dissertation predominantly focused on describing the patterns and structures of urban networks in Southeast Asia, while the explanation of these characteristics is relatively thin and mainly descriptive. This is largely due to the current lack of complete or coherent attribute data (e.g. population, GDP, investment and tourism) for most of the studied cities in this region. A next step could be to combine relational data analysis and attribute data analysis, that is, use city attribute to explain the city hierarchy, spatial patterns, and overall structure in a statistical way to provide a more convincing interpretation. This can be achieved by conducting a QAP regression (Zhang, 2017) or incorporating socio-cultural determinants into our generative network model.

Last but not the least, since six different methods to extract the backbones of urban networks in Southeast Asia have been processed in different software packages, this dissertation does not address the issue of computational efficiency in the comparison. This highlights the necessity to develop a single package to include all backbone extraction methods, which would also be useful for a range of other reasons as well. In addition, the need for assessing computational efficiency is more pronounced in light of the emergence of big data on transport networks. For example, smart transit card systems in individual cities are recording human trajectories at unprecedented spatial and temporal granularity (Liu et al., 2015). Testing how the backbone extraction methods fare against these emerging big urban data points to another avenue for future research.

References

Armstrong, H., Read, R., 2006. Geographical 'handicaps' and small states: Some implications for the Pacific from a global perspective. Asia Pacific Viewpoint 47, 79-92.

Bowen, J., 2000. Airline hubs in Southeast Asia: national economic development and nodal accessibility. Journal of Transport Geography 8, 25-41.

Bowen, J.T., 2004. The geography of freighter aircraft operations in the Pacific Basin. Journal of Transport Geography 12, 1-11.

Bunnell, T., 2013. City Networks as Alternative Geographies of Southeast Asia. TRaNS: Trans-Regional and-National Studies of Southeast Asia 1, 27-43.

Burger, M.J., Van der Knaap, B., Wall, R.S., 2014. Polycentricity and the multiplexity of urban networks. European Planning Studies 22, 816-840.

Ducruet, C., Beauguitte, L., 2014. Spatial Science and Network Science: Review and Outcomes of a Complex Relationship. Networks and Spatial Economics 14, 297-316.

Ducruet, C., Notteboom, T., 2012. The worldwide maritime network of container shipping: Spatial structure and regional dynamics. Global Networks 12, 395-423.

Freeman, D.B., 1996. Doi Moi policy and the small-enterprise boom in Ho Chi Minh City, Vietnam. Geographical Review 86, 178-197.

Huff, G., Angeles, L., 2011. Globalization, industrialization and urbanization in pre-World War II Southeast Asia. Explorations in Economic History 48, 20-36.

Lee, D., 2015. The European and Southeast Asian Single Aviation Markets, EU Centre, Background Brief No. 15. UNSPECIFIED.

Lewis, K., Kaufman, J., Gonzalez, M., Wimmer, A., Christakis, N., 2008. Tastes, ties, and time: A new social network dataset using Facebook. com. Social Networks 30, 330-342.

Li, Y., Phelps, N., 2016. Megalopolis unbound: Knowledge collaboration and functional polycentricity within and beyond the Yangtze River Delta Region in China, 2014. Urban Studies 55, 443-460.

Liu, X., Song, Y., Wu, K., Wang, J., Li, D., Long, Y., 2015. Understanding urban China with open data. Cities 47, 53-61.

Neal, Z., 2012. The connected city: How networks are shaping the modern metropolis. Blackwell, New York, U.S.

Page, S., 2001. Gateways, hubs and transport interconnections in Southeast Asia: Implications for tourism development in the twenty-first century, In: Teo, P., Chang, T.C., Ho, K.C. (Eds.), Interconnected Worlds: Tourism in Southeast Asia. Pergamon, Oxford, U.K., pp. 84-99.

Pflieger, G., Rozenblat, C., 2010. Urban networks and network theory: the city as the connector of multiple networks. Urban Studies 47, 2723-2735.

Pumain, D., Swerts, E., Cottineau, C., Vacchiani-Marcuzzo, C., Ignazzi, A., Bretagnolle, A., Delisle, F., Cura, R., Lizzi, L., Baffi, S., 2015. Multilevel comparison of large urban systems. Cybergeo: European Journal of Geography [Online], Systems, Modelling, Geostatistics, Document 706, posted January 715, 2015.

Sien, C.L., 2003. Southeast Asia transformed: a geography of change. Institute of Southeast Asian Studies, Singapore.

Tranos, E., Gillespie, A., 2011. The urban geography of Internet backbone networks in Europe: roles and relations. Journal of Urban Technology 18, 35-50.

Vértes, P.E., Alexander-Bloch, A.F., Gogtay, N., Giedd, J.N., Rapoport, J.L., Bullmore, E.T., 2012. Simple models of human brain functional networks. Proceedings of the National Academy of Sciences 109, 5868-5873.

Walsh, J.C., 2010. Land transportation network development in the Greater Mekong Sub-region. Journal of Management 8, 17-29.

Zhang, W., 2017. Multiplex urban networks in the Yangtze River Delta: Spatial patterns and their explanatory factors. Ghent University, Ghent, Belgium.

.

Summary

The structure, modelling and abstraction of urban networks in Southeast Asia: evidence from intercity transport networks

As the world's third largest market and marked by rapidly growing economies, Southeast Asia has been experiencing both accelerated urban transformations and regional integration in the wider context of globalization processes. Urban development is however not evenly spread across this region and has been characterized by the emergence of megacities, transnational urban corridors, and sub-regional cooperation. Understanding the characteristics of the regional urban system is thus of the utmost interest to scholars. This dissertation contributes to this research domain by adopting an 'urban network approach' to explore the structure of the Southeast Asian urban system. In this light, two conceptual topics are studied:

- The spatial patterns are examined in the regional urban system based on composite (i.e. road, rail, and air) transport linkages among 47 Southeast Asian cities in 2016. The urban network approach helps revealing the urban hierarchy, sub-network structures, and spatial inequality at both city and community levels. The results reflect the influences of entrenched uneven development, fragmented geography, and economic and political policies in this region.

- The evolving structures are also examined in the regional urban system based on air transport linkages among all Southeast Asian airport cities over the period 1979-2012. The multilayer complex network approach helps revealing a relatively stable topological structure with a changing multilayered geographical structure. The multilayered core-bridge-periphery structures vary over time, mainly with the core layer additionally including the most economic vibrant secondary cities and tourist destinations recently and the bridge layer being highly volatile. These can be explained by a series of socio-economic and politico-institutional dynamics in Southeast Asia.

As urban network analysis has long been fertilized by a range of scientific fields, employing advanced techniques from other disciplines could enhance our understanding of the structures of transport-based urban networks in Southeast Asia. These dissertation contributes to this

aspect by specifically focusing on modelling and abstraction of urban networks using the case of Southeast Asia as an example. In this light, two methodological topics are studied:

- A generative network model is proposed to model urban networks by considering both geographical effects (distance, border, city size) and topological effects (transitivity). It combines factors commonly analyzed through traditional spatial simulation models (e.g., gravity models) and topological simulation models (e.g., ABSM) in a single framework. The model is validated against empirical data on the transport networks connecting 51 major cities in Southeast Asia. The results show the model has potential to better model urban networks as well as offer insights into the importance of different underlying forces.

- A systematic comparative analysis of different techniques is offered to abstract urban networks in general and transport networks in particular. Six frequently-used methods are reviewed in geography and in other disciplines but with strong relevance to intercity transport-network study, i.e. global weight thresholding, k-core decomposition, minimum spanning tree analysis, primary linkage analysis, multiple linkage analysis, and the disparity filter algorithm. The backbones extracted from the Southeast Asia air network in 2012 are compared in terms of their topological properties and spatial patterns using the initial network as a benchmark. This comparison is then used to explore under which circumstances or for which research objective the different techniques are particularly useful (or less so).

Based on the findings drawn from the analysis of these four topics, this dissertation presents some avenues for further research in terms of analyzing urban networks in terms of multiplexity, multiscalarity, and explaining network characteristics in a more convincing statistical manner, as well as on integrating different abstraction methods into a single package.

Samenvatting

De structuur, modellering en abstractie van stedelijke netwerken in Zuidoost-Azië: een analyse van interstedelijke transportnetwerken

Als ‘s werelds derde grootste markt en gekenmerkt door snelgroeiende economieën, wordt Zuidoost-Azië zowel gekenmerkt door snelle stedelijke transformaties als door regionale integratie in de bredere context van mondialiseringsprocessen. Stedelijke ontwikkelingen zijn echter niet gelijkmatig verspreid over deze regio, en worden gekenmerkt door zowel de opkomst van megasteden als transnationale stedelijke corridors. Inzicht in de veranderende kenmerken en structuur van het regionale stedelijke systeem is dan ook van groot belang voor geografen. Dit proefschrift draagt bij tot dit onderzoeksdomein door op basis van een 'stedelijke netwerkbenadering' de structuur van het stedelijke systeem in Zuidoost-Azië te analyseren. Hierbij worden twee conceptuele onderwerpen behandeld:

- De ruimtelijke patronen in het regionale stedelijke systeem worden onderzocht op basis van samengestelde transportverbindingen (weg-, spoor- en luchttransport) tussen 47 Zuidoost-Aziatische steden in 2016. De netwerkbenadering helpt de stedelijke hiërarchie, subnetwerkstructuren en ruimtelijke structuur bloot te leggen op zowel stedelijk als op sub-regionaal niveau. De resultaten weerspiegelen de invloed van ongelijke ontwikkeling, gefragmenteerde fysiografie, en recent economisch en politiek beleid in de regio.

- De evoluerende structuren worden onderzocht op basis van de evoluties in luchtvaartverbindingen tussen Zuidoost-Aziatische steden in de periode 1979-2012. De toepassing van een complexe netwerkbenadering suggereert een relatief stabiele topologische structuur met een veranderende meerlagige geografische structuur. De meerlagige kern-brug-periferie structuren variëren in de loop van de tijd, voornamelijk doordat de kernlaag recent ook de economische sterkst ontwikkelde secundaire steden en toeristische bestemmingen is beginnen omvatten. Deze wijzigingen kunnen worden verklaard door een reeks sociaaleconomische en politiek-institutionele dynamieken in Zuidoost-Azië.

Aangezien de analyse van stedelijke netwerken wordt beïnvloed door evoluties in andere wetenschappelijke domein, kan het gebruik van geavanceerde technieken uit andere disciplines ons inzicht in de structuur van stedelijke netwerken verhogen. Deze dissertatie draagt bij tot deze kruisbestuiving door de analyse specifiek te richten op nieuwe benaderingen in het modelleren en abstraheren van stedelijke netwerken, en dit aan de hand van de case van Zuidoost-Azië. Twee methodologische bijdragen worden geleverd:

- Een generatief netwerkmodel wordt opgesteld en geïmplementeerd om stedelijke netwerken te modelleren met inachtname van zowel geografische effecten (afstand, grens, stadsgrootte) als topologische effecten (transitiviteit). Het model combineert factoren die vaak worden geanalyseerd via traditionele ruimtelijke simulatiemodellen (bijvoorbeeld zwaartekrachtmodellen) en topologische simulatiemodellen (bijvoorbeeld ABSM) in een enkelvoudig analytisch raamwerk. Het model wordt gevalideerd op basis van empirische gegevens over de transportnetwerken die 51 steden in Zuidoost-Azië met elkaar verbinden. De resultaten suggereren dat het model mogelijkheden biedt om stedelijke netwerken beter te modelleren en inzicht te bieden in het relatieve belang van verschillende onderliggende krachten.

- Een systematische vergelijkende analyse van verschillende netwerk-abstractietechnieken helpt de beste techniek te selecteren om stedelijke netwerken in het algemeen en vervoersnetwerken in het bijzonder te vereenvoudigen tot hun ‘backbone’. Zes veel gebruikte methoden worden beoordeeld en vergeleken, met name: global weight thresholding, k-core decomposition, minimum spanning tree analysis, primary linkage analysis, multiple linkage analysis, en het disparity filter algorithm. De backbones die voor 2012 uit het Zuidoost-Aziatische luchtnetwerk worden gefilterd, worden vergeleken met het originele netwerk op basis van hun topologische eigenschappen en ruimtelijke patronen. Deze vergelijking wordt vervolgens gebruikt om na te gaan onder welke omstandigheden of voor welke onderzoeksvraag de verschillende technieken relatief meer/minder nuttig zijn.

Op basis van de bevindingen die voortvloeien uit de gedetailleerde analyse van deze vier onderwerpen, biedt dit proefschrift pistes voor verder onderzoek in het analyseren van stedelijke netwerken in termen van multiplexiteit, meerschaligheid en het statistisch meer zinvol begrijpen van de netwerkkenmerken van stedelijke systemen.

Curriculum Vitae (Bibliography)

Liang Dai (°1989) was born in Zhenjiang, Jiangsu Province, China. She obtained a Bachelor's (2011) and a Master's Degree (2013) in the School of Geographic and Oceanographic Sciences from Nanjing University (Nanjing, China). In September of 2013, she became a PhD student in Social and Economic Geography at Ghent University, and a member of the Globalization and World Cities (GaWC) Research Network. Her PhD research has been funded by the Flemish Fund for Scientific Research (FWO) and mainly focuses on 1) exploring and interpreting spatial and temporal structures of the Southeast Asian urban networks and 2) employing state-of-the-art and innovative modelling, analytical, and visualization techniques into the analysis of city networks. She has had 11 first/corresponding authored papers published in peer-reviewed journals (including Chinese journals). She has attended 5 international conferences and workshops where she presented some of her doctoral research, and won the Best Poster Award at the 7th Belgian Geography Day in Liège. After graduation, she will continue her new academic career as an associate professor in the School of Public Administration at the Nanjing University of Finance and Economics (Nanjing, China).

This dissertation aims to contribute to ongoing research on the structure of urban system in Southeast Asia from a network perspective, as well as to integrating recent advances in network analysis from different disciplines into the modelling and abstraction of urban networks. It is acknowledged that transport infrastructures contribute to the economic development of cities and regions by facilitating accessibility and connectivity, in this way reducing transaction costs, stimulating trade and investment, and improving social welfare. Against this backdrop, this dissertation seeks to examine the spatial patterns and structural evolution of the Southeast Asian urban networks through the lens of composite transport linkages and air transport linkages, after which the modelling and abstraction techniques are employed into the analyses of these networks.

Liang Dai (°1989) obtained her Master's Degree in Land Resources Management at Nanjing University in 2013. She started working at the Social and Economic Geography research unit of Ghent University in the same year. Her PhD research is funded by the Flemish Fund for Scientific Research (FWO).

ISBN 978-9-4619761-2-3