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Introduction

1 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 (inter-city 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).

2 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 inter-city transportation networks in Southeast Asia.

3 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.

Literature review

Urban network analysis

4 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 inter-city 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 inter-city connections develop over time.

5 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, 2013). 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).

6 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 (inter-city connections). The structure of the latter remains somewhat implicit in the operational model. That is, although it is posited that scaling laws emerge from inter-city 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.

Space and topology in the simulation of urban networks

7 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 inter-city 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).

8 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).

Previous approaches to the simulation of urban networks

9 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).

10 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 inter-city 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 inter-city network.

11 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-Oriented Models (SAOM, 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 SAOM 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).

12 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: inter-city air transport connections are much less bound by distance decay effects than say, rail networks.

13 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.

Data and Methodologies

Data: Inter-city transport networks in Southeast Asia

14 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 inter-city connections in different transportation networks.

15 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 1 and Figure 1 list and map the 51 cities.

Figure 1: Distribution of selected cities in Southeast Asia. City abbreviations used in the figure are given in Table 1, hereafter.

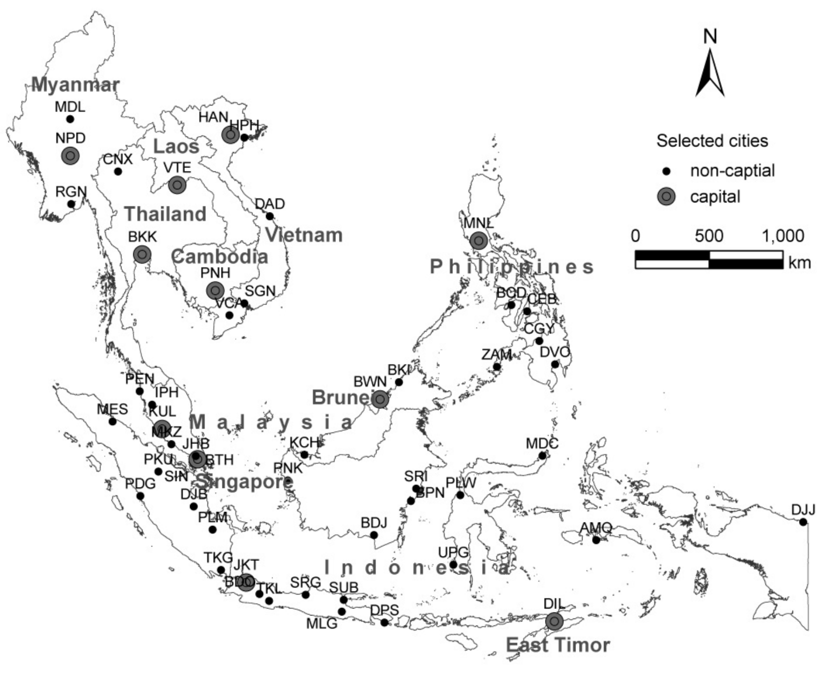


Table 1: List of selected cities

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.

16 Our composite transport network provides a surrogate measure of three individual transport networks: road, rail, and air transport. Based on the 51 selected cities, inter-city 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. Inter-city bus and ferry connections were acquired from national and international online-bus/ferry websites of each country[1]; for train connections we consulted websites of railway agencies and national railway administrations for individual countries[2]; 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).

17 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:

(1)

$$x_{ij} = \frac{x_{ij} - Min(x_{ij})}{Max(x_{ij}) - Min(x_{ij})}$$

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

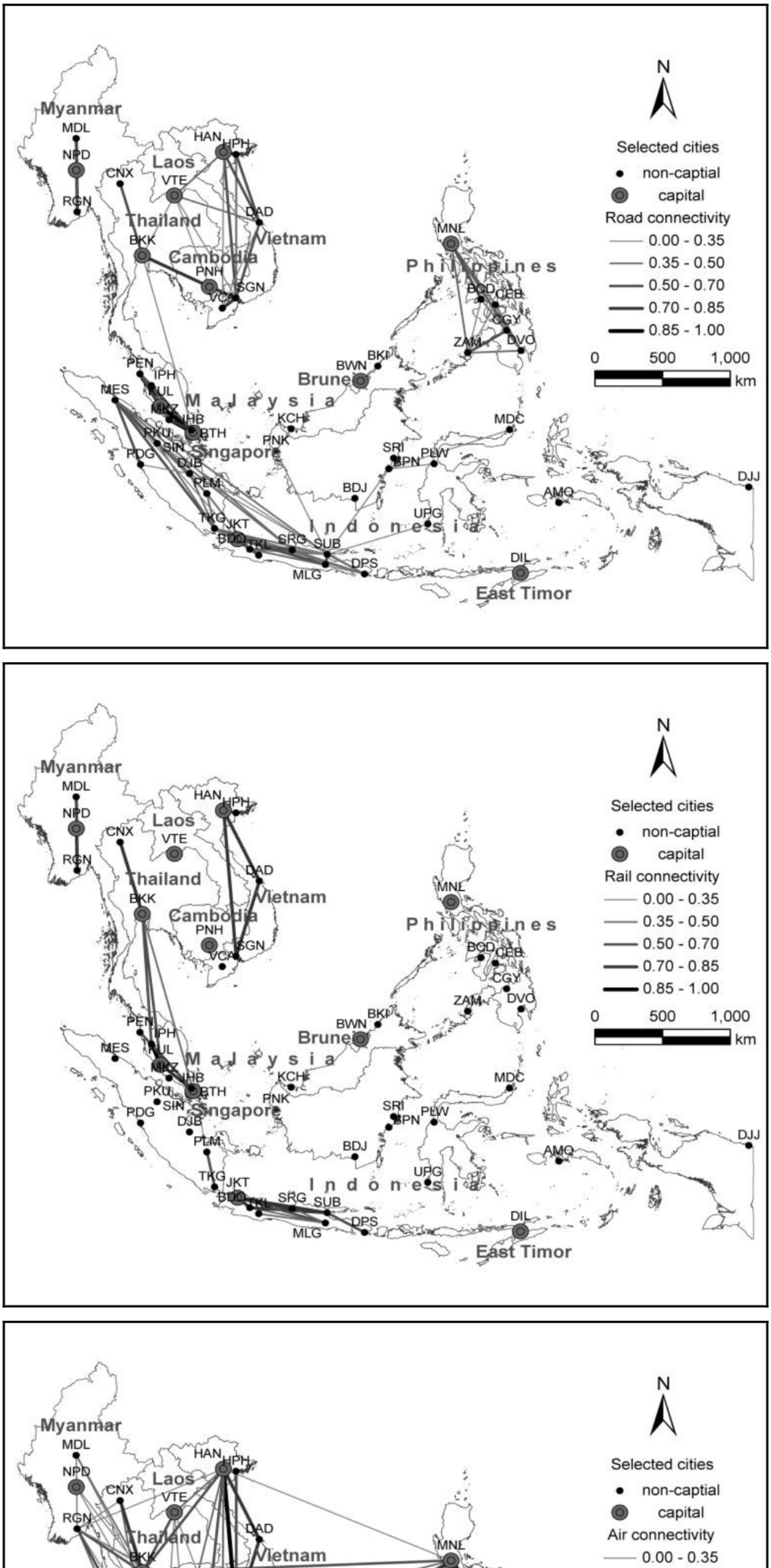
19 All three data layers thus have a distribution between 0 (minimum connectivity) and 1 (maximum connectivity), after which edges in the composite network were derived by taking the average score of the logged and normalized values in each of the different layers.

20 The connections in each of the three layers are shown in Figure 2, while the 10 strongest connections are presented in Table 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 inter-city accessibility. The strongest inter-city 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.

Table 2: The 10 strongest inter-city connections in different layers in Southeast Asia

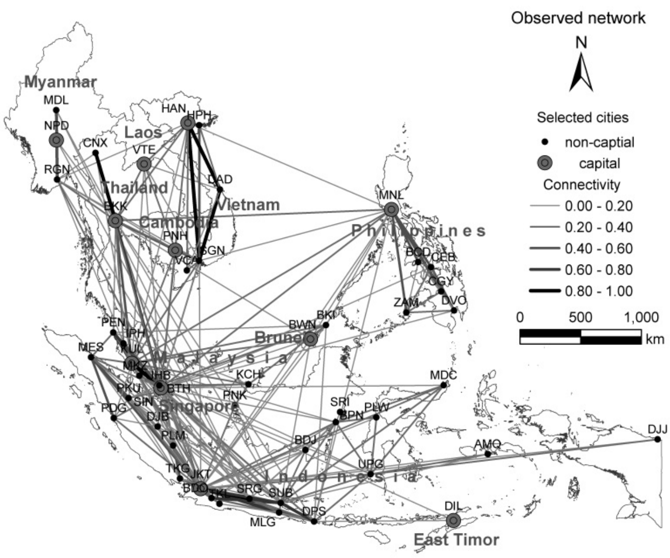
Rank	Inter-city connection	Road	Inter-city connection	Rail	Inter-city connection	Air	Inter-city connection	Composite
1	Kuala Lumpur-Singapore	1190	Kuala Lumpur-Ipoh	119	Jakarta-Surabaya	406	Kuala Lumpur-Singapore	0,857
2	Kuala Lumpur-Johor Bahru	1190	Jakarta-Semarang	49	Manila-Cebu	337	Kuala Lumpur-Johor Bahru	0,792
3	Kuala Lumpur-Penang	861	Yangon-Mandalay	49	Denpasar-Jakarta	275	Bangkok-Chiang Mai	0,762
4	Malacca-Singapore	735	Bangkok-Chiang Mai	42	Kuala Lumpur-Singapore	257	Ho Chi Minh City-Hanoi	0,759
5	Kuala Lumpur-Ipoh	448	Hanoi-Da Nang	42	Ho Chi Minh City-Hanoi	240	Jakarta-Semarang	0,737
6	Ho Chi Minh City-Can Tho	336	Singapore-Johor Bahru	42	Jakarta-Medan	235	Ho Chi Minh City-Da Nang	0,716
7	Kuala Lumpur-Malacca	322	Yangon-Naypyidaw	42	Jakarta-Singapore	217	Hanoi-Da Nang	0,695
8	Phnom Penh-Ho Chi Minh City	273	Bandung-Jakarta	42	Kuala Lumpur-KotaKinabalu	203	Jakarta-Surabaya	0,681
9	Malacca-Johor Bahru	252	Jakarta-Surabaya	35	Manila-Davao	197	Kuala Lumpur-Ipoh	0,621
10	Hanoi-Hai phong	238	Ho Chi Minh City-Hanoi	35	Jakarta-Palembang	182	Kuala Lumpur-Penang	0,595

Figure 2: The three layers used in the construction of the composite network



21 In the observed network of composite network displayed in Figure 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.

Figure 3: Connections in the observed network of composite transport in Southeast Asia



Model specification

22 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 inter-city connectivity is consolidated between nodes having nearest neighbours in common. The resulting specification can be written as:

(2)

$$P_{ij} \propto \frac{(\mathrm{pop}_i \cdot \mathrm{pop}_j)^{\alpha}}{{d_{ij}}^{\beta}} \cdot \frac{1}{\theta} \cdot {k_{ij}}^{\gamma}$$

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 inter-city connections. If 0<θ<1, then borders stimulate inter-city connections (an unlikely scenario); if θ=1, borders, then have no effect; and and if θ>1, then borders have an adverse effect on inter-city connections.

23 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:

(3)

$$\mathrm{SN}_{ij} = \sum_{k=1}^{n} x_{ik} \cdot x_{kj}$$

24 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 $\mathrm{dyad}_{i\text{-}k}$ and $\mathrm{dyad}_{k\text{-}j}$.

Model parameter estimation

25 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.

26 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'.

27 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.

28 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:

(4)

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

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.

Results

Comparisons between the simulated and the observed networks

29 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:

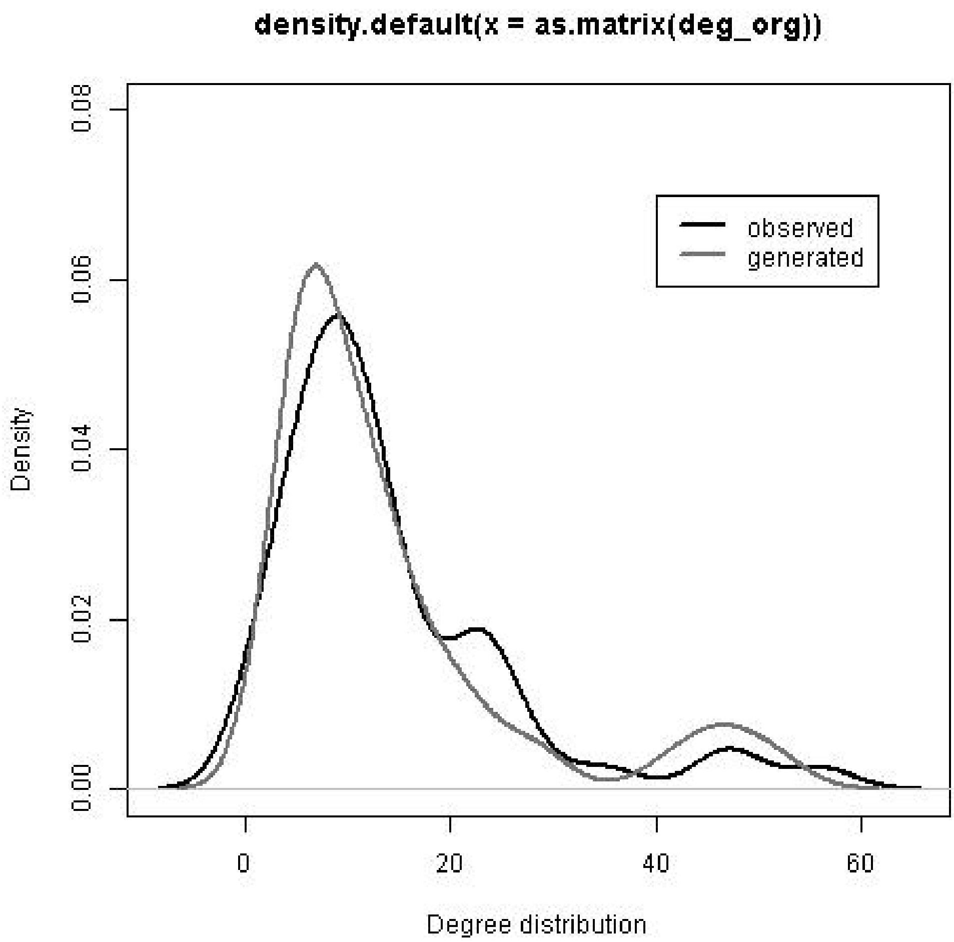
$$P_{ij} \propto \frac{(\mathrm{pop}_i \cdot \mathrm{pop}_j)^2 \cdot (\frac{1}{\mathrm{d}_{ij}{}^{3.5}}) \cdot \mathrm{k}_{ij}}{\text{if i and j are located in the same country} = 1, \text{else} = 2}$$

30 Table 3 and Figure 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 5. Topologically, both networks are very similar, especially in terms of average clustering coefficient, global efficiency and degree distribution.

Table 3: Network metrics for the observed and the simulated networks

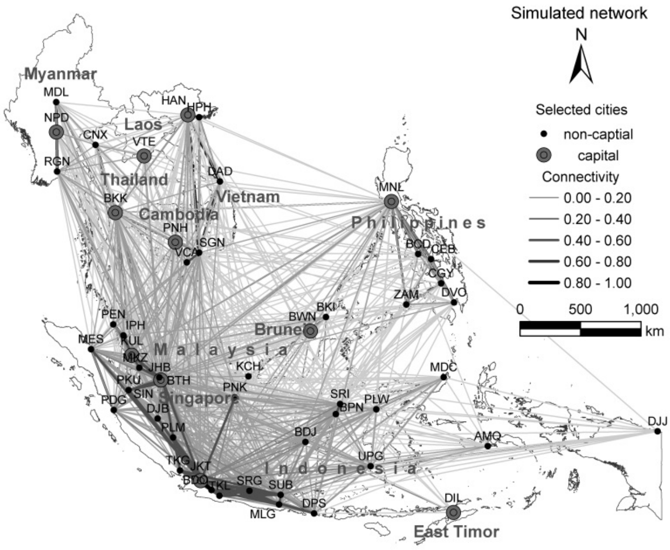
Network	M	C	E	D	QAP (Sig.)	pE	pC	pM	pD	EV
Observed	0.481	0.496	0.534	Figure 4	0.309 (0.001)	7.9E-07	5.1E-12	7.8E-51	7.6E-07	4.2E+73
Simulated	0.345	0.453	0.510							

Figure 4: Degree distributions in the observed and the simulated networks



31 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.

Figure 5: Connections in the simulated networks



32 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).

33 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.

34 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.

Analyses of each driving factor underlying network formation

35 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 and Figure 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 7 displays the spatial patterns of the four networks.

Table 4: Network statistics for the simulated networks after removal of driving force

Force removed	α	β	θ	γ	M	C	E	D	QAP (Sig.)	pE	pC	pM	pD	EV	
Population	0	3.5	2	1	0.326	0.432	0.536		0.260 (0.001)	3.6E-01	1.6E-22	1.5E-54	3.3E-15	3.6E+90	
Distance	2	0	2	1	0.247	0.378	0.586	Figure 6	0.161 (0.005)	8.2E-68	8.1E-68	5.3E-10	1.52E-12	2.3E+248	
Border	2	3.5	1	1	0.350	0.460	0.493		0.166 (0.004)	8.0E-09	6.8E-07	2.2E-53	0.0E+00	∞	
Transitivity	2	3.5	2	0	0.259	0.268	0.601		0.190 (0.000)	2.4E-12	2.40E-11	1.55E-11	3 0.0E+00	∞	

Figure 6: Degree distributions after each removal of the different forces

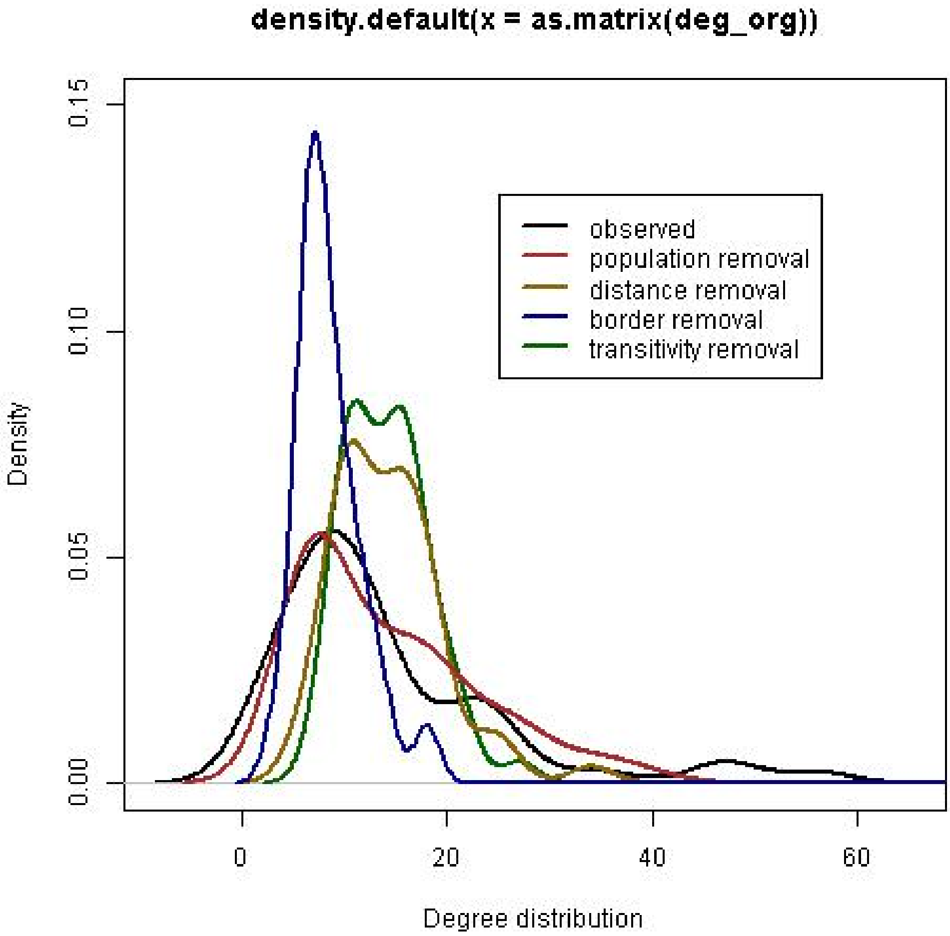
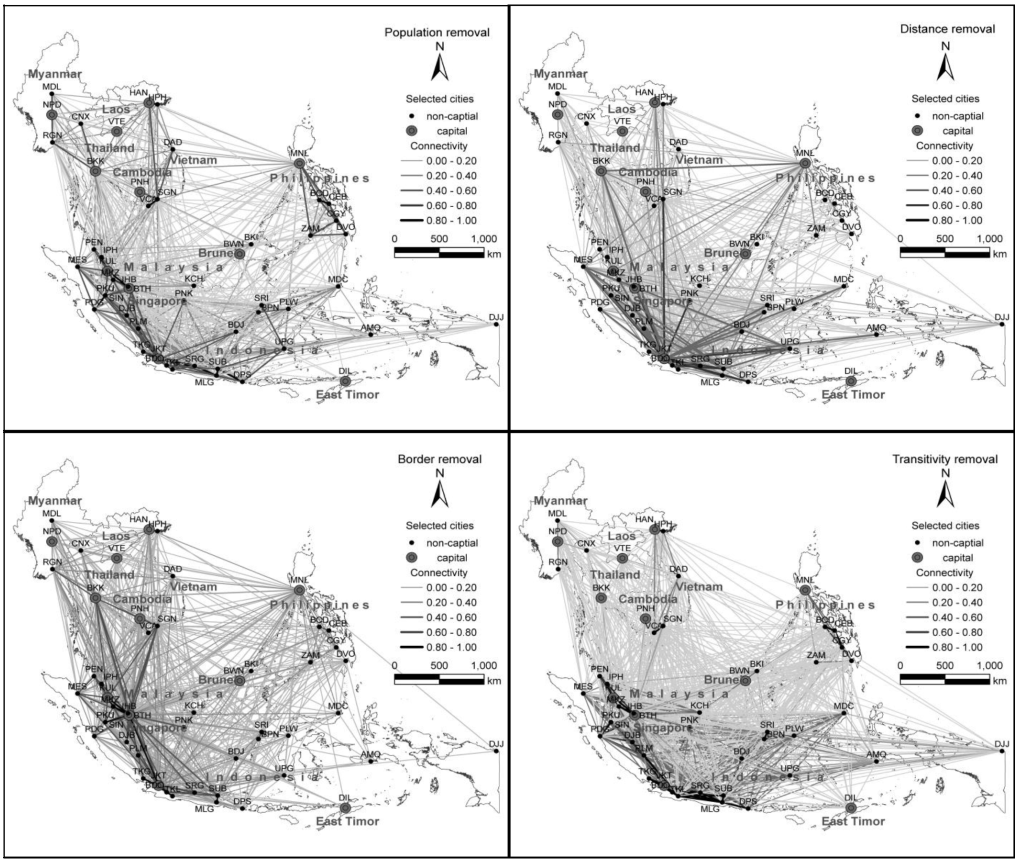


Figure 7: Simulated networks after removal of the different forces



36 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.

37 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 inter-city 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).

38 The border effect is another main force in this region to shape the inter-city 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).

39 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 coeeficients and degree distribution. Disregarding distance yields more connections between remote cities that in reality belong to different communities.

40 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 inter-city 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.

Conclusions and avenues for further research

41 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 inter-city 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.

42 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.

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Notes

1 Source: www.busonlineticket.com; myanmarbusticket.com; www.vietnambustickets.com; www.busonlineticket.co.th; www.camboticket.com; www.kramatdjati.co.id; www.indonesiaferry.co.id; travel.2go.com.ph.

2 Source: vietnam-railway.com; www.gahanoi.com.vn; www.thairailways.com; www.ktmb.com.my; www.myanmarmtetours.com; www.pnr.gov.ph; tiket.kereta-api.co.id

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Droits d'auteur

Résumés

This paper examines the driving forces of urban network formation through the simulation of inter-city 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 (i.e., 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 (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 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.

Un modèle générateur de réseau pour simuler les réseaux de transport inter-urbains en Asie du Sud-Est

Cet article examine les forces motrices à l'origine de la formation de réseaux en les reconstruisant par simulation à partir de l'exemple des réseaux de transport inter-urbains en Asie du Sud-Est. Nous présentons un modèle générateur de réseau (GNM) qui intègre des effets géographiques et topologiques, en combinant dans un même cadre des facteurs analysés généralement par des modèles de simulation spatiale (par exemple, les modèles gravitaires) et des modèles de simulation topologiques (par exemple, des modèles stochastiques de mise en réseau d'acteurs). Dans notre GNM, on suppose que la probabilité de connexion entre des villes émerge de forces concurrentes. Les facteurs incitatifs sont une mesure de taille de la ville (la population) et une règle topologique favorisant la formation de connexions entre les villes qui partagent les voisins les plus proches (effets transitifs). Les facteurs dissuasifs sont la distance physique entre les deux villes, ainsi que la distance institutionnelle (les effets de frontière). Nous discutons du modèle dans le contexte des collaborations entre la recherche en géographie urbaine et la science des réseaux, et nous validons sa plausibilité en le confrontant à des données empiriques sur les réseaux de transport reliant 51 grandes villes en Asie du Sud-Est. Nos résultats montrent que (1) les réseaux simulés se rapprochent de ceux observés en termes de longueur moyenne des arêtes, de connexité, de modularité, d'efficacité et de corrélation (par procédure d'affectation quadratique (QAP)) entre le réseau composite observé et celui généré, et que (2) GNM réalise de meilleures performances lorsque des facteurs topographiques et topologiques sont considérés simultanément. Chaque facteur contribue différemment à la formation du réseau, les effets transitifs jouant le rôle le plus important.

Entrées d'index

Mots-clés : modèle générateur de réseau, réseau de transport, transitivité, Asie du Sud-Est
Keywords : generative network model, transport network, transitivity, Southeast Asia