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Simulating infrastructure networks in the Yangtze River Delta (China) using generative urban network models

Simuleren van infrastructuurnetwerken in de Yangtze-rivierdelta door middel van generatieve stedelijke netwerk-modellen

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Résumés

English Nederlands

This paper explores the urban-geographical potential of simulation approaches combining spatial and topological processes. Drawing on Vértes *et al.*'s (2012) economical clustering model, we propose a generative network model integrating factors captured in traditional spatial models (e.g., gravity models) and more recently developed topological models (e.g., actor-oriented stochastic models) into a single framework. In our urban network-implementation of the generative network model, it is assumed that the emergence of inter-city linkages can be approximated through probabilistic processes that speak to a series of contradictory forces. Our exploratory study focuses on the outline of the infrastructure networks connecting prefecture-level cities in the highly urbanized Yangtze River Delta (China). Possible hampering factors in the emergence of these networks include distance and administrative boundaries, while stimulating factors include a measure of city size (population, gross domestic product) and a topological rule stating that the formation of connections between cities sharing nearest neighbors is more likely (i.e., a transitive effect). Based on our results, two wider implications of our research are discussed: (1) it confirms the potential of the proposed method in urban network simulation in that the inclusion of a topological factor alongside geographical factors generates an urban network that better approximates the observed network; (2) it allows exploring the differential extent to which driving forces influence the structure of different urban networks. For instance, in the Yangtze River Delta, transitivity plays a less important role in the Internet-network formation; GDP and boundaries more strongly affect the rail network; and distance decay effects play a more prominent role in the road network.

Dit artikel analyseert het potentieel binnen stadsgeografisch onderzoek van simulatiebenaderingen die zowel ruimtelijke als topologische processen in rekening brengen. Op basis van Vértes et al.'s (2012) economisch clustering-model stellen we een generatief netwerk-model voor dat factoren samenbrengt die doorgaans apart worden geanalyseerd in meer traditionele ruimtelijke modellen (bvb. zwaartekrachtmodellen) en in meer recente topologische modellen (bvb. actor-georiënteerde stochastische modellen). In onze stedelijke netwerk-implementatie van het generatief netwerk-model wordt aangenomen dat de totstandkoming van inter-stedelijke verbindingen kan ingeschat worden door middel van stochastische processen die analyseren hoe bepaalde krachten in variërende mate de vorming van die verbindingen versterken of afzwakken. Onze verkennende studie focust op de geografische structuur van de infrastructuurnetwerken die de voornaamste steden in de sterk geurbaniseerde Yangtze River Delta (China) met elkaar verbinden. Mogelijke afremmende factoren in de totstandkoming van deze netwerken zijn afstand en administratieve grenzen. Mogelijke stimulerende factoren zijn het belang van de stad (bevolkingsomvang of bruto regionaal product) en een topologische regel die aangeeft dat de vorming van connecties tussen steden waarschijnlijker is wanneer zij een 'dichtste buur' delen (m.n. een transitief effect). Twee bredere implicaties van ons onderzoek worden besproken aan de hand van de resultaten: (1) de resultaten bevestigen het potentieel van de voorgestelde methode voor de simulatie van stedelijke netwerken in de zin dat het opnemen van een topologische factor naast geografische factoren een stedelijk netwerk genereert dat een betere inschatting geeft van het geobserveerde netwerk; (2) de methode laat toe om de differentiële impact te meten van de verschillende stuwende factoren. In de Yangtze River Delta speelt transitiviteit bijvoorbeeld een minder belangrijke rol in de totstandkoming van het Internet-netwoerk; economische output en grenzen spelen een belangrijkere rol in de totstandkoming van het spoorweg-netwerk; en afstandsverval speelt een prominentere rol in de totstandkoming van het wegennetwerk.

Entrées d'index

Keywords : generative network model, infrastructure network, transitivity, Yangtze River Delta, China

Trefwoorden : generatieve netwerkmodellen , infrastructuurnetwerken, transitiviteit, Yangtze-rivierdelta, China

Texte intégral

Introduction

1 There is a growing body of literature stressing the potential of a network approach to urban systems. This is not only visible in a proliferation of theoretical frameworks (e.g., Castells, 1996; Shearmur & Doloreux, 2015), but also in methodological terms (e.g., Aujean *et al.*, 2007; Hanssens & Derudder, 2011). From a 'network perspective', urban systems are approached as organizational constellations of immaterial and material relations connecting individual cities, whereby cities' positionalities are thought to be facilitated and/or constrained by the structure of the myriad networks in which they are embedded (Dietsche, 2009). The increased popularity of 'network thinking' in urban geography calls for the forging of closer relationships between geography and network science, albeit that the adoption of some of the more advanced methods has recently been described as 'limited and dispersed' (Ducruet & Beaugitte, 2014, p. 1). The formative purpose of this paper is to explore the urban-geographical potential of one of these new methods.

2 When reviewing the literature on urban network analysis, it can be observed that there are in fact two main research agendas. The first research agenda focuses on the description of cities' positions in network structures; the second focuses on the modeling and simulation of how these networks have developed over time. Research in the first domain mainly deals with the formulation and calculation of a series of network metrics. First, the importance of cities is examined by means of diverse

centrality measures such as degree, closeness and betweenness centrality as in Lin & Ban (2014), as well as eigenvector and recursive centrality as in Neal (2011, 2013). Second, clique analysis (Shin & Timberlake, 2000) and community detection methods (Blondel *et al.*, 2010) are applied to explore the spatial structures within urban networks. Third, Quadratic Assignment Procedures (QAP) have been used to assess the structural equivalence of different urban networks in Choi *et al.* (2006). And fourth, complex-network metrics are employed to reveal the topological properties of urban networks. For example, Wang *et al.* (2011) identify small-world characteristics (Watts & Strogatz, 1998) in China's air transport network, with city-pairs separated by just a few links and the topological property of the network exhibiting a high local clustering coefficient. All of these frequently used techniques contribute to a better understanding of patterns and structures of urban systems. However, they shed little light on the formation mechanism of the observed urban networks *per se*.

3 The second research agenda attempts to reproduce key topological properties of observed urban networks. It seems fair to state that to date this literature is relatively less well-developed. Clark & Stabler (1991), Pumain *et al.* (2015), Bretagnolle & Pumain (2010) have shown that broad, structuring forces 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), pointing 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, and this is the topic we will address in this paper.

4 More specifically, in this paper, we attempt to show that inter-city connections can be modeled by employing a number of recent advances in spatial/topological simulation that may help bridge the gap between spatial science and network science (cf. Barthélémy, 2011). To this end, we present an exploratory attempt to model urban networks as measured by inter-city infrastructure connections through an application of Vértes *et al.*'s (2012) generative network model (GNM). The modeling technique, derived from an application in neurobiology, combines both spatial and topological processes. We hypothesize that such an approach can enhance our understanding of the formation processes underlying an urban network when compared with techniques that do not include a topological dimension. The hypothesis is tested against empirical data on infrastructure networks connecting 25 major cities in the Yangtze River Delta, China. In addition, the merits of the hypothesized network-generating processes are examined through a comparison between the simulated networks for different types of infrastructure.

5 The remainder of this paper is organized in five sections. In the next section, we review the principal driving forces underlying urban-network formation, as well as previous approaches used in urban-network modeling and simulation in order to frame the position of the GNM approach. We then introduce our study area, describe our datasets, and elaborate the model specification and parameter estimation procedure. The model is subsequently operationalized and validated through an empirical study on infrastructure networks in the Yangtze River Delta, showing how transitivity, distance, boundary and city size play out in the formation of different infrastructure networks. The final section discusses the main implications of our analysis and outlines some avenues for further research.

Background

6 For many years, research on the formation of inter-city linkages predominately focused on the spatial processes such as distance decay effects and socio-economic proximity (e.g., Carrère, 2006; Lewer & Van den Berg, 2008; Morley *et al.*, 2014). With the employment of network theories and methodologies in urban geography, topological processes are found to be part and parcel of urban network formation (Vinciguerra *et al.*, 2010; Liu *et al.*, 2013a, b), that is, the inter-city structural dependencies at the local scale can contribute to the overall patterns of urban networks at the global scale. In spite of different assumptions, considerations either on spatial or topological processes have their own strengths and limitations in empirical studies (Table 1).

Table 1. Review on driving factors and methodologies of spatial and topological modelling for urban networks. (GM: Gravity-type models; ERGM: Exponential Random Graph Models; SAOM: Stochastic Actor-Oriented Models).

Category	Driving factor	Methodology	Limitations	Strengths
Spatial processes	Demography,economy, policy	GM	Structural independence among cities	Intuitive concept
	Physical and administrative distance			straightforward operation
	Cultural proximity			Flexible addition of other factors
Topological processes	Density	ERGM	Degeneracy problems	Structural interdependence among cities
	Preferential attachment		Binary edges	
	Triadic closure (Transivity)	SAOM	Longitudinal datasets	
	Other local structural configurations		Vague definition	

Driving forces in urban network formation

7 Various factors may influence the formation of urban networks. 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, the presence of globalized business services firms has been shown to be one of the most pertinent variables in explaining the presence of airline connections (Van De Vijver *et al.*, 2014). Meanwhile, Phang's (2003) analysis of the over-provision of Singapore's airline capacity shows that the formation and reinforcement of many air linkages to the rest of the world can be attributed to Singapore's aggressive aviation policies and strategies.

8 Factors at the dyadic level have also proven to impinge on inter-city connections. For instance, physical distance and borders often increase transaction costs, leading to a relatively lower connectivity of long-distance and trans-national linkages (Vinciguerra *et al.*, 2010). Meanwhile, colonial legacies as specific examples of institutional facilitators of inter-city connections have been shown to be pertinent in the shaping of airline networks (cf. the London-Nairobi dyad as explained in Pirie, 2010).

9 In addition to these quasi-obvious geographical dimensions, there is a topological feature that requires closer attention when considering the driving forces underlying urban-network formation. Empirical studies have shown that there are also strong localization components in networks that do not have a specific spatial component (Robins *et al.*, 2009). For instance, many networks exhibit transitive tendencies in the sense that nodes sharing neighbors are more likely to have direct connections (e.g., two persons knowing each other will have a lot of common acquaintances and friends, as is clearly shown in Facebook networks). Thus the higher probability of short-range connections than geographically distant connections (see Taylor *et al.*, 2013; Liu *et al.*, 2014; Shin & Timberlake, 2000) may be due to either topological and/or spatial effects. Indeed, topological and spatial effects are not mutually exclusive: they may exert overlapping (yet separate) influences on the shaping of urban networks (cf. Pflieger & Rozenblat, 2010); this is because city-dyads characterized by topological proximity (i.e., two nodes that have a strong direct

connection) are in most cases located near each other. Put differently, interdependent cities are generally close to each other in 'real' space.

Simulating urban network formation

10 Simulating urban networks obviously implies exploring which, and to what extent, such driving forces explain the observed outline of the urban network at hand. Arguably the most frequently adopted strategy for modeling urban networks starts from pointing to the analogies with Newton's law of gravity. The flow and interaction intensity between pairs of cities is hereby 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 (Carrère, 2006), migration (Lewer & Van den Berg, 2008), and tourism (Morley *et al.*, 2014). In addition to its intuitive conceptual appeal and straightforward operationalization, the popularity of the gravity-type models lies in their potential for flexible addition of other factors with a spatial impact. For instance, border dummy variables (Feenstra, 2002), remoteness variables (Head and Mayer, 2000) and heterogeneous coefficients (Behrens *et al.*, 2012) have been incorporated to provide more accurate approximations of spatial characteristics of the simulated urban networks. However, in spite of these elaborations, strong assumptions of *structural independence* among nodes loom large. From a network perspective, it is precisely the lack of independence of nodes – i.e., the interdependence of nodes (e.g. transitivity) – that defines a network. The strength of linkages among 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).

11 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 (e.g. a preferential attachment process) and spatial effects (e.g., borders) help to explain the shape of this particular inter-city network.

12 Two recent approaches from the network analysis literature that may be applied for modeling the topological properties of urban networks can be found in the work of Liu *et al.* (2013a, b). Both papers apply stochastic network models, i.e., Exponential Random Graph Models (ERGM, Liu *et al.*, 2013a) and Stochastic Actor-Oriented Models (SAOM, Liu *et al.*, 2013b). 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 network formation. These processes, however, are much more complicated and difficult to interpret than those with gravity-type models. In addition, both approaches have their drawbacks in the context of urban network simulation. EGRMs, for instance, are prone to degeneracy problems (i.e., failure to converge and hence become unstable) and are at present confined to modeling binary edges. Meanwhile, while SAOM clearly has potential for simulating urban networks that are produced by well-defined agents (e.g., firms), this simulation needs a clear-cut definition of key actors and their network-generating behavior, making the implementation difficult at times (Broekel *et al.*, 2014).

13 In our study, we therefore propose to extend Vinciguera *et al.*'s (2010) network

modeling approach incorporating both spatial and topological factors. To this end, we apply Vértes *et al.*'s (2012) generative network modeling approach (GNM), which was initially developed for studying functional human brain networks. In Vértes *et al.* (2012), the authors successfully modeled brain networks as the outcome of trade-offs between a limited number of plausible generative forces: a constraint on connection distance and a tendency for transitive processes, resulting in spatial and functional clustering of connections among brain cells. We will illustrate our method with a case study of infrastructure networks in the Yangtze River Delta, China.

Study area and data

Study area

14 The Yangtze River Delta (YRD) region in China spans across the Jiangsu and Zhejiang provinces, as well as Shanghai, a municipality directly under the central government (Figure 1). The YRD region is one of the most populous and developed regions of China. Although the YRD only accounts for 2.2% of China's total land area, it generates 19.9% of the national GDP and is home to 11.7% of the national population (Chinese Statistical Yearbook, 2014). The overall urbanization level of the region has reached 60% and all 25 prefecture-level cities in the region[1] have more than one million inhabitants (Table 2). The region is well endowed with infrastructure networks, boasting amongst other things twelve high-speed railroads, seven international airports, eight seaports, highway access for all comprising cities, as well as numerous large-scale bridges across major rivers such as the Yangtze and the Qiantang. These dense networks were developed through a layered process of uneven historical development, recent economic growth, and city-regional planning (Gu *et al.*, 2006; Li & Wu, 2013).

Figure 1. Study area.

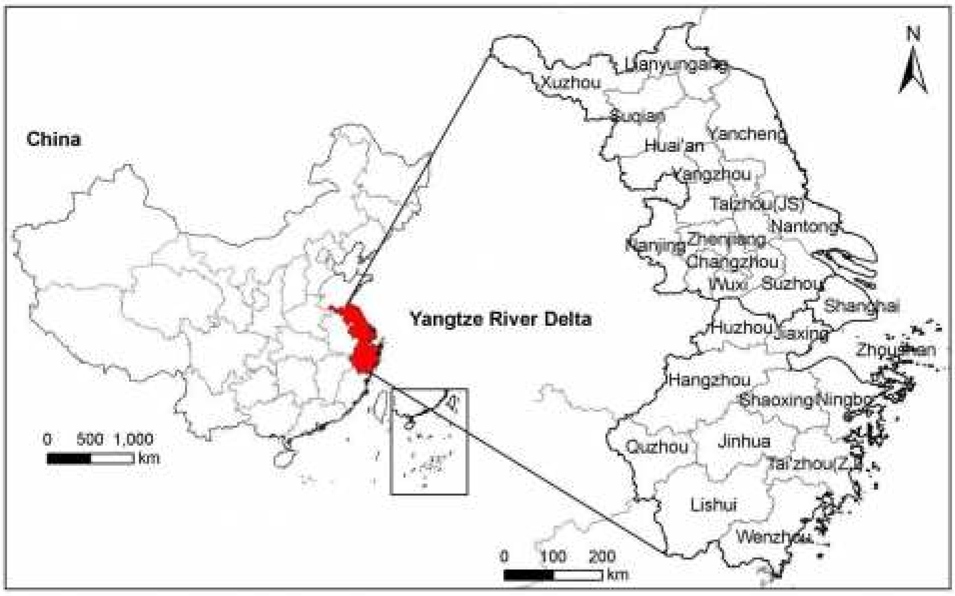


Table 2. Properties of 25 cities in the Yangtze River Delta.

No.	City	Province	Population (10^6)	GDP (10^9)	GDP per capita(10^3)
1	Wuxi	Jiangsu	6.47	130.31	20.14
2	Suzhou	Jiangsu	10.55	210.17	19.92
3	Nanjing	Jiangsu	8.16	129.37	15.85
4	Hangzhou	Zhejiang	8.8	134.72	15.31
5	Ningbo	Zhejiang	7.64	115.11	15.07
6	Changzhou	Jiangsu	4.69	70.42	15.01
7	Zhenjiang	Jiangsu	3.15	47.26	15.00
8	Shanghai	Shanghai	24.15	348.81	14.44
9	Zhoushan	Zhejiang	1.14	15.03	13.19
10	Shaoxing	Zhejiang	4.94	64.06	12.97
11	Yangzhou	Jiangsu	4.47	52.51	11.75
12	Jiaxing	Zhejiang	4.54	50.83	11.19
13	Nantong	Jiangsu	7.3	81.36	11.15
14	Taizhou	Jiangsu	4.63	48.55	10.49
15	Huzhou	Zhejiang	2.91	29.12	10.01
16	Jinhua	Zhejiang	5.4	47.78	8.85
17	Tai'zhou	Zhejiang	6.01	50.92	8.47
18	Xuzhou	Jiangsu	8.56	71.63	8.37
19	Quzhou	Zhejiang	2.12	17.06	8.05
20	Yancheng	Jiangsu	7.22	56.12	7.77
21	Lishui	Zhejiang	2.12	15.87	7.49
22	Huai'an	Jiangsu	4.8	34.81	7.25
23	Wenzhou	Zhejiang	9.16	64.65	7.06
24	Lianyungang	Jiangsu	4.41	28.83	6.54
25	Suqian	Jiangsu	4.8	27.55	5.74

Source: data are compiled based on statistical yearbooks (2014) of Shanghai, Zhejiang and Jiangsu on their respective bureau of statistics websites, that is, www.stats-sh.gov.cn, www.jssb.gov.cn and www.zj.stats.gov.cn. GDP is given in dollar converted from the *yuan* according to the average exchange rate of that year (1 dollar =6.193 *yuan*).

Data

15 Infrastructure is, of course, a vital socio-economic asset, and transport infrastructures in particular are believed to structure space and determine mobility in an industrial economy (Short and Kopp, 2005). It influences the movement and redistribution of goods, labor, capital, and so forth by reducing and unevenly transforming travel time and trade cost. Meanwhile, in an increasingly globalized economy, Internet infrastructure networks help to move value in new ways, by providing people access to freer and seemingly boundless means to exchange information, knowledge, and technologies (Choi *et al.*, 2006). Places that are well connected in these kinds of infrastructure networks possess an improved accessibility and connectivity to a wider market, which tends to contribute to a better economic performance (cf. Tranos, 2012).

16 Our analysis focuses on both physical and digital infrastructure networks connecting the 25 YRD cities at the prefecture level or above. For every infrastructure network under investigation, the data collection process involves creating a 25-by-25, weighted and symmetric matrix, which captures the strength of inter-city connections. As for physical infrastructures, we focus on highways and railroads. Inter-city connectivity in rail and road transportation networks is measured through the number of daily direct trains and non-stop buses in October of 2014, respectively. For rail transport connections, data were obtained from the official website for Chinese railway services (http://www.12306.cn/mormhweb/). Likewise, for road connections, we consulted the bus timetable on a national online booking platform for bus tickets (http://www.12308.com/), after which the data were cross-referenced with databases from other websites (e.g., http://51766.com/and http://checi.cn/).

17 With regards to digital interactions, we approximate the intercity flows of information based on the Baidu Index (Xiong *et al.*, 2013). Baidu is the leading search engine in China with a market share of nearly 70% (CNZZ, 2014). The Baidu Index is a program recently launched by the company to approximate information flows between localities. The index from city A to city B records the times per day that people in city A (reflected by their IP address) search the name of city B through the Baidu search engine. Figure 2 illustrates the interface of Baidu Index and the estimated digital connections from Shanghai to Hangzhou. For every city dyad, we use the mean value of daily Baidu Index from January to December in 2014. In our Shanghai → Hangzhou example, this implies using the value 1004, suggesting that the word 'Hangzhou' is on average 1004 times searched per day from Shanghai via the Baidu search engine).

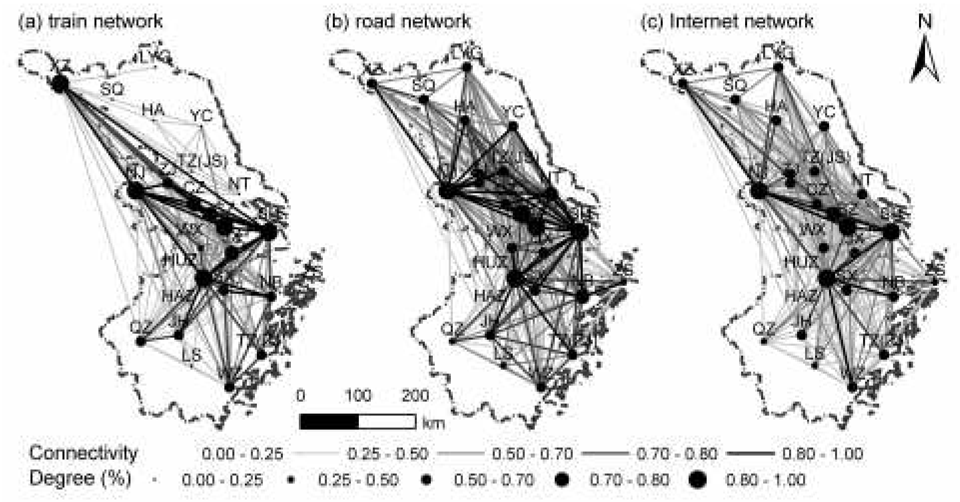
Figure 2. A screenshot of the acquisition of the inter-city Baidu index.

18 As our interest is in symmetric urban networks, each of the three infrastructure network matrices was symmetrized by averaging the value from city A to city B and that from city B to city A. The connectivity values were logged to alleviate the skewness in the distributions, and subsequently normalized by applying formula (1) so that the data layers have a distribution between 0 (minimum connectivity) and 1 (maximum connectivity). The final connectivity in the rail, road, and Internet networks are shown in Figure 3.

$$x_i = \frac{x_i - Min(x)}{Max(x) - Min(x)} \qquad (1)$$

19 We can observe from Figure 3 that the three infrastructure networks have a markedly different structure. The rail network is more clustered around railway hubs such as Xuzhou, Nanjing, Shanghai and Hangzhou. The strongest rail connection is Shanghai-Nanjing with 227 scheduled trains per day, among which inter-city high-speed rail accounts for 75.8%. The top-10 inter-city rail connections are among cities in the Taihu Lake Basin[2], which is the most developed sub-region in the YRD. The road network appears relatively decentralized in comparison, with a number of less-developed cities in central and northern Jiangsu standing out. The strongest road connection is Shanghai-Suzhou with 314 inter-city buses per day, followed by Shanghai-Nantong (250) and Hangzhou-Shaoxing (225). Road transportation is, to a certain extent, complementary to rail transportation for peripheral cities in gaining access to regional hub cities like Nanjing, Shanghai and Hangzhou. As can be expected, the Internet network is more evenly distributed, which is also shown by the Gini coefficients of the degree distributions for the Internet, rail and road networks (0.240, 0.533 and 0.328, respectively) – the Internet does indeed create a more complex and varied topology of interactions through quasi-borderless transmission of information (see, however, Graham *et al.*, 2016) . The two strongest inter-city Internet connections are Shanghai-Suzhou (1057) and Shanghai-Hangzhou (1054).

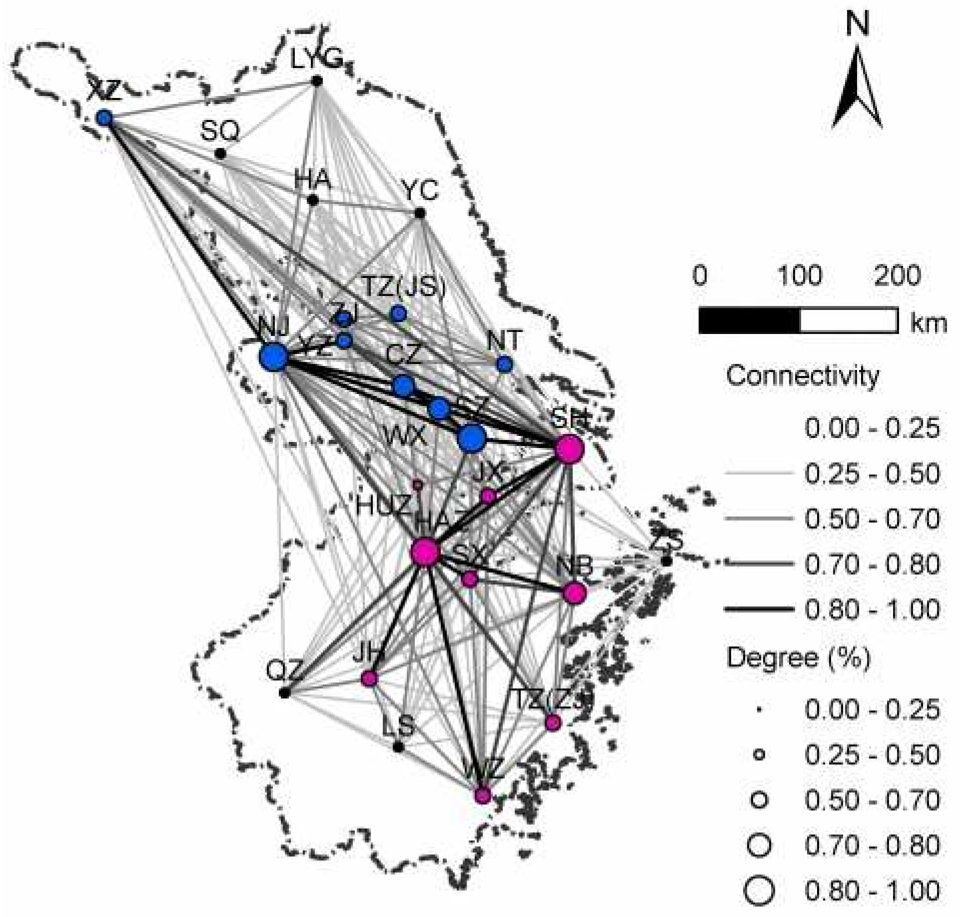
Figure 3. Inter-city connectivity in the observed rail (a) road, (b) and Internet (c) networks.



(Shanghai: SH; Hangzhou: HAZ; Ningbo: NB; Jiaxing: JX; Huzhou: HUZ; Shaoxing: SX; Zhoushan: ZS; Taizhou(ZJ): TZ(ZJ); Jinhua: JH; Wenzhou: WZ; Lishui: LS; Quzhou: QZ; Nanjing: NJ; Wuxi: WX; Suzhou: SZ; Changzhou: CZ; Nantong: NT; Yangzhou: YZ; Zhenjiang: ZJ; Taizhou(JS): TZ(JS); Xuzhou; XZ; Huaian: HA; Yancheng: YC; Lianyungang: LYG; Suqian: SQ, hereafter)

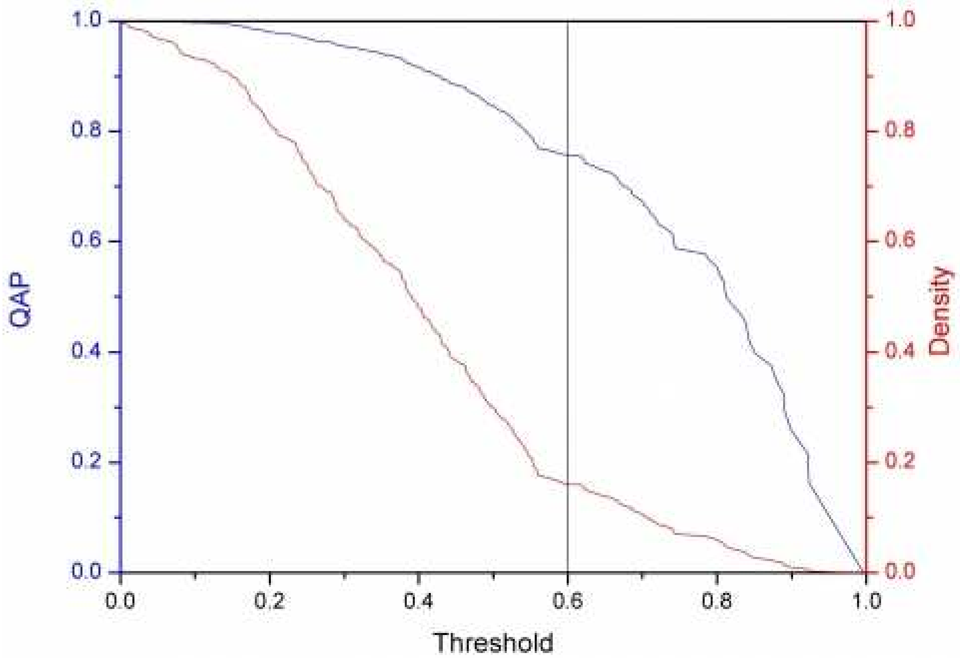
20 For the composite infrastructure network, inter-city connectivity was computed by taking the average of the values in each of the three layers (Figure 4). Cities in this network can be divided into three groups using the community detection technique of 'fast greedy modularity optimization' algorithm implemented in R (Clauset e*t al.,* 2004). Xuzhou, Yangzhou, Taizhou (JS), Nantong, Zhenjiang, Nanjing, Changzhou, Wuxi and Suzhou comprise the central-south Jiangsu community. Shanghai, Hangzhou, Jiaxing, Shaoxing, Huzhou, Ningbo, Jinhua, Wenzhou, Taizhou (ZJ) and Quzhou compose the Zhejiang community. Lianyungang, Suqian, Yancheng, Huaian in North Jiangsu and Zhoushan, Lishui in Zhejiang are combined into the peripheral community in this region. The Nanjing-Shanghai-Hangzhou corridor stands out with Shanghai acting as the pivot connecting the Jiangsu and Zhejiang clusters, since the connectivity between Nanjing and Hangzhou (0.79) is much weaker than that of Nanjing-Shanghai (0.90) and Hangzhou-Shanghai (0.92) dyads. Additionally, Nanjing and Hangzhou are hub cities connecting the cities in central YRD and the southern YRD, respectively, while Xuzhou is a secondary centre in the northern YRD. Taken together, boundary effects, distance decay, transitive effects and city size seem to be interwoven to form the observed composite infrastructure network.

Figure 4. Inter-city connectivity in the composite infrastructure network. Cities in the same community are labeled with the same color.



21 The resulting composite network is nearly fully-connected, i.e. most nodes in the network are connected with each other. The analysis of a fully connected network is not very appealing from a topological point of view (Hennemann and Derudder, 2014). For instance, a fully connected network assumes there are no gateways, which is not a very realistic proposition in infrastructure networks. To circumvent this problem, which largely emanates from the fully connected Internet network, we impose a connectivity threshold to remove small and therefore conceptually not very meaningful connections (see, however, Serrano *et al.*, 2009). To this end, we s*et* all edges in the composite network with a value < 0.60 to 0. The resulting network has a much lower density[3]of 0.16, but nonetheless a sizable QAP correlation[4] of 0.76 with the original network. However, as some cities do not have connections above the 0.60 threshold, we chose to retain at least the three strongest connections for every city. Figure 5 shows that while these transformations significantly reduce the number of ties and therefore the network density, the structure of the composite network very closely follows the structure of the original network. In the next section, we explain how we model the spatial and topological outline of this composite network.

Figure 5. Evolution of QAP and network density in light of the threshold.



Methodology

Model specification

22 Following Vinciguerra *et al.* (2010), in our urban network-implementation of GNM, it is assumed that the probability of a connection between two cities emerges from competing forces. In our operationalization, stimulating factors are a measure of city size (e.g., population or GDP) and a topological rule stating that there is more likelihood of the formation of connections between cities sharing nearest neighbors (i.e., a transitive effect). The hampering factors are physical distance between two cities as well as administrative boundary effects. The resulting specification can be written as:

$$P_{ij} \propto \frac{(\mathrm{Size}_i\,\mathrm{Size}_j)^{\alpha}}{d_{ij}^{\;\beta}}\,\frac{1}{\theta}\;k_{ij}^{\;\gamma} \qquad (2)$$

23

where:

24 - P_{ij} is the probability of a connection between cities *i* and *j*;

- Size_i and Size_j are the (logged) city size of city *i* and city *j*, respectively (either population or GDP);

- d_{ij} is the Euclidean distance separating both cities;

- k_{ij} is the number of first-order neighbors that city *i* and *j* have in common;

- α, β, γ are the model parameters: α and γ refer to strength of the facilitating impact of city size and transitivity, while β is an impedance factor reflecting the friction of distance;

- θ is a parameter assessing the impact of boundary effects in inter-city connections. If $0<\theta<1$, then boundaries stimulate inter-city connections (an unlikely scenario); if $\theta=1$, boundaries have no effect and if $\theta>1$, then boundaries have an adverse effect on inter-city connections.

25 The major difference between a traditional gravity model with boundary effects and this economical clustering model lies in the transitivity component k_{ij}^{γ}, which assesses network topology rather than geography in that the simulation considers to what degree connectivity is consolidated between nodes having common nearest

neighbours. The manifestation of transitivity can, for instance, be linked with the presence of transport corridors such as major rail or road links (Bruinsma *et al.*, 1997; Chen, 2012). From this perspective, this approach may help addressing some of the previously discussed shortcomings of existing approaches for modelling urban networks that is either topological or spatial (Broekel *et al.*, 2014). In addition, the model also fits non-binary networks, thus avoiding the computational limitations of EGRM and the need to define meaningful micro-network behaviour of actors as in SABM.

Model estimation

26 Although the overall logic underlying Vértes *et al.*'s (2012) GNM is straightforward, its major force lies in its potential to reveal which configuration of what set of generative factors best explains the geographical and topological structure of an observed network. GNM entails, consecutively, identifying a set of factors potentially explaining an observed network; generating networks for different parametric configurations of the different hypothesized factors; and assessing which set of factors/parameters generates a network that best approximates the observed network. As generative network models produce probabilities, a common research strategy is to use a Monte Carlo approach and re-run models to generate a simulated network that is most similar to the observed network.

27 In practice, the modelling exercise entails finding the combination of α, β, γ and θ that generates a Monte Carlo version of a network that most closely resembles the structures of the observed network. As always with model fitting, in addition to the parameters being informative in their own right, the deviations between observed and simulated networks can also be shown. For each combination of four parameters varying from 0 to 4 in steps of +0.5 (excluding 0 for θ), we generated ten versions of simulated networks after which we used the median value for the four key network metrics to calculate proximities and thereupon the model energy. As for the factor of city size, population and GDP were used and compared in each simulation to achieve a better model fit. All the simulating processes were implemented on the R platform.

28 The assessment of the 'similarity' of the generated and the observed networks is relatively non-trivial in comparison with other forms of model fitting. In Vértes *et al.*'s (2012) approach, the parameters used for each model were optimized by searching for the minimal 'energy value' of the generated network in comparison with the observed network with respect to key topological features. In practice, for each generated network, the four crucial network statistics are considered: (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 neighboring nodes; (3) average path length (L), a measure of average number of steps along the shortest paths for all possible node pairs; (4) and global efficiency (E), a measure of network integration inversely related to path length. The optimization starts from the calculation of the probability p that the median value of the observed and the generated network are statistically different for each of the aforementioned metrics. The 'energy value' is then given by 1/(p(M)*p(C)*p(L)*p(E)). The larger the p-values, the lower the energy value and the less likely there is a statistical difference between the metrics of the observed and the generated networks.

Results and discussion

Comparisons between the simulated and the observed composite infrastructure networks

29 Comparing the model fits reveals that GDP performs better in simulating the composite infrastructure network. The model fit with the lowest energy value was obtained for the following set of parameters: α=4, β=2, θ=2, and γ=1. Table 3 compares the values of network metrics for the observed and the simulated networks, while the latter are mapped in Figure 6.

30 Topologically, both networks are similar, especially in terms of modularity, average path length and global efficiency. The QAP correlation between the two networks is 0.278, which is statistically significant at the 5% level. This is acceptable given that our random network generation process is governed by only four parameters. Furthermore, the size of QAP correlation in our case is comparable with those reported in Vinciguerra *et al.* (2010). In addition, as the approach only searches for the parameter space of 0.5, 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 infrastructure networks connecting 25 cities in the YRD region reasonably well.

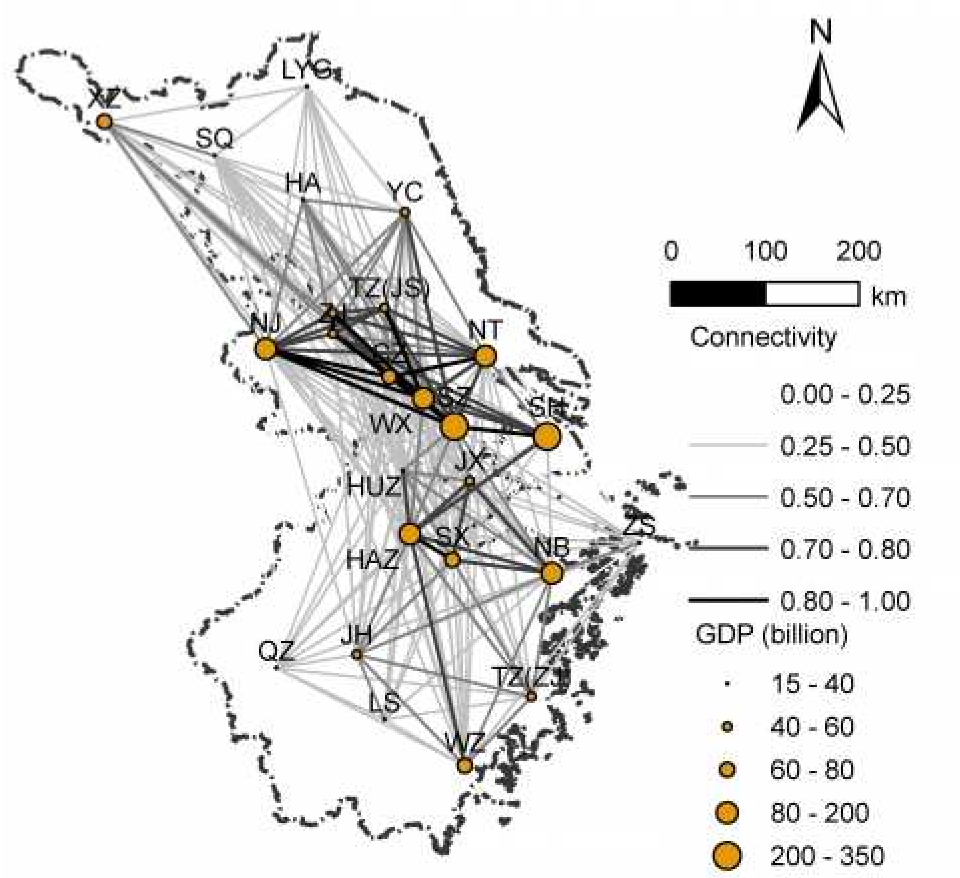
Table 3. Network metrics for the observed network and the simulated network.

Network	Optimal model	QAP (Sig.)	M	C	L	E
Observed	$P_{ij} \propto \frac{(GDP_i GDP_j)^4}{d_{ij}^2} \frac{1}{2} k_{ij}$	0.278* (0.011)	0.260	0.503	1.995	0.419
Simulated			0.249	0.551	2.093	0.403

Note: **significant at the 0.01 level, *significant at the 0.05 level, hereafter.

31 The simulated network reflects three key spatial and structural characteristics of the observed network (Figure 6). First, it captures the importance of *Ning-Hu-Hang* development axes, which connect the three regional centers: Nanjing (called as *Ning*in Chinese for short), Shanghai (*Hu*), and Hangzhou (*Hang*). This observation echoes with Zhao and Tang's (2010) analysis of the region's inter-city corporate network as well as Li & Wu's (2013) interpretation of the YRD regional plan. Second, the simulated network highlights dense connections among the cities of Changzhou, Wuxi and Suzhou in South Jiangsu. This is consistent with the south Jiangsu cluster identified in our earlier community detection exercise, as well as Zhang's (2006) observation that these three cities, along with Nanjing and Shanghai, are forming a mega city-region through functional specialization and integration. For example, Suzhou focuses on developing an advanced manufacturing and exported-oriented economy, Changzhou evolves into a high-tech industrial base, and Wuxi functions as the logistic centre (Gu *et al.*, 2006). In addition, through plans aiming at regional integration that have been actively pursued in the YRD (Li & Wu, 2013), special efforts have been made to foster economic connections amongst these three cities (Luo & Shen, 2008; 2009). Third, the simulated network also picks up the relatively less weak-connectedness in the northern part of Jiangsu. There exists a north-south divide within Jiangsu province, with the economy of northern Jiangsu relatively lagging (Table 2; Wei & Fan, 2000). This also corroborates the north-Jiangsu cluster emerging from network community detection.

Figure 6. Inter-city connectivity in the simulated composite network.



32 There are, however, some discrepancies between the observed and the simulated network. First, our model does not pick up Xuzhou's importance in infrastructure networks, as we have not accounted for the effects of spatial development policies. Situated at the intersection of several rail arteries, Xuzhou has long played an important role in the country's railroad network. In addition, the city also served as the anchor of various regional economic development plans targeted at (re)vitalizing northern Jiangsu, and these plans invariably seek to strengthen the connections between Xuzhou and the more developed southern part of the province (Gu *et al.*, 2006; Li & Wu, 2013). For example, our exploratory community detection analysis identifies Xuzhou as part of the central-south Jiangsu network community. Second, as our model does not include terrain factors and physical barriers, the connections to outlying cities such as Zhoushan and Quzhou are usually under-estimated: the city of Zhoushan is on an offshore island, while Quzhou lies in the mountainous western part of Zhejiang (Figure 1). Third, connections among cities in Zhejiang are relatively underestimated. This could partly be ascribed to the longer distances among Zhejiang cities than those in southern Jiangsu, suggesting that the model can be further refined with geographically weighted parameters.

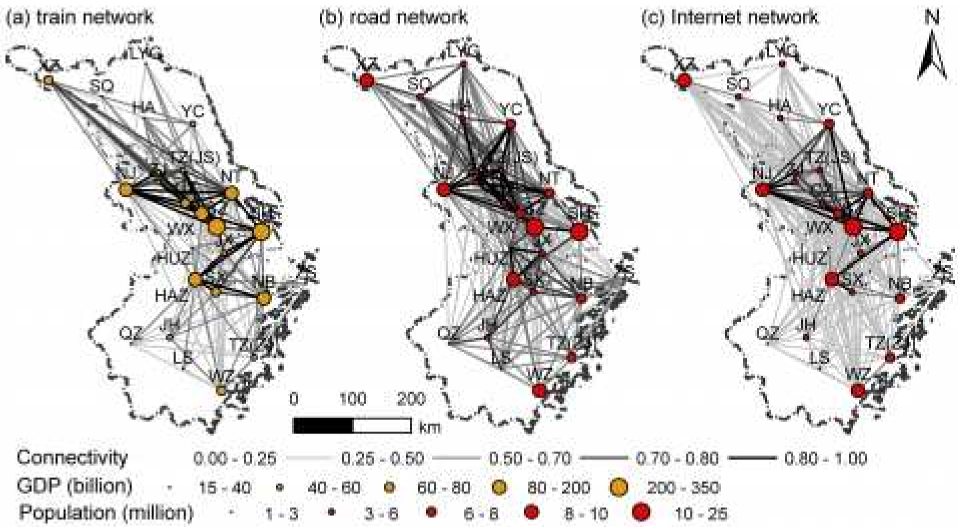
Analyses of driving factors underlying the formation of different infrastructure networks

33 To explore the differences in the driving forces underlying network formation, the rail, road and Internet networks were separately modelled. Table 4 gives the optimal combinations of the four parameters in different infrastructure networks and Figure 7 displays the spatial patterns for each of the three separate generated networks.

Table 4. The optimal combinations of parameters for different infrastructure networks.

Network	α	β	θ	γ	City size	QAP	Sig.
Composite	4	2	2	1	GDP	0.278*	0.011
Rail	4	2	3.5	1	GDP	0.282*	0.024
Road	0.5	3.5	1.5	1	Population	0.323**	0.002
Internet	3.5	2	1.5	0.5	Population	0.299*	0.012

Figure 7. Inter-city connectivity in the simulated rail (a), road (b) and Internet networks (c).



34 All simulated networks, and the generated road network in particular, have sizeable, statistically significant (at 5% level or below) QAP correlations with the observed networks. Interestingly, the results suggest that the transitivity effect does influence each of the different infrastructure networks in the YRD region, while this is exactly the kind of topological feature that would not be picked up in classical gravity modelling. This finding is in line with previous statements that growth models for analysing the formation of complex systems can be more successful by considering an additional topological term in the connection probability function (Yook *et al.*, 2002). Nevertheless, the transitivity exerts a different impact in the different networks. As can be seen in Table 4, the parameter of transitivity in the Internet network is only half of that in other networks, indicating a relative weaker effect in inter-city Internet connections. Unlike physical infrastructure networks, the Internet network is often approximated by the mechanism of a nonlinear preferential attachment (Capocci *et al.*, 2006; Zhou & Mondragón, 2004). New nodes entering the Internet network will prefer to create links with nodes that are already well connected, suggesting that a star-configuration more than a triangle-configuration at the local scale contributes to the global outcomes. From this perspective, boundaries also matter less.

35 Although both rail and road networks are land transportation networks influenced by the same level of transitivity, the spatial structures and the way in which they are shaped by city size, distance and boundaries are quite different. In terms of city size, the connectivity distribution in the rail network corresponds more with the GDP distribution, while population is a better predictor in the road network simulation. This seems to be reflecting the stronger connections all the way to the far northern and less developed cities in the road network than in the rail network. That is because the development of the railway system, especially the high-speed railway network, has been prioritized in more developed core regions (Vickerman, 2006), while the most widespread road transportation by bus considers all basic demands of

passengers (Jenelius, 2009). Distance has a more pronounced effect in the road network than in the rail network. As reported in Wang's (2009) research on comparisons of distance impact on different inter-city traffic flows in China, railway passenger flows decrease more slowly than road passenger flows. It is also found that the number of people to choose road transportation shows a significant decline with every increase of 50 kilometres, while there is little change until 300 kilometres in rail transportation (Li, 2009). With regards to administrative boundaries, this parameter is stronger in the rail network than in the road network, and this is due to the 'hub-and-spoke' structure of rail connections compared to a relative dispersed and uniform distribution of the fully connected road network.

Table 5. The relationship between degree centrality and city size in the YRD.

	Descriptive Statistics		Correlations	Population
City's degree in the road network	Mean	12.009	Pearson	0.823**
	Std. Deviation	2.958	Sig. (2-tailed)	0.000
	N	25		25
City's degree in the rail network	Mean	6.747	Pearson	0.527**
	Std. Deviation	4.105	Sig. (2-tailed)	0.007
	N	25		25

Conclusions

36 In this paper, we have explored the potential of combining spatial and topological elements in urban network simulation. To this end, we have investigated the potential of recent advances in network modelling and re-specified Vértes *et al.*'s (2012) economical clustering model to propose a generative network model (GNM) for simulating urban networks.

37 We applied GNM to three types of infrastructure networks connecting prefecture-level cities in the Yangtze River Delta, and focused on two potential qualities of this approach. First, it confirms the potential of the proposed method in urban network simulation. The major finding is that the inclusion of topological factors (transitivity) alongside geographical factors as archetypically captured in (extended) gravity modelling helps to understand how urban networks are shaped. Second, it allows exploring the extent to which driving forces influence the structure of the different urban networks. In our study area, transitive effects play a less important role in the Internet-network formation; GDP is a stronger predictor than population for the rail network, while the opposite is true for the Internet and road network. The boundary effect plays a bigger role in shaping the rail network, while the distance decay effect is stronger in the road network.

38 The prime purpose of this paper has been methodological, and the results are therefore above all of an exploratory nature. This is because in our particular example results clearly reflect some of our operational choices. Both our selection of infrastructure modes and their relative importance, as well as how these networks were consecutively measured, transformed, and combined have an impact on our results. For instance, there is clearly some bias in merely counting Internet flows through the Baidu engine, despite its high usage, to approximate the real inter-city Internet linkages. Furthermore, the equal weighting and the particular choice for the three separate infrastructure networks in an integrated infrastructure network can be debated. However, that said, we would argue that these issues do not relate to simulation approach per se. Possible improvements of data operationalization nonetheless abound, as do more elaborate specifications of the model. The latter could include recognizing physical barriers alongside administrative boundaries, accounting for city-regional plans that target at inter-city collaborations and

connections, as well as factoring in variables that reflect socio-cultural proximity.

Bibliographie

AUJEAN L., CASTIAU E., ROELANDTS M. and VANDERMOTTEN C. (2007), "Le Positionnement Des Villes Belges Dans Le Réseau Global Des Services Avancés", *Belgeo*, *8*, 1, pp. 9-12, http://belgeo.revues.org/11621.
DOI : 10.4000/belgeo.11621

BARTHÉLEMY M. (2011), "Spatial Networks", *Physics Reports*, *499*, pp. 1-101.
DOI : 10.1016/j.physrep.2010.11.002

BEHRENS K., ERTUR C. and KOCH W. (2012), "'Dual'gravity: Using Spatial Econometrics to Control for Multilateral Resistance", *Journal of Applied Econometrics*, *27*, pp. 773-794.

BLONDEL V., KRINGS G. and THOMAS I. (2010), "Regions and Borders of Mobile Telephony in Belgium and in the Brussels Metropolitan Zone", *Brussels Studies*, *42*, pp. 1-12.
DOI : 10.4000/brussels.806

BRETAGNOLLE A. & PUMAIN D. (2010), "Simulating Urban Networks through Multiscalar Space-time Dynamics: Europe and the United States, 17th-20th Centuries", *Urban Studies*, *47*, pp. 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", *Papers in Evolutionary Economic Geography (No.13.25),* Utrecht University, http://econ.geo.uu.nl /peeg/peeg1325.pdf

BRUINSMA F. R., RIENSTRA S. A. & RIETVELD P. (1997), "Economic Impacts of the Construction of a Transport Corridor: A Multi-level and Multiapproach Case Study for the Construction of the A1 Highway in the Netherlands", *Regional studies*, *31*, pp. 391-402.
DOI : 10.1080/00343409750132991

CAPOCCI A., SERVEDIO V. D., COLAIORI F., BURIOL L. S., DONATO D., LEONARDI S. & CALDARELLI G. (2006), "Preferential Attachment in the Growth of Social Networks: The Internet Encyclopedia Wikipedia", *Physical review E*, *74*, pp. 036116.

CARRÈRE C. (2006), "Revisiting the Effects of Regional Trade Agreements on Trade Flows with Proper Specification of the Gravity Model", *European Economic Review*, *50*, pp. 223-247.
DOI : 10.1016/j.euroecorev.2004.06.001

CASTELLS M. (1996), *The Information Age: Economy, Society, and Culture. Volume I: The Rise of the Network Society*, Oxford, U.K., Blackwell.

CHEN C.-L. (2012), "Reshaping Chinese Space-economy through High-speed Trains: Opportunities and Challenges", *Journal of Transport Geography*, *22*, pp. 312-316.
DOI : 10.1016/j.jtrangeo.2012.01.028

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*, pp. 81-99.
DOI : 10.1111/j.1471-0374.2006.00134.x

CLARK J. S. & STABLER J. C. (1991), "Gibrat's Law and the Growth of Canadian Cities", *Urban Studies*, *28*, pp. 635-639.
DOI : 10.1080/00420989120080701

CLAUSET A., NEWMAN M. E. and MOORE C. (2004), "Finding Community Structure in Very Large Networks", *Physical review E*, *70*, pp. 066111.
DOI : 10.1103/PhysRevE.70.066111

CNZZ (2014), "Internet Data", http://data.cnzz.com/.

DIETSCHE C. (2009), "Networking against Stakeholder Risks: A Case Study on SMEs in International Shrimp Trade", *Belgeo*, *10*, 1, pp. 27-42, http://belgeo.revues.org/7805.
DOI : 10.4000/belgeo.7805

DUCRUET C. & BEAUGUITTE L. (2014), "Spatial Science and Network Science: Review and Outcomes of a Complex Relationship", *Networks and Spatial Economics*, *14*, pp. 297-316.
DOI : 10.1007/s11067-013-9222-6

FEENSTRA R. C. (2002), "Border Effects and the Gravity Equation: Consistent Methods for Estimation", *Scottish Journal of Political Economy*, *49*, pp. 491-506.
DOI : 10.1111/1467-9485.00244

GU C., ZHANG M., ZHANG C., ZHANG X., CHEN L. & WANG C. (2006), "Development of Urban Agglomeration in the Yangtze River Delta", *Resources and Environment in the Yangtze*

Basin, *15*, pp. 771-775 (in Chinese).

GRAHAM M., STRAUMANN R. K. & HOGAN B. (2016), "Digital Divisions of Labour and Informational Magnetism: Mapping Participation in Wikipedia", *Annals of the Association of American Geographers*, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2657107.

HANSSENS H. & DERUDDER B. (2011), "The Urban Geography of Advanced Producer Service Transaction Links in Belgium", *Belgeo*, 1-2, pp. 17-28, http://belgeo.revues.org/6345.
DOI : 10.4000/belgeo.6345

HEAD K. & MAYER T. (2000), "Non-Europe: The Magnitude and Causes of Market Fragmentation in the EU", *Review of World Economics*, *136*, pp. 285-314.
DOI : 10.1007/BF02707689

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*, pp. 392-412.
DOI : 10.1068/b39108

JENELIUS E. (2009), "Network Structure and Travel Patterns: Explaining the Geographical Disparities of Road Network Vulnerability", *Journal of Transport Geography*, *17*, pp. 234-244.
DOI : 10.1016/j.jtrangeo.2008.06.002

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*, pp. 5317-5325.

LEWER J. J. & VAN DEN BERG H. (2008), "A Gravity Model of Immigration", *Economics Letters*, *99*, pp. 164-167.
DOI : 10.1016/j.econlet.2007.06.019

LI M. (2009), "Influence of Inter-city Railway in Highway Freight Transport and the Countermeasures of the Highway", *Logistics Technology*, *28*, pp. 34-36 (in Chinese).

LI Y. & WU F. (2013), "The Emergence of Centrally Initiated Regional Plan in China: A Case Study of Yangtze River Delta Regional Plan", *Habitat International*, *39*, pp. 137-147.
DOI : 10.1016/j.habitatint.2012.11.002

LIN J. & BAN Y. (2014), "The Evolving Network Structure of US Airline System During 1990-2010", *Physica A: Statistical Mechanics and its Applications*, *410*, pp. 302-312.

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*, http://onlinelibrary.wiley.com/doi/10.1111/pirs.12060/full.

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*, pp. 947-966.
DOI : 10.1068/a45350

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*, pp. 51-66.

LUO X. & SHEN J. (2008), "Why City-region Planning Does Not Work Well in China: The Case of Suzhou-Wuxi-Changzhou", *Cities*, *25*, pp. 207-217.

LUO X. & SHEN J. (2009), "A Study on Inter-city Cooperation in the Yangtze River Delta Region, China", *Habitat International*, *33*, pp. 52-62.
DOI : 10.1016/j.habitatint.2008.04.002

MORLEY C., ROSSELLÓ J. & SANTANA-GALLEGO M. (2014), "Gravity Models for Tourism Demand: Theory and Use", *Annals of Tourism Research*, *48*, pp. 1-10.
DOI : 10.1016/j.annals.2014.05.008

NATIONAL BUREAU OF STATISTICS OF THE PEOPLE'S REPUBLIC OF CHINA (2014), "Chinese Statistical Yearbook", http://www.stats.gov.cn/tjsj/ndsj/2014/indexch.htm.

NEAL Z. (2011), "Differentiating Centrality and Power in the World City Network", *Urban Studies*, *48*, pp. 2733-2748.
DOI : 10.1177/0042098010388954

NEAL Z. (2013), "Does World City Network Research Need Eigenvectors?", *Urban Studies*, *50*, pp. 1648-1659.
DOI : 10.1177/0042098013477702

PFLIEGER G. & ROZENBLAT C. (2010), "Urban Networks and Network Theory: The City as the Connector of Multiple Networks", *Urban Studies*, *47*, pp. 2723-2735.
DOI : 10.1177/0042098010377368

PHANG S.-Y. (2003), "Strategic Development of Airport and Rail Infrastructure: The Case of Singapore", *Transport Policy*, *10*, pp. 27-33.
DOI : 10.1016/S0967-070X(02)00027-6

PIRIE G. (2010), "Trajectories of North-South City Inter-relations: Johannesburg and Cape Town, 1994-2007", *Urban Studies, 47,* pp. 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*, http://cybergeo.revues.org/2519.
DOI : 10.4000/cybergeo.2519

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*, http://cybergeo.revues.org/26730.
DOI : 10.4000/cybergeo.26730

ROBINS G., PATTISON P., KALISH Y. & LUSHER D. (2007), "An Introduction to Exponential Random Graph (p*) Models for Social Networks", *Social Networks*, *29*, pp. 173-191.

ROBINS G., PATTISON P. & WANG P. (2009), "Closure, Connectivity and Degree Distributions: Exponential Random Graph (p*) Models for Directed Social Networks", *Social Networks*, *31*, pp. 105-117.

SERRANO M. Á., BOGUÑÁ M. & VESPIGNANI A. (2009), "Extracting the Multiscale Backbone of Complex Weighted Networks", *Proceedings of the National Academy of Sciences*, *106*, pp. 6483-6488.
DOI : 10.1073/pnas.0808904106

SHEARMUR R. & DOLOREUX D. (2015), "Central Places or Networks? Paradigms, Metaphors, and Spatial Configurations of Innovation-Related Service Use", *Environment and Planning A*, *47*, pp. 1521-1539.
DOI : 10.1177/0308518X15595770

SHIN K.-H. & TIMBERLAKE M. (2000), "World Cities in Asia: Cliques, Centrality and Connectedness", *Urban Studies*, *37*, pp. 2257-2285.
DOI : 10.1080/00420980020002805

SHORT J. & KOPP A. (2005), "Transport Infrastructure: Investment and Planning. Policy and Research Aspects", *Transport Policy*, *12*, pp. 360-367.
DOI : 10.1016/j.tranpol.2005.04.003

SNIJDERS T. A. B. & DOREIAN P. (2010), "Introduction to the Special Issue on Network Dynamics", *Social Networks*, *32*, pp. 1-3.
DOI : 10.1016/j.socnet.2009.12.002

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*, pp. 497-511.
DOI : 10.1111/j.1475-5661.2012.00545.x

TRANOS E. (2012), "The Causal Effect of the Internet Infrastructure on the Economic Development of European City Regions", *Spatial Economic Analysis*, *7*, pp. 319-337.
DOI : 10.1080/17421772.2012.694140

VAN DE VIJVER E., DERUDDER B., BASSENS D. & WITLOX F. (2014), "Filling Some Black Holes: Modeling the Connection between Urbanization, Infrastructure, and Global Service Intensity", *The Professional Geographer*, *66, pp*. 82-90.

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*, pp. 5868-5873.
DOI : 10.1073/pnas.1111738109

VICKERMAN R. 2006, "Indirect and Wider Economic Impacts of High Speed Rail", *in*: *Paper for 4th Annual Conference on Railroad Industry Structure, Competition and Investment*, Universidad Carlos III de Madrid, Location.

VINCIGUERRA S., FRENKEN K. & VALENTE M. (2010), "The Geography of Internet Infrastructure: An Evolutionary Simulation Approach Based on Preferential Attachment", *Urban Studies*, *47*, pp. 1969-1984.
DOI : 10.1177/0042098010372685

WANG C. (2009), "Function Simulation and Regularity of Distance Decay of Inter-urban Traffic Flow in China", *Progress in Geography*, *28*, pp. 690-696 (in Chinese).

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*, pp. 712-721.

WATTS D. J. & STROGATZ S. H. (1998), "Collective Dynamics of ‘Small-world’networks", *Nature*, *393,* pp. 440-442.

WEI Y. D. & FAN C. C. (2000), "Regional Inequality in China: A Case Study of Jiangsu Province", *The Professional Geographer*, *52*, pp. 455-469.
DOI : 10.1111/0033-0124.00238

XIONG L., ZHEN F., WANG B. & XI G. (2013), "The Research of the Yangtze River Delta Core Area’s City Network Characteristics Based on Baidu Index", *Economic Geography*, *7*, pp. 67-73.

YOOK S. H., JEONG H. & BARABÁSI A. L. (2002), "Modeling the Internet's Large-scale Topology", *Proceedings of the National Academy of Sciences*, *99*, pp. 13382-13386.
DOI : 10.1073/pnas.172501399

ZHANG X. (2006), "Characteristics of the Yangtze River Delta Mega-city Region", *Acta Geographica Sinica*, *61*, pp. 1025-1036 (in Chinese).

ZHAO M. & TANG Z. (2010), "A Network-Based Measurement for Urban Hinterland Area in Yangtze River Delta", *Economic Geography*, *3*, pp. 371-376 (in Chinese).

ZHOU S. & MONDRAGÓN R. J. (2004), "Accurately Modeling the Internet Topology", *Physical review E*, *70*, pp. 066108.
DOI : 10.1103/PhysRevE.70.066108

Notes

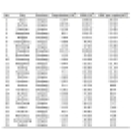
1 There are two ‘Taizhou’s in this region. The spellings of these two cities are identical in English. We therefore use Taizhou (JS) to denote Taizhou in Jiangsu and Taizhou (ZJ) for the one in Zhejiang.

2 Taihu Lake Basin refers to Nanjing, Zhenjiang, Wuxi, Suzhou, Changzhou, Shanghai, Huzhou, Jiaxing and Hangzhou in terms of administrative division.

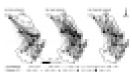
3 Network density refers to the proportion of all possible dyadic connections that are actually present and is given by dividing the number of connections that have a value different from 0 by the total number of pairs.

4 The QAP correlation is a nonparametric methodology to test the relationship between multiple relational matrices in a regression framework.

Table des illustrations

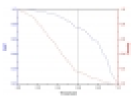
	**Titre**	Table 1. Review on driving factors and methodologies of spatial and topological modelling for urban networks. (GM: Gravity-type models; ERGM: Exponential Random Graph Models; SAOM: Stochastic Actor-Oriented Models).
	URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-1.jpg
	Fichier	image/jpeg, 64k
	**Titre**	**Figure 1. Study area.**
	URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-2.jpg
	Fichier	image/jpeg, 140k
	**Titre**	Table 2. Properties of 25 cities in the Yangtze River Delta.
	Crédits	Source: data are compiled based on statistical yearbooks (2014) of Shanghai, Zhejiang and Jiangsu on their respective bureau of statistics websites, that is, www.stats-sh.gov.cn, www.jssb.gov.cn and www.zj.stats.gov.cn. GDP is given in dollar converted from the *yuan* according to the average exchange rate of that year (1 dollar =6.193 *yuan*).
	URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-3.jpg
	Fichier	image/jpeg, 120k
	**Titre**	**Figure 2. A screenshot of the acquisition of the inter-city Baidu index.**

URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-4.jpg
Fichier	image/jpeg, 52k
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-5.jpg
Fichier	image/jpeg, 4,0k



Titre	**Figure 3. Inter-city connectivity in the observed rail (a) road, (b) and Internet (c) networks.**
Légende	(Shanghai: SH; Hangzhou: HAZ; Ningbo: NB; Jiaxing: JX; Huzhou: HUZ; Shaoxing: SX; Zhoushan: ZS; Taizhou(ZJ): TZ(ZJ); Jinhua: JH; Wenzhou: WZ; Lishui: LS; Quzhou: QZ; Nanjing: NJ; Wuxi: WX; Suzhou: SZ; Changzhou: CZ; Nantong: NT; Yangzhou: YZ; Zhenjiang: ZJ; Taizhou(JS): TZ(JS); Xuzhou; XZ; Huaian: HA; Yancheng: YC; Lianyungang: LYG; Suqian: SQ, hereafter)
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-6.jpg
Fichier	image/jpeg, 1,0M

Titre	**Figure 4. Inter-city connectivity in the composite infrastructure network. Cities in the same community are labeled with the same color.**
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-7.jpg
Fichier	image/jpeg, 588k



Titre	**Figure 5. Evolution of QAP and network density in light of the threshold.**
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-8.jpg
Fichier	image/jpeg, 180k
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-9.jpg
Fichier	image/jpeg, 4,0k
Titre	Table 3. Network metrics for the observed network and the simulated network.
Légende	Note: **significant at the 0.01 level, *significant at the 0.05 level, hereafter.
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-10.jpg
Fichier	image/jpeg, 20k

Titre	**Figure 6. Inter-city connectivity in the simulated composite network.**
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-11.jpg
Fichier	image/jpeg, 540k
Titre	Table 4. The optimal combinations of parameters for different infrastructure networks.
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-12.jpg
Fichier	image/jpeg, 24k

Titre	**Figure 7. Inter-city connectivity in the simulated rail (a), road (b) and Internet networks (c).**
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-13.jpg
Fichier	image/jpeg, 1,2M
Titre	Table 5. The relationship between degree centrality and city size in the YRD.
URL	http://journals.openedition.org/belgeo/docannexe/image/17087/img-14.jpg

Fichier	image/jpeg, 32k

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