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Scale effects on spatially embedded contact networks

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ABSTRACT

Spatial phenomena are subject to scale effects, but there are rarely studies addressing such effects on spatially embedded contact networks. There are two types of structure in these networks, network structure and spatial structure. The network structure has been actively studied. The spatial structure of these networks has received attention only in recent years. Certainly little is known whether the two structures respond to each other.

This study examines the scale effects, in terms of spatial extent, on the network structure and the spatial structure of spatially embedded contact networks. Two issues are explored, how the two types of structures change in response to scale changes, and the range of the scale effects. Two sets of areal units, regular grids with 24 different levels of spatial extent and census units of three levels of spatial extent, are used to divide one observed and two reference random networks into multiple scales. Six metrics are used to represent the two structures.

Results show different scale effects. In terms of the network structure, the properties of the observed network are sensitive to scale changes at fine scales. In comparison, the clustered spatial structure of the network is scale independent. The behaviors of the network structure are affected by the spatial structure. This information helps identify vulnerable households and communities to health risks and helps deploy intervention strategies to spatially targeted areas.

1. Introduction

Human contact networks play a critical role in disease dispersion, as repeatedly stressed in reports on some of the most dangerous communicable diseases, such as SARS, Avian Flu (H5N1), and Ebola (Chan, 2014; Ferguson et al., 2005; Ferguson et al., 2006; Riley et al., 2003). A ‘contact network’ refers to a network of human contacts, where nodes represent individuals and edges represent contact relationships between these individuals (Newman, 2010). Understanding the properties of contact networks helps us gain insights into how communicable diseases disperse through a population (Eames & Keeling, 2003; Keeling & Eames, 2005; Newman, 2002; Smith, 2006).

Disease dispersion is inherently a spatial process (Bian, 2013; Bian et al., 2012). A contact network, once projected into space, becomes a spatially embedded network where nodes are projected according to, for example, individuals' home and workplace locations and edges are projected according to the contact relationship between individuals. The spatial characteristics of disease dispersion can be readily studied in such networks (Zhong & Bian, 2016).

Disease dispersion is inherently a spatial process, while scale is involved in all spatial phenomena. Spatial resolution and spatial extent are two common connotations of spatial scale. Spatial resolution is the size of the finest distinguishable areal grains that collectively constitute a study area. It represents the level of detail that is of interest to researchers. Spatial extent is the size of a study area that consists of a large number of areal units (Bian & Walsh, 1993; Lam & Quattrochi, 1992; Turner, O'Neill, Gardner, & Milne, 1989). It represents the spatial context of an investigation.

The effect of spatial resolution commonly refers to changes in phenomena properties when areal units are aggregated to different levels, while keeping the same study area. A typical example is the well-known ‘modifiable areal unit problem’ (MAUP) (Fotheringham, 1989; Jiang & Sui, 2014; Liu, Sui, Kang, & Gao, 2014; Openshaw, 1983; Openshaw & Taylor, 1979). In comparison, the effect of spatial extent refers to changes in phenomena properties in response to enlarged study areas, while keeping the same resolution (Bian & Walsh, 1993; Lam & Quattrochi, 1992). Many studies are based on an arbitrarily selected spatial extent, and results may not be generalizable to studies of different extents (Turner, Gardner, & O'neill, 2001; Wu & Wu, 2013). Between the two connotations, the effect of spatial extent is less studied, and collectively, there are rarely studies addressing the scale effects on network properties.

Network structure is the most important network property, as it determines how nodes are connected and affects the dynamics of epidemics (Eubank et al., 2004; Keeling & Eames, 2005; Newman, 2010; Smith, 2006). Spatially embedded contact networks have two sets of structures, the network structure and the spatial structure. The network

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structure has been actively studied, while the spatial structure of contact networks has received attention only in recent years. Little is known whether the two structures respond to each other and whether using one could infer the behavior of the other (Barthélemy, 2011; Bian, 2013; Riley, 2007; Tang & Bennett, 2010).

Further, the networks are known for their resistance in structures when a fraction of nodes or edges are removed (Albert, Jeong, & Barabási, 2000; Buldyrev, Parshani, Paul, Stanley, & Havlin, 2010; Callaway, Newman, Strogatz, & Watts, 2000; Gao, Liu, D'Souza, & Barabási, 2014; Liu, Slotine, & Barabási, 2011). Most resistance studies, however, have focused on simulated random networks. Results may not be applicable to complex yet common structures in empirically observed networks (Holme, 2004; Holme, Kim, Yoon, & Han, 2002). Empirical network studies, on the other hand, indeed focus on actual networks, but seldom on their resistance properties (Karrer & Newman, 2010; Newman, 2009). Neither kind of study has looked into the network resistance to spatial structures.

This study aims to examine the scale effects, in terms of changing spatial extent, on the network structure and the spatial structure of contact networks. Specifically, we evaluate (1) the changes in the two contact network structures in response to changes in scale, and (2) the ranges of scale at which contact networks are scale dependent. To achieve these goals, three networks, one observed and two randomly structured, are partitioned into multiple levels of 'unit' networks, each in a smaller, independent spatial extent. The network structure and the spatial structure of the unit networks are compared across scales, where the two structures are represented by six network indices. Two sets of areal units, one set of regular grid and one set of irregularly shaped census unit are used to support the intended scale study.

Findings of this study provide a better understanding of the properties of contact networks at multiple scales. This knowledge could help researchers and policy makers design scale-adaptive strategies to control and prevent communicable diseases effectively.

The remainder of this article is organized as follows. Due to the number of concepts involved in the subsequent discussion, the following background section describes the network structure and the spatial structure, along with the six network metrics. Section 3 introduces the observed contact network data. Section 4 describes the three networks, the two sets of areal units, and the division of networks into unit networks at multiple scales. Section 5 evaluates the scale effects on the networks, and Section 6 summarizes the findings.

2. Background

The network structure and the spatial structure of networks refer to how nodes are connected from the network and spatial perspectives, respectively. Component size, clustering coefficient, and average path length are the essential set of metrics used to describe the structure for various networks, including spatially embedded contact networks (Albert et al., 2000; Kovacs & Barabasi, 2015; Liu et al., 2011; Newman, 2010; Watts & Strogatz, 1998). Two additional metrics are considered in this study to measure the spatial structure, the statistical distribution of edge distance and the statistical distribution of the distance of the lost edges when dividing networks into smaller area. Each metric is described below.

Component is a cluster of nodes within a network. All nodes within a cluster are directly or indirectly (through a chain of other nodes) connected to all other nodes within the cluster, but disconnected with nodes in other clusters (Newman, 2010). A network can have multiple components. The number of nodes in a component defines its size. The component is a global measurement of how cohesively a network is connected. Two metrics are commonly used to express component size, the relative size of the largest component (denoted as S) and the average size of other components (denoted as $\langle s \rangle$) (Newman, 2010; Wasserman & Faust, 1994). The relative size of the largest component is the ratio of the size of the largest component to the size of the network:

$$S = \frac{n_{max}}{n} \tag{1}$$

where n_{max} is the size of the largest component, and n is the size of the network (the total number of nodes in the network). The average size of other components is defined as:

$$\langle s \rangle = \frac{\sum_{1}^{c} s_i}{c-1} \qquad i \neq max \tag{2}$$

where s_i is the size of component i, and c is the total number of components in the network. A greater S value indicates a more cohesive network, while a smaller $\langle s \rangle$ value also indicates the same. For cohesive networks, a large S value usually accompanies a small $\langle s \rangle$ value. Otherwise, for fragmented networks, both S and $\langle s \rangle$ values can be low.

The clustering coefficient of a node is the number of connections between its direct neighboring nodes, divided by the number of all possible connections between these nodes. This metric represents local clustering by measuring how tightly a node's neighbors are clustered together (Watts & Strogatz, 1998). Eq. (3) expresses the clustering coefficient c_i of node i as:

$$c_i = \frac{2e_i}{k_i(k_i-1)} \tag{3}$$

where k_i is the number of neighboring nodes of i, and e_i is the number of connections between the neighboring nodes. The clustering coefficient of an entire network is the average over the clustering coefficients of all nodes:

$$cc = \frac{\sum_{i=1}^{n} C_i}{n} \tag{4}$$

A higher cc means a stronger locally clustered structure. Within a component, there may exist a number of highly localized clusters.

The path length is the number of consecutive edges between a pair of nodes. Among all possible paths between the two nodes, the one with the shortest length is called the shortest path. The average path length of the entire network is the average of the shortest paths between all possible pairs of nodes (Watts & Strogatz, 1998). This metric measures the efficiency of how a node can be connected from any other node in the component. It is defined as:

$$l = \frac{1}{n(n-1)} \sum_{i \neq j} l(v_i, v_j) \tag{5}$$

where $l(v_i, v_j)$ is the length of the shortest path between nodes v_i and v_j. A shorter l implies a more efficiently connected network structure. As an absolute measurement, this metric is sensitive to network size when the network is divided into multiple levels of smaller size. To eliminate this effect and be consistent with the relative scale of S and c, l is standardized as the relative average path length l'

$$l' = \frac{l}{lmax} \tag{6}$$

where $lmax$ is the diameter of the network, i.e. the maximum of all shortest path length in a network (Watts & Strogatz, 1998).

The statistical distribution of edge distance (*Dist*) in a network measures the spatial structure (Barthélemy, 2011). A negatively skewed distribution indicates the dominance of short edges, thus a spatially clustered structure, while a positively skewed distribution implies a spatially sparse network. Otherwise a normal distribution indicates a spatially random network. When the original network is divided into multiple levels of unit networks in smaller spatial extent, those edges