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Pig trade networks through live pig markets in Guangdong Province, China

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Abstract
This study used social network analysis to investigate the indirect contact network between counties through the movement of live pigs through four wholesale live pig markets in Guangdong Province, China. All 14,118 trade records for January and June 2016 were collected from the markets and the patterns of pig trade in these markets analysed. Maps were developed to show the movement pathways. Evaluating the network between source counties was the primary objective of this study. A 1-mode network was developed. Characteristics of the trading network were explored, and the degree, betweenness and closeness were calculated for each source county. Models were developed to compare the impacts of different disease control strategies on the potential magnitude of an epidemic spreading through this network. The results show that pigs from 151 counties were delivered to the four wholesale live pig markets in January and/or June 2016. More batches (truckloads of pigs sourced from one or more piggeries) were traded in these markets in January (8,001) than in June 2016 (6,117). The pigs were predominantly sourced from counties inside Guangdong Province (90%), along with counties in Hunan, Guangxi, Jiangxi, Fujian and Henan provinces. The major source counties (46 in total) contributed 94% of the total batches during the two-month study period. Pigs were sourced from piggeries located 10 to 1,417 km from the markets. The distribution of the nodes' degrees in both January and June indicates a free-scale network property, and the network in January had a higher clustering coefficient (0.54 vs. 0.39) and a shorter average pathway length (1.91 vs. 2.06) than that in June. The most connected counties of the network were in the central, northern and western regions of Guangdong Province. Compared with randomly removing counties from the network, eliminating counties with higher betweenness, degree or closeness resulted in a greater reduction of the magnitude of a potential epidemic. The findings of this study can be used to inform targeted control interventions for disease spread through this live pig market trade network in south China.

KEYWORDS
animal movement, disease control, new intervention strategies, social network, veterinary epidemiology

1 | INTRODUCTION

Live animal movement is a critical pathway for disease spread between farms, regions and countries (Bigras-Poulin, Thompson, Chriel, Mortensen, & Greiner, 2006; Ortiz-Pelaez, Pfeiffer, Soares-Magalhaes, & Guitian, 2006; Soares Magalhaes et al., 2010; Volkova, Howey, Savill, & Woolhouse, 2010). Understanding these movements is a key component of disease prevention and control. Social network analysis (SNA) has been utilized to investigate the potential for disease transmission through animal movements; determine the magnitude and control of potential epidemics (Dube, Ribble, Kelton, & McNab, 2009; Gates & Woolhouse, 2015); predict the infection risk for premises (Bigras-Poulin et al., 2006); and guide risk-based surveillance approaches and decisions (e.g. early detection) (Kiss, Green, & Kao, 2006; Martin et al., 2011). Besides movement of live animals, attention has also focused on the network of indirect contacts between farms (Brennan, Kemp, & Christley, 2008; Dent, Kao, Kiss, Hyder, & Arnold, 2008; Rossi et al., 2017), because many animal diseases, including swine influenza (SI) and African swine fever (ASF), can spread indirectly via contaminated fomites (e.g. vehicles, equipment and clothing) and people (Grontvedt et al., 2013; Lauterbach et al., 2018). A previous study in southern China highlighted the use of poor biosecurity practices by local pig farmers when selling pigs as less than half of the farms implemented an 'all-in-all-out' practice for pigs in a pen; thirty per cent of buyers entered a piggery to select and collect pigs; and only about half of the surveyed farms always required all external vehicles to be disinfected (Li et al., 2019). These behaviours in pig trade have the potential to facilitate the spread of contagious diseases via live pig trade networks.

Although pigs are usually transported directly from farms to slaughterhouses in most provinces of China, there is trade of live pigs through wholesale markets in Guangdong Province, in south China. Estimations have suggested that around 10% of the pigs slaughtered in the province, were traded through wholesale live pig markets (P. Chen, personal communication, July 10, 2018). Home slaughter of pigs is illegal in Guangdong Province and is rarely considered to occur in the field (People's Government of Guangdong Province, 2011). Small abattoirs in townships offer a slaughter service at a cost of 30 RMB (4.5 USD) per head. Abattoirs with larger slaughter capacity are usually located in suburban areas of a city. All wholesale live pig markets in this province are located in the cities of Guangzhou and Foshan, and it is estimated that approximately 5.7 million pigs are supplied annually to these two cities via live pig markets (P. Chen, personal communication, July 10, 2018). Approximately 90% of the pigs traded at these markets originate from piggeries located within Guangdong Province (P. Chen, personal communication, July 10, 2018). In 2015, small piggeries, that sell <50 pigs in a year, contributed 87.5% of the total number of pig farms in Guangdong Province (Statistic Beurau of Guangdong Province, 2016). The live pig traders or their employees usually visit pig farms in several counties every day to collect pigs for subsequent resale in the markets. These pigs are transported to the markets in trucks either owned or hired by the traders, and which usually carry pigs sourced from multiple piggeries. However, some pig farmers transport their pigs directly to the live pig markets. At the markets, the traders rent pens which are used to contain pigs purchased from multiple pig farms. The pens are separated from each other by either an open metal fence or a low brick wall (approximately 1 m high). Pigs are then purchased by butchers/meat sellers. Some pig traders will offer a 'slaughter and delivery service' where the pigs selected by the butchers are identified and sent to a slaughterhouse, with the carcass subsequently delivered directly to the meat seller's stall. The meat sellers' stalls are not in the live pig trade markets and are often in a vegetable and meat market near residential areas. No pork is sold in these live pig trade markets. Pigs may stay in the markets for hours to days until being sent to slaughterhouses.

In 2016, the pig population in Guangdong Province was estimated at 20.5 million (Ministry of Agriculture & Rural Affairs, 2017) and the province is considered a key area for the emergence of some important swine diseases in China. For example, the first case of FMD subtype A infection in a pig was found in the province in 2013 (OIE, 2018) and in 2018, a novel coronavirus, swine acute diarrhoea syndrome coronavirus, was identified as the pathogen causing high mortality in four commercial pig farms in the province (Zhou et al., 2018). There are also a variety of influenza strains circulating in pigs in the province and surveillance data indicates that the gene reassortment among local isolates is far more complicated than that among isolates from other Chinese provinces (Cao et al., 2013; Liu et al., 2011; Ninomiya, Takada, Okazaki, Shortridge, & Kida, 2002; Xie et al., 2014; Yang et al., 2016; Zhou et al., 2014).

The live animal market trade system plays a critical role in the circulation of pathogens among areas in China, especially for long-distance disease spread (Martin et al., 2011; Zhou et al., 2015). However, live pig trade patterns in the markets have rarely been described and the characteristics of these networks and their impact on disease spread and control strategies to adopt have never been studied in China. This study was designed to investigate the indirect contact network between source counties through the movement of live pigs via these wholesale markets. This study aims to provide evidence for improved decision making and resource allocation to areas for prevention and control of disease. Trade patterns in live pig markets were described, and properties of the networks in January (winter, busy trade season) and in June (summer, quiet trade season) were compared to study the stability of the live pig market trade network in different months/seasons. Different strategies were compared to illustrate the benefit of taking a risk-based intervention to constrain potential disease spread through this network. The findings of this study can be used to inform targeted interventions to control disease spread through the live pig market trade network.

2 | MATERIALS AND METHODS

The objective of this study is to evaluate the trade network between the source counties and the traders in wholesale live pig markets. This study was conducted in Guangdong Province, South China. SNA was used to explore the characteristics of this trade network. The trade data were collected by the China Animal Health and Epidemiology Center (CAHEC) during a routine survey in 2017. The study was approved by the Murdoch University Human Ethics Committee [Project Number: 2017/113].

2.1 | Data sources

Trade records were extracted from health certificates of pigs and were collected from all four wholesale live pig markets in Guangdong Province, south China. In China, each batch of pigs requires a pig health certificate provided by the local official veterinarians. The pig health certificates are paper-based. The farmers give the pig health certificates to traders, so the traders can transport pigs to markets or slaughterhouses. If traders did not offer pig health certificates, the markets or slaughterhouses will not accept their pigs (People's Government of Guangdong Province, 2011). Market managers are required by local authorities to collect these health certificates and to keep them for at least one year. Three of these markets (Jiahe market—market 1; Furong market—market 2; and Baiyun market—market 3) are located in Guangzhou city, and Wufeng market (market 4) is situated in Foshan city. In total, 14,118 trade records from January (8,001) to June (6,117) 2016 were collected. The data cover trade events from all traders in all four wholesale live pig markets. These markets are open every day of the year, except for a short closure (1–2 weeks) during the spring festival. Sheep, goat and cattle were also traded in Furong market, while all other markets only traded pigs. Data for each batch (a truckload of pigs that had been collected from one or more farms from the same county) were collected, including the source counties of the pigs (91.3% of the data had source counties recorded), the loading date, number of pigs, destination markets and the destination pig pen(s) at the market (76.1% of the data recorded the destination pen, which is usually owned by one trader).

2.2 | Data analyses

The patterns of pig trade in the four live pig markets were analysed. Maps were developed using ArcGIS 9.3 (ESRI Inc.) to show the transport pathways from supply counties to the four markets and the average distance individual batches were transported was calculated. The total number of pigs traded in each month, the average size of a batch, the number of pig pens and the source counties of the pigs were also calculated for each market. A batch was a group of pigs from one or more farms transported to the live markets on one truck, irrespective of the number. A county that contributed at least 20 batches in one month was classified as a major supply county. The total number of batches to the markets from these major source counties was compared to check the stability of supply for January and June.

The SNA was conducted with the packages 'igraph' (Nepusz, 2006) and 'tnet' (Tore Opsahl, 2009) in R (R Core Team, 2018). The study unit in the network was source county and trader. Firstly, the network was established as an undirected bipartite network, and the number of batches was set as the link weight. The source and destination nodes were set as the source counties and the pens (each pen owned by a trader) in the markets, respectively. The 2-mode network was then transformed into a 1-mode network by removing the pens, to focus on the network between source counties.

The static networks for markets 3 and 4, which had complete trade records, were compared between the two months (seasons) to evaluate the stability of the live pig trading networks through these markets. The 15 counties that contributed the most pigs to the two markets in January and June 2016 were compared to check the stability of the pig supply. The 'power.law.fit' function in igraph was used to test if a network had free-scale property. The Kolmogorov–Smirnov test was used to test the goodness of fit for nodes with ten or more degrees using a confidence level of 95% (a p-value >.05 indicated that the nodes' degree fit a power-law distribution, and thus, the network has free-scale property).

Parameters (edge density, clustering coefficient, diameter and the average length of pathways) of the networks were calculated and compared (Nepusz, 2006). Fast-greedy community detection was performed using the 'fastgreedy.community' function in 'igraph' to determine the number of communities in a network (Clauset, Newman, & Moore, 2004). R0 was investigated across the networks. R0 is defined as the average number of secondary cases produced by a case during its infectious period in a susceptible population (Lin & Vandendriessche, 1992). R0 is affected by the characteristics of the pathogen (e.g. pathogenicity and environmental resistance of the pathogen). It is also determined by the method and frequency of contact between units of interest. In this study, we focused on the impact of the trader network on a disease transmitted among supply counties. To illustrate the impact of the network structure on the spread of diseases, we compared the R0s of existed networks in different seasons to simulate random networks with the same number of nodes. 'R0(network)/R0(random)' was calculated for the two static networks in January and June 2016 (Marquetoux, Stevenson, Wilson, Ridler, & Heuer, 2016).

Trade data from January and June 2016 were joined to create a combined social network. The 2-mode network was then transformed into a 1-mode network by removing the pens (traders). There were 37 nodes deleted from the network because they were isolated nodes in the 1-mode network. These isolated counties infrequently supplied pigs to only one trader in the markets. The degree, betweenness and closeness of each node were calculated. The correlations between the nodes' scores in degrees and betweenness and closeness were checked using Pearson's correlation test. A map was developed to show the degrees of source counties in this network. The distributions of degrees, betweenness and closeness of the nodes in the combined network were illustrated with figures. To illustrate the impact of the key players on the potential magnitude of epidemics spreading through this network, the methodology of Marquetoux et al. (2016) was used to compare the decrease of the GWCC in the network with different strategies. One involved randomly removing a node in the network, while the others involved deleting the nodes in sequence according to their scores of three indicators of centrality: degree, betweenness and closeness.

Definitions of the technical terms used in this paper relating to SNA are provided in Table 1.

3 | RESULTS

3.1 | Trade patterns of the live pig market trade network

Pigs from 151 counties were delivered to the four markets in January and/or June 2016. There were at least 238 pens in operation in the four markets in these two months in 2016. On average, 67 pigs were consigned in a batch. The daily trade volume in the four markets varied from 1,021 to 7,138 head (16 to 124 batches). Market 1 had the highest daily trade volume (5,954 and 7,138 pigs, and 77 and 124 batches in January and June, respectively). More batches were traded in the four markets in January (8,001) than in June 2016 (6,117). However, pigs were sourced from more counties in June (136) than in January 2016 (90) (Table 2).

The number of pens that a county was linked to during a month varied from 1 to 86. On average, pigs from a county were supplied to 12 (median: 5) pens in January and 8 (median: 2) pens in June 2016. The sourcing counties were predominantly inside Guangdong Province (92% of all batches), along with counties in Hunan, Guangxi, Jiangxi, Fujian and Henan provinces (Figure 1). The number of pigs supplied from different counties varied between January and June, but the supply from the major source counties was stable with the counties that contributed the most pigs/batches in January also providing the most in June (Figure 2). The major source counties (46) contributed 94% of the total batches during the two months. Pigs were sourced from piggeries from 10 to 1,417 km from the markets, with average distances of 223 and 307 km in January and June 2016, respectively.

TABLE 1 Definitions of social network analysis terms used in the study on trade networks through live pig markets in Guangdong Province

Parameter	Definition
General terms	
Node	A node refers to a unit of interest in a network (Dube et al., 2009). In this study, supply counties and traders (sale pens in markets) are nodes in trade networks.
Edge	An edge represents a contact between individuals in the susceptible Population (Shirley & Rushton, 2005). In this study, counties were supplying pigs to a pen (2-mode network), or two counties were connected by the same trader(s). Links between a county and a pen (2-mode network) or between counties (1-mode network) were taken as an edge.
Weight of links	In the bipartite network of counties and pens, the weight of a link was defined as the number of batches between a county and a pen, during a defined period. When projected as a 1-mode network of counties, the weight of a link was defined as the total number of paths (through pens) between two source counties, during a defined period.
Edge density	A value reflecting the density of the network and can be calculated using equation: $L/k(k-1)$. L means the number of exiting edges, and k means the number of nodes in a network (Wasserman & Faust, 1994)
Diameter	The longest geodesic between any pair of nodes in the network (Wasserman & Faust, 1994)
Average path length	For any two given nodes, the shortest path between them over the paths between all pairs of nodes in the network (Dube et al., 2009)
Measures of centrality	
Degree	This parameter was calculated for the 1-mode network of source counties. It represents the total number of contacts of a county to other counties in the network. A higher degree means more connection to other nodes in the network (Marquetoux et al., 2016).
Betweenness	The frequency by which a node falls between pairs of other nodes on the shortest path connecting them (Dube et al., 2009). Betweenness is a measure of centrality used to quantify a node's potential to 'control' the flow or curtail paths within a network (Marquetoux et al., 2016).
Closeness	The sum of the shortest distances (not geographical, but path length) from a source livestock operation to all other reachable operations in the network (Shirley & Rushton, 2005)
Measures of cohesion	
Clustering coefficient	This parameter was calculated for the 1-mode network of source counties. It represents the proportion of one county's neighbours who are also neighbours to another (Watts & Strogatz, 1998).
Giant weakly connected component (GWCC)	The weakly connected component is the undirected subgraph in which all nodes are linked, not taking into account the direction of the links (Robinson & Christley, 2007). GWCC is the largest weak component in the network (Dube et al., 2009). In this study, the network among source counties was considered as an undirected network, so we use GWCC as the indicator for the potential magnitude of an epidemic.

TABLE 2 Trade statistics for the wholesale live pig markets in Guangdong in 2016

Market	Month	Number of batches	Total number of pigs	Average batch size ± *SD*	Number of recorded pig pens	Averaged daily trade volume (head) ± *SD*	Number of supply counties
1	January	3,838	221,293	58 ± 33	96	7,138 ± 1,506	65
1	June	2,376	184,577	78 ± 24	4*	6,153 ± 3,425	89
2	January	503	31,638	63 ± 33	1*	1,021 ± 121	22
2	June	491	34,367	70 ± 17	1*	1,146 ± 154	41
3	January	1,515	126,112	83 ± 11	53	4,068 ± 282	38
3	June	1,357	112,175	83 ± 17	51	3,739 ± 286	54
4	January	2,145	125,527	59 ± 22	79	4,049 ± 661	36
4	June	1,893	111,196	59 ± 23	85	3,707 ± 444	48
Total		14,118	946,885	67 ± 24	–	–	151

*Most data in this month did not include a record of the pen code. For the other unmarked numbers, the number of recorded pig pens was the number of pens in operation in that market during the respective month.

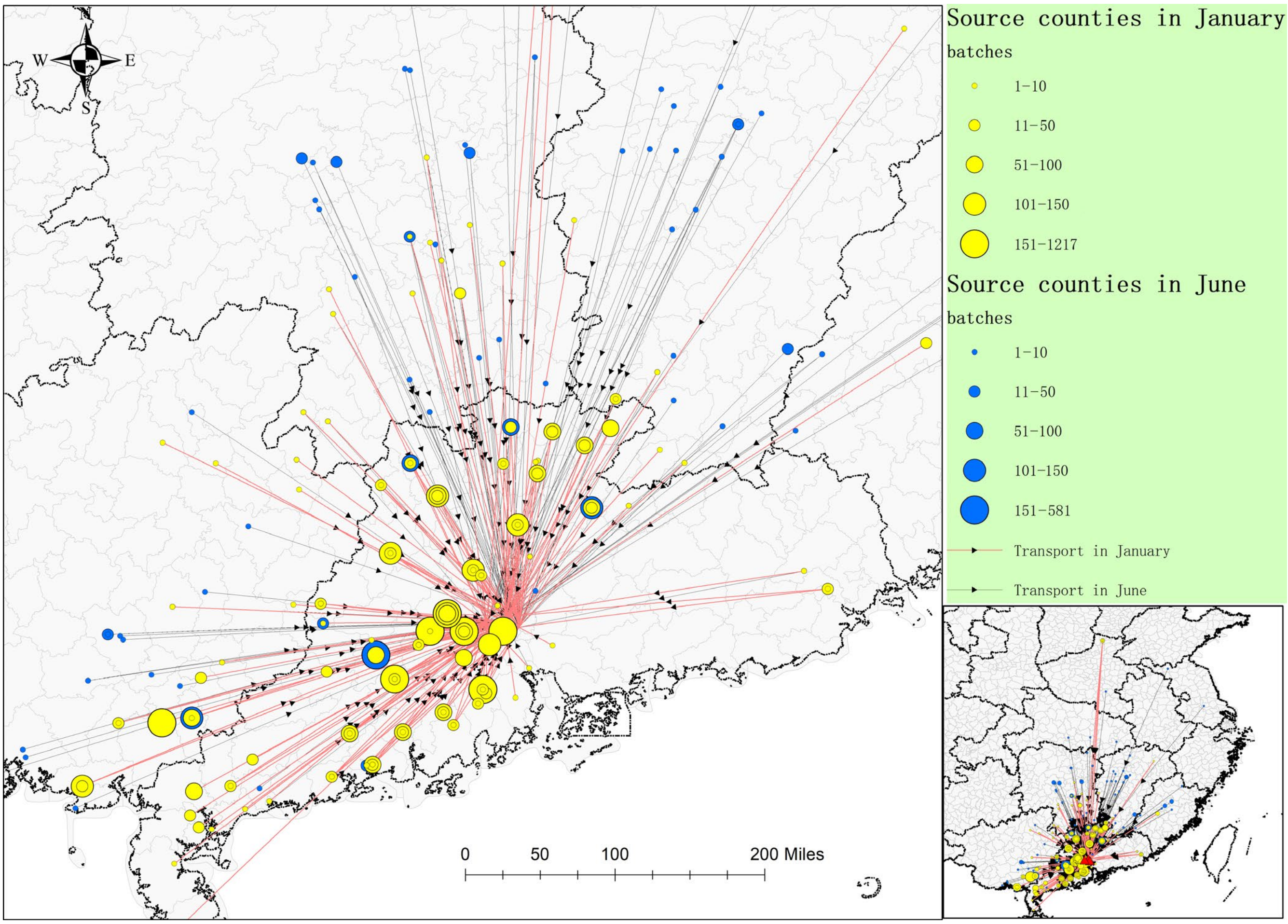

FIGURE 1 Transport of pigs to the wholesale live pig markets in Guangdong in January (high demand month) and June (low demand month) 2016. Yellow circles represent the source counties in January 2016, and blue circles represent the source counties in June 2016. Size of the circles indicates the number of batches transported. Circles overlapped for some counties because these counties supplied pigs to more than one market and each of the overlapping circles indicates the number of batches delivered to one of the markets [Colour figure can be viewed at wileyonlinelibrary.com]

3.2 | Trade networks in different months

The 2-mode trade network was analysed to determine the stability of the trade between the two months/seasons. Twelve of the 15 counties supplying the most batches were similar in the two seasons. They contributed 84% and 78% of the total number of batches in January and June, respectively. Notably, all the links between the source counties in January still existed in June, with

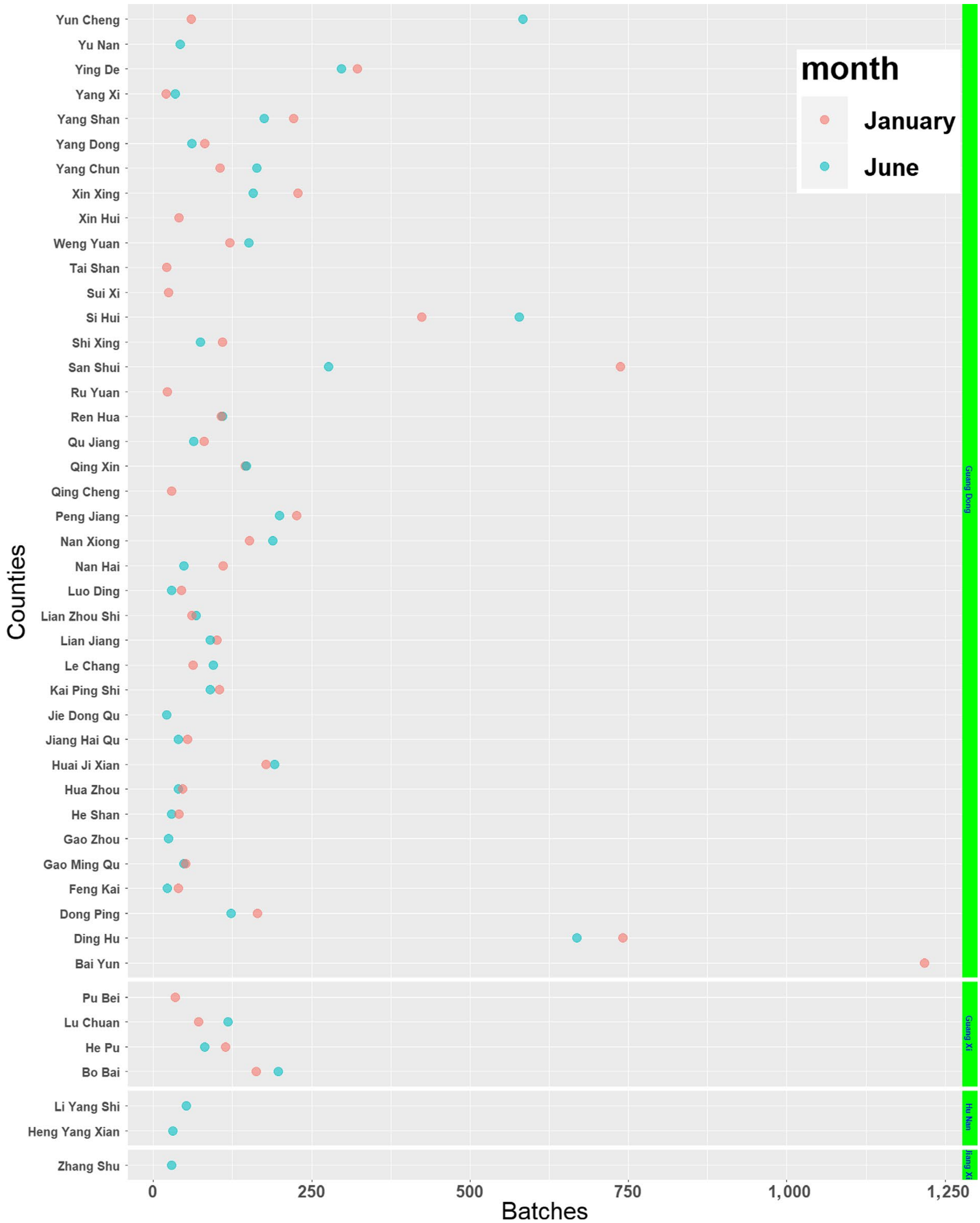

FIGURE 2 Number of batches from major supply counties (supplying ≥20 batches/month) to the wholesale live pig markets in Guangdong in January and June 2016. Provinces of these counties are identified on the far right [Colour figure can be viewed at wileyonlinelibrary.com]

only 9% of the links in June being new links to the trade network; on the other hand, these new links only contributed 1.5% of the total number of batches in June.

The distributions of the degrees of the nodes in both January and June indicate free-scale network property (Figure 3; *p*-values of .14 and .52, respectively); thus, a few nodes have much higher connectivity than other nodes in this network. However, the network in January had a higher clustering coefficient and a shorter average pathway length than that in June (Table 3).

With 46 new source counties being added to the markets in June, new communities were formed in the live pig trade network (Appendix 1).

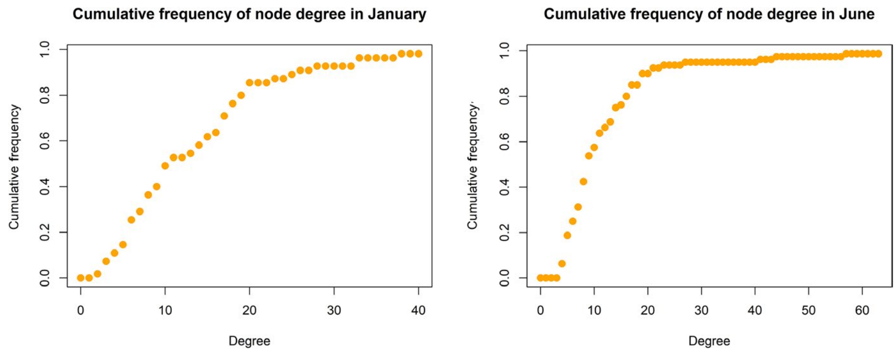

FIGURE 3 Distributions of the degrees of source counties in the live pig trade networks through wholesale live pig markets in Guangdong in January and June 2016 [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Properties of pig trade networks through live pig markets in Guangdong Province in January and June 2016

Network properties	Month: January	Month: June
Edge density	0.24	0.15
Clustering coefficient	0.54	0.39
Diameter	5	4
The average length of pathways	1.91	2.06
Number of communities	4	7
R0(network)/R0(random)	1.23	1.29

3.3 | Properties of the combined static 1-mode network

The parameters of the combined static network are summarized in Table 4. Most of these parameters are between the parameters of the static networks of January and June. The combined static network is displayed in Figure 4.

The degree, betweenness and closeness of each source county in this network are summarized in Appendix 2. The degree of each source county indicated that the most connected counties of the network were in the central, northern and western regions of Guangdong Province (Figure 5).

3.4 | Influence on GWCC by different 'control' strategies

The distribution of degree, betweenness and closeness is displayed in Appendices S1–S3. The nodes that had higher degrees also had higher betweenness (correlation coefficient of .88, $p < .001$) and higher closeness (correlation coefficient .74, $p < .001$). Compared with randomly removing counties from the network, eliminating counties with higher betweenness, degree or closeness resulted in a greater reduction in the magnitude of a potential epidemic. Of the three risk-based strategies, isolating the nodes according to their betweenness had the greatest effect in decreasing the size of GWCC in most of the steps (Figure 6).

TABLE 4 Properties of the combined (January and June) static social network of live pigs traded through live pig markets in Guangdong Province in 2016

Network properties	Value
Edge density	0.18
Clustering coefficient	0.47
Diameter	4
The average length of pathways	1.93
Number of communities	5
R0(network)/R0(random)	1.29

The GWCC reduced slowly when deleting the first few nodes with the highest degree, betweenness and closeness, and significant reductions only occurred when more nodes were deleted. For example, when <7 nodes were deleted from the network, there was no difference between the different strategies in terms of decreasing the size of the GWCC. However, if the 45 counties with the highest betweenness or degree from the network were removed, the GWCC decreased to approximately 10 counties, while if 45 counties were randomly removed, the GWCC decreased to only 65 counties (Figure 6).

4 | DISCUSSION

To our knowledge, this is the first study that described the pattern and explored the network of live pig trading through wholesale live pig markets in China. Live animal markets provide a location where there is direct contact and mixing between animals and humans that can facilitate disease spread (Bowman et al., 2014; Dutkiewicz et al., 2018; He et al., 2014; Kiss et al., 2006; Myers et al., 2006; Robinson & Christley, 2007; Van der Poel et al., 2018; Zhou et al., 2015). Furthermore, long-distance transport and mixing of animals at live animal markets is stressful (Dalla Costa, Lopes, & Dalla Costa, 2017; Earley, Buckham Sporer, & Gupta, 2017; Sommavilla et al., 2017; Zurbrigg et al., 2017), allowing greater opportunity for pathogen and disease spread between animals.

Significant differences were found in the connectivity of source counties. 'Free-scale' pattern was found in this market trading network. Studies conducted in other countries on livestock movement

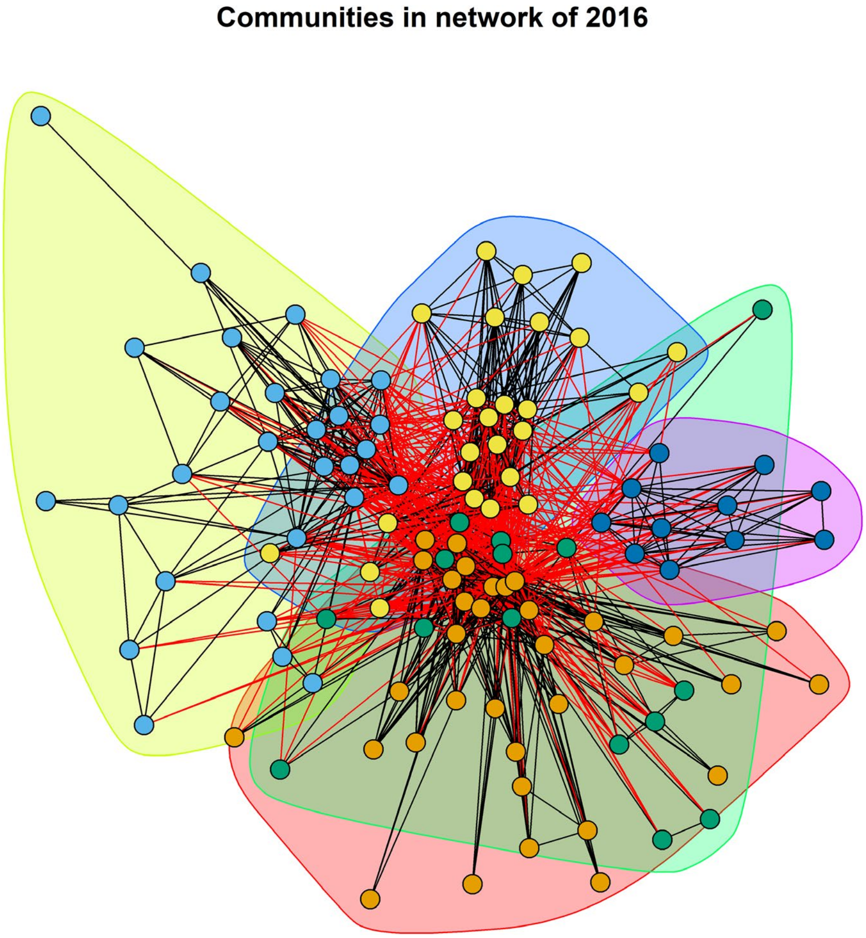

FIGURE 4 Graph of the combined static network of pig movement through wholesale live pig markets in Guangdong in January and June 2016. Different coloured areas represent five different communities in the network, and nodes with the same colour belong to the same community [Colour figure can be viewed at wileyonlinelibrary.com]

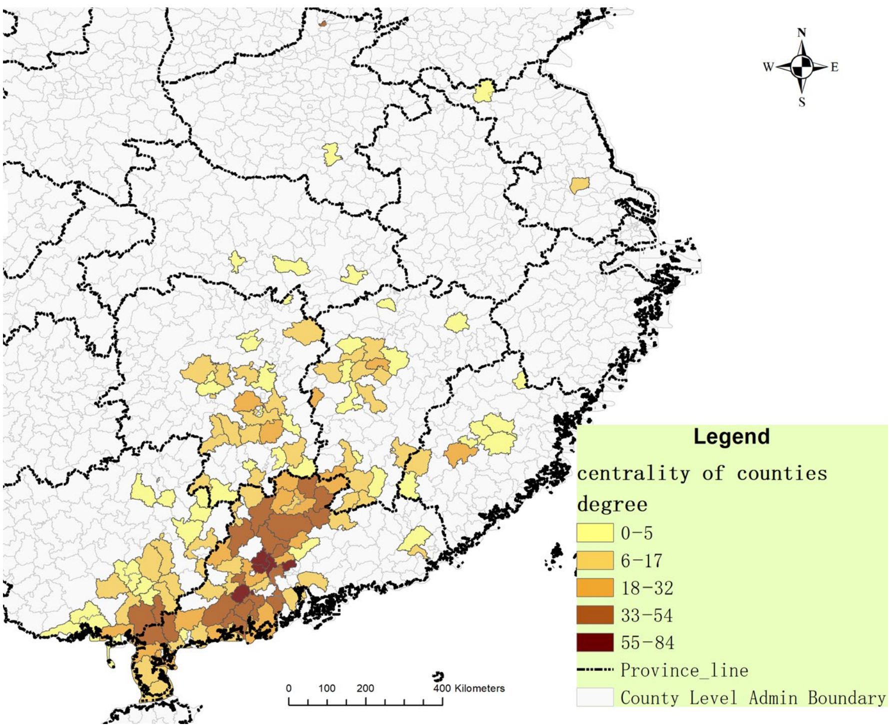

FIGURE 5 The connectivity of source counties in the combined static network of pig movement through wholesale live pig markets in Guangdong in January and June 2016 [Colour figure can be viewed at wileyonlinelibrary.com]

networks have also reported 'free-scale' property (Earley et al., 2017; Kiss et al., 2006; Lentz, Kasper, & Selhorst, 2009; Molia et al., 2016; Soares Magalhaes et al., 2010; Woolhouse et al., 2005). This indicates that they are potentially key players in a network, which should be targeted for disease control strategies. The connectivity was measured with different parameters in this study: degree,

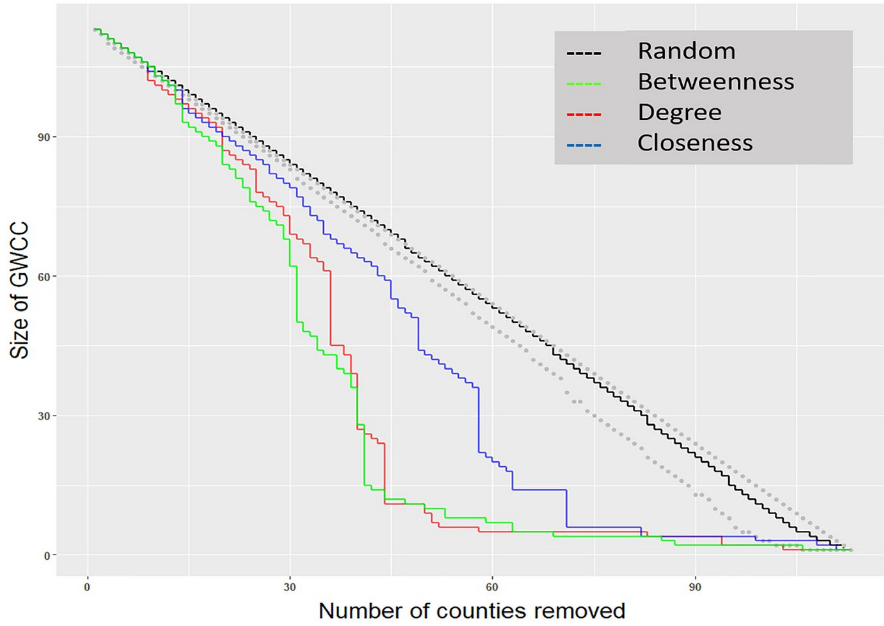

FIGURE 6 The decrease in the size of GWCC of the pig movement network through wholesale live pig markets in Guangdong in January and June 2016 under different control scenarios. The grey dotted lines representing the 95% CI of the size of the GWCC when removing counties randomly [Colour figure can be viewed at wileyonlinelibrary.com]

betweenness and closeness. Most of the counties with the highest degree were located in central, northern and western Guangdong. It is worth noting that the counties with high degree scores also had high betweenness and closeness values. These counties had larger pig populations than counties with lower connectivity. Thus, they are more likely to supply pigs to many markets at the same time. This result indicates that it will be very challenging to stop pig movement in counties with higher connectivity, during an emergency response to an epidemic. We suggest that besides movement suspension, other control measures such as emergency vaccination, enhanced quarantine, promotion of better biosecurity practices in the trading sector and education programs should also be implemented during emergency disease responses.

The results of this study have provided insight on approaches for implementation of emergency responses to SI and other pig diseases in Guangdong Province. For example, the transmission of ASF in China (Ge et al., 2018; Normile, 2018; Wang, Sun, & Qiu, 2018) has been the result of long-distance movement of live pigs allowing the epidemic to propagate (Wang et al., 2018). Our findings show that the supply counties of the live pig markets in Guangdong Province included, not only counties inside this province but also counties from Guangxi, Hunan, Jiangxi, Fujian, Jiangsu and Henan provinces. Animal health authorities in Guangdong Province should pay more attention to outbreaks in these provinces, especially Hunan and Guangxi. These provinces contributed more pigs to the live pig markets in Guangdong Province than did other provinces (excluding Guangdong Province) and some counties in the middle of Hunan and east Guangxi had relatively high connectivity in the live pig market trading network. For early detection of ASF in Guangdong Province, counties inside/adjacent to Guangzhou and to the north and south-west of the province should also be targeted for active surveillance. Control measures against ASF adopted in China have included mass field screening of pigs, widespread sampling and testing, movement restrictions, thorough cleaning and disinfection of trucks transporting pigs, and registration of live pig traders (Ministry of Agriculture & Rural Affairs, 2018). However, these measures can be a big burden for local governments. Social network analysis on animal movement can contribute to improving the efficiency of control measures when resources are limited by targeting priority areas. The current results indicate that, in an emergency response where often there are limited diagnostic and human resources, targeted surveillance and intervention would be a better strategy to control the potential magnitude of an outbreak among the source counties included in the market trading network. In this study, we found that if we isolated the 45 counties with higher connectivity (e.g. by movement restriction or enhanced quarantine), the magnitude of a potential epidemic could decrease substantially, in contrast to conducting control measures across the same number of randomly selected counties (10 vs. 70).

The findings of this study can also help to improve the efficiency of routine surveillance on influenza in this area. Influenza is one of the most significant zoonotic diseases (Bowman et al., 2014; Lauterbach et al., 2018; Ma et al., 2015; Myers et al., 2006). Pigs can be infected by swine influenza strains, as well as some human strains, and genetic reassortment between swine and human influenza strains may facilitate the evolution of new strains circulating in pigs or even pandemic strains in humans (Kuntz-Simon & Madec, 2009; Rajao et al., 2017; Zhou et al., 1999). A recent study indicated a poor level of biosecurity being adopted by pig farmers in Guangdong when selling pigs (Li et al., 2019). There is evidence to indicate that workers on pig farms and markets in China have a higher risk of acquiring SI influenza than the general population (Ma et al., 2015; Yin et al., 2014). To improve the efficiency of surveillance of SI in Guangdong, those traders in the markets with more contacts to different counties and those pig farms within the counties with higher connectivity in the network should be targeted for human influenza and SI surveillance, respectively.

The clustering coefficient was higher in the trade network of January than June 2016 (0.54 vs. 0.39). Thus, via this market trading network, an epidemic in January would spread faster than in June. The average path length in the combined static network was <2, which means that any two counties in the network can be connected via just another county. Interestingly, the average path length was shorter in the trade network of January than that in June, which illustrates that it would be easier for a pathogen to spread among nodes in this trade network in January than in June. Furthermore, the lower temperature in January could preferentially influence the survival of pathogens in the environment (Botner & Belsham, 2012). Local animal health authorities should be aware that this market trade network would require more attention in January.

The dynamics of the live pig trade can lead to new directions for pig diseases spread through this market trading network. We evaluated the consistency of the live pig market trading network by comparing the source counties in January and June 2016. The links among the dominant source counties and the live pig pens were stable in the different months, although there were 55 more counties from neighbouring provinces involved in pig supply in June. However, these newly added counties contributed <2% of the pigs, and the trade frequency of these counties was low. When we transformed the 2-mode network into the 1-mode network, many of these counties became isolated nodes. We decided to simplify the network by deleting these nodes, because these counties which only occasionally supply pigs should have a low impact on the spread of disease between counties. It was not surprising that more pigs were traded in these markets in January than in June (504,570 vs. 442,315) because January is close to the Chinese Spring Festival and demand for meat increases before this festival (Pan et al., 2016). The increase in the number of source counties in June may be due to the change in the pig density in Guangdong Province arising from a policy to restrict the number of pig farms in the province implemented in 2014, resulting in some farms being forced to close or to relocate to other counties (China State Council, 2013). As displayed in Figure 2, Baiyun (suburban area of Guangzhou city) and Sanshui (suburban area of Zhongshan city) supplied many pigs in January 2016, but the numbers supplied in June 2016 decreased dramatically. During our field investigation, we were told that many pig farms in these areas were closed in 2016 because of concerns arising from their environmental impact. Another reason could be price changes in neighbouring provinces, which may have provided incentives for traders to collect pigs from more distant counties. A study on live poultry movement in China reported that when the price of poultry changed in neighbouring provinces, the direction of movement of live poultry also changed accordingly (Li et al., 2018). It is worth noting that the increased supply counties in this network resulted in a change in the structure of the local market trade network. Newly produced communities can result in new disease circulating directions between counties. We suggest that local veterinary authorities should pay attention to the impact of policy or price changes on livestock movement. Monitoring the changes in the structure of this market trade network is needed.

Several model limitations need consideration. Firstly, the 'removal of the counties from this network' cannot be totally achieved because illegal trade could be present. However, animal movement suspension has been implemented on several occasions in China (e.g. emergency responses for PPR and ASF) (Ministry of Agriculture & Rural Affairs, 2019) and is required by the animal health law in China (China State Council, 2015). Although it is impossible to prevent all illegal trade, suspending legal trade would dramatically reduce the trade volume from selected counties. Besides movement restriction, other control measures, such as emergency vaccination, intensive screening for cases, enhancing biosecurity within the trading sector and implementing education programs, could also reduce disease risk in targeted counties. These control measures could also result in the targeted areas being 'removed' from the network in terms of spreading disease. Secondly, in reality authorities would not randomly select places to implement an emergency response. The places are usually selected according to their current infection status or potential for infection. However, early detection of an epidemic in a county can be challenging, especially for an exotic disease (Liu et al., 2019), and choosing counties based on convenience is unlikely to be effective. We used randomness to model these non-targeted scenarios, and we believe that our model, even with its limitations, has offered new insights for decision-makers to understand the disease risk in places before an epidemic occurs. The same methodology has been used in another similar study (Marquetoux et al., 2016). It is worth noting that this study only focused on the pig movement network through local wholesale markets. Pigs are also traded through other systems in this province. For example, breeding pigs are often traded directly between pig farms, and weaners are often moved from breeding farms to fattening farms. Further studies on the movement of live pigs among local farms are needed.

It is a better strategy for disease control to understand the risk of disease spread through live animal movements before an epidemic actually occurs (Shirley & Rushton, 2005). In recent years, many countries and companies have established databases to record livestock movement (Bigras-Poulin et al., 2006; Kiss et al., 2006; Lee et al., 2017; Marquetoux et al., 2016). These data would be critical in tracing livestock movement during emergency responses and would favour SNA being used to inform the establishment of a proper disease control contingency plan. However, livestock trade (source and destination) is poorly recorded in many livestock markets in China. The most common source of live pig movement records in China is the official health certification of the traded pigs, which has limitations. Firstly, the certification record often lacks the name and location of the source farm, which makes it difficult, if not impossible, to effectively trace back to farms/animals in outbreak investigations. Secondly, data from the health certification system are not shared between provincial animal health authorities, even though live pig movements often cross provincial boundaries.

A more comprehensive national database should be established in China. Detailed information on the location, species, farm size, type of source piggery (breeding, fattening, etc.) and livestock movements should be recorded and updated in a timely manner.

5 | CONCLUSIONS

The live pig market trading network in Guangdong involved pigs sourced from at least 151 counties in 2016. The trading network had connected counties in Guangdong, Guangxi, Hunan, Fujian, Jiangxi, Hubei, Henan and Jiangsu provinces. For emergency disease control, targeted surveillance is required, and for this to eventuate nation-wide, a more comprehensive database of livestock movement is needed at the national level. The findings in this study could be used to offer insights into SI surveillance, emergency responses and control of ASF and other swine diseases in Guangdong Province and southern China.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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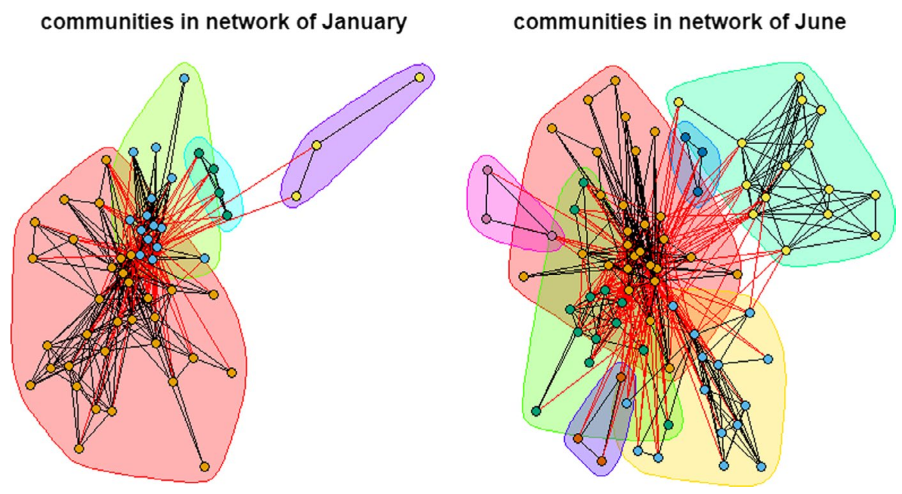
APPENDIX 1

Communities in the pig movement network through wholesale live pig markets in Guangdong in January and June 2016. Areas with a different color represent different communities in the network, and nodes with the same color belong to the same community. [Colour figure can be viewed at wileyonlinelibrary.com]



APPENDIX 2

The degree, betweenness and closeness of each source county in the pig market trading network in Guangdong Province, 2016

County	Degree	Betweenness	Closeness
Sanshui	76	673.845	0.003745
Yuncheng	54	282.91	0.00346
Dinghu	85	919.031	0.003876
Jianghai	36	47.586	0.003257
Electric white	10	0	0.002967
Pengjiang	46	120.534	0.003367
Hepu	32	134.029	0.003215
New	43	89.974	0.003333
Four	80	773.088	0.003802
Kaiping	40	109.745	0.003289
Enping	54	169.576	0.00346
Huaiji	47	206.345	0.003378
Nanhai	34	44.231	0.003215
Lianzhou	12	2.748	0.002959
Yangchun	50	153.602	0.003413
Yangxi	26	23.637	0.003145
Yingde	44	144.877	0.003333
Longyuqu	10	0	0.002967
Cold water beach	8	0.462	0.002899
Pubei	7	3.138	0.002571
Gaoyao	24	22.674	0.003125
Fresh	44	81.639	0.003344
Guiping	10	0	0.002865
Xiangxiang	11	0	0.002907
Closed	26	38.288	0.003106
Huazhou	39	131.357	0.003289
Qingcheng	49	153.498	0.003401
Heshan	39	60.046	0.003279
Lu Chuan	36	178.41	0.003257
Huadu	25	13.504	0.003135
Xinxing	60	277.728	0.003534
Nansha	10	0	0.002882
Yunan	10	0	0.002882
Yangdong	36	37.917	0.003247
Taishan	31	17.68	0.003195
Xingan	15	3.777	0.002985
Camphor	25	30.527	0.003135
High security	10	0	0.002865
Conghua	4	0	0.00277
Fenyi	4	0	0.002786
Lechang	29	48.335	0.003185
Pingnan	6	3.75	0.002747
Taixing	9	0	0.00289

(Continues)

APPENDIX 2 (Continued)

County	Degree	Betweenness	Closeness
Maonan	3	0	0.002725
Fogang	18	5.232	0.003067
Changting	6	0	0.002801
Hengxian	10	0	0.002967
Baiyun	57	378.2	0.003497
Linwu	12	2.265	0.002899
Qinbei	5	0	0.002825
Qiyang	6	0	0.002841
Jiangyong	8	0.462	0.002899
On the high	10	0	0.002865
Feng	4	0	0.002786
Foshanshixiaqu	5	0	0.002793
Qintang	5	0	0.00274
Nanxiong	29	48.354	0.003165
Ma Zhang	22	13.027	0.003086
Renhua	35	61.119	0.003236
Wengyuan	33	47.35	0.003205
Qujiang	30	36.742	0.003175
Luoding	10	4.479	0.002778
Gaoming	16	6.776	0.00277
Yangshan	34	54.171	0.003205
Zhongshan	10	0	0.002825
Lianjiang	34	78.909	0.003226
Suixi	22	18.111	0.003096
Yong'an	18	6.722	0.003067
Bobai	34	82.422	0.003236
Zhenjiang	20	8.872	0.002899
Gaozhou	21	8.177	0.002907
Yunan	9	2.712	0.002786
Shixing	33	53.825	0.003226
Xuwen	6	0	0.002591
Leizhou	10	0	0.00266
Wujiang	14	3.057	0.002801
Beiliu	16	17.137	0.003003
Lian Shan Zhuang Yao Autonomous	8	7.199	0.002907
Big	19	5.907	0.002793
Ruyuan Yao Autonomous	28	24.369	0.003175
Lotus	19	2.854	0.003077
Zhongshan	1	0	0.002381
Nankang	14	2.332	0.002717
Wuchuan	15	1.418	0.002841
Lingling	6	0	0.002639
Longnan	12	1.499	0.002674

(Continues)

APPENDIX 2 (Continued)

County	Degree	Betweenness	Closeness
Yangshuo	3	0	0.002545
Dingnan	15	8.674	0.002959
Leping	5	0	0.002817
Slope head	18	7.592	0.002899
Jiangcheng	13	0.806	0.002941
Rongxian	9	7.849	0.002874
Leiyang	22	27.371	0.003049
Changning	14	3.239	0.00295
Dongguan	8	0	0.002865
Hengyang	32	64.884	0.003155
Steaming	9	0	0.00277
Hengdong	14	3.239	0.00295
Hengnan	14	1.739	0.002976
Lianping	9	0	0.002882
Jiedong	11	0.549	0.002924

APPENDIX 2 (Continued)

County	Degree	Betweenness	Closeness
Lianyuan	17	8.113	0.003003
Xinhua	17	9.945	0.002976
Ruijin	7	0	0.002809
Pingjiang	10	0	0.002907
Fengshun	3	0	0.002558
Jishui	7	0	0.002809
Lengshuijiang	4	0	0.002786
Double clear	9	0	0.00277
Xinfeng	10	0	0.00266
Yuanzhou	7	0	0.002809
Yunxi	5	0	0.00277
Anyuan	5	0	0.00277
Zixing	12	2.754	0.002924
Yushui	8	1.057	0.002833