Mapping the Port Influence Diffusion Patterns: A Case Study of Rotterdam, Antwerp and Singapore

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Abstract. Ports play a vital role in global oil trade and those with significant influence implicitly have better control over global oil transportation. To provide a better understanding of port influence, it is necessary to analyze the development of the mechanisms underlying port influence. In this study, we adopt a port influence diffusion model to modelling diffusion patterns using vessel trajectory data from 2009 to 2016. The results of the case study of Rotterdam, Antwerp and Singapore ports shows: 1) ports with a strong direct influence control their neighboring ports, thereby building a direct influence area; 2) directly influenced ports show path-dependent characteristics, reflecting the importance of geographical distance; 3) the indirect influence of the initial diffusion port creates hierarchical diffusion, with directly influenced ports affected by previous diffusion-influenced ports. 4) a port's indirect influence and efficiency can be increased via an increase in the number of significant ports it influences directly or by increasing its influence on significant ports in an earlier diffusion stage.

Keywords: Global oil transport patterns · Vessel trajectory · Ports · Influence diffusion · Direct influence · Indirect influence

1 Introduction

The global oil trade continues to show tremendous growth [1], and maritime transportation is considered the most important trade mode for global oil. By combining locational advantages with long-term high-quality operational processes, some ports have achieved greater competitiveness and influence. Ships and oil companies will prioritize these ports for selection when designing routes. Hence, the growing transport network has been concentrating around these hub ports over time, and traffic distribution has shown place-dependent characteristics as well [2]. As a result, the emergence of patterns of port influence has produced the Matthew effect [3]; that is, the influence of these significant ports has progressively grown. Studying the formation and evolution of port influence is necessary to help optimize port trade relations, and provide theoretical support for port development.

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Recently, scholars have built a series of index systems [4–6] based on the characteristics of a port's natural conditions, locational advantages, and operational efficiencies to design port evaluation methods [7–9] and study the competitiveness of different ports, reflecting port influence from new perspectives.

Networks are also a vital medium for spreading information on port competitiveness. They are the conduits by which the innovative efforts of oil companies and port technology are disseminated. Information externalities and spillover from the concentration of oil and tanker companies in a port city can influence the port network. In turn, the spread of a port's influence can reinforce its reputation and competitiveness, which attracts more oil traffic. Common network models reveal port influence via certain network indicators [10–13] such as degree and betweenness centrality.

Although several scholars have studied port competitiveness and network indicators to reflect port influence, the methods used to date have some limitations. Among these, port-related data and statistics are not always completely available and updated. Thus, it is often difficult to obtain complete infrastructure data for all ports involved in the world oil trade, making it problematic to verify a large-scale port competitiveness assessment. In addition, Peng et al. found that there were several transshipment characteristics in oil transportation [14]; specifically, port influence had multiple propagation and cumulative effects, which could not be measured by network centrality indicators alone. In a quantitative study of the influence diffusion of ports involved in oil transportation, Peng et al. found that port influence had multiple diffusion characteristics [15].

Against this backdrop, the aim of this study is to fill the gaps in the literature by adopting a port influence diffusion model to explore the evolution of the influence of different oil ports, considering direct and indirect influence. We do this through a case study of Rotterdam, Antwerp and Singapore using worldwide vessel trajectory data from 2009 to 2016.

2 Data and Model

2.1 Data for Global Oil Transport Network

In this study, we used vessel trajectories generated from AIS data from 2009 to 2016 to construct global oil transport networks. We adopted a weighted directed graph $G(N_y, E_y, W_y)$ to represent the global oil transport network, N_y represents all ports involved in oil trade in year y (namely, 2009,…,2016); E represents all edges (namely, routes between port pairs) linking pairs of nodes in N_y; and W_y the weights for all routes, expressed by the annual total freight volume on the route in each year y. Due to the cargo volume of each voyage cannot be accurately calculated by the data. The deadweight of each vessel was assumed to reflect the vessel's transport capacity, and it is all offloaded at a calling port.

2.2 Port Influence Diffusion Model

To study the evolution of port influence, our approach was to model the diffusion paths of the ports and the scale and geographical distribution of the ports affected at each diffusion stage. Figure 1 shows a schematic diagram of the port influence diffusion model.

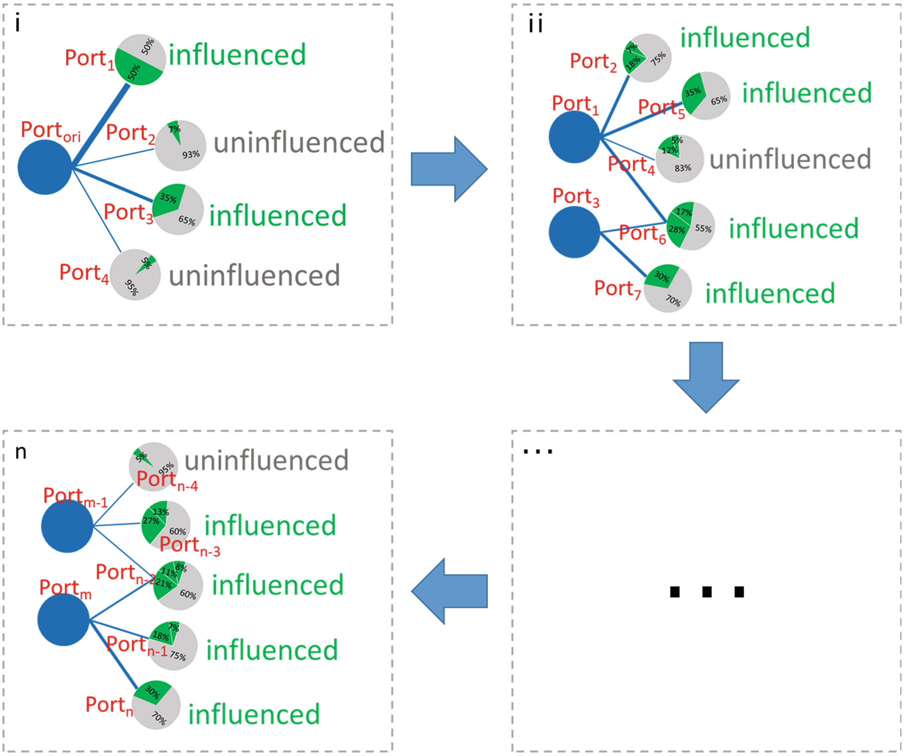

Fig. 1. Schematic diagram of the port influence diffusion model (Color figure online)

Figure 1(i) shows the first diffusion stage of the port influence mechanism. Here, $Port_{ori}$ refers to the port with the initial influence diffusion; the blue line refers to the diffusion path, where the thickness captures the freight volume from the original port to the target port, and the green sector captures the proportion of the freight volume from $Port_{ori}$ to the affected port out of all the import freight volume to the affected port. Therefore, the influence coefficient b_{uv}^{i} of port u on port v in the i th diffusion, $i = (1, 2, \ldots)$ is given as follows:

$$b_{uv}^{i} = \frac{FreightVolume_{u}^{out}(v)}{\sum\limits_{w \in N(v)^{i}} FreightVolume_{v}^{in}(w)} \tag{1}$$

where $FreightVolume_u^{out}(v)$ is the total freight volume from port u to port v (using formula (2)). $FreightVolume_v^{in}(w)$ denotes the total freight volume from port w to port v (using formula (3)), where $N(v)^i$ is the group of all ports that transport cargo directly from other ports in the network to port v in the i th diffusion, $i = (1, 2, \ldots)$.

$$FreightVolume_u^{out}(v) = \sum VesselFreightVolume_u^{out}(v) \tag{2}$$

$$FreightVolume_v^{in}(w) = \sum VesselFreightVolume_v^{in}(w) \tag{3}$$

where $VesselFreightVolume_u^{out}(v)$ denotes the freight volume of a vessel departing from port u to port v. $VesselFreightVolume_v^{in}(w)$ is the freight volume of a vessel from port w to port v, expressed in terms of the vessel's deadweight.

At this stage, the cumulative influenced value θ_v^i of port v at the i th diffusion stage is expressed as:

$$\theta_v^i = \sum_{u \in N(v)^i} b_{uv}^i \tag{4}$$

As an influenced port's influence spreads over the network, other uninfluenced ports in the network may become "influenced" (labeled "influenced" in Fig. 1) or may remain "uninfluenced" (labeled "uninfluenced"). The model is expressed in formula (5).

$$f_{influence_i}(v) = \begin{cases} influenced & \theta_v^i \geq \theta_v \\ uninfluenced & \theta_v^i < \theta_v \end{cases} \tag{5}$$

where $f_{influence_i}(v)$ indicates whether port v is influenced (labeled influenced around the node) in the i th diffusion, $i = (1, 2, \ldots)$. θ_v is the threshold of being influenced by adjacent nodes. When the accumulated influence of all neighboring influential ports of port v is greater than the threshold θ_v, port v changes to influenced status at the ith $+1$ diffusion stage, and remains with an influenced status until the diffusion ends. Otherwise, the diffusion fails to occur, but the influence coefficient is accumulated until the next stage. Without loss of generality, we set the threshold for all ports at 0.2. This meant that the node was influenced when its cumulative impact (freight volume) reached at least 20% of its total impact (freight volume). This is substantial enough to represent a significant influence of the original port on a target port.

At the first diffusion stage, $port_1$ and $port_3$ become influenced, while other ports do not change their status. The influence in the first diffusion of the port also denotes the direct influence of the initial diffusion port.

Figure 1(ii) shows the second diffusion stage. Ports that become influenced at the first diffusion stage are considered diffusion ports at the second diffusion stage. Moreover, the influence coefficient at the second diffusion stage can also be calculated by formula (1), and influence accumulated using the influence coefficient in the first diffusion stage (formula (4)) to calculate the cumulative influence coefficients of all ports at the second diffusion stage.

For port v, the accumulated influence weight of all ports is bounded by the unit value and expressed as follows:

$$\sum_{u \in N(v)^i} b_{uv}^i \leq 1 \tag{6}$$

It should be noted that at this stage, some ports are activated by the influence of stage two only, such as $port_5$ and $port_7$; while some ports are activated by the influence of both stage one and stage two, such as $port_2$.

According to the above process, we can calculate successive influence diffusion stages of the ports iteratively. Figure 1(n) shows the n_{th} stage influence diffusion, that is, the last effective influence diffusion to obtain all the ports affected by the initial diffusion port. The ports affected at the first diffusion stage are all directly influenced ports, while after the first diffusion stage are all indirectly influenced ports. Moreover, the higher the diffusion stage, the lower efficiency of the port influence diffusion.

3 Case Study

We use the above-mentioned method to calculate the influence of Rotterdam, Antwerp, and Singapore ports from 2009 to 2016. We set the influence of the port's first stage based on years, using 2009, 2013, and 2016 as representative years to analyze the development of port influence. Visualizing the path of influence diffusion at different stages and we focus on the first diffusion stage in our model as well, that is, the direct influence of the ports.

Figure 2(a)-(c) shows the first influence diffusion stage of Rotterdam. From the perspective of the spatial distribution of the influenced ports, Rotterdam's oil trade developed early as its facilities were relatively complete. In 2009, it was important in the global oil trade, and its influence area was far greater than other ports. However, due to the relatively regional scale of its oil trade, its influenced areas were concentrated in Northwest Europe, the Mediterranean region, and North America (Fig. 2(a)). At the first diffusion stage, there were 84 ports influenced by Rotterdam. This includes six ports of influence that only influenced one other port.

With the rapid development of navigation technology and the increase in the size of ships, long-distance transportation has increased, which has accelerated the spread of port influence to a certain extent. By 2013, Rotterdam's direct influence on other ports showed expansion geographically, influencing 313 ports in 71 countries, and even 12 East Asia ports including Shenzhen Port (Fig. 2(b)). Rotterdam's *direct influence ratio* reached 77.28% (out-degree of 405, $direct\ influence\ ratio = \frac{number\ of\ directly\ influenced\ ports}{out-degree\ of\ the\ port}$), indicating that most of the ports it has trade relations with were under its direct influence. In 2013, it directly influenced 96 ports in the first diffusion stage compared with 2009, but the influence among these ports was small, including only one port that could influence more than 10 ports (Kiel). In 2016, the number of directly influenced ports increased rapidly to 391 in 89 countries, and the proportion of directly affected ports reached 82.84% (out-degree of 472), indicating that the scale of directly influenced ports grew. Rotterdam had increased its influence over adjacent ports, such as the number of ports influenced in the UK and the US, which increased from 34 and 17 in

2013, to 42 and 28 in 2016, respectively. However, there was a decrease in the number of influenced ports farther away geographically from Rotterdam. For example, there was only one influenced port in East Asia (Fig. 2(c)). Among the ports directly influenced by Rotterdam in 2016, 209 were the same as those directly influenced by it in 2013, which indicates a path dependence among the ports directly influenced by Rotterdam. In addition, the number of ports of influence increased slightly, reaching 112. However, at that time, the number included some ports with significant influence including Kiel (influencing 32 ports), Montreal (influencing 18 ports), Quintero (influencing 10 ports), and Colon (influencing 7 ports).

With the rapid increase in the direct influence of a given port, its indirect influence also showed obvious growth. Not only did the number of ports influenced through fewer diffusion stages show rapid growth, but the number of ports with more influence also reflected significant growth.

In Fig. 3, we show the number of ports of influence affected by Rotterdam, Antwerp, and Singapore, at different diffusion stages (1, 2, …, 8 denote the diffusion stages). As shown in the figure, there was only one port of influence that was influenced by Rotterdam during the second diffusion stage in 2009. By 2013, there were 74 and 68 ports of influence affected by Rotterdam at diffusion stages two and three, respectively. Notably, the top 10 most influential ports in the world, except Ichihara (located in Japan, influenced in the third diffusion stage), were all influenced in the second diffusion stage. In 2016, 83 and 98 ports of influence had been influenced by Rotterdam in the second and third diffusion stages, respectively. Moreover, most of the ports with significant influence were affected in the second stage including Antwerp and Istanbul. However, the ports with significant influence in East Asia, which are relatively farther away from Rotterdam, were all influenced in the third diffusion stage, including Ichihara and Yokohama in Japan, Yeosu in South Korea, and Shanghai in China.

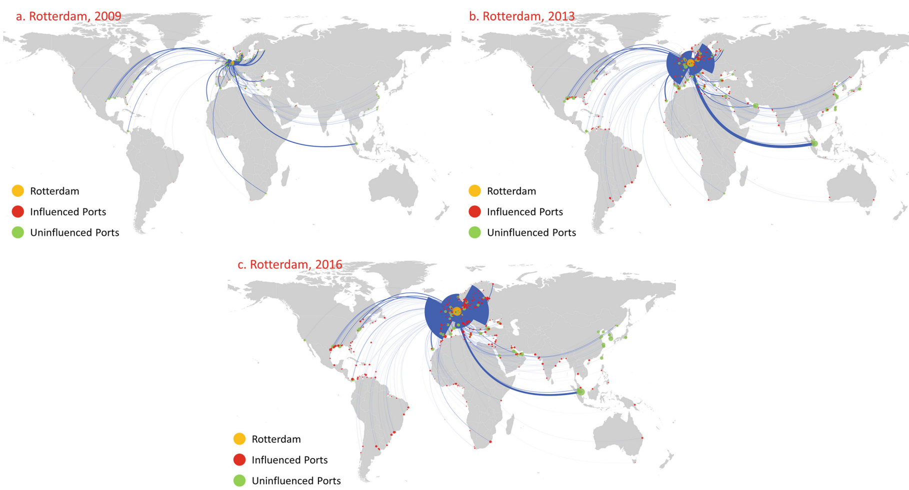

Fig. 2. Influence diffusion at first stage: Rotterdam (Color figure online)

Note: The orange node represents the initial diffusion port, while the blue line represents the real route from the initial diffusion port to other ports worldwide. The red node connected with the blue line represents a node that had been influenced at the first stage, namely, the direct influenced ports. The green node represents a node not yet influenced.

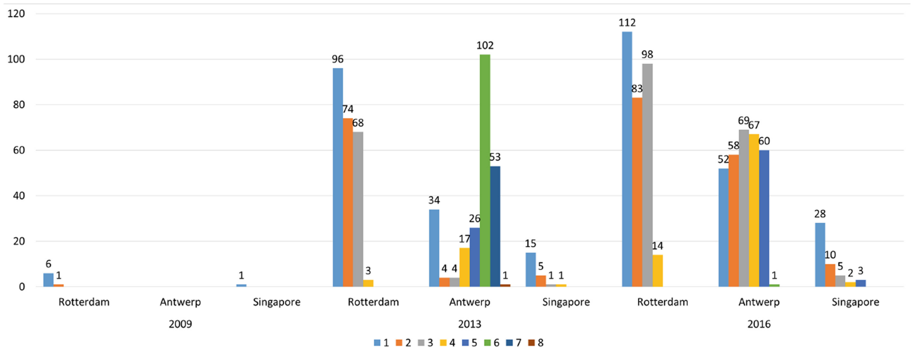

Fig. 3. Number of influenced ports of influence at different diffusion stages

Figure 4(a)-(c) shows Antwerp's first influence diffusion stage. The initial influence of Antwerp Port was relatively small. It only influenced 12 ports in 2009, and these ports were limited to Northwest Europe (Fig. 4(a)). However, the direct influence of Antwerp Port shows strong growth over time. By 2013, it directly influenced 160 ports in 49 countries (out-degree of 325), while its *directinfluenceratio* reached 49.23%. Its direct influence on the geographical distribution of the ports also reflected a relative expanding trend, included Northwest Europe, the Mediterranean region, and the Americas (Fig. 4(b)). The directly influenced ports included 34 ports all with less influence (Fig. 3). For example, the most influential port was Kristiansund, which only influenced five other ports. By 2016, the direct influence of the ports had expanded further with Antwerp affecting 228 ports in 66 countries (out-degree of 373), with a *directinfluenceratio* reaching 61.13%, and the geospatial scope of the influenced ports expanded further. In addition to the previous regions, the expansion included ports in East Africa and South Asia (Fig. 4(c)). Among the directly influenced ports, there were 52 ports of influence, although these ports had relatively little influence. Of them, Kiel was the most influential port, followed by San Vicente (affecting seven ports). The number of ports directly influenced by Antwerp, along with the number of ports of influence, and their geographical distribution were all less than that of Rotterdam. Therefore, ultimately, its direct influence was less than that of Rotterdam.

In terms of indirect influence, Antwerp reflected significant growth there as well, although still much smaller than Rotterdam. Although in 2009, Antwerp had no indirect influence, by 2013, its indirect influence showed rapid growth, which could influence almost all ports through the seven diffusion stages. Yet, the number of ports of influence it affected were all influenced in the later diffusion stages. Only four ports of influence were affected in the second and third diffusion stages. Except for Kiel, the

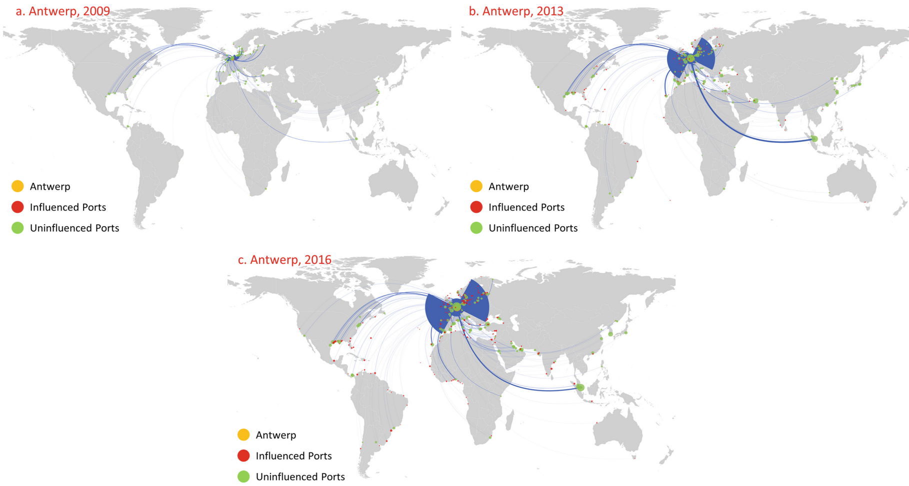

Fig. 4. Influence diffusion at first stage: Antwerp

top 10 ports with significant influence were affected in the fifth or sixth diffusion stages, while most were influenced at the sixth diffusion stage. The conclusion here is that the majority of the ports were influenced in the sixth and seventh diffusion stages, indicating that although the number of ports influenced was relatively large, the indirect influence diffusion efficiency was relatively low. However, in 2016, Antwerp's indirect influence increased significantly. Specifically, among the top 10 significant ports, Rotterdam, Istanbul, Amsterdam, and Balboa were all influenced during the third diffusion stage and most of the ports of influence were affected before the fifth diffusion stage; in the second and third stages the numbers increased to 58 and 69 ports, respectively (Fig. 3). However, Rotterdam's diffusion efficiency was greater than Antwerp's. For example, Istanbul, which ranked fourth, was affected during the second diffusion stage, and Antwerp was influenced in the third diffusion stage. With an increase in direct influence and an increase in the number of ports of influence at lower diffusion stages, diffusion efficiency of port influence improves. The most direct embodiment of this is the number of ports influenced by Antwerp's first five diffusion stages, which accounts for 91.80% of all ports influenced compared with 2013.

Figure 5(a)-(c) presents Singapore's first influence diffusion stage. Singapore's direct influence is relatively small compared with both Rotterdam's and Antwerp's. In 2019, it only influenced 14 ports, and the geographical distribution of these ports was relatively limited to the neighboring Middle East region and Southeast Asia (Fig. 5(a)). Furthermore, its first diffusion stage only influenced one port of influence, namely, Piraeus in Greece. In 2013, the number of ports influenced by Singapore's first diffusion stage increased to 115, and its *directinfluenceratio* increased to 32.86% (out-degree of 350). These directly influenced ports began to spread rapidly to East Asia, the Americas, and the Mediterranean region (Fig. 5(b)). During the first diffusion stage, Singapore was able to influence 15 ports of influence, but the influence of these ports was small (a maximum of two ports were influenced). In 2016, Singapore influenced

138 ports at the first diffusion stage, and its *directinfluenceratio* increased slightly to 34.67% (out-degree of 398), with its influenced area somewhat more concentrated in the vicinity of its port (Fig. 5(c)). The affected ports included 28 ports of influence, but these ports had a relatively small influence. For example, San Francisco had the most influence but could only influence five ports. The relatively small number of ports directly influenced by Singapore, the relatively concentrated spatial distribution of the influenced ports, and the relatively small number of ports with significant influence resulted in the direct influence of Singapore ports being much smaller than that of Rotterdam and Antwerp.

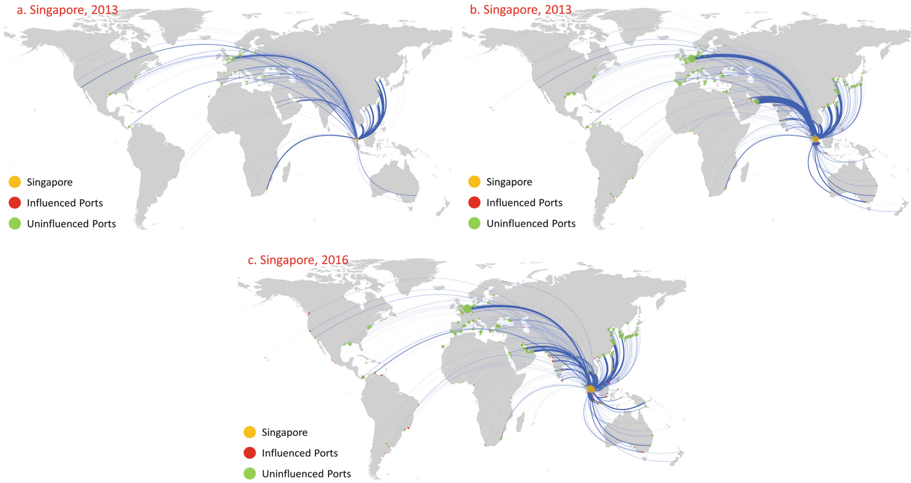

Fig. 5. Influence diffusion at first stage: Singapore

Singapore's indirect influence did, however, show an upward trend. However, the number of influential ports affected through its multiple diffusion stages remained relatively small (Fig. 3), and the number of ports affected by these ports of influence were also small, which, to some extent, limited the further expansion of its indirect influence. In 2009, Singapore had two diffusion stages, but the second diffusion stage did not affect any port of influence. In 2013 and 2016, the number of influential ports affected by the second diffusion stage increased slightly to 5 and 10, respectively, while the numbers of influential ports affected by other diffusion stages were lower. Among these ports, Sharjah in the United Arab Emirates (influenced at the third diffusion stage in 2013) was the most influential port, but still only influenced three ports. The number of indirectly influenced ports was also relatively small, and the spatial scope of the influenced ports relatively concentrated, resulting in Singapore's indirect influence being far less than that of Rotterdam or Antwerp.

4 Conclusion

Our study developed a port influence diffusion model to comprehensively analyze the evolution of the influence of Rotterdam, Antwerp and Singapore ports. The methodology considers two aspects: direct and indirect port influence based on global oil vessel trajectory data. The model identifies the influence of each port via their diffusion patterns and recursively the number of ports influenced in the network. We can get the following conclusion. The geospatial range of the ports directly influenced by these three ports continues to expand in scope to neighboring areas, and reflects rapid expansion globally. As ports with greater influence continuously strengthen their direct control, their direct influence continues to expand and grow rapidly, and the directly influenced ports become path dependent. In addition, the strong direct influence of the port improves its indirect influence to a certain extent (i.e., the number of ports influenced after two stages of diffusion) and the diffusion efficiency of the port (i.e., the number of ports influenced through fewer diffusion stages increases), forming a hierarchical diffusion pattern. Moreover, by increasing the number of ports of influence via direct influence while expanding geographical scope, indirect influence is also increased further. Thus, port diffusion efficiency can be improved by strengthening port influence on ports of influence at a lower diffusion stage. It should be noted that there is no foreshadowed relationship between the number of routes and direct port influence.

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