ANALYSIS OF TRAVEL MOBILITY UNDER COVID-19:

Application of Network Science Analytics

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Abstract

COVID-19 is substantially reshaping the tourism and hospitality industries but studies on the changes in travel behaviour in response to the pandemic are limited. Using tourism big data, this research applies network science analytics to determine behavioural changes in travel mobility of domestic travellers who visited Jeju Island, Korea, from June 2019 to December 2020. The findings reveal significant reductions in the number of trips to a destination but also limited spatial connectivity and diversity in travel flow during the pandemic. A higher intensity of travel mobility to outdoor and coastal areas and shorter travel distances are evident during COVID-19.

Keywords: Big data, COVID-19, Destination management, Network science, Travel mobility

1 Introduction

The World Health Organisation (WHO) declared the coronavirus (COVID-19) outbreak as a public health emergency of international concern on 30 January 2020, and a pandemic on 11 March 2020. The impact of COVID-19 has been enormous on most societies in general and the tourism and hospitality industries in particular. The United Nations World Tourism Organisation (UNWTO) (2020) reported that tourism is one of the sectors most influenced by COVID-19, which produces enormous negative influences on economies, livelihoods, public services, and opportunities. For example, the revenue from tourism fell to $910 billion from $1.2 trillion in 2020, associated with the reduction of the global GDP to 1.5% from 2.8% (ibid.). This scenario can put over 100 million direct tourism jobs at risk.

Recognising the substantial impact of COVID-19 and challenges in the tourism industry, a number of studies with special issues in academic journals (e.g. *Annals of Tourism Research, Tourism Geographies*, *Sustainable Tourism*) have discussed COVID-19 in tourism in terms of destination and accommodation demand (Dolnicar & Zare, 2020; Liu et al., 2021), the market valuation of tourism firms (Sharma & Nicolau, 2020), and strategic responses during and after the pandemic (Jiang & Wen, 2020; Y. R. Kim & Liu, 2022). For example, Yang, Zhang and Chen (2020) suggested that the influence of the coronavirus outbreak on the tourism sector caused by the declining health status is directly related to labour productivity and efficiency as well as tourism demand. Tourism and hospitality firms – including hotels, airlines, cruises, and car rentals – instantly responded to the pandemic yet suffered a substantial fall in market valuation (Sharma & Nicolau, 2020). In addition to assessing market reactions to the pandemic, tourism scholars have attempted to understand the psychological responses of travellers/residents/employees to the pandemic (Kock, Nørfelt, Josiassen, Assaf & Tsionas, 2020), including the willingness to pay social costs (Qiu, Park, Li & Song, 2020), and travel planning behaviours (Li, Nguyen & Coca-Stefaniak, 2020) as well as employees' stress and well-being (Chen, 2020). More importantly, however, this study argues that the research to understand changes in travel behaviours in response to the pandemic is largely limited.

Research to explicate the behavioural changes of travel flow within a country/destination is particularly scarce (Zenker & Kock, 2020). Insights exhibiting the behavioural changes of travellers before and during/after COVID-19 should be crucial for tourism destinations to develop strategies to prevent the spread of the coronavirus by visitors and to develop destination plans for the post-pandemic period. A recent article published in *Science* has demonstrated the association between human mobility and the spatial distribution of COVID-19 cases in China (Kraemer et al., 2020). However, Kraemer et al. (2020) did not examine the daily travel flow and patterns pre- and during-COVID-19 and the properties and characteristics of the spatial distribution and heterogeneity of the movement of travellers during the pandemic. Additionally, many studies lack in theoretical importance when analysing travel flow; past studies have focussed on how to track travel flows and methodological contributions to analysing travel mobility. Accordingly, this study analyses tourism big data representing information about daily travel flow and aims to provide empirical evidence of the changes in travel mobility between before and during the pandemic by adopting the theorem of network science and complexity to theoretical discuss the behavioural changes of travel mobility elicited.

Indisputably, the COVID-19 crisis is exclusive in its impact on various aspects of our society, which represents multiple typologies. Rather than investigating a single aspect (or association) of such an impact, Zenker & Kock (2020) suggested an approach to characterise a complex and connected typology and to employ chaos theory and/or system theory to reveal non-linear relations. In this sense, network science is not only a study of identifying network systems consisting of numerous nodes and edges based upon mathematical techniques, but also a key theorem of understanding a social-spatial system as a network of structures (Baggio, 2017). The approach of network science enables tourism researchers to explore or characterise destination complex systems associated with travel flow and thus uncover the structural features and model the dynamic behaviours in destination networks (Newman, Barabási & Watts, 2006; Xu, Li, Belyi & Park, 2021), in which this current study applies.

To address the research purpose, this research aims to empirically analyse the behavioural changes in travel mobility before and during COVID-19 using network science and complexity theory. This research analyses a large set of tourism big data, collected from a car navigation application, of domestic travellers who visit Jeju Island in the Republic of Korea (hereafter Korea), providing empirical evidence of the actual patterns of traveller mobility before and during COVID-19. Since the dataset contains information about the visitors' daily travel flow from the middle of 2019 (*Before COVID-19*) to the end of 2020 (*During COVID-19*), this study was eligible to compare the quantitative indicators of network science analytics representing travel flow and to understand the travel flow patterns and mobility behaviours pre- and during-COVID-19. Note that Korea did not carry out the lockdown on people's movement within the country at the start of the pandemic outbreak, which meant that travellers were allowed to travel to any place and any time in the country. This allowed the researchers to monitor travel mobility without the potential influence of a government restriction policy, which was unique at the time when other countries implemented strict travel restrictions and containment measures (e.g. border closures). Thus, the chosen research context and unique data demonstrate significant contributions to the existing travel behaviour and crisis management literature and empirical evidence.

Applying the theory of network science and complexity, this study scopes tourism as a non-linear, complex, and dynamic system. Coupled with the assumptions of protection motivation theory and risk perception, data-driven evidence of changes in travel mobility within Jeju pre and during COVID-19 confirms existing literature (e.g. Li et al., 2021; Park et al., 2021) but also expands the theoretical knowledge of travel behaviour and mobility in the perspective of network science and properties in the context of crisis management. The findings of this research provide important data-driven implications for tourism organisations and destinations in preparing for accommodating the influx of visitors post-pandemic by understanding the network properties of travel behaviour and mobility within Jeju and changes in travel preferences and subsequently developing strategies (e.g. digital tools to monitor crowding, design open spaces and natural attractions to accommodate tourists in the long run, etc.) to prevent the pandemic crisis and revive the tourism phenomenon.

The rest of the paper is organised as follows. Section 2 reviews existing work on travel behaviour and crisis management in tourism and the application of network science analytics in tourism. Section 3 presents the data and methods of collection and analysis. Section 4 presents the findings and analyses of the data, identifying the travel flow and behavioural patterns using network analytics. Section 5 concludes with the discussion of the findings and summary of the implications for knowledge and practice.

2 Literature Review

2.1 Travel Behaviour and Crisis Management in Tourism

In the history of modern tourism, unexpected events such as a crisis or disaster have led to significant impacts on travel behaviours or flow but also tourism demand, leading to wider socioeconomic consequences for both the destination and wider economy (Mair, Ritchie & Walters, 2016). For example, Rosselló, Santana-Gallego & Awan (2017) inferred a significant decline in tourist arrivals in countries that were affected by Malaria, Ebola, Dengue and Yellow Fever. With COVID-19, Karabulut, Bilgin, Demir & Doker (2020) and Yang et al. (2020) studied its implications for tourism demand and arrival in various country contexts. Examples not only include epidemics/pandemics and natural disasters, but also economic downturns (Sheldon & Dwyer, 2010), political turmoil, and terrorist activities (Scott, Laws & Prideaux, 2007). Despite the increasing volume of tourism crisis management literature, still many tourism destinations struggle to prepare and respond to crises, which has been evident with the recent pandemic.

Each crisis or disaster has its own causes, impacts and recovery patterns but it has been evident in the tourism crisis literature that the industry tends to be more resilient than others in terms of recovery speed and adapt to change (Reddy, Boyd & Nica, 2020). A possible explanation could be the complex but open and adaptive nature of the tourism system, which can lead to alternative travel behaviours and distribution of flow. Understanding the tourist mobility is a central issue for understanding tourist behaviour, what attractions, goods and services can be offered to tourists in a specific place/space and time and can support governance bodies and policymakers in planning and development that are empirically driven (Lew & McKercher, 2006). Tourist mobility has been evaluated from the perspective of tourist arrivals or revenue (e.g., Huang et al., 2020; Yang et al., 2019) and at different scales – i.e. inter- and intra-destination flow patterns (e.g., Deng & Hu, 2019). In times of crises, any disruption to a destination leads to significant alterations in travel flows, from intensity (e.g., volume and frequency) to direction and pattern (e.g., static and dynamic flow) (Lew & McKercher, 2006), which can lead to changes in the dynamics of tourism demand and supply during such circumstances. Following the affiliation motivation theory (Hill, 2009), tourists tend to visit places where many people visit as human beings desire social contact with others, which forms clusters of tourists within attractions and destinations. However, in times of crises, tourists tend to have high levels of perceived risk when places are crowded and highly clustered, leading to social distancing according to social contact theory (Im et al., 2021; Park et al., 2021). The risks of COVID-19 transmissions directly impact on travel flow and behaviour. For example, tourists avoid travelling to crowded environments to mitigate the spread of infection (Hu et al., 2021; Sigala, 2020) based on the protection motivation theory (Nazneen et al., 2022). Travel frequency and distance would decrease (Bae & Chang, 2020; Li et al., 2021; Yang et al., 2018), and tourists tend to avoid congestion, seasonality and overtourism. Diversification of travel patterns is evident where tourists prefer open spaces, individual travel and luxury travel (Park et al., 2021). Kim and Kang (2021) showed that perceived crowding during the COVID-19 directly impacts on leisure activity participation and high risk perception leads to social distancing behaviours (Kim & Liu, 2021).

Additionally, tourism mobility has been examined using traditional methods of data collection such as surveys and interviews (Shoval & Ahas, 2016), which restricts the analysis of travel flow and mobility to a micro scale and limited sample size. With increasing access to tracking sensor such as GPS, Wi-Fi positioning, cell-tower identification, Bluetooth and mobile data, inter- and intra-destination flow patterns have been investigated (e.g. Deng & Hu 2019, Xu et al., 2021). Yet, behavioural changes in travel flow within a destination are still limited, especially in times of crises (Zenker & Kock, 2020) and when considering the complexity of change in travel flow. It is important to acknowledge the spontaneous and unpredictable nature of a crisis but also the dynamic changes in mobility that can redirect tourism flow and spending in non-affected regions in response to a crisis.

Crises are chaotic and dynamic, which has huge implications for tourism destinations. Chaos and complexity theories can be used to explain the dynamical behaviour of a tourism destination (or system) (Tinsley & Lynch, 2001). These theoretical applications consider tourism destinations or operations as a nonlinear and complex interaction of the system's elements or actors, combined with the influence of external (unforeseen) factors (Baggio, Scott & Cooper, 2010; McKercher, 1999). Crises and their impact on tourism destinations challenge the Newtonian (linear) thinking of stability and predictability (Reddy et al., 2020), but existing risk or crisis management models have typically been structured linear and logical, that are unable to embrace the complexity and chaotic nature of crises and disasters (McKercher, 1999; Zahra & Ryan, 2007). Therefore, the complex system approach has been considered a more effective framework for understanding changes in tourism: how crises influence the sector and individual tourist movement.

Many scholars have referred to tourism as a non-linear, complex, and dynamic system, which can be explained by the chaos theory (Zahra & Ryan, 2007). Thus, in times of crises and uncertainty, it can be argued that the chaos and complexity theory is a more appropriate theoretical perspective to analyse destinations and the abrupt changes at the individual tourist level (i.e. travel behaviour, movement and motivation), sector level but also at the spatial level (Baggio & Sainaghi, 2011). There are various ways of analysing such complex systems, of which one is network (science) theory (Casanueva, Gallego & García-Sánchez, 2016; Lozano & Gutiérrez, 2018). Different interconnected elements or agents are strongly influenced by the topology of connecting networks, which models the network system. Given the complex and dynamic nature of a tourism system, a destination can be seen as a network system and travel patterns and flows tend to form different networks and clusters based on spatial clustering (e.g. Kim et al., 2021) and affiliation motivation theory (e.g. Park et al., 2021). Alternative methods of analysing complex systems include non-linear dynamics and statistical physics (Baggio, 2009) but these modelling techniques are still limited in capturing the self-organisation and self-similarity phenomenon in a tourism system. Tourism demand models have taken non-linear dynamics and statistical physics (Song & Li, 2008) and spatial aspects have been considered in visitor flow patterns and spillover effects (e.g. Kim et al., 2022) but such spatial models remain linear. Thus, to embrace the nonlinear, chaotic and complex interactions within a tourism destination and analyse dynamic changes in travel mobility, network science analytics is most suitable in the context of the current study. The following section will review network science in tourism.

2.2 Network Science in Tourism

Originating from mathematical models of the graph theory, network science is a study of network models that aims to identify possible unifying principles to describe structural features and model dynamic network behaviours to explain what is happening in the observed systems (Park, Xu, Jiang, Chen & Huang, 2020). Networks are represented by graphs composing nodes (vertices) with links between them (edges) (Xu et al., 2021), and they tend to be analysed in three levels: microscopic (properties of single nodes, e.g. closeness, betweenness, centrality), mesoscopic (intermediate network structures from a modularity analysis, e.g. edges, communities, directionality and weights), and macroscopic (global topological characteristics, e.g. degree distributions, average path lengths) (Baggio, 2017). Yet, networks are not only understood as topological objects, but as a dynamical system framework derived from both empirical and theoretical questioning (Newman et al., 2006). For example, understanding tourism flow between destinations and routes, relationships and networks of stakeholders, and managing relations between tourist and/or destinations, etc. (Casanueva et al., 2016).

Network science can improve the understanding of the complex and adaptive tourism system. For example, understanding topological (e.g., Baggio et al., 2010) and structural characteristics of destinations and tourism supply chains (e.g., Tran et al., 2016), formation and effects of social capital (e.g., Sainaghi & Baggio, 2014), virtual or digital destination ecosystems (e.g., Becheru et al., 2016), and stakeholder collaboration and networks (e.g., Scott et al., 2008). A major application of network science is the mobility of tourists. In the context of tourist mobility or flow, network science provides methodological tools to measure the relationships among destinations and to describe and visualise network structures, illustrating spatial distributions of tourism mobility (S. Park et al., 2020). Lozano & Gutiérrez (2018) explored global tourism networks via origin and destination market structures and interactions using tourism big data. Wu, Wang & Pan (2019) used network analysis and agent-based modelling to network inbound tourism in China. Xu et al. (2021) have used large-scale mobile positioning data to characterise destination networks via movement patterns of international tourists in Korea.

Philosophically related to systems theory, the social network theory also conceptualises a tourism destination as a network of organisations (Casanueva et al., 2016). From a social network perspective, crises put pressure and tension on such networks and relationships, which leads to significant changes in the relationships but also the social (and travel) behaviour within and across networks (Scott et al., 2007). For example, SARS significantly reduced international tourist arrivals in Australia but a boost in domestic travel to the Gold Coast (ibid.). Litvin & Alderson (2003) found significant impacts on the Charleston Convention and Visitors Bureau from the 9/11 crisis via diversifying promotion expenditures to different markets. However, understanding changes in travel behaviour in response to a pandemic is largely limited; this is crucial for destinations to develop strategies to mitigate the spreading of the virus but also to better plan and manage the destination.

It is acknowledged that there are non-tourism studies on COVID-19 and network analytics to understand human mobility. Hâncean et al. (2021) studied the impact of human mobility networks on the COVID-19 spread in 203 countries but the focus on the behaviour of travellers, which are different from migrants and residents, is minimal. Chang et al. (2020) examined human mobility network models in response to COVID-19, focussing on the inequities of racial and socio-economic disparities in infections and deaths. Yet, the focus of leisure-purposed travel mobility is neglected, which can present distinct behavioural patterns under different government restriction policies. Klise et al. (2021) analysed mobility data to understand the contact network of COVID-19 and inform strategic containment measures. However, this paper used aggregate mobility data and interactions of mobility at places of interest such as restaurants, schools and parks and at home. Similar to other studies, the focus on attractions and destinations and thus leisure-purposed travel mobility has had little attention, mainly due to national lockdown measures in many countries. The network science approach can embrace the nonlinear, chaotic and complex interactions within a tourism destination combined with the influence of unforeseen external factors, i.e. COVID-19, and analyse dynamic changes in travel mobility within a destination. Additionally, the context of Korea, where domestic travel was not restricted at the first wave of COVID-19, provides a unique research case to explore travel mobility and its networks before and during the early outbreak of COVID-19 and understand the spatial behaviours and characteristics in a destination.

3 Methodology

3.1 Data Collection

This study explores Jeju Island (hereafter Jeju) that is the largest island in Korea and is bigger than other popular destinations in Asia, such as Hong Kong, Macau, and Singapore. Jeju contains a number of world heritage sites and a variety of travel attractions, attracting over 15 million visitors in 2019 and make it the most popular tourism destinations in Korea (The Jeju Weekly, 2020). As a result, Jeju can be selected as an important case study and that the findings from the data analysis generate essential insights in travel mobility.

The authors have collaborated with one of the largest telecommunication companies in Korea, providing a mobile navigation application. Daily mobile navigation records of domestic travellers visiting Jeju Island were collected over a time span of one and a half year (1 June 2019 – 31 December 2020). Note that travellers have been defined as those who visit Jeju but whose residential places are outside of Jeju. Car rental is the most popular transportation method when domestic travellers visit a Jeju island (Jeju Tourism Organization, 2020). Thus, analysis of mobile navigation data can address a representative issue in understanding travel mobility. The high-resolution three-dimensional data covers space (latitude and longitude of origins and destinations in Jeju) and time (daily trip dates) with the activity category associated with points of interest (POIs) and the number of travellers showing an identical travel flow. The full data set includes over 13 million records during the period of the data collection. More specifically, Table 1 shows an example of the aggregated daily navigation data sets reflecting the usage of the navigation app when car drivers find their routes in Jeju during their trips. The coordinate information (latitude and longitude) of origins and destinations denote the central points of grids scaling 100m × 100m. Origin refers to the place where the car drivers access the navigation app, and destination denotes the place where the car drivers arrive following the routes suggested by the app. This data set includes two types of demographic information: gender (female and male) and age (10, 20, 30, 40, 50, 60, and 70 years old or above). Furthermore, the information about POIs associated with the features of destinations has been recorded. Lastly, count refers to the total number of daily navigation users who have shown identical origins and destinations with the same features of demographics and who seek the same activities on the same dates. Overall, the data set provides a fine-grained view of tourist mobility in terms of both time and space as well as certain activities at the destination. Note that the first confirmed COVID-19 case in Korea was recorded on 20 January 2020, and the WHO declared the COVID-19 outbreak to be a public health emergency on 30 January 2020. Thus, the data of 'before COVID-19' includes the information for travel flow from 1 June 2019 to 31 January 2020, and 'during COVID-19' ranges from 1 February 2020 to 31 December 2020.

[Please insert Table 1 here]

3.2 Data Analysis

Initially, a set of descriptive statistics were computed for domestic travellers in Jeju to develop an understanding of the travellers' characteristics and daily trip count patterns over time. The large-scale navigation data set was analysed for the periods before and during COVID-19, respectively.

Having explored the nature of the data through a basic statistical approach, we proceed to employ network science methods to analyse traveller mobility patterns. More specifically, this research explores a set of network properties that allow researchers to uncover the characteristics of the destination network and define network models (Barabási, 2003; González et al., 2008). The main purposes of investigating network properties are to quantify the distributions of network attributes and network structures and to statistically compare their differences between before and during the pandemic. A destination (i.e., Jeju) represents the underlying large-scale network which contains a set of nodes and edges (Xu et al., 2021). In this study, a node is defined as an area situated within a 100m x 100m km space, and an edge connects any two nodes via travel flow. The network is undirected models before and during COVID-19 separately based on the topology of directed networks. That is, the undirected network contains both directions of travel flow between the two places (or grids). With regard to the human mobility in network science (Shida et al., 2021), a series of network attributes and mobility indicators are estimated including numbers of nodes and edges (or network size), degree, node in-strength, network density, and distance travelled. Furthermore, the attempts to identify the models that best fit the distributions of the attributes (Power-law vs log-normal vs exponential fit) and relationships between network attributes are conducted.

Node degree, k_i, refers to the number of edges to which a node is connected. An undirected network does not differentiate between in-degree and out-degree; therefore, the total degree is the total number of regions connected to a node. The total degree of a node i is given by k_i:

$$k_i = k_i^{in} + k_i^{out} \tag{1}$$

where k_i^{in}refers to the number of edges directed to the destination (i^{th}node) and k_i^{out}refers to the number of edges to which the destination (i^{th} node) is directed. The total number of edges, E, in a network is measured by the sum of node degrees divided by two:

$$E = \frac{1}{2}\sum_{i=1}^{N} k_i \tag{2}$$

where k_i is the degree of the i^{th} node and N is the total number of nodes.

In a weighted network, an edge carries the information for the number of tourists travelling between the two grids (or nodes), also known as an edge weight, $w(e_{j,i})$. The node in-strength sums all the edge weights directed to a particular node and represents the total number of trips using the mobile navigation application to find directions while travelling Jeju; edge weights correspond to the number of application usage in a certain travel flow. The node in-strength, s_i, of a node i is defined as follows:

$$s_i = \sum_{e_{j,i} \in E_i} w(e_{j,i}) \tag{3}$$

where $w(e_{j,i})$ refers to the weight of edges connecting to the j^{th} node and the i^{th} node in the destination network and vice versa.

Undirected network density, C, expresses the number of edges in a network as a proportion of total potential edges. This value is computed by the following equation:

$$C = \frac{2E}{N(N-1)} \tag{4}$$

where N refers to the number of nodes in the network, implying that $N(N-1)$ represents total possible edges and E refers to total edges.

The distance travelled is measured using the haversine formula (Mahmoud & Akkari, 2016), where d is the distance between central points of two grids with longitude and latitude (ϕ, φ) and r is the radius of the Earth:

$$d = 2rsin^{-1}\left(\sqrt{\sin^2\left(\frac{\phi_2-\phi_1}{2}\right)+\cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\varphi_2-\varphi_1}{2}\right)}\right) \tag{5}$$

The haversine formula is commonly used in Geographic Information Systems (GIS) and navigation as it computes the distance between two coordinate points, assuming a spherical curvature of the earth (Chopde & Nichat, 2013).

The spatial visualisations of node degree and node in-strength allow us to directly identify network differences prior to and during the pandemic with respect to each metric. To visualise the network according to node degree, we compute the average node degree at each node across the eight months starting in June 2019. This is repeated for the four months during the COVID-19 pandemic in a separate figure. The two figures are scaled by size so that only points that exceed or are equal to the threshold (an average degree value of 250) are visible on the map. The average node degree for undirected networks, ⟨k⟩, is given by the following equation:

$$\langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i = \frac{2E}{N} \tag{6}$$

where *N* refers to the number of nodes in the network and *E* refers to the number of edges.

Similarly, we compute the average node in-strength at each node before and during the COVID-19 pandemic. Average node in-strength, $\langle s_i \rangle$, is computed by the following equation:

$$\langle s_i \rangle = \frac{1}{N}\sum_{e_{j,i} \in E_i}^{N} w(e_{j,i}) \tag{7}$$

where $w(e_{j,i})$ refers to the weight of edges connecting to the j^{th} node and the i^{th} node in the destination network and vice versa and N refers to number of nodes.

Next, the distributions of node degree and node in-strength evoke important insights. These distributions provide an understanding of the statistical probability of nodes with metric values above or equal to a specified level. Degree distribution, p_k, measures the probability of any selected node with a degree value above or equal to level k. p_k counts the frequency of nodes with degree value k, N_k, and computes the proportion of N_k in a network of N nodes. The normalised probability, p_k, is given by the following equation(s):

$$p_k = \frac{N_k}{N} \tag{8}$$

$$\sum_{k=1}^{\infty} p_k = 1 \tag{9}$$

The fitted distributions were assessed to reveal differences in connectivity across the network before and during the pandemic. The identical approach has been applied to analyse the in-strength of all the nodes. This reflects the variations in the number of in-bound tourists across destinations in Jeju before and during COVID-19.

4 Results

4.1 Descriptive Statistics

Figure 1 presents the number of daily travel flows (i.e. origin–destination trips) in Jeju over a year (a solid blue line) and the number of daily COVID-19 cases in Korea (a dashed red line).

The count distribution of daily trips in 2019 appeared relatively stable, while some seasonality patterns were observed during the holiday seasons. Educational institutions in Korea go on break for the summer holidays, mostly from June through August. In this sense, tourist visits peaked in August and the maximum daily number of trips on 2 August 2019 was 46,244 trips. Mid-March marked the absolute minimum daily number of trips of just below 650. We also noticed a spike in trip counts at the start of May; during May in Korea, a series of consecutive public holidays encourage employees to take extra days off work and enjoy a longer break.

[Please insert Figure 1 here]

More importantly, the daily trip counts show a gradual downturn starting from February 2020 to April 2020. The daily new COVID-19 cases instinctively show a negative correlation with the daily trip counts. The WHO officially confirmed the COVID-19 outbreak to be a global pandemic on 11 March 2020. Consistently, by the end of March, the number of new cases in Korea plummeted and continued to drop throughout April and May. In April, when the number of new COVID-19 cases was notably reduced, the number of daily trips showed gradual growth in addition to national holidays in Korea. Once the COVID-19 situation seems better, the number of trips in Jeju increases from May to August 2020. In September and December 2020, the change of trip counts is quite responsive to showing a negative relationship between trip count and new COVID-19 cases in Korea. Accordingly, the results suggest the noteworthy impact of COVID-19 on travel behaviours.

4.2 Tourism Network Properties

This section estimates the impact of COVID-19 on traveller mobility in Jeju using network science methods. To analyse behavioural changes of visitors with travel purposes before and during COVID-19, we capture the travel flow of tourists during their visits to the destination. For each network model, nodes represent particular areas (or 100m x 100m grids) in Jeju that serve as origins or destinations unless specifically stated. These designated nodes encompass over 400,000 numbers of granularity around Jeju. Each node connects to other regions across Jeju via the travel flow of inbound or outbound travellers, and these connections are referred to as edges.

Table 2 shows the statistical results of undirected network models according to three-time phases: before (1 June 2019–31 January 2020) and during (1 February 2020–31 December 2020) COVID-19 as well as the overall (the entire year-long data collection period). During the pandemic, the results revealed fewer average nodes, edges and in-strengths in destination networks, implying that the pandemic outbreak brings about the decrease of travel flow across the destination network.

[Please insert Table 2 here]

The individual statistical results presenting the trends of the network science indicators over time are shown as follows (see Figures 2A–2C). Figure 2A shows the monthly average degree in Jeju. This degree was at its maximum value of 35.05 in August 2019. This means that on average, a destination node is connected to 35 different nodes (or 100m by 100m spatial grids) via travel flow. Given the pattern before COVID-19, the average degree remained quite stable during this period, from 26.85 to 35.05. This implies that few changes occurred in the connectivity of a destination node before the pandemic. Importantly, the pattern of node connectivity showing a dramatic decline in average degree during COVID-19 is identified: a lower number of connections per node or less spatial interactions occurring among origin–destination places within the network. The average degree reached its minimum in March and June at values of 19.33 and 19.15 respectively, revealing that a destination has spatial interactions by an average of 19 links to other areas in Jeju. As a result, during COVID-19, one would less likely encounter connections between any two regions in Jeju. Similar to trip counts (Figure 1), the average degrees in September and December 2020 when new COVID-19 cases sharply increase were dropped considerably. This means that the situations of COVID-19 affect not only the number of trips but also travellers' mobility patterns (compressed movement behaviours) at the destination.

[Please insert Figure 2A here]

Figure 2B shows the average travel distance (kilometres) per trip at the destination. Consistent with the average node degree results, the average distance travelled – approximately 11.15km – was observed to be steady before COVID-19. In comparison, average travel distances during COVID-19 have been more dynamic since February 2020. Considering the COVID-19 timeline of Korea, there are a couple of pandemic waves: the first wave (30^{th} January 2020 – 18^{th} February 2020) and the second wave (12^{th} August 2020 – 30^{th} September 2020). During the first wave, while travel distance has rapidly dropped right after the pandemic outbreak, it has been quickly recovered after the situation of new COVID cases was stable. Interestingly, the distance has been reached even beyond one before COVID-19. After the second wave, however, the average travel distance was reached at the lowest level and it has not been recovered promptly unlike the pattern in the first wave. This implies that the travellers' perceived risks of COVID-19 between the first and second waves show distinct differences, which generates heterogeneous travel mobility patterns (Ren et al., 2022). This supports literature on how perceived risk directly impact on travel behaviour and mobility as tourists fear the risk of disease transmission and tend to travel shorter distances (Li et al., 2021). Additionally, slower recovery of travel distance after the second wave could suggest higher levels of perceived risks as the COVID-19 spread evolved over time. This also implies the importance of monitoring risk perception and travel mobility patterns over time.

[Please insert Figure 2B here]

Figure 2C plots the monthly network density of Jeju, showing that before COVID-19, such network density ranged between 0.00070 and 0.0008224. As expected, August 2019 exhibited the strongest network density, which means that the proportion of the total number of edges (travel flows) within the Jeju network relative to the number of possible edges is relatively high. This suggests substantial traveller movement between many different areas across Jeju during August 2019. Along with the pandemic outbreak, however, the network density dropped to 0.00063, 0.00060 and 0.00058 in February, March and April 2020, respectively. This result suggests that travellers were less likely to visit diverse places as well as tended to avoid the high-density places and fulfil social distancing during their trips. This supports the diversification of travel mobility where tourists prefer open spaces, individual travel and luxury travel owing to social contact theory and social distancing which argues that people will try to avoid contact with others during a pandemic and thus avoid travel to crowded environments (Park et al., 2021). Yet, taking the view of network science and destination as a complex system, the strong network density and viewing a destination as a system of networks supports the application of network science in such study context and scope. As mentioned above, the state of COVID-19 in Korea improved substantially after April, which justifies the strong network density in May. This dynamic pattern has been observed in December 2020 when the new cases of COVID-19 reach the highest volume.

[Please insert Figure 2C here]

In addition to statistical comparisons of network science indicators, this section presents the spatial features and areas influenced by the occurrence of COVID-19 based on degree and in-strength. Figures 3A and 3B visualise the quantitative results, where the magnitude of the corresponding feature is represented as a circle and colours. Areas with the largest values are also annotated to emphasise and compare the scales of key places. For instance, the circles in Figure 3A visualising the average degree are coloured and sized according to average degree value where dark red colour symbolises destinations with high average degree values as opposed to blue colour referring to low values. The network before COVID-19 appears to be more populated with red and orange colour circles, which demonstrates several high dense places throughout the destination network. The drop in average degree across Jeju during COVID-19 is evident; dot-sized blue points (or purple circles) dominate the network, meaning that most places at the destination possess a limited degree with other areas. A lower average degree implies more concentrated connectivity and reduced spatial interactions among nodes (or spatial grids). For example, the central area of Jeju – Seogwipo (the 2nd largest city in the mid-south of the island) – looks less connected during COVID-19, while the coastal areas and places to enjoy natural resources are still highly connected to other places. The south-east area of Jeju was not considered as a key place with negligible degree values. This is because, based on local knowledge, the south-east area comprises of popular attractions such as folk villages and theme parks, which operated during the COVID-19 outbreak and where close contact between travellers are required. In addition to the spatial interactions, the results about in-strength (i.e., number of trips using the navigation app) have provided consistent findings. According to Figure 3B, two coastal areas (i.e., left-top and -bottom of Jeju) have been newly observed as places with a high number of trips visited during COVID-19. Note that Appendix I provides more detailed spatial interactions in a by network analysis. In brief, the movement patterns driving between North and South areas in the island have been apparently observed before COVID-19 whereas the travel mobility during COVID-19 disappeared. Instead, the travel routes across coastal areas have been more noticeable during COVID-19. Travel preferences and mobility behaviour are directly influenced by risk factors such as the threat of COVID-19 infection and thus the change in travel routes towards more open spaces and natural attractions are a result of tourists' perceived risk and avoidance of contact-intensive places based on the protection motivation theory (Nazneen et al., 2022). Yet, empirical evidence on such changes in travel flow and mobility has been limited due to the lack of granular data to capture such real time and dynamic data of tourists. Using network science, data-driven evidence supports existing theories on behavioural change in times of crises but also confirms empirical insights.

[Please insert Figure 3A and 3B here]

4.3 Modelling Network Formation

This section estimates the distributions of node degree and node in-strength in a large destination network to understand the attractiveness of specific places in Jeju. We first considered the candidate distribution best fit for travel flow data. The distributions of both the node degree and node in-strength data are visualised and compared by the goodness of distribution fits for the power law, lognormal, and exponential distributions (Alessandretti et al., 2017). Having evaluated the log-likelihood ratio and the significance of this likelihood value, the results suggest that the network distribution of degree and in-strength can be best fit by the lognormal distribution. Initially, this means a heterogeneity of place attractiveness in Jeju: few places have a large number of visits although many places attract few visitors.

In Figures 4A and 4B, we plot the fitted lognormal complementary cumulative probability distributions (CCDF) for degree and in-strength before and during COVID-19, respectively. In terms of degree (Figure 4A), the plot represents the proportion of nodes with degree k (node: spatial grids in Jeju). The statistical results reveal that the standard deviation (σ) of the logarithm of node degree is higher during COVID-19 than one before COVID-19, suggesting more spatial occurrences and greater connectivity between areas in Jeju before the pandemic. That is, few places in Jeju have large numbers of links to other places during COVID-19, which demonstrates the consistent argument with Figure 3A. Normalised in-strength refers to the proportion of trips visiting node i. We found that the σ value of the logarithm of node in-strength is higher before COVID-19 (Figure 4B). This means that few places have a large number of visits while many places attract few visitors. Indeed, travellers during COVID-19 are likely to visit selective places with limited diversity of travel mobility rather than widely distributed into various places.

[Please insert Figure 4A and 4B here]

4.5 Relationships between Network Properties

In addition to identifying the distribution best fits of network degree and in-strength, this section estimates the relationships between them, such as degree and in-strength. This allows identifying key hubs of attraction within the network. Two plots are shown for each relationship studied before (Figure 5A) and during (Figure 5B) COVID-19. The similarity in distributions indicates that COVID-19 did not majorly influence the relationship between node degree and node in-strength. Both figures demonstrate a non-linear relationship, which gradually disperses in the dimensions of degree and in-strength. In general, this means that extremely few destinations within Jeju have both high degree and high in-strength, a finding that resonates with the preferential attachment principle in network science (Hébert-Dufresne et al., 2011). Preferential attachment, also known as the rich-get-richer phenomenon, proposes that any new node in a network is more likely to link with a highly connected node rather than a node with few edges (Barabási, 2016). The application of network science and chaos and complexity theory in the context of tourism is important in revealing the changes in networks within a destination (Park et al., 2020) in response to COVID-19. Therefore, these destinations and properties ultimately become hubs within the network, which can be further explored and strategised for the post-pandemic era.

[Please insert Figure 5A and 5B here]

5 Discussion and Conclusion

The COVID-19 pandemic has substantially influenced the tourism and hospitality industries and is entirely reshaping these sectors (Sigala, 2020). This research analysed tourism big data collected from a mobile navigation application, which includes 13 million trip records referring to the daily travel flow of domestic visitors to Jeju in Korea from June 2019 to December 2020. Taking a complex system approach (Baggio & Sainaghi, 2011), this study applied network science analytics to determine behavioural changes in travel mobility from travellers who visited Jeju in periods before (June 1, 2019–January 31, 2020) and during the pandemic (February 1, 2020–December 30, 2020). The results reveal that not only the number of trips to a destination have declined, but travel flow has also shown limited spatial connectivity and diversity during the pandemic. Additionally, travellers visiting a destination (Jeju) during COVID-19 tend to show a higher intensity of travel mobility in specific areas at destinations with shorter travel distances than those who travelled before COVID-19. Furthermore, travellers during the pandemic are likely to visit coastal areas and nearby beaches rather than stay in the inner city of Jeju. This research provides important theoretical and practical implications.

Given the limited understanding of travel behavioural changes in response to a pandemic but also other forms of disaster/crisis, this study significantly contributes to the existing knowledge of travel behaviour and movement in three folds. First, grounding this study on complexity and chaos theory in understanding travel behaviour in response to a crisis theoretically and empirically deepen our understanding of the nonlinear and dynamic nature of intra-destination travel flow patterns (Zenker & Kock, 2020). Any disruption to a destination leads to significant alterations in travel flows, from intensity to direction and pattern (Lew & McKercher, 2006), leading to changes in the dynamics of tourism demand and supply. It is important to acknowledge the complex and chaotic nature of crises and how that influences travel mobility to strategical respond and better manage destinations. The current study therefore challenges the Newtonian (linear) thinking of stability and predictability, especially in the context of a crisis (Reddy et al., 2020; Zahra & Ryan, 2007), and further contributes to the complexity theory in better understanding travel mobility under crises.

Second, network science theory further contributes to this understanding. Despite, the network theory has been studied in the tourism context for some time (S. Park et al., 2020), the understanding of the dynamic changes in travel behaviour before and during/after a crisis is limited. The network theory conceptualises a tourism destination or system as a network of organisations and individuals and crises puts significant tension on such system, leading to abrupt changes in the travel behaviour within and across networks (Scott et al., 2007). Owing to the privileged access to tourism big data, the network science approach was able to significantly encounter the nonlinear, chaotic and complex interactions within a tourism system coupled with the influence of COVID-19 to analyse the dynamic changes in travel mobility within a destination. This significantly contributes to the emerging tourism COVID-19 literature but also the existing crisis management literature.

Third, despite the current study is an exploratory data-driven study, findings also contribute to existing theories of risk perception, protection motivation theory, affiliation motivation theory and social contact theory. The changes in travel behaviour and mobility patterns during the first and second wave of COVID-19 have led to shorter travel distances, travel preferences to open and less crowded spaces compared to pre-COVID-19. This supports existing arguments that tourists tend to have high levels of perceived risks in times of crises (i.e. pandemic) and tend to reduce social contact and avoid highly congested places to protect their health (Park et al., 2021; Li et al., 2021). Such theoretical reasonings have complemented the key theories of complexity and network science in this study to understand the behavioural changes in travel mobility of domestic travellers in Jeju during the first and second wave of COVID-19 in Korea.

Korea did not implement a national lockdown, unlike many countries, which did not restrict the movement within the country. Thus, travellers were allowed to travel to any place at any time in the country, which enabled the researchers to examine the travel mobility during the pandemic, which is rare for other major destinations. The findings of this research therefore provide unique and important implications for tourism organisations in developing strategies to prevent the pandemic crisis and revive the tourism phenomenon post-crisis. Significant reductions in travel in response to COVID-19 were evident combined with the tendency to travel shorter distances, resulting in limited movement across attractions within a destination. Yet, it was found that more travellers are likely to visit destinations with many connections. This may suggest that during a crisis, travellers tend to stay in one region rather than travel between different regions. This could be due to their perception of minimising the risk associated with too much movement but at the same time satisfying their travel needs (Bae & Chang, 2020).

Despite social distancing measures being raised, Jeju attracted over 1 million tourists three times in 2020 (Yonhap, 2021) and in 2021, visitor numbers in Jeju marked over 12 million with 99.6% of domestic travellers (Ng, 2022). As travel flows increase, tourism organisations and destinations need to prepare for a potential influx of travel and the need for health and safety measures (e.g. social distancing rules, hygiene checks, etc.) when travel restrictions are eased or lifted, depending on each national or regional circumstances. Given that travellers tend to visit destinations with many connections, destinations should also plan for visitor crowd management to minimise human contact using digital tools and applications such as virtual queueing and leverage the use of big data to inform travellers with areas of high/low visitor concentration by region and time so that they can also self-manage their mobility and risk (WTTC, 2020). Recently, the Jeju Tourism Organisation launched a big data-based tourism service platform (Pick Map) where tourists can check the distribution of residents and tourists in real time so they can visit places that are less congested and travel safely (UNWTO, 2022). This demonstrates the application of big data in smart destination management.

The network degree and in-strength analysis have shown significant travel preferences to outdoor and natural attractions rather than indoor and cultural attractions where there is less human contact and social distancing can be ensured. In the case of Jeju, during COVID-19, it was evident that travellers travelled to coastal areas. WTTC (2020) reported that travellers prefer the familiar, predictable and trusted with an increasing trend in domestic and outdoor travel in the short-term, which tourism businesses and destinations have already adapted too. Yet, with possible long-term lifestyle and behavioural changes of individuals in response to the ongoing pandemic, travel behaviours and preferences may also change in the longer term. Considering this, tourism organisations will also have to adapt to these changes and plan and manage their operations accordingly to ensure health protective measures and meet needs of tourists with different levels of risk perceptions and travel preferences (Ren et al., 2022).

This study has only captured the first wave of the COVID-19 pandemic in the context of Jeju Island in Korea. The subsequent waves of COVID-19 could have shown further changes in travel mobility and behaviour, in which further research is recommended. Additionally, this study only focused on domestic travellers and different types of travellers (e.g. travel purpose, international travellers, etc.) were not considered. Previous literature has argued that different types of travellers behave differently but the heterogeneity of travellers was not considered in this current study. This research also focuses on a single destination to explore the mobility changes by emergence of COVID-19. It is suggested for future researchers to consider multiple destinations with various influencing factors apart from a matter of the pandemic. Future research should explore the movement patterns of different types of travellers to gain a broader understanding of the diverse travellers that contribute to the complex tourism destination system. In this vein, this current research has focused mainly on undirected network. Future researchers are strongly suggested to explore directed network so that the directional travel flow can be elucidated. Finally, the application of network science can be advanced by analysing the visitor journeys or routes in more detail – e.g. brokerage effects, identifying attractions that are gatekeepers, etc. (D'Agata et al., 2013) – which can provide evidence-based specific travel routes and flow patterns that a destination can plan and manage.

Declaration of interest statement

No potential competing interest was reported by the authors.

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Appendices

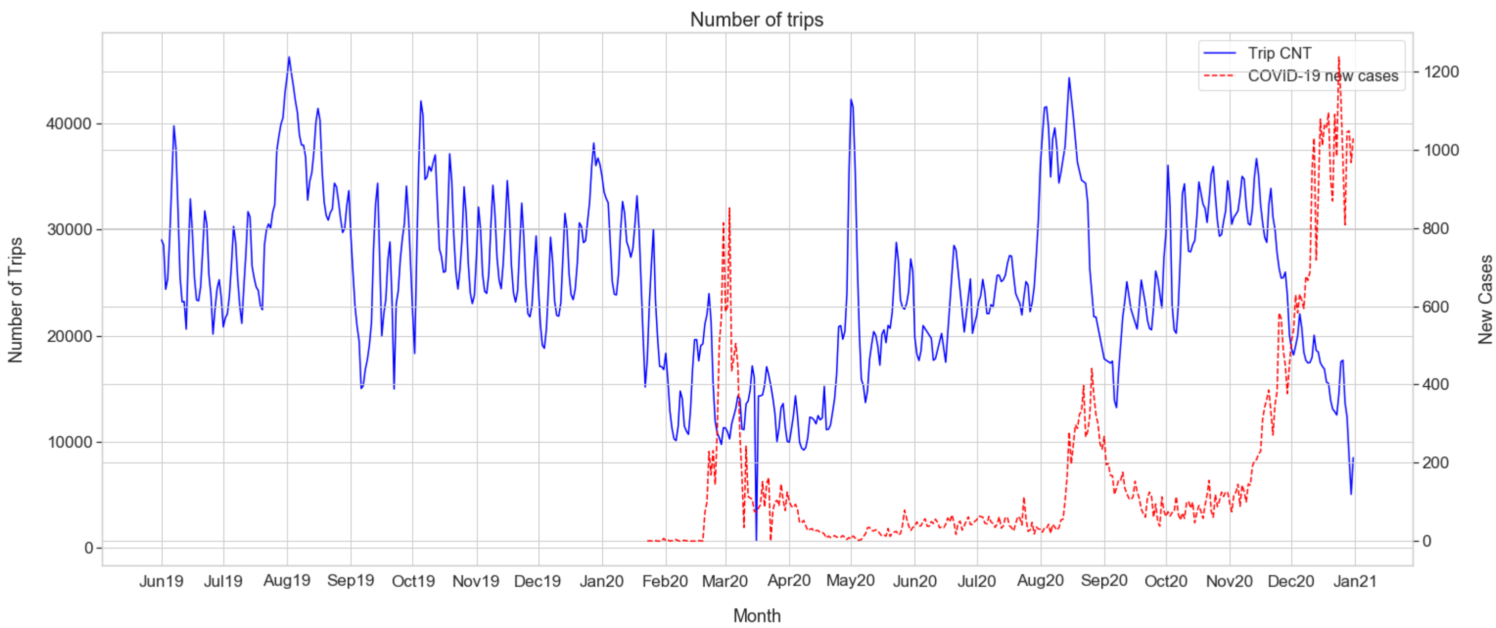
Appendix I. Destination network before COVID-19 and during COVID-19

Before COVID-19

During COVID-19

Note: Aggregated destination in-strength is denoted by the circular points; node degree is denoted by the edges connecting nodes and line depth is based on travel flow count

Figures and Tables



Note: Trip CNT refers to trip counts

Figure 1. Daily number of origin-destination trips in Jeju from June 2019 to December 2020

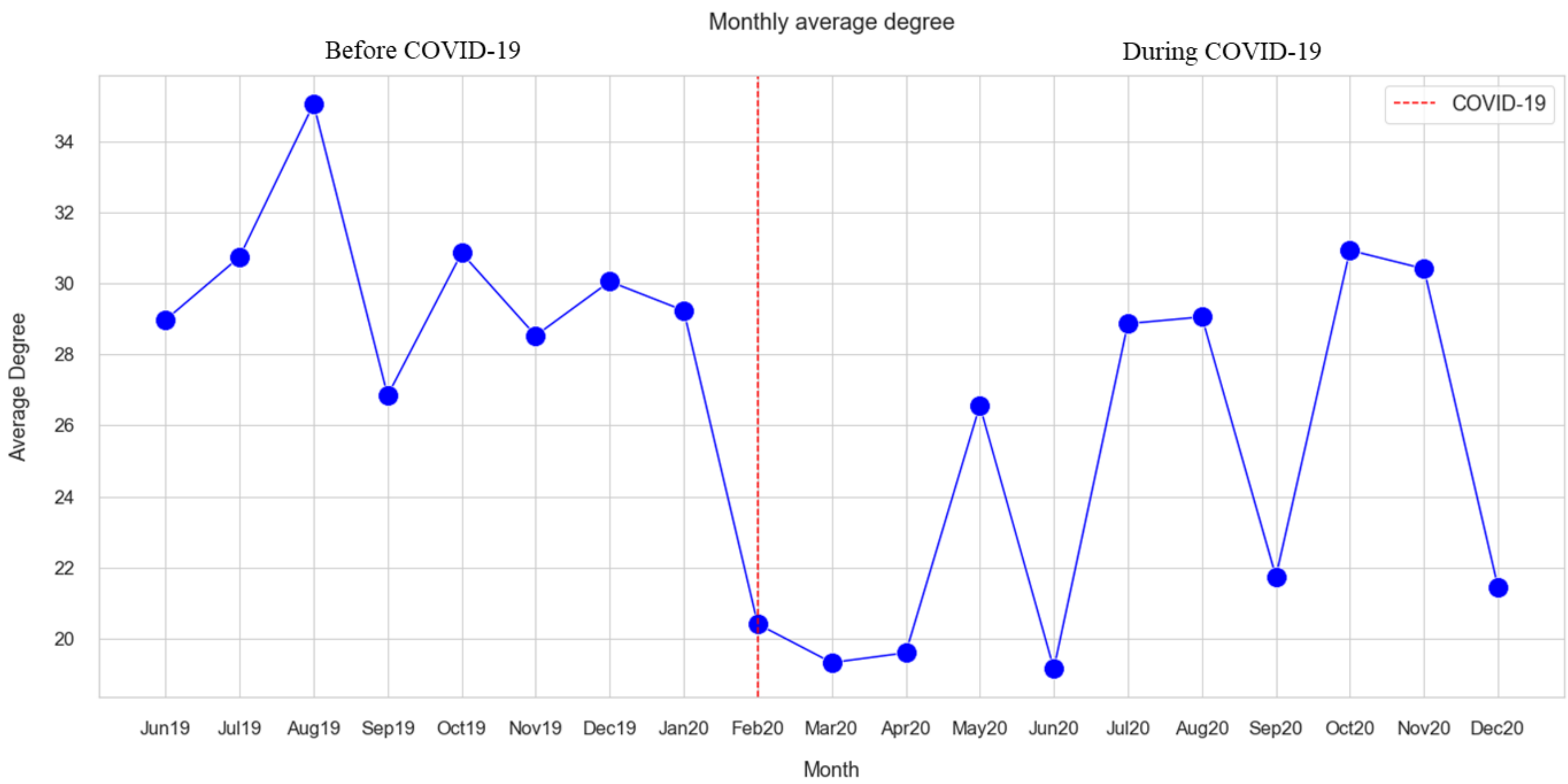


Figure 2A. Distribution of monthly average node degree

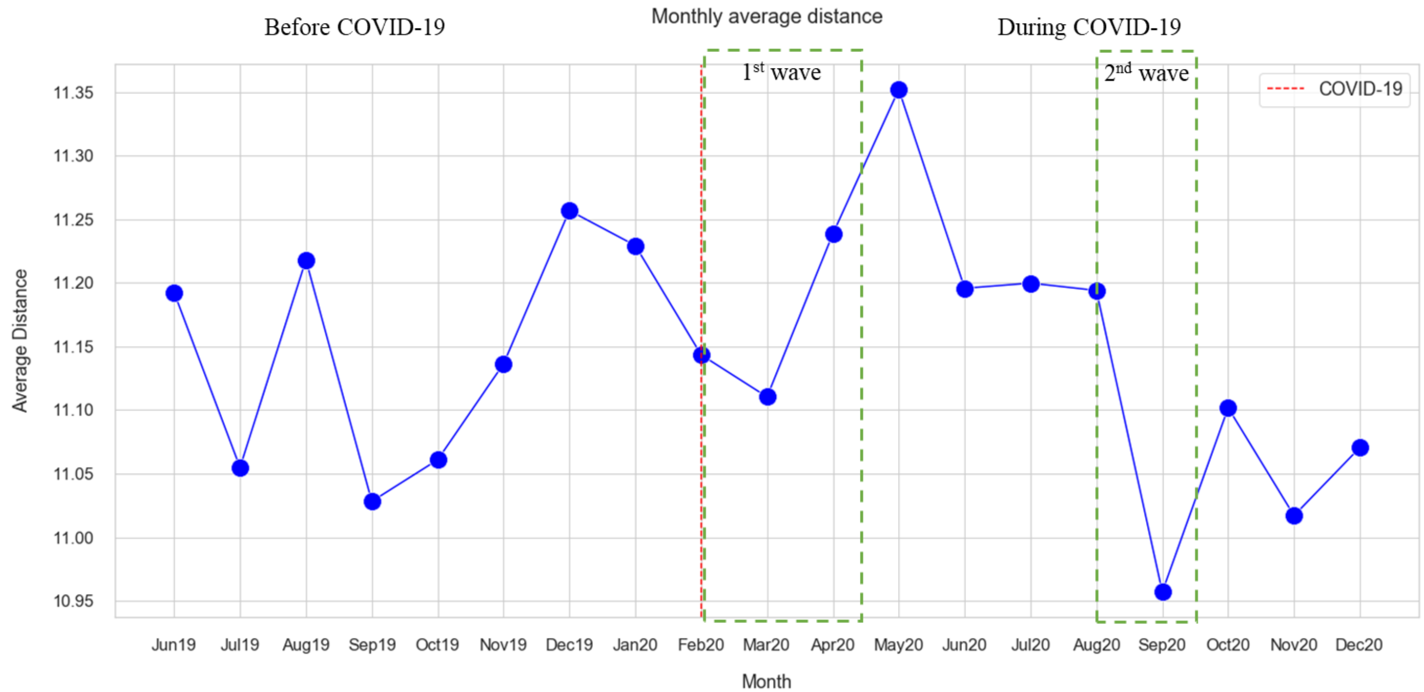


Figure 2B. Distribution of monthly average travel distance

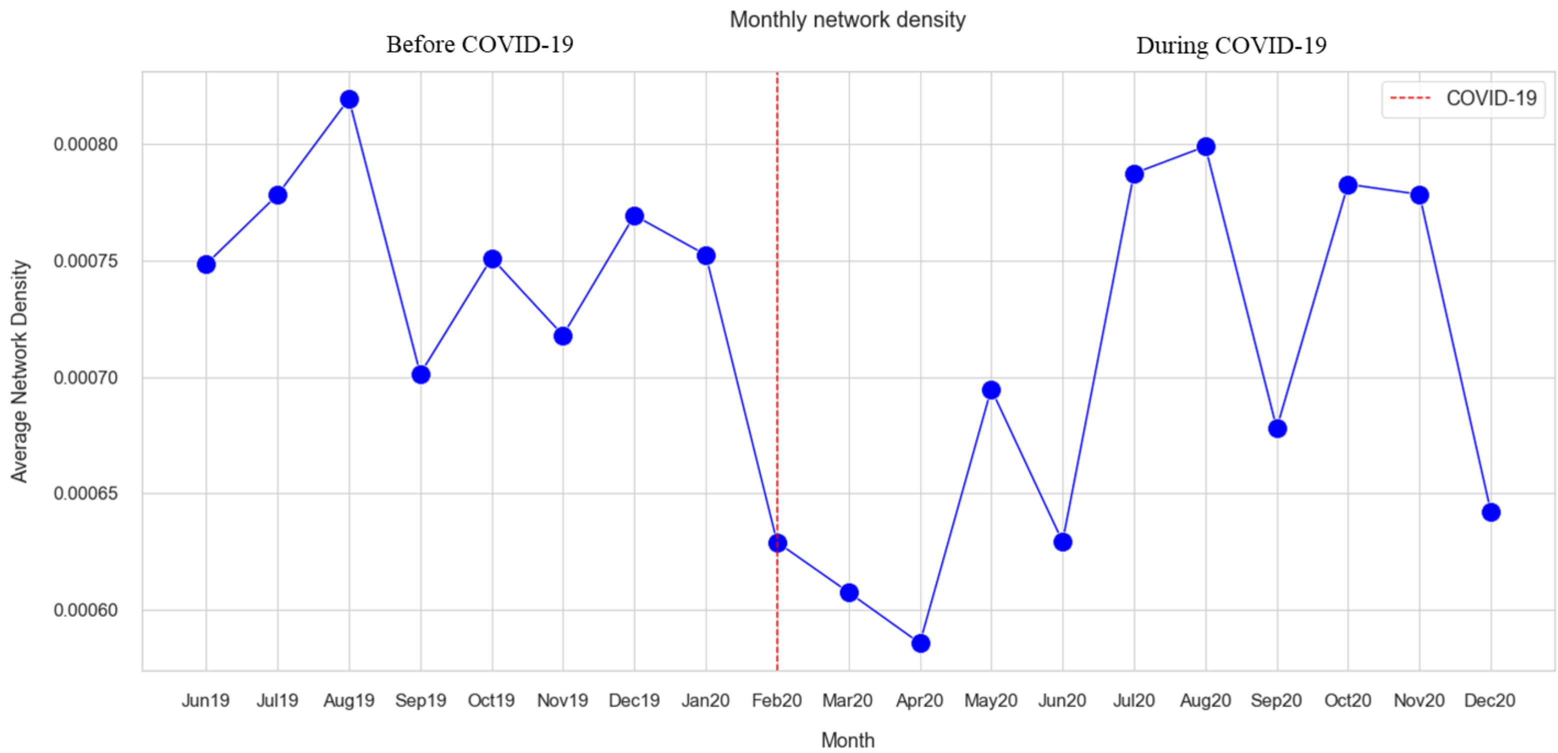


Figure 2C. Distribution of monthly average network density

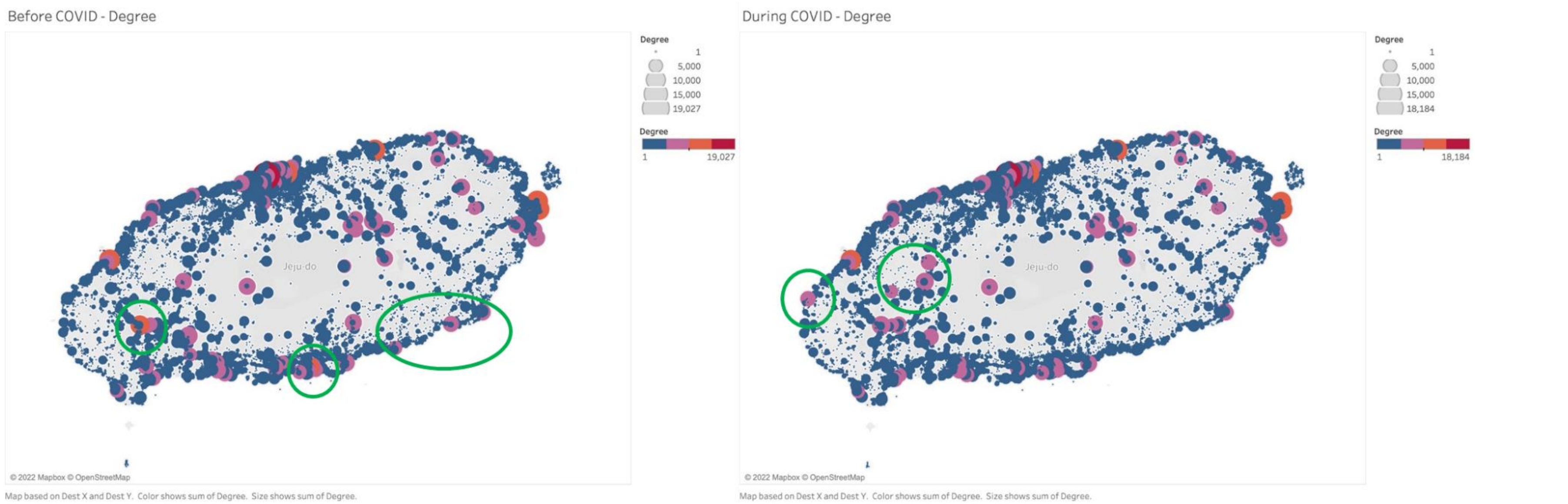


Figure 3A. Destination network based on average degree for before COVID-19 and during COVID-19

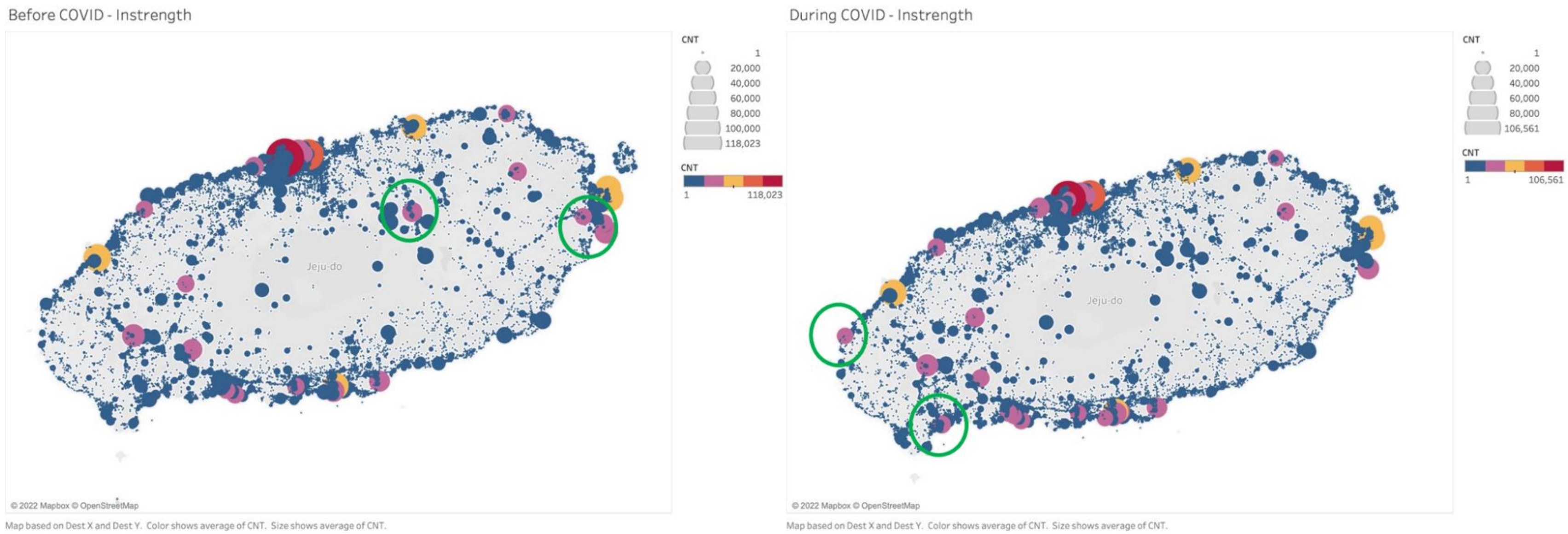


Figure 3B. Destination network based on average in-strength for before COVID-19 and during COVID-19

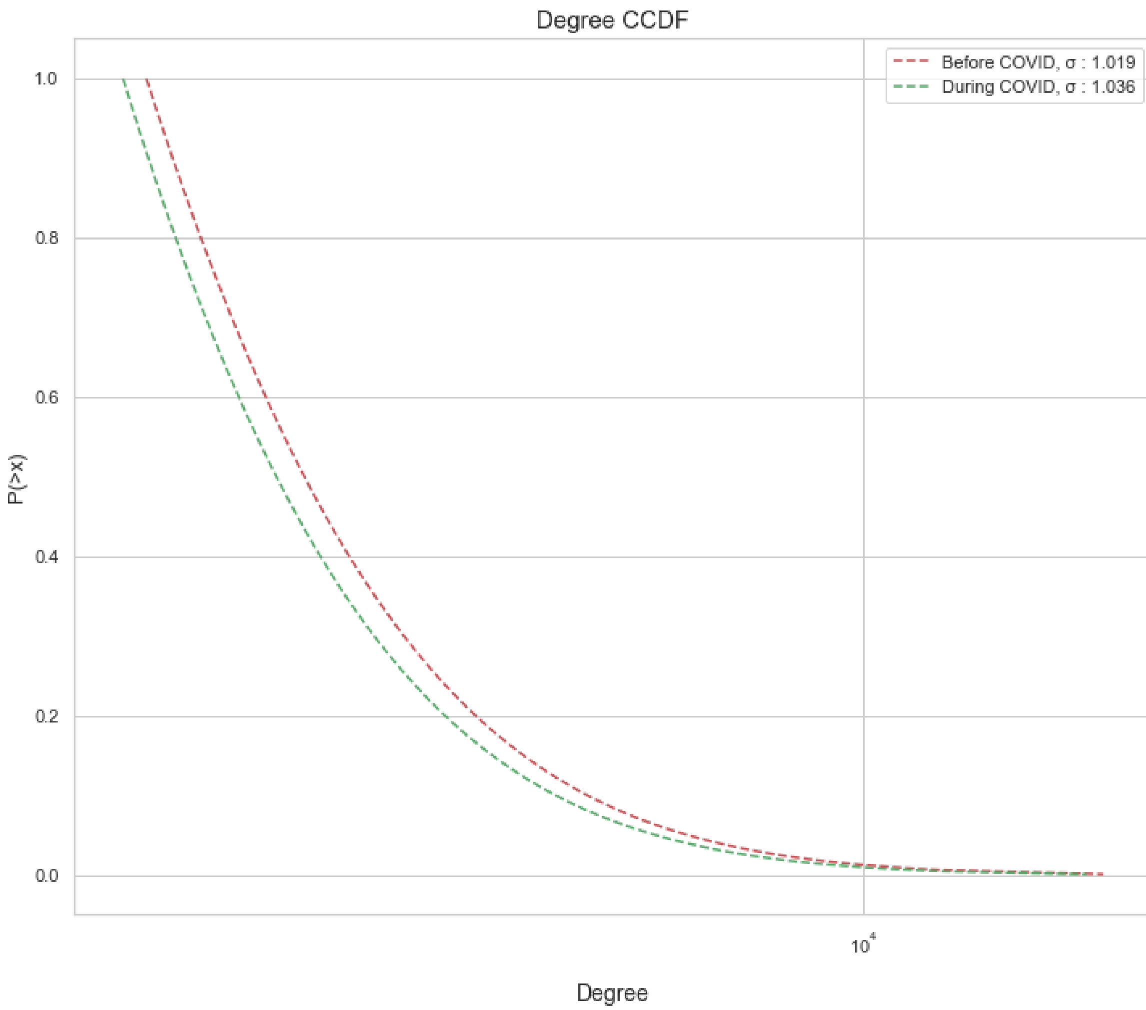


Figure 4A. Complementary cumulative probability distributions of node degree

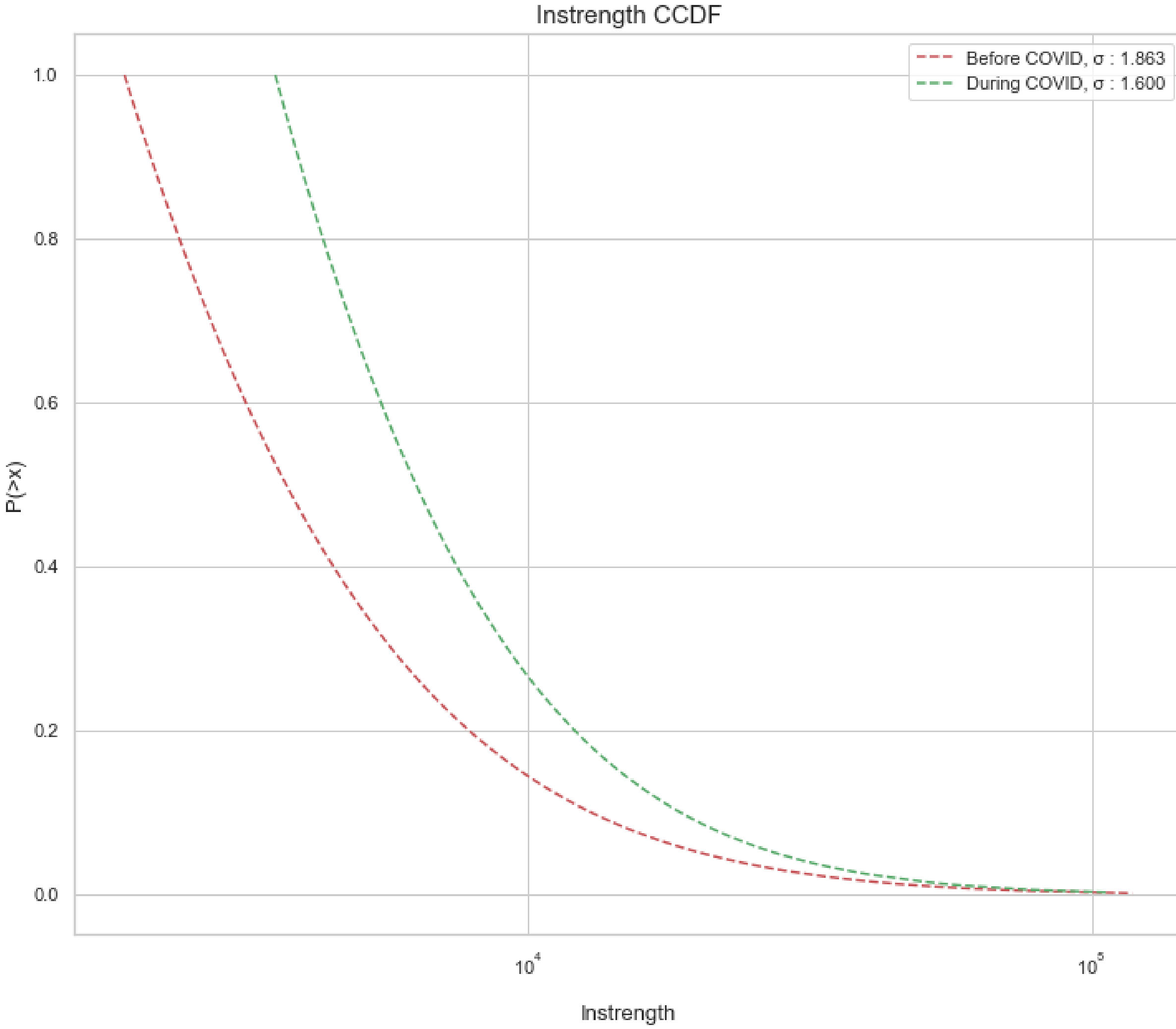


Figure 4B. Complementary cumulative probability distributions of in-strength

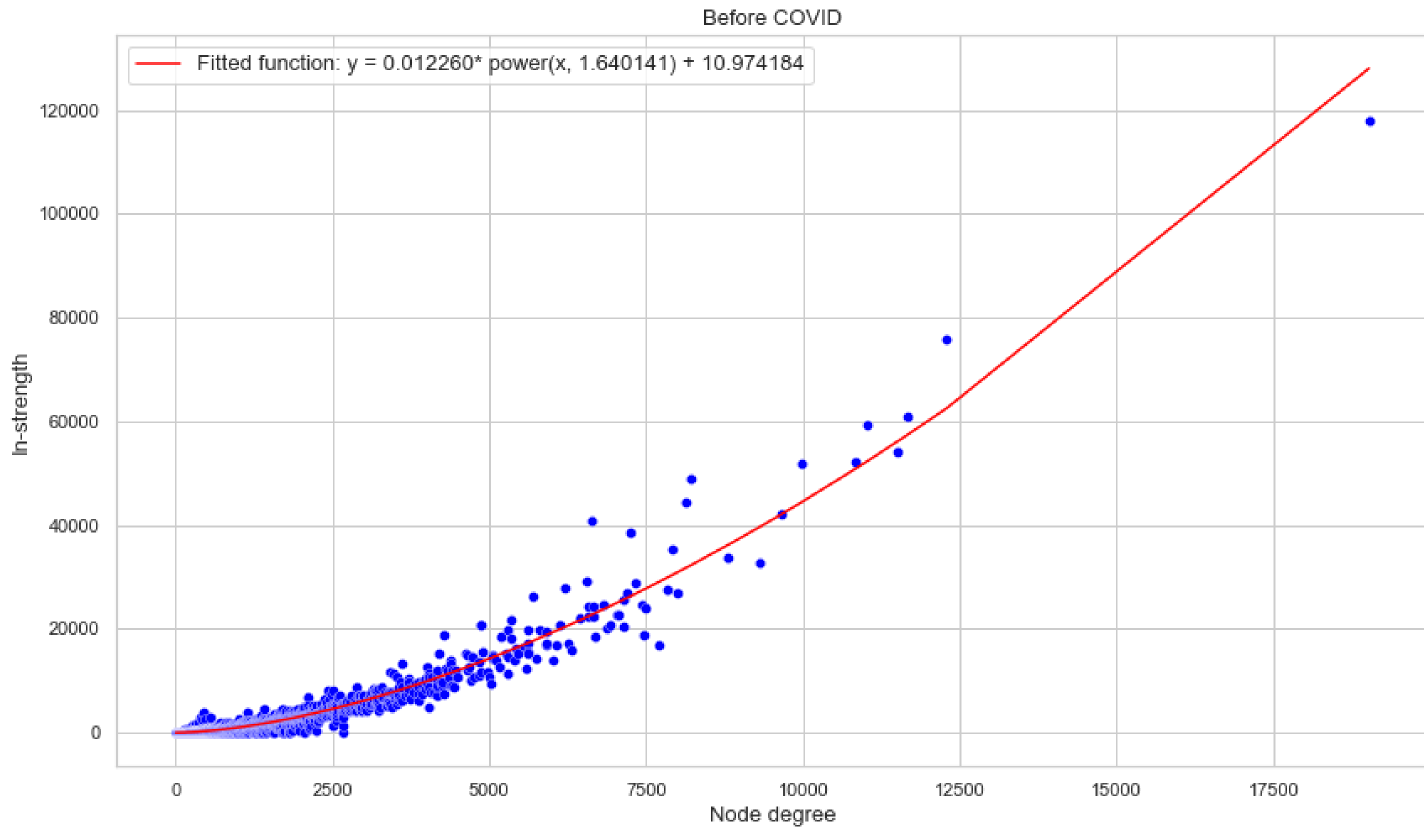


Figure 5A Relationship between node degree and in-strength before COVID-19

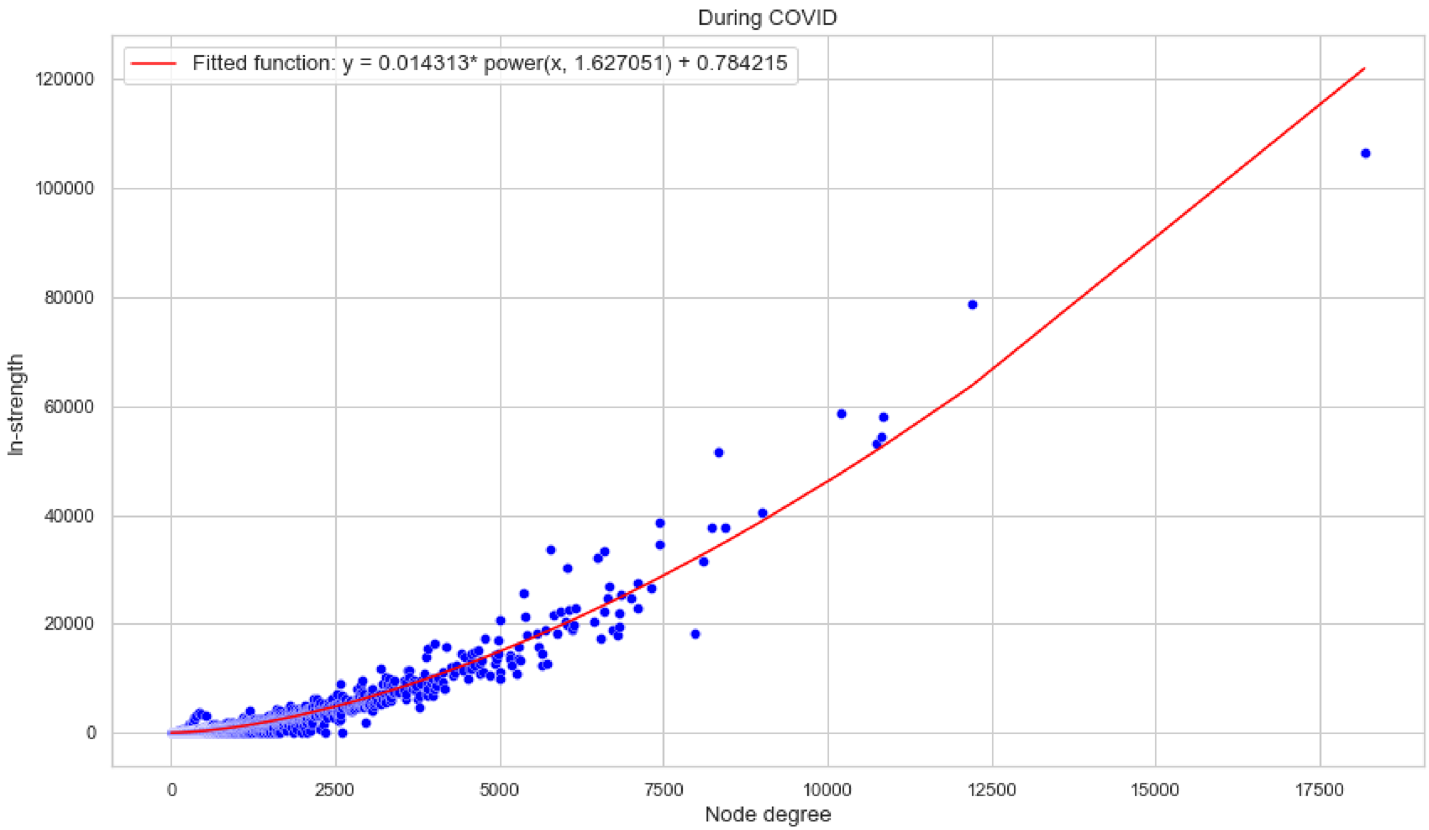


Figure 5B. A Relationship between node degree and in-strength during COVID-19

Table 1. Example of navigation records provided in the dataset

Date	**Gender**	**Age**	**Origin Latitude**	**Origin Longitude**	**Destination Latitude**	**Destination Longitude**	**Destination Category**	**CNT**
2019-06-01	Female	10	33. ***	126. ***	35. ***	125.***	Travel & Leisure	5
2019-06-01	Male	20	33. ***	126.***	35. ***	125.***	Medical service	2
….	….	….	….	….	…	…	….	….
2020-05-31	Female	60	32. ***	127. ***	31.***	128.***	Transportation	3
2020-05-31	Male	70	32. ***	127. ***	31.***	128.***	Travel & Leisure	4

Note: CNT refers to counts

Table 2. Summary of network statistics for before COVID-19, during COVID-19, and overall

	Before COVID-19	**During COVID-19**	**Overall**
Number of Nodes	68,868	67,012	80,827
Number of Edges	3,116,081	2,967,127	5,066,680
Average degree	90	89	125
Average edges	12,719	9,728	9,212
Network density	0.00131	0.00132	0.00155
Average In-strength	452	446	822
Average distance	11.15	11.14	11.15

Note: Overall refers the period of the entire year-long data collection