Analyzing cross-country pandemic connectedness in COVID-19: Network analysis using a spatial-temporal database

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Abstract

Background: Communicable diseases, such as coronavirus disease 2019, pose a major threat to public health across the globe. To effectively curb the spread of communicable diseases, timely prediction of pandemic risk is essential.

Objective: Our objective is to analyze travel data retrieved from the online Collaborative Arrangement for the Prevention and Management of Public Health Events in Civil Aviation (CAPSCA) dashboard, which contains up-to-date and comprehensive meta information about civil flights from 193 national governments according to the airport, country, city, latitude, and longitude of flight origin and destination. Unlike official travel data sources, such as the Federal Aviation Administration (FAA) and the International Air Transport Association (IATA), the travel data of CAPSCA is free and publicly available.

Methods: Because air travel is a common route of communicable disease dissemination and network analysis is a powerful way to estimate pandemic risk, a spatial-temporal database allowing us to analyze cross-country pandemic connectedness is important. This database can construct useful travel data records for network statistics other than common descriptive statistics. In this study, we display analytical results by time series plots and spatial-temporal maps to illustrate or visualize pandemic connectedness.

Results: We find similar patterns in the time series plots of worldwide daily flights from January to early-March in 2019 and 2020. A sharp drop in daily flight numbers recorded in mid-March 2020 was likely related to large-scale air travel restrictions due to the COVID-19 pandemic.

The levels of connectedness between places are strong indicators of pandemic risk. When COVID-19 cases began to appear across the globe, high network density and reciprocity in early March were early signals of the COVID-19 pandemic and were associated with the rapid increase in COVID-19 cases in mid-March. The spatial-temporal map of connectedness in Europe on 13 March 2020 shows the highest level of connectedness between the European countries, reflecting the severe outbreak of the COVID-19 pandemic in late March and early April.

As a quality control, we use the aggregated international flight counts from April to October 2020 to compare the official reported counts by the ICAO with the data collected from the CAPSCA dashboard, and find high consistency between the two datasets.

Conclusions: The flexible design of the database gives users access to network connectedness at different periods, places, and spatial levels by various network statistics calculation methods according to their needs. The database can facilitate early recognition of the pandemic risk of current communicable diseases and newly emerged communicable diseases in the future.

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Analyzing cross-country pandemic connectedness in COVID-19: Network analysis using a spatial-temporal database

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Abstract

Background: Communicable diseases, such as coronavirus disease 2019, pose a major threat to public health across the globe. To effectively curb the spread of communicable diseases, timely surveillance and prediction of pandemic risk are essential.

Objective: The aim of this study is to analyze free and publicly available data to construct useful travel data records for network statistics other than common descriptive statistics. In this study, we display analytical results by time series plots and spatial-temporal maps to illustrate or visualize pandemic connectedness.

Methods: We analyze data retrieved from the online Collaborative Arrangement for the Prevention and Management of Public Health Events in Civil Aviation (CAPSCA) dashboard, which contains up-to-date and comprehensive meta information about civil flights from 193 national governments according to the airport, country, city, latitude, and longitude of flight origin and destination. We use the database to provide visualization of pandemic connectedness through the workflow of travel data collection, network construction, data aggregation, travel statistics calculation, and visualization with time series plots and spatial-temporal maps.

Results: We find similar patterns in the time series plots of worldwide daily flights from January to early-March in 2019 and 2020. A sharp drop in daily flight numbers recorded in mid-March 2020 was likely related to large-scale air travel restrictions due to the COVID-19 pandemic. The levels of connectedness between places are strong indicators of pandemic risk. When COVID-19 cases began to appear across the globe, high network density and reciprocity in early March were early signals of the COVID-19 pandemic and were associated with the rapid increase in COVID-19 cases in mid-March. The spatial-temporal map of connectedness in Europe on 13 March 2020 shows the highest level of connectedness between the European countries, reflecting the severe outbreak of the

COVID-19 pandemic in late March and early April. As a quality control, we use the aggregated international flight counts from April to October 2020 to compare the official reported counts by the International Civil Aviation Organization with the data collected from the CAPSCA dashboard, and find high consistency between the two datasets.

Conclusions: The flexible design of the database gives users access to network connectedness at different periods, places, and spatial levels by various network statistics calculation methods according to their needs. The analysis can facilitate early recognition of the pandemic risk of current communicable diseases and newly emerged communicable diseases in the future.

Keywords: Air traffic; coronavirus; human mobility; network analysis; travel restrictions

Introduction

Communicable disease remains a major public health threat across the globe. The coronavirus disease 2019 (COVID-19) pandemic is a stark reminder of the ongoing challenge posed by communicable diseases on human health [1]. Timely surveillance and estimation of pandemic risk are crucial for curbing the spread of communicable diseases. Without efficacious medications and vaccines, implementing non-pharmaceutical interventions, such as air travel restrictions and social distancing measures, is vital for controlling communicable diseases [2]. The conventional method of pandemic risk estimation based on confirmed case counts alone provides limited information about pandemic trends. Network analysis is a powerful way to estimate pandemic risk through network connectedness [3] while air travel is a common route of communicable disease dissemination [4]. By conducting network connectedness analysis using air travel data records, the effect of air travel restrictions on pandemic connectedness can be visualized.

The risk of in-flight communicable disease transmission was a global health concern well before the emergence of COVID-19 [5]. A number of in-flight communicable disease transmissions have been documented, including influenza [6], severe acute respiratory syndrome (SARS) [7], multi-drug resistant tuberculosis [8], measles [9], meningococcal infections [10], norovirus [11], shigellosis [12], and cholera [13]. Studies of pandemic influenza [14] and SARS [15] transmission on aircraft further indicated that air travel can serve as a channel for the rapid spread of newly emerging communicable diseases. An investigation of COVID-19 control in Latin America suggested that countries serving as air transportation hubs are more prone to disease transmission. The practicable use of travel data for the prediction of COVID-19 pandemic risk was also reported [16].

We analyze travel data retrieved from the online Collaborative Arrangement for the Prevention and Management of Public Health Events in Civil Aviation (CAPSCA) dashboard [17], which contains up-to-date and comprehensive meta information about civil flights from 193 national governments according to the airport, country, city, latitude, and longitude of flight origin and destination. Unlike official travel data sources, such as the Federal Aviation Administration (FAA) and the International Air Transport Association (IATA), the travel data of CAPSCA is free and publicly available. The use of an Automated Dependent Surveillance Broadcast (ADS-B) system as one of the travel data collection elements enables CAPSCA to provide up-to-date travel location, among other travel data (latitude and longitude of flight origin and destination alongside a timestamp) [18, 19]. CAPSCA provides civil flight data for both passenger and cargo flights. While it is common knowledge that cargo flight crews may spread the disease through air travel, cargo is not always considered a health risk [20]. Travel data containing both passenger and cargo flights are therefore more comprehensive for pandemic connectedness analysis.

Flexible analysis of travel data can be performed through in-database processing. Specifically, users can analyze travel data with various network statistics calculations, including network analysis [3], network density [21], and reciprocity [22], which are powerful ways to estimate pandemic risk through network connectedness. A simple display with time series plots and spatial-temporal maps provides clear visualization of the analytic results. Time series plots show changes in network density and reciprocity, which are likely to be early signs of pandemic risk alteration [21]. The spatial-temporal maps of network analysis illustrate the connectedness between places, reflecting changes in pandemic risk earlier than the unprocessed data of confirmed case counts [16]. Moreover, diverse scope of analyses of pandemic connectedness can be performed.

The database allows us to integrate travel data from different airports to illustrate connectedness at city, country, or regional level according to users' preference, facilitating research and policymaking at local and global levels and providing a spatial outlook of how the pandemic network evolves for predicting and assessing the pandemic risk of the communicable diseases.

Methods

Workflow of Data Collection and Analysis

The database provides visualization of pandemic connectedness through the workflow of travel data collection, network construction, data aggregation, travel statistics calculation, and visualization with time series plots and spatial-temporal maps. The workflow of data collection and analysis is summarized in Fig. 1.

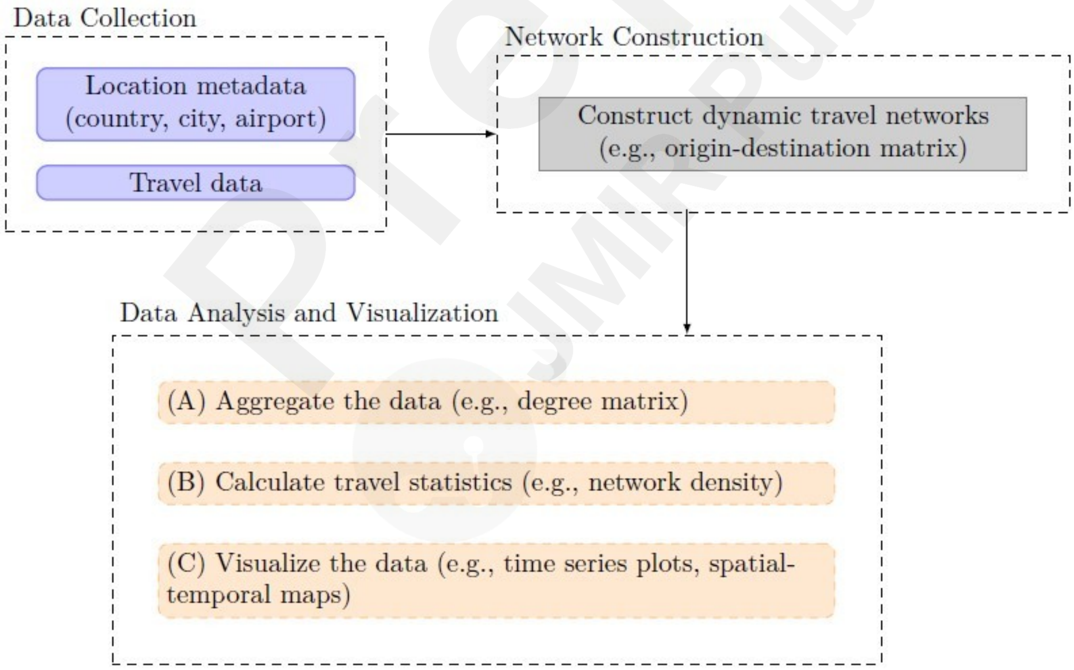

Figure 1: Workflow of data collection and analysis

Data Collection

Travel data and meta information were retrieved from the CAPSCA dashboard through two separate procedures:

1. Extracting the airport meta information from the rendered JavaScript object “airportData” by HyperText Transfer Protocol (HTTP) request.
2. Downloading and extracting the flight numbers of civil flights, including both passenger and cargo flights, from the JavaScript Object Notation (JSON) responses by multiple Asynchronous JavaScript and Extensible Markup Language (AJAX) requests.

The travel data collected were filtered for valid International Civil Aviation Organization (ICAO) formatted airport codes. Raw JSON responses contain formatted airport codes from various data sources, such as the ICAO, IATA, and FAA. Each type of formatted airport code has its specific format. Valid ICAO codes starts with a letter only and have four letters or digits, valid IATA codes consist of three letters, while valid FAA codes are three- to five-character alphanumeric code. The format of each type enables the development of a filtering system to extract travel data with specific codes.

Data Records

A live version of the data record, which will be kept up-to-date with the latest numbers, can be downloaded from our travel database project repository [23]. The data records consist of two major parts: aggregated raw input and calculated/computed records.

The aggregated raw inputs are *location metadata* which include data at multiple levels – country, city, airport, and geolocation (latitude-longitude) – and *travel data* which contain daily information regarding flight origin and destination starting from Jan 2019. It covers more than 200 countries and regions in the world.
The data records (details) are structured into three comma-separated value (CSV) files, as follows.

1. [ICAO_airport_meta.csv] Table of the location meta (ICAO-CAPSCA airport meta). The fields of the table are:
    a. *countryName* is the name of the country
    b. *countryCode* is the ISO-3166 alpha-3 code of the country
    c. *airportName* is the name of the airport
    d. *airportCode* is the ICAO code of the airport
    e. *cityName* is the name of the city
    f. *latitude* is the geolocation (latitude) of the airport
    g. *longitude* is the geolocation (longitude) of the airport

2. [flight_2019-01-01_2020-12-03.csv] Table of travel data (daily flight numbers from origin to destination). The fields of the table are:
    a. *date* is the record date
    b. *num_flight* is the number of flights from origin airport to destination airport
    c. *orig_airportCode* is the ICAO airport code of the origin airport
    d. *orig_airportName* is the airport name of the origin airport
    e. *orig_countryCode* is the ISO-3166 alpha-3 country code of the origin airport
    f. *orig_countryName* is the country name of the origin airport
    g. *orig_cityName* is the city name of the origin airport
    h. *orig_latitude* is the geolocation (latitude) of the destination airport

i. *orig_longitude* is the geolocation (longitude) of the destination airport
j. *dest_airportCode* is the ICAO airport code of the destination airport
k. *dest_airportName* is the airport name of the destination airport
l. *dest_countryCode* is the ISO-3166 alpha-3 country code of the destination airport
m. *dest_countryName* is the country name of the destination airport
n. *dest_cityName* is the city name of the destination airport
o. *dest_latitude* is the geolocation (latitude) of the destination airport
p. *dest_longitude* is the geolocation (longitude) of the destination airport

3. [network_statistics.csv] Table of the calculated network statistics. The fields of the table are:
   a. *date* is the reference date of the network statistics at time t
   b. V_t is the number of vertices (V_t) at time t
   c. E_t is the number of edges (E_t) at time t
   d. D_t is the edge density (D_t) at time t
   e. R_t is the reciprocity (R_t) at time t

Dynamic Network Construction and Data Aggregation

The travel data can be used to construct the travel network structure [24]. The basic network components involve nodes (vertices) and links (edges). The nodes represent the target entity (location), such as airport, city, or country. As the travel data contain detailed airport-airport records, it can be transformed by merging the information from the airports to form nodes of city, country, region, or groups of any geolocations according to users' preference. A link represents a relationship (connection) between two target entities. The relationship can be binary or numeric (e.g., flight frequency), indicating the existence or strength of travel connection, respectively.

For example, if we focus on global analysis, we aggregate the airport data at the country level and put the country data as a new set of nodes to form travel sub-networks, which are represented by the country-country origin-destination matrix with entries being the flight frequencies between two countries.

Data Analysis: Travel Network Statistics

We can further aggregate the travel data to obtain overall worldwide flight information. We show the time series plots of worldwide daily flights in 2019 and in 2020 in Fig. 2A. By comparing the two time series in Fig. 2A, we find similar patterns of worldwide daily flights from January to early-March in 2019 and 2020. A sharp drop in daily flight numbers recorded in mid-March 2020 was likely related to large-scale air travel restrictions due to the COVID-19 pandemic. In addition, the sub-network can be further used for the calculation of the degree matrix, where its diagonal entries contain the number of edges connected to different nodes (number of connected countries of each node). By using both the origin-destination matrix and the degree matrix, we can produce spatial-temporal maps (Fig. 3).

We let V_t be the number of vertices of the dynamic network at time t, and E_t be the number of edges of the dynamic network at time t. For example, in the dynamic networks in Fig. 3, countries are represented by vertices and travel connections are represented by edges. Based on V_t and E_t, network statistics such as D_t (Network density [21]) and R_t (Reciprocity [22]) can be calculated (Fig. 2B).

Network density D_t is based on an undirected network structure, and is defined by

$$D_t = 2E_t / V_t(V_t - 1),$$

referring to the ratio of the number of connections with respect to the maximum possible connections among countries. It illustrates how dense the connections in the dynamic network are at time t.

Reciprocity R_t is based on a directed network structure and is defined by

$$R_t = E_t^{<->} / L_t\,,$$

where R_t is the ratio of the number of links pointing in both directions, $E_t^{<->}$ (mutual links), to the total number of links, L_t. In other words, the value of R_t represents the average possibility that a link is reciprocated.

Results

Data Visualization

The network statistics data can be visualized using time series plots. In addition, data records of origin-destination matrix and degree matrix can be visualized using spatial-temporal maps.

Fig. 2 display the time series plots of worldwide daily flights (Fig. 2A), global network statistics (Fig. 2B), and daily reported COVID-19 confirmed cases (Fig. 2C). It is found that changes in network density can serve as an early signal of pandemic risk.

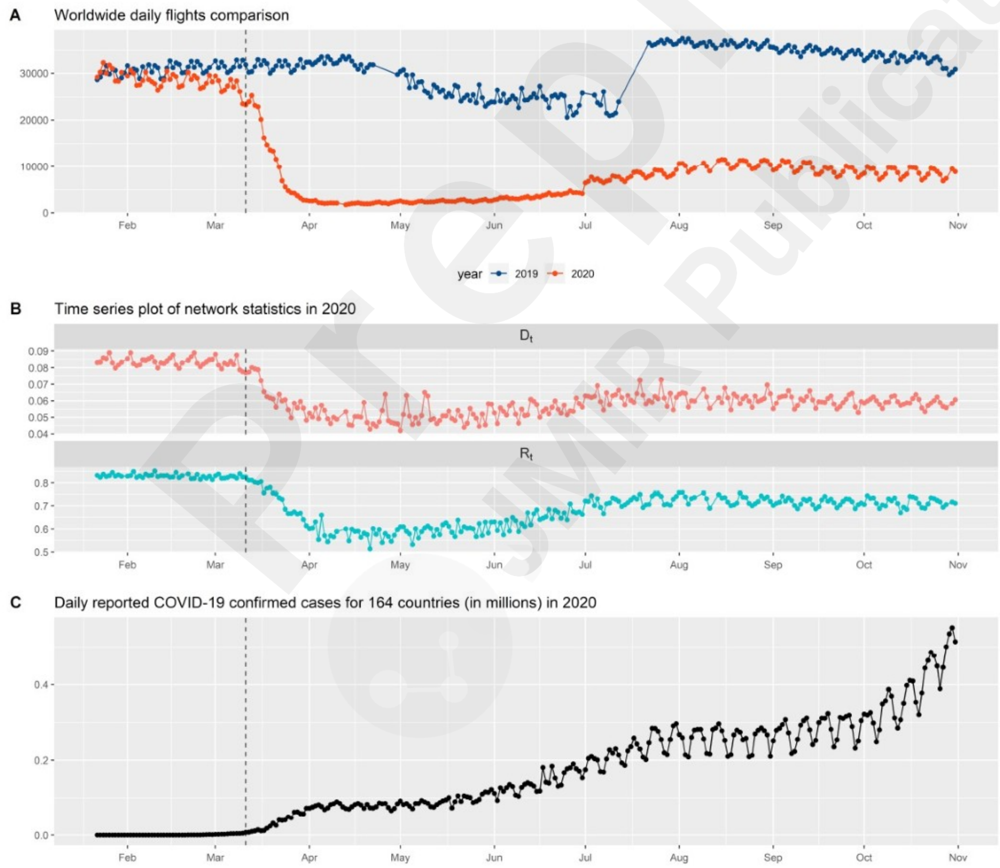

Figure 2: Time series plots of (A) worldwide daily flights, (B) global network statistics, and (C) daily reported COVID-19 confirmed cases

The time series plots of network density and reciprocity shown in Fig. 2B demonstrate the practical use of network statistics for global pandemic risk prediction. When COVID-19 cases began to appear across the globe, high network density and reciprocity in early March were early signals of the

COVID-19 pandemic and were associated with the rapid increase in COVID-19 cases reported by the World Health Organization (WHO) in mid-March (Fig. 2C). The sharp decrease of network density and reciprocity in mid-March suggests the easing of the pandemic risk as associated with steady number of daily confirmed cases from mid-March to May. The gradual increase of network density and reciprocity starting from mid-May suggests the increase in the pandemic risk as associated with the rapid surge of COVID-19 cases from mid-May to August. The in-database processing system allows users to analyze network density and reciprocity at local or global levels during selected periods in order to identify possible trends of pandemic risk evolution.

Fig. 3 shows some spatial-temporal maps to illustrate the network connectedness between countries under different spatial levels. The levels of connectedness between places are strong indicators of pandemic risk. The spatial-temporal maps showing the connectedness between places are constructed based on the origin-destination matrix and degree matrix, which offer the directional data and summarized node data (degree of vertices), respectively. The maps display the connectedness between places in the form of connections and bubbles. The connections (links) illustrate the connectedness between places. The bubbles (vertices), which contain aggregated information presented by the node size, further enhance the visualization of the connectedness, especially when the network density is high. The in-database processing system allows users to generate spatial-temporal maps at multiple spatial levels, such as airport, city, country, or any region of interest, with various temporal settings, such as different periods and time-intervals. The flexibility of the database facilitates data analysis according to the needs of users.

For example, to analyze the connectedness in Europe during the first wave of the COVID-19 pandemic earlier this year, spatial-temporal maps of Europe in 14-day intervals between March and April were generated (Fig. 3A). Maps displaying connectedness at country level are plotted with each bubble representing a country. The size of the colored bubbles represents the number of vertices or countries. The color intensity of the bubbles gives the number of daily confirmed COVID-19 cases per one million population of the country. The light green colored connections (links) represent the daily flight counts. The thicker the green line, the more connectedness between two countries. The map of 13 March 2020 shows the highest level of connectedness between the European countries, reflecting the severe outbreak of the COVID-19 pandemic in late March and early April. The significant decrease in connectedness from 13 March to 24 April indicates that the first wave of the pandemic subsided in May.

Fig. 3B shows a different set of spatial-temporal maps to analyze the connectedness in Europe before the second wave of the COVID-19 pandemic. Spatial-temporal maps of Europe in 14-day intervals between May and June are generated. As countries serving as air transportation hubs were particularly prone to the spread of COVID-19 [16], spatial-temporal maps at hub country level are plotted to investigate network connectedness between hub countries during the pandemic's development. Each bubble represents a country with airports defined as among the top 10 air transportation hubs in Europe by the Official Airline Guide (OAG) 2019 MegaHub Index [25]. The color indicates the accumulated total number of COVID-19 confirmed cases per one million population of a particular country at time *t* (ratio_Xit_per1M in Fig. 3B). The significant increase in connectedness in mid-June indicates the increase of the pandemic risk in Europe, especially among hub countries.

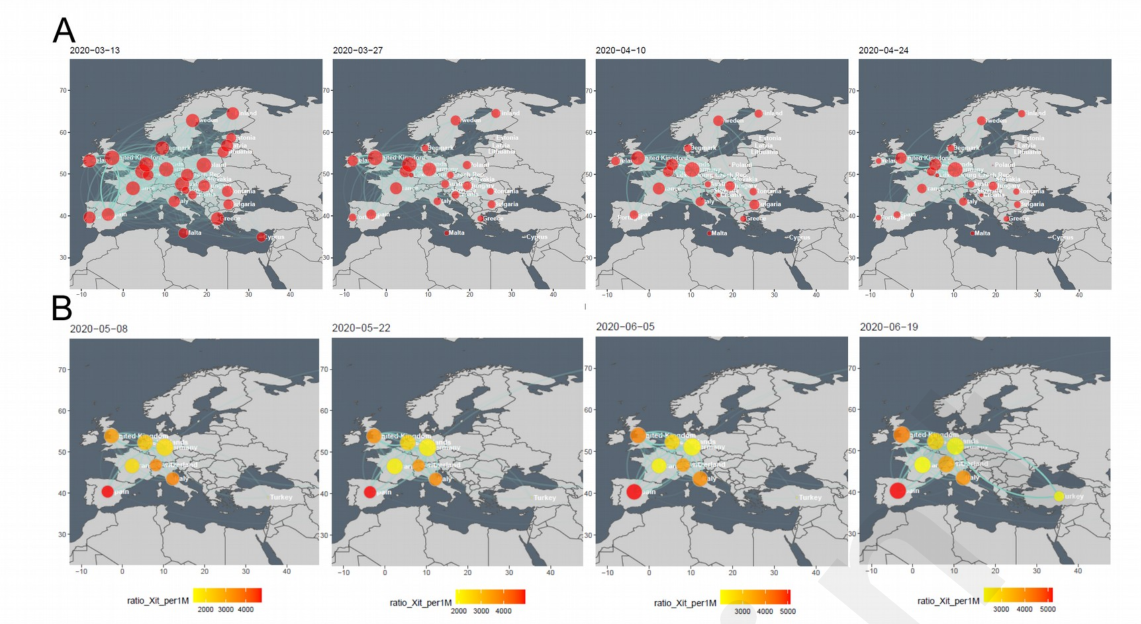

Figure 3: Spatial-temporal maps of connectedness in Europe at (A) country level between 13 March and 24 April 2020, and (B) air transportation hub level between 8 May and 19 June 2020.

The above visualization can be conducted by package igraph in R or software for creating network visualization, such as Gephi.

Technical Validation

CAPSCA is a voluntary cross-sectorial and multi-organizational collaborative program managed by the ICAO with support from the WHO. The data quality of the dashboard should be guaranteed. As a quality control, we use the aggregated international flight counts from April to October 2020 to compare the official reported counts [26] by the ICAO with the data collected from the CAPSCA dashboard. We calculate the correlation between the two datasets for seven different regions identified by the ICAO, including Asia Pacific, East and South Africa, Europe and North Atlantic, Middle East, North America and the Caribbean, South America, and West and Central Africa, in the said period. The results are shown in Table 1. It is found that most of the correlations are greater than 0.99, except for the Asia Pacific region's, which is around 0.96. The difference is possibly due to the data synchronization (lagging by 3 days) performed by the ICAO after collecting the daily raw counts.

Table 1. Correlation between ICAO reported counts and our aggregated counts from the CAPSCA dashboard on seven different regions identified by ICAO from April to October 2020

ICAO Regions	**Correlation**
Asia Pacific	0.960
East and South Africa	1.000
Europe and North Atlantic	1.000
Middle East	1.000
North America and the Caribbean	0.994
South America	0.999
West and Central Africa	1.000

Discussion

Ongoing systematic surveillance is important to facilitate early outbreak detection and/or to evaluate the effectiveness of public health measures and programs [27, 28]. In this paper, we attempt to conduct flexible analysis of freely available travel data collected from CAPSCA dashboard to discover some patterns and early signals for COVID-19 pandemic which may be useful for policy makers to take appropriate actions. When we link the database to daily COVID-19 confirmed cases, we can develop a user-friendly platform for timely and flexible visualization of network connectedness to facilitate surveillance and early recognition of pandemic risk, including the high network density and reciprocity in early March 2020 via time series analysis and the high level of connectedness between the European countries on 13 March 2020 via spatial-temporal map. The surveillance and findings are important for curbing the spread of communicable diseases and balancing disease control and economic recovery.

We provide a clear workflow of data collection and analysis and the suggested software for analysis. Because air transportation is highly relevant to the dissemination of communicable diseases, the database and the analysis can also be applied to investigate the pandemic risk of other communicable diseases occurring currently and emerging in the future. In addition, researchers may replicate the research work on pandemic connectedness using the same database or other databases.

To ensure the data quality, we conduct a correlation analysis to validate the database. We compare the official reported counts on the aggregated international flights for seven regions from April to October 2020 by the ICAO with those corresponding data we collected from the CAPSCA dashboard. We found there is a little difference only and the possible reason of the difference may be due to the data synchronization performed by the ICAO after collecting the daily raw counts. We expect that this paper will help researchers to explore and validate freely available health-related databases to conduct ongoing and systematic analysis and interpretation to discover early warning signals for necessary actions to prevent and control the spread of communicable diseases.

Conclusions

In this paper, we demonstrate how we analyze freely available travel data retrieved from CAPSCA dashboard, together with the COVID-19 confirmed cases from WHO, for systematic surveillance. Flexible analysis of the travel data can be performed through in-database processing which allows us to visualize and analyze the pandemic risk and connectedness via different structures such as time series plots and spatial-temporal maps. The analysis facilitates early recognition of the pandemic risk of current communicable diseases and newly emerged communicable diseases in the future.

Acknowledgements

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Author Contributions

AMYC and MKPS developed the idea and research. JNLC collected the data. JNLC, AMYC, and MKPS processed the data. AMYC, JTYT, and JNLC drafted the manuscript. AT and MKPS finalized the manuscript. All authors read and approved the final version of the manuscript.

Conflicts of Interest

None declared.

Abbreviations

ADS-B: Automated dependent surveillance broadcast
AJAX: Asynchronous JavaScript and extensible markup language
CAPSCA: Collaborative Arrangement for the Prevention and Management of Public Health Events in Civil Aviation
CSV: Comma-separated value
FAA: Federal Aviation Administration
IATA: International Air Transport Association
ICAO: International Civil Aviation Organization
ISO: International Organization for Standardization
JSON: JavaScript object notation
OAG: Official Airline Guide
SARS: Severe acute respiratory syndrome
WHO: World Health Organization

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Supplementary Files

Untitled.
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Figures

Workflow of data collection and analysis.

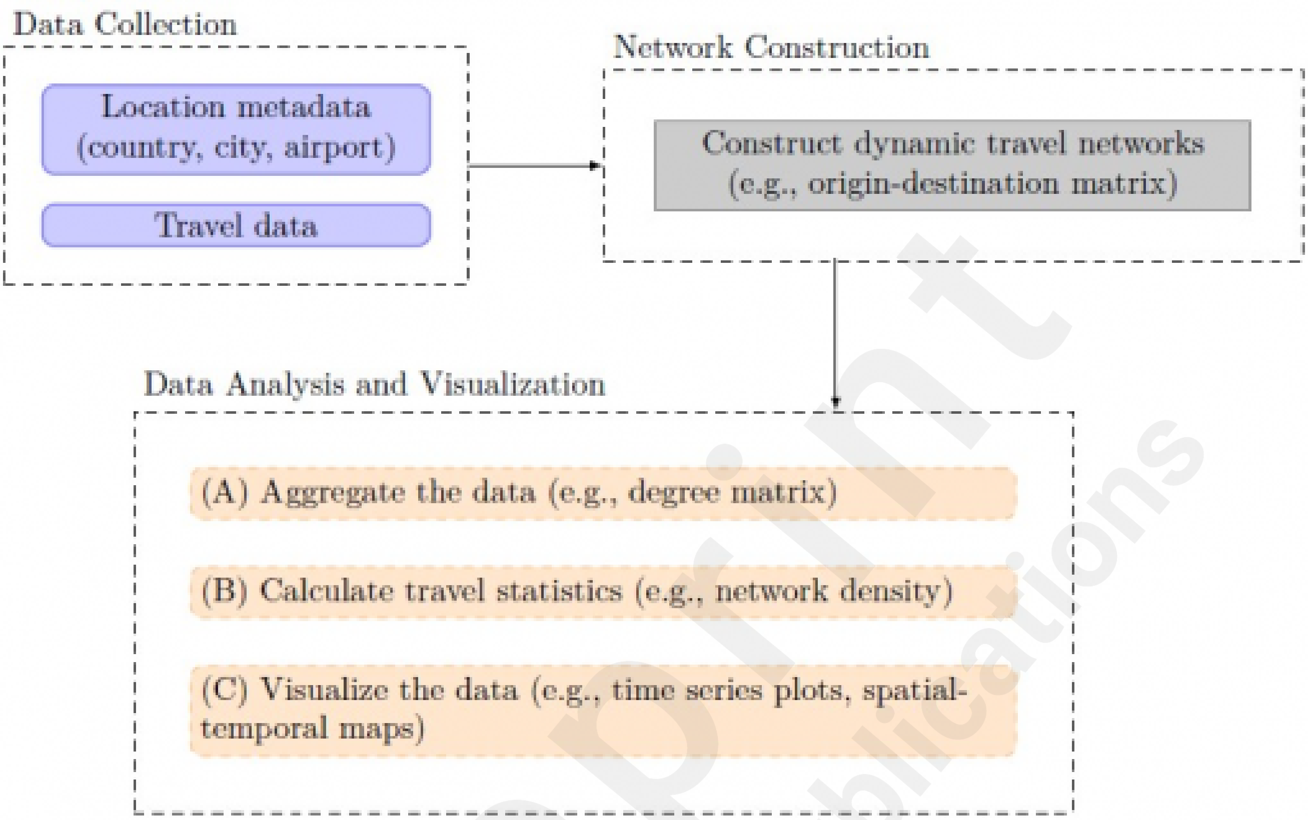

Figure 1: Workflow of data collection and analysis

Time series plots of (A) worldwide daily flights, (B) global network statistics, and (C) daily reported COVID-19 confirmed cases.

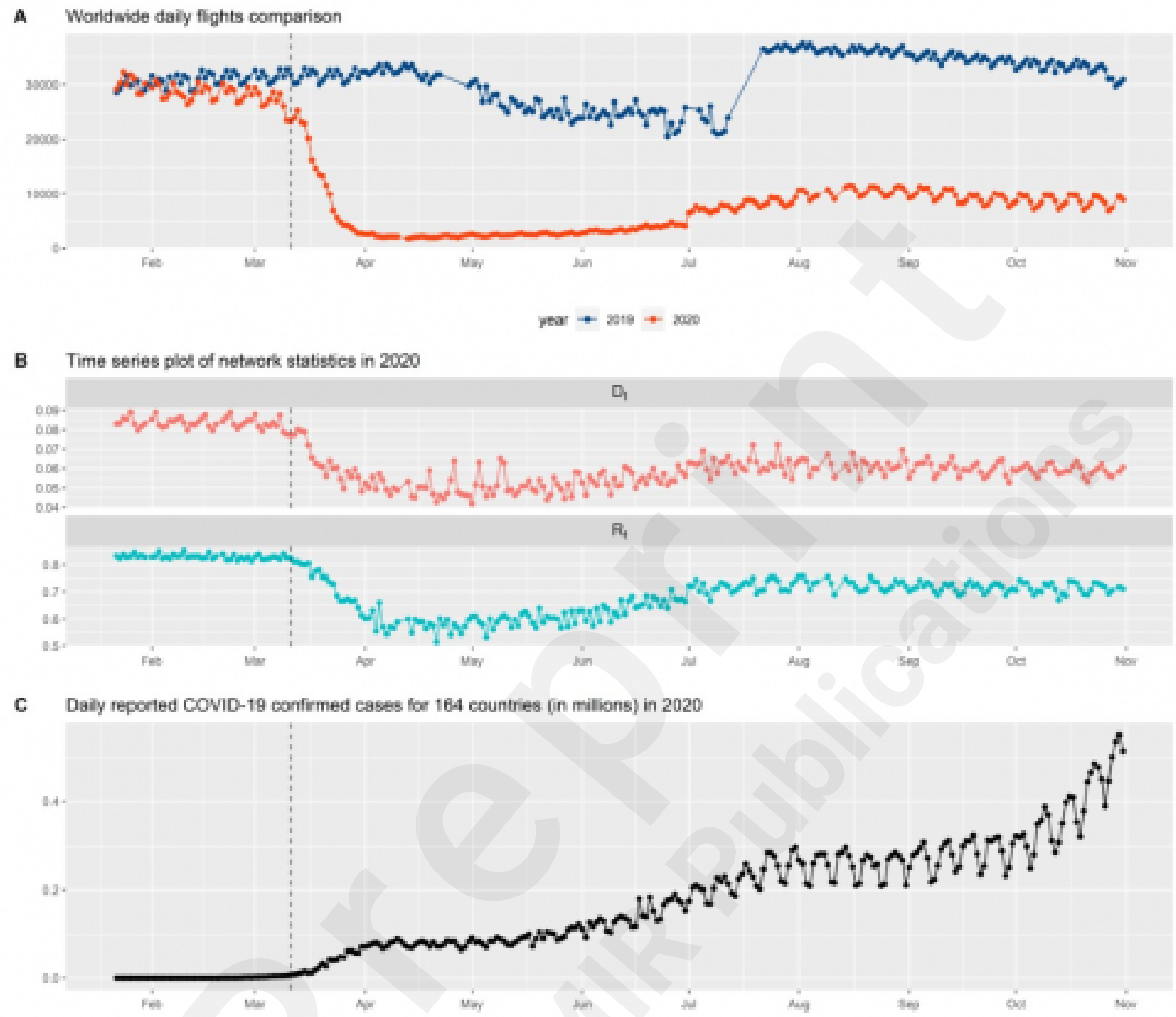

Figure 2: Time series plots of (A) worldwide daily flights, (B) global network statistics, and (C) daily reported COVID-19 confirmed cases

Spatial-temporal maps of connectedness in Europe at (A) country level between 13 March and 24 April 2020, and (B) air transportation hub level between 8 May and 19 June 2020.

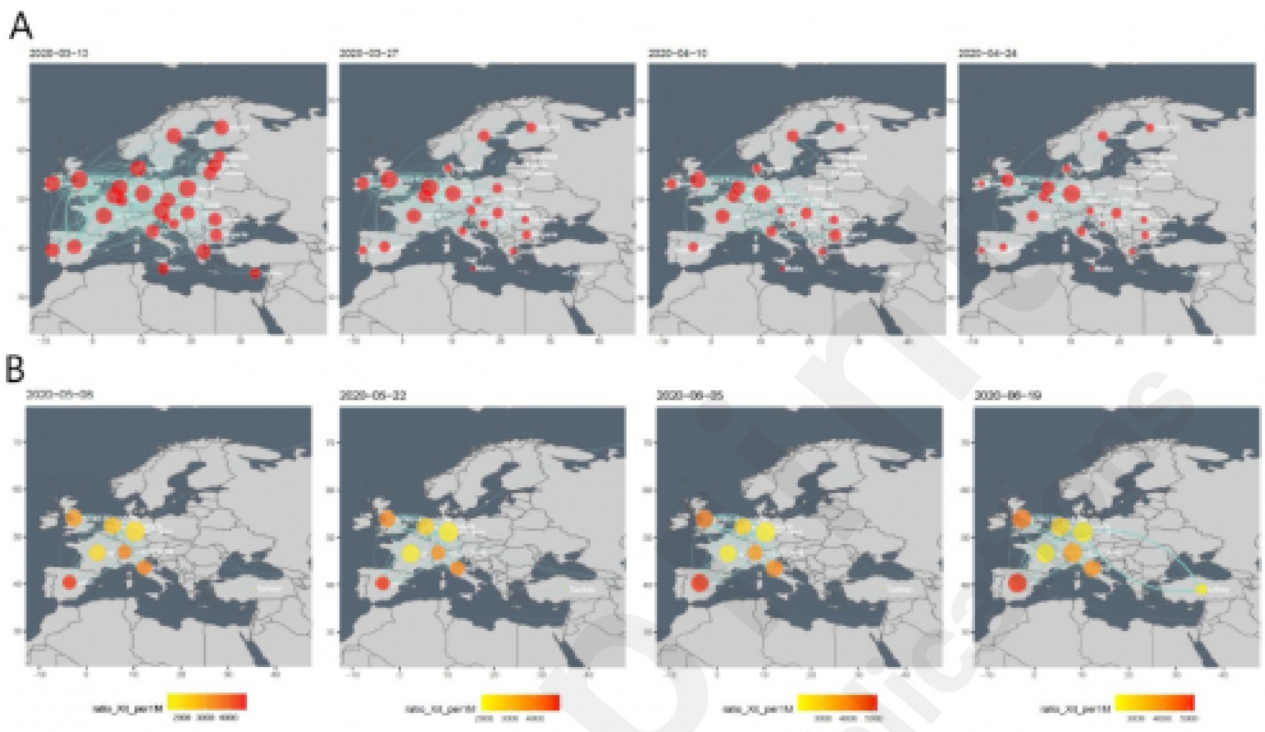

Figure 3: Spatial-temporal maps of connectedness in Europe at (A) country level between 13 March and 24 April 2020, and (B) air transportation hub level between 8 May and 19 June 2020.