GEOGRAPHICAL AND STRUCTURAL CHANGES IN THE GLOBAL TOURISM NETWORK DUE TO COVID-19

George TSOULIAS
Department of Regional and Economic Development, School of Applied Economics and Social Sciences, Agricultural University of Athens, Amfissa, Greece.
getsoulias@aua.gr

Dimitrios TSIOTAS
Department of Regional and Economic Development, School of Applied Economics and Social Sciences, Agricultural University of Athens, Amfissa, Greece.
tsiotas@aua.gr

Abstract
The COVID-19 pandemic has significantly affected the tourism economy, causing a severe global shock and effects on tourism mobility unevenly geographically distributed across regions. This paper detects changes in the global tourism flows network (GTN) in the period 2018-2020 due to COVID-19 and explains the GTN dynamics from a network science perspective. The analysis reveals the effect of underlying economic geography, as the pandemic introduced a new social distancing friction that induced centrifugal forces to the tourism network. The network's topological pattern was described by small-world network characteristics before the pandemic outbreak, while during the pandemic there was a statistically significant reshape into more lattice-like characteristics accompanied by peripheral markets expansion of local hierarchy. The findings also demonstrate a reduction in the number of tourism flows and spatial connectivity, a simplification of the macroeconomic travel behavior, and a resilient performance of the main tourism hubs shaping and a distinctive core-periphery network structure. Overall, this paper contributes to a better understanding of the response of tourism mobility to the pandemic.
Keywords: network analysis, tourism mobility, tourism flows, network structure, global tourism, tourism geography.

1. INTRODUCTION

The World Health Organization (WHO) declared COVID-19 a pandemic in March 2020 that caused serious consequences for public health, the economy, political balance, and society (Gossling et al., 2020). The pandemic was also particularly damaging for tourism and especially for global tourism mobility, as due to the high contagiousness of the virus most countries were forced to impose measures to restrict domestic and global travel (Uglis et al., 2022; De Palma et al., 2022). One of the main reasons for the widespread impact on the tourism industry was the simultaneous impact on the supply and demand for travel (Bai et al., 2020). In comparison with other crises, COVID-19 caused a bigger disruption in terms of duration and severity (Ding et al., 2021). The changes caused in tourism mobility had different

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manifestations, as the pandemic manifested with different waves and mutations, and hence the tourism industry a period of fluctuations in travel patterns (Zenker and Kock, 2020; Yu et al., 2023).

The tourism and hospitality industry is one of the most sensitive to political and socio-economic changes due to crises, wars, disasters, pandemics, and external factors in general (Williams and Balaz, 2015; Barbhuiya and Chatterjee, 2020). Researching the disruptions that had an impact on tourism before the pandemic occurred was mainly local as the resulting crises were specific to individual regions (Duro et al., 2022). Each crisis and shock in the tourism industry resulted in significant changes in travel behavior and tourism demand (Mair et al., 2016) and an important finding is the resilience of the tourism industry in terms of recovery and adaptation to change, because of its dynamic nature and the generation of alternative behaviors and trends in travel choices and travel distribution (Reddy et al., 2020; Park et al., 2022). Social distancing regulations, isolation policies, and border travel restrictions are the direct factors under which the COVID-19 pandemic impacted tourism flows (Sucheran, 2021). One of the most important changes is the promotion of domestic tourism markets as safe areas relative to global ones, which were more affected by mobility restrictions (Duro et al., 2022). The most common approach to addressing global tourism flows has focused on tourist arrivals and tourism revenues (Shao et al., 2020).

The network perspective in global tourism research is a method that can be used to detect the location and behavior of actors in a network based on its structure, strength, and patterns of relationships that develop within it (Casanueva et al., 2014). The use of complex network analysis and complexity theory can contribute to a better understanding of the non-linear nature of tourism flow patterns (Zenker and Kock, 2020). Under the network paradigm and the pandemic externality, this paper assumes that COVID-19 affected the structure and functionality of the Global Tourism Network (GTN) and investigates its evolution over three years, starting from 2018 up to the year of the pandemic. In the GTN, each node represents a destination, whereas network connections represent flow paths between nodes. The analysis provides insights into travel behaviors research and tourism market resilience due to the pandemic and also contributes to tourism and economic geography by considering the effect of network connectivity on tourism and generally spatial markets. The research builds on a dataset of indistinguishable total tourist movements from origin to destination countries and explores central and regional markets before and during COVID-19. Through the data processing, the analysis compares quantitative indicators of network topology for each year to clarify the mobility behavior that unfolded during the study period. The approach of this study is in line with existing theories of travel motivation and risk perception during pandemics (Aaditya and Rahul, 2023; Airak et al., 2023) and is expected to expand theoretical paradigms around travel behavior during crises and disruptions.

The key question raised by the paper is whether the pandemic has affected the setting and distribution of the tourism flows globally and it is examined in a structural and functional network analysis context. The results can be evaluated in a second reading to analyze the evolution of the pattern of network organization and its nodes. The contribution of the paper lies in two aspects: the clarification of the differences in the spatial distribution of tourist flows before and at the beginning of the COVID-19 pandemic and the analysis of the travel pattern over three years. In structural terms, the paper is organized as follows: section 2 summarizes the existing theory on the relationship between transport and tourism, the applications of network science in tourism, and the role of COVID-19 in tourism. Section 3 presents the data and the research methodology, and Section 4 shows the results of the study. Finally, Section 5 includes the conclusions offered by the analysis of the data from the thesis, as well as future research and specialization recommendations.

2. LITERATURE REVIEW

Global tourism is one of the most important economic activities worldwide and has a positive impact on increasing long-term economic growth in different ways (Brida and Pulina, 2010). In the global economy, tourism is a fundamental growth stimulus and a key source of income in developed and developing countries (Hall et al., Costa 2017). Part of the research has focused on how the relationship between the core and the periphery can affect regional tourism development (Papatheodorou, 2004). This relationship has its basis in the neo-Marxist dependency theory, stating the lack of growth is the result of external forces rather than internal causes (Treacy, 2022). Moreover, instability in global economic conditions is likely to lead to shocks in the demand of the center countries and thus be detrimental to peripheral countries, as their economic activity is based on the economic conditions of developed countries (Agius and Chaperson, 2023). The relational patterns in a global tourism network build on the tourists' flows and create a social system, where network analysis can be used to uncover the underlying relationships (Marin and Wellman, 2011). The global travel market is characterized by uncertainty (Lynch and Morrison, 2006), and the COVID-19 pandemic was accompanied by a period of uncertainty (Williams et al, 2022). In the year of the pandemic, the pandemic was estimated to alter tourist behavior and cause turbulence in the tourism industry (Kock et al., 2020), while in the later years was highlighted that travel restriction policies influenced tourists' travel behavior (Fan et al., 2023).

Network science has so far provided methodological tools for identifying the relationships between tourist destinations and capturing the spatial distributions of tourist movements (Park et al., 2020). In terms of tourism mobility, it has focused on movements within certain regions (Zeng, 2018) and between countries (Shao et al., 2020). Beyond being a complex system (Baggio, 2008), tourism is a networked industry and spatially dispersed, consisting of businesses and relationships (Gonzalez-Diaz et al., 2015). Due to its composite socioeconomic and geographical nature, a tourism system can be described by complex network relationships (Wu et al., 2021), where tourist flows constitute collective shifts of tourists occurring in space and are subject to changes in time, direction, and scale (Tsiotas and Tselios, 2022; Wang et al., 2022), the dynamics of which are examined. Compared to general travelers, tourist mobility is spatially different because tourists are behaviorally interactive and do not act solely on individual criteria (Wu et al., 2021). For a long time, economic theory ignored concepts such as distance, space, and transport costs. The theory of the New Economic Geography (NEG) developed in the 1990s by Krugman (1991) highlighted the importance of space in the geographical distribution of economic activity. Going beyond, evolutionary economic geography (Boschma and Martin, 2010) has incorporated recent advances to explain the processes through which the spatial organization of economic activity changes over time, examining the factors that affect the economic development of a region. In a tourist context, this approach is challenging in incorporating non-linearity, unstable nature, adaptability, and complexity of the tourism destinations market (Sanz-Ibanez, 2017). Tourist destinations share common characteristics with complex systems and exhibit adaptability to local and global changes (Baggio, 2008; Agarwal, 1994).

The COVID-19 pandemic affected multiple industries (Yarovaya et al., 2021; Uglis et al., 2022) particularly tourism, which is historically differently affected by each health crisis (Kuo et al., 2008) in the supply and demand for travel (Gossling et al., 2020; Lin and Falk, 2021) and their spatio-temporal distribution (Sigala, 2020; Tsiotas and Tselios, 2022). COVID-19 restriction policies were global, regional, and local, including social distancing, and national and global travel restrictions (Fotiadis et al., 2021; Jeczmyk et al., 2023). As an open economy, tourism enjoys high networking with the external environment (with technological, socioeconomic, political, economic, and ecological dimensions), thus being susceptible to externalities (Ugur and Akbıyık, 2020). Provided that the effects of the COVID-19 economic crisis on tourism in terms of scale, duration, and severity differ from previous crises (Ding et al., 2021), it is challenging to examine how the pandemic affected global tourist flows that have been one of the most important channels of the virus transmission across national borders and countries (Farzanegan et al., 2021). A recent study (Tsiotas and Tselios, 2022) revealed that the global spatio-temporal patterns of virus transmission are largely determined by network connectivity and centrality rather than spatial proximity. Research on tourism mobility and its relationship with the pandemic initially focused on the way travelers were potential transmission vectors (Iaquinto, 2020) and, progressively, on unveiling changes in tourists' travel behavior, consumption patterns, etc. (Kock et al., 2020; Ren et al., 2022). The variations in travel and travel patterns are reflected in the tendency of tourists to avoid crowding, seasonality, and over-tourism while reducing the distances of travel (Bae and Chang, 2021). Another trend regarded the preference of open spaces, individual, and luxury travel (Park et al., 2021), and tourists' perception of tourism activities involving crowding meant social distancing behaviors (Kim and Liu, 2022). Tourists' social distancing behavior is attributed to social contact theory (Park et al., 2021) and conflicts with tourists' motivation theory describing the tourist tendency to visit locations that other people visit, seeking social contact (Zhou and Yu, 2022). The literature has indicated that the pandemic affected travel choices, leading tourists to seek recreation in their home country and to discover alternative domestic destinations (Chansuk et al., 2022). Moreover, travel motivations are less related to social networking and participation (Fan et al., 2023). In contrast to domestic tourism, which has proven to be more resilient to the pandemic, international tourism experienced a severe hit, which suggested a tendency of tourists to avoid traveling either voluntarily or due to pandemic management policies (Arbulu et al., 2020).

3. METHODS AND DATA

3.1. Data collection and database construction

This paper examines changes in the topology of the Global Tourism Flows Network (GTN) for the years 2018 (pre-pandemic), 2019 (pre-pandemic and slight spread), and 2020 (on-pandemic), to capture the effect of the pandemic on the global tourism market. The datasets were extracted from the Organization for Economic Co-operation and Development (OECD, 2023) and included inbound and outbound tourism flows of the five largest tourism markets (representing countries) for a set of available OECD and non-OECD countries. The database used in this paper was the result of merging the top-5 inbound and outbound market (countries) tables of the OECD (2023) database. In particular, the inbound OECD's tourism table included the top-5 (in terms of tourism flows' volume) countries of origin per destination country. Conversely, the OECD's outbound tourism table included the top-5 destination countries per country of origin. In the GTN, OECD's tourist destination and origin countries represent nodes and their pairwise tourism flows represent edges. The top-5 tourism market-countries limitation in data collection interprets GTN as a core (major) instead of a total tourism market, thus allowing interpreting changes in the GTN size (number of network nodes) in economies of scale context (the more participating nodes/countries, the higher economies of scale applying in the total tourism market). In particular, the evolution of GTN's size from 62 (in 2008), 63 (in 2019), and 59 (in 2020) nodes (countries) indicates that the total tourism market reduced its economies of scale due to the COVID-19 emergence.

3.2. Methodology

This paper uses network analysis (Miguens and Mendes, 2008; Tsiotas and Tselios, 2022) to investigate changes in the structure and topology of GTN due to the impact of COVID-19. The methodological framework followed for the annual analysis of the GTN is represented in the flow chart of Figure 1.

The family of 3 annual GTN networks allows considering GTN as a multilayer network (Figure 2) consisting of the $GTN_{(2018)}$; $GTN_{(2019)}$; and $GTN_{(2020)}$ layers. Each layer corresponds to a directed, connected, and weighted spatial network of international tourist flows (Baggio, 2017; Tsiotas and Tselios, 2022). According to this model, countries are the actors of the network, and travel paths from one country to another, regardless of the transport mode, are the links of the network. Network analysis is carried out by calculating a series of measures, as it is shown in Table A (see Appendix).

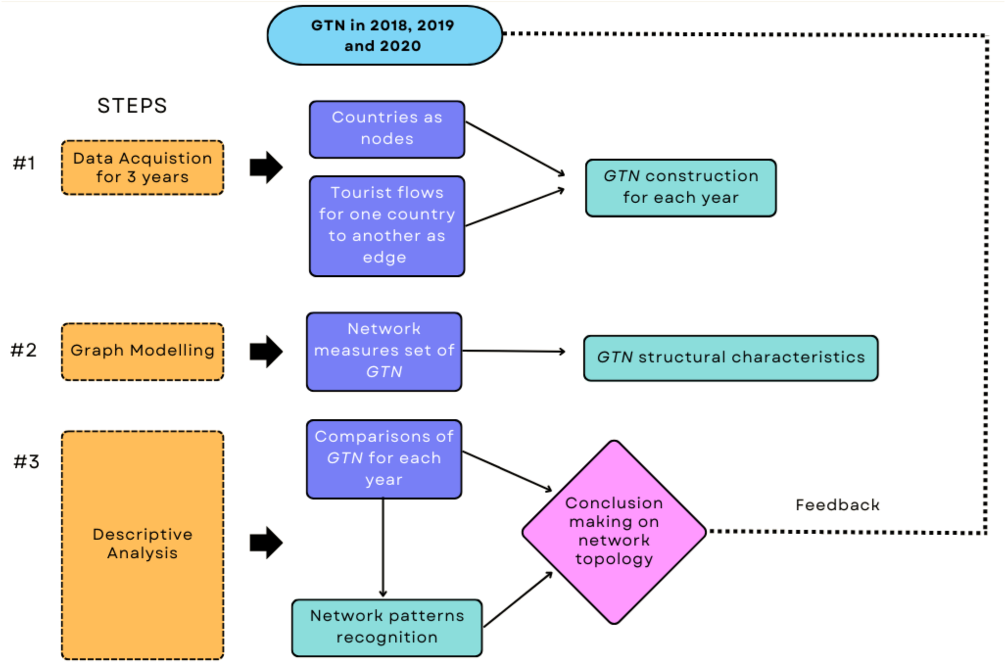

FIGURE 1 - THE METHODOLOGICAL FRAMEWORK OF THE GTN STUDY

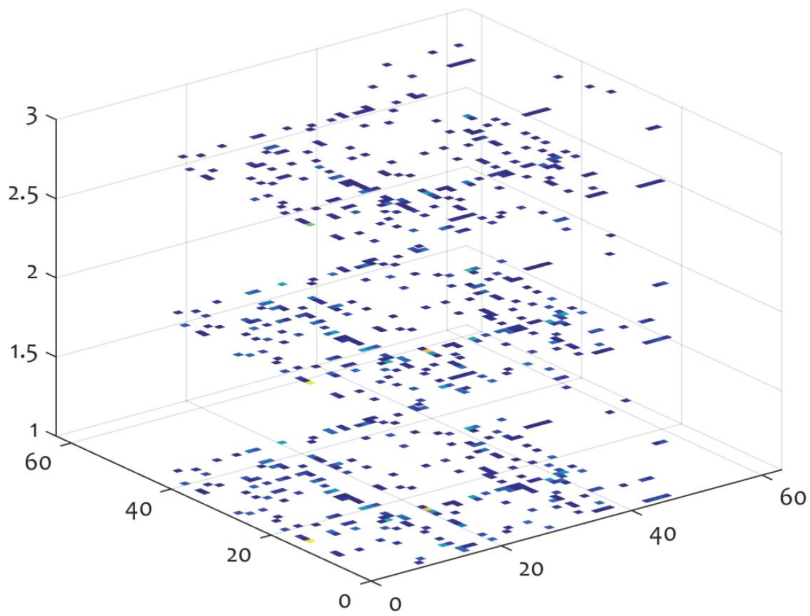

FIGURE 2 - SPY PLOTS OF THE MULTILAYER GTN FOR THE YEARS 2018 (BOTTOM), 2019, AND 2020 (TOP). LIGHTER COLORS INDICATE HIGHER WEIGHTS (VOLUME OF TOURISM FLOWS).

Beyond the topological measures, we use the "omega index" for the small-world detection of Telesford et al. (2011) and the diagonal distance of Tsiotas (2019), for pattern recognition of the GTN. The omega (ω) index (Telesford et al., 2011) detects either a small-world, lattice-like, or random-like topology in a network, by comparing network clustering to that of an equivalent lattice network ($\langle c\rangle_{latt}$) and path length to that of an equivalent random network ($\langle l\rangle_{rand}$), according to the following equation:

$$\omega = \left(\langle l\rangle_{rand} / \langle l\rangle\right) - \left(\langle c\rangle / \langle c\rangle_{latt}\right) \quad (1)$$

The null models are computed using the random algorithm of Maslov and Sneppen (2002) and the "latticization" algorithm of Lubinov and Sporns (2010), in which the degree distribution of the source network is preserved. Values of ω close to zero add up to a small-world attribute, whereas positive values illustrate random-like characteristics and negative values indicate more regular or lattice-like characteristics.

The diagonal distance (dd) is a spectral metric (Tsiotas, 2019) that distinguishes the scale-free (SF) property amongst random-like and lattice-like equivalent SF topologies. The measure computes the average distance from the main diagonal of the non-zero elements in the adjacency matrix of a graph and was shown to be more capable of distinguishing between different SF topologies with the same degree distribution, in comparison with the existing metrics. Beyond detecting the SF property amongst network variations with the same degree distribution, this measure can be useful in distinguishing between a total disconnected topology and the topology of a complete graph K_n. In particular, a self-connected topology is a pattern of a fully dispersed network where nodes express disconnected markets (closed economies). In such a case, only the cells in the main diagonal of the adjacency matrix are ones, thus yielding a diagonal distance dd=0. On the other hand, a complete graph K_n topology expresses a fully centralized pattern, where all nodes are directly connected. In that sense, all elements in the adjacency matrix of the graph are ones, and the diagonal distance yields asymptotically dd$\rightarrow 0.25n$ (deescalated by the four sides of the matrix), where n is the number of nodes.

4. RESULTS AND DISCUSSIONS

4.1. Measures of network topology

The results of the network measures' analysis are shown in Table 1. As previously discussed, the network size differentiates across the three years due to the top market (countries inflows and outflows) changes, providing insights into the extent of economies of scale in the total tourism network. In terms of graph density, we can observe that the annual GTN scores are in the same order of magnitude as the graph density computed for the World Tourism Web (2019) by Kostelic and Turk (2021). This observation supports the representativeness of the GTN as a graph model, although it is modeled in the top-5 market (countries) context. The emergence of the pandemic did not cause disconnectedness to the GTN, as the minimum degree was preserved, however, the hub connectedness (as expressed by the maximum degree) was considerably decreased (7%). The comparison of the average node degree between the years 2019 and 2020 shows the impact of the pandemic on spatial interactions. In weighted terms, a decrease was observed in the weighted average degree in Table 1, whereas the increase in network diameter and modularity interprets that the pandemic made GTN more diffused and modular (divisible). As far as network distance is concerned, we can observe that both GTN's average path length and network diameter were considerably increased (6% and 3%, respectively) due to the pandemic. This observation implies that GTN's topological distance (which – in a network context – represents communication cost) increased favoring the emergence of peripheral markets in the context of the NEG. In terms of the clustering coefficient, we can detect in Table 1 a large drop from 2019 to 2020, indicating that, locally, the GTN reduced its peripherality. This observation can be interpreted in the context that the uncertainties and constraints of the pandemic led to changes in travel behavior resulting in a reduction in GTN's peripheral connections locally, interpreting that local tourism markets became more central due to the pandemic. This topological transformation illustrates a weakening in the diversification of tourist preferences for local tourism poles and the strengthening of the central role of important tourist hubs in terms of influence and connectivity. This topological transformation may also be accompanied by either an increase in domestic tourism or an increase in the diversification of tourist preferences for other, not major, local tourism destinations. Finally, the GTN experienced a slight increase in modularity due to the pandemic but not in communities' number, implying that COVID-19 slightly increased the tourism network's divisibility.

TABLE 1 - RESULTS OF THE GTN NETWORK MEASURES' ANALYSIS*

		GTN Layers[(a)]			Growth rate (%)[(b)]	
Metric/Size	**Unit**	**GTN$_{(2018)}$**	**GTN$_{(2019)}$**	**GTN$_{(2020)}$**	**2018-19**	**2019-20**
Number of nodes	#[(c)]	62	**63**	*59*	2	**–6**
Number of edges	#	253	**248**	*206*	–2	**–17**
Maximum degree	#	**41**	**41**	38	0	**–7**
Minimum degree	#	1	1	1	0	0
Average degree	#	**4.081**	3.937	*3.492*	3.5	**–11**
Weighted average degree	Tourists	4,276,868	**4,352,736**	1,471,292	2	**–66**
Average path length	#	*2.489*	2.522	**2.679**	1	**6**
Network diameter (binary)	#	6	6	**8**	0	**3**
Graph density	net[(d)]	**0.067**	0.063	*0.060*	**–6**	**–5**
Average clustering coefficient	net	**0.265**	0.259	*0.210*	–2	**–19**
Modularity	net	*0.322*	0.330	**0.337**	2	2
Number of communities	#	6	5	6	.17	
Number of nodes per community	#	11; 14; 8; 14; 3; 12	15; 10; 14; 19; 5	8; 11; 13; 7; 3; 17		

a. Cases in **bold** indicate **max** and in *italic* indicate *min* scores
b. Cases in **bold** indicate growth rates ≥ 5%
c. Number of elements
d. Dimensionless number
*. Decimal numbers are rounded up to the third decimal place

As far as spatial distributions are concerned, the spatial distribution of the GTN's degree throughout the examined period is shown in Figure 3. An overall observation is that Europe is the central core in terms of GTN connectivity advantage for 2018 and 2019. In 2020 only specific countries such as Germany and Italy strongly maintain this advantage, while network connections are declining. Croatia and Belgium entered the list of the top nodes in connectivity for 2020, but they are in the low-ranking zone. Further, directional information on degree is provided in the bar charts shown in Figure A_1 (see Appendix). As can be observed, the country with the most incoming connections in 2018 is Germany. Some countries have zero incoming connections, which occurs due to a lack of available data. In the year 2019, the same countries occupy the top five positions, while in the year 2020, Russia shows a very large drop and is visibly affected by the occurrence of the pandemic. Regarding the measure of the out-degree for 2018, Germany has the highest value, followed by Russia, Italy, the US, and France. The picture is similar for the year 2019 except for the descent of the US, while in the year 2020, there are significant changes. Germany is again a strong market for other countries, while Russia is weakening in its strong tourism feeder role. Compared to the year 2018, in the next two years, Peru will gain an important role in terms of the connections it generates as a market. High prices on outbound connections in general may reveal a variety and diversification in the preferences of outbound tourists.

Directional information on the weighted degree distribution is also provided in the bar charts shown in Figure A_2 (see Appendix). The best-performing country in terms of tourist arrivals (weighted in-degree) is Italy, followed by Germany, France, Austria, and Turkey. The performance ranking in the measure remains the same for 2019. In 2020, a remarkable reshuffling of the ranking is noticeable, as Italy comes fourth in the top ranking, with Austria first, France second, Germany third and Turkey fifth. In the weighted out-degree ranking, the country that is the most advantageous in the year 2018 is Germany, followed by Russia, France, Italy, and the US. The same picture prevails in the following year, with the only difference being an improvement in the position of the Netherlands compared to the US. In the year of the pandemic, there is again a strong reclassification and an expected fall in prices. Germany retains its advantageous role, with the Netherlands being the second node in the ranking. The inability of certain hubs to act as tourism transmitters is reflected in the fact that in the year of the pandemic, Spain and the USA, countries with a respectable presence in previous years, are absent from the top ten tourism suppliers in the year of the pandemic.

Subsequently, the spatial distribution of the clustering coefficient shown in Figure 4 appears similar for the first two years. The existence of large values of the coefficient is associated with interconnected areas and the existence of neighbors in those areas that are connected. Nodes with the highest degree values tend to have a lower clustering coefficient, which is common in social networks (Kostelic and Turk, 2021).

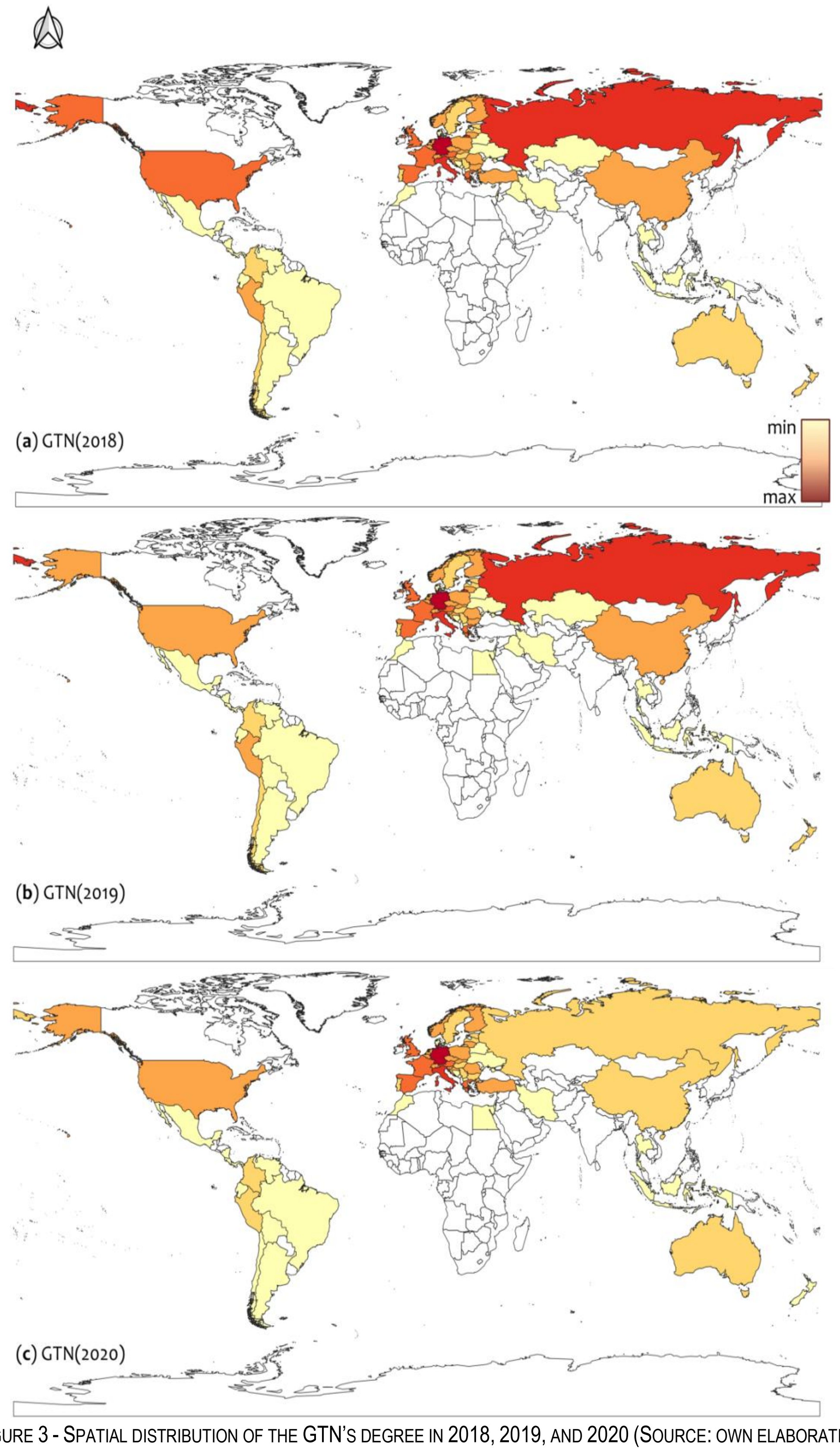

FIGURE 3 - SPATIAL DISTRIBUTION OF THE GTN'S DEGREE IN 2018, 2019, AND 2020 (SOURCE: OWN ELABORATION)

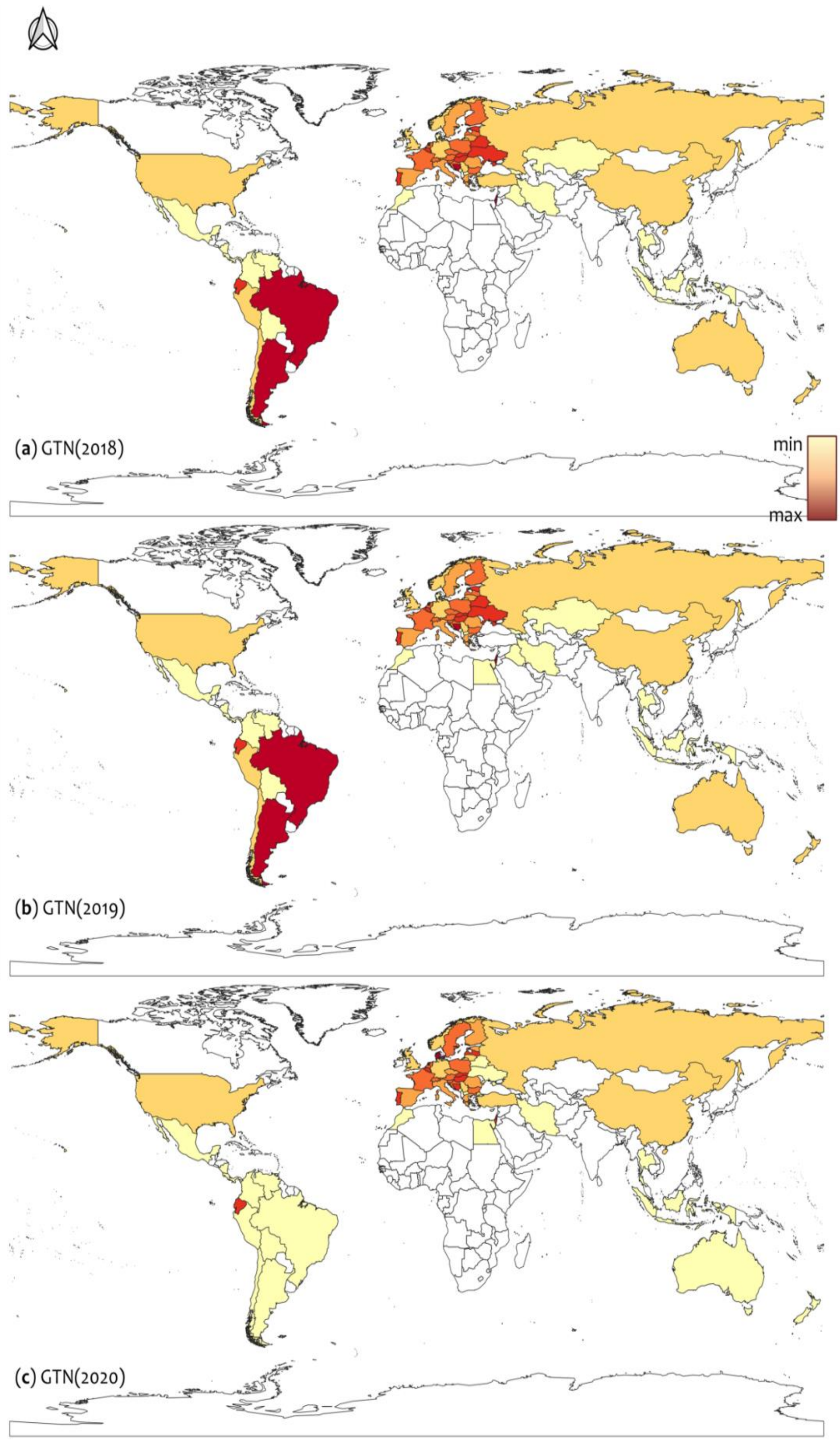

FIGURE 4 - SPATIAL DISTRIBUTION OF THE GTN'S CLUSTERING COEFFICIENT FOR THE YEARS 2018, 2019, AND 2020 (SOURCE: OWN ELABORATION)

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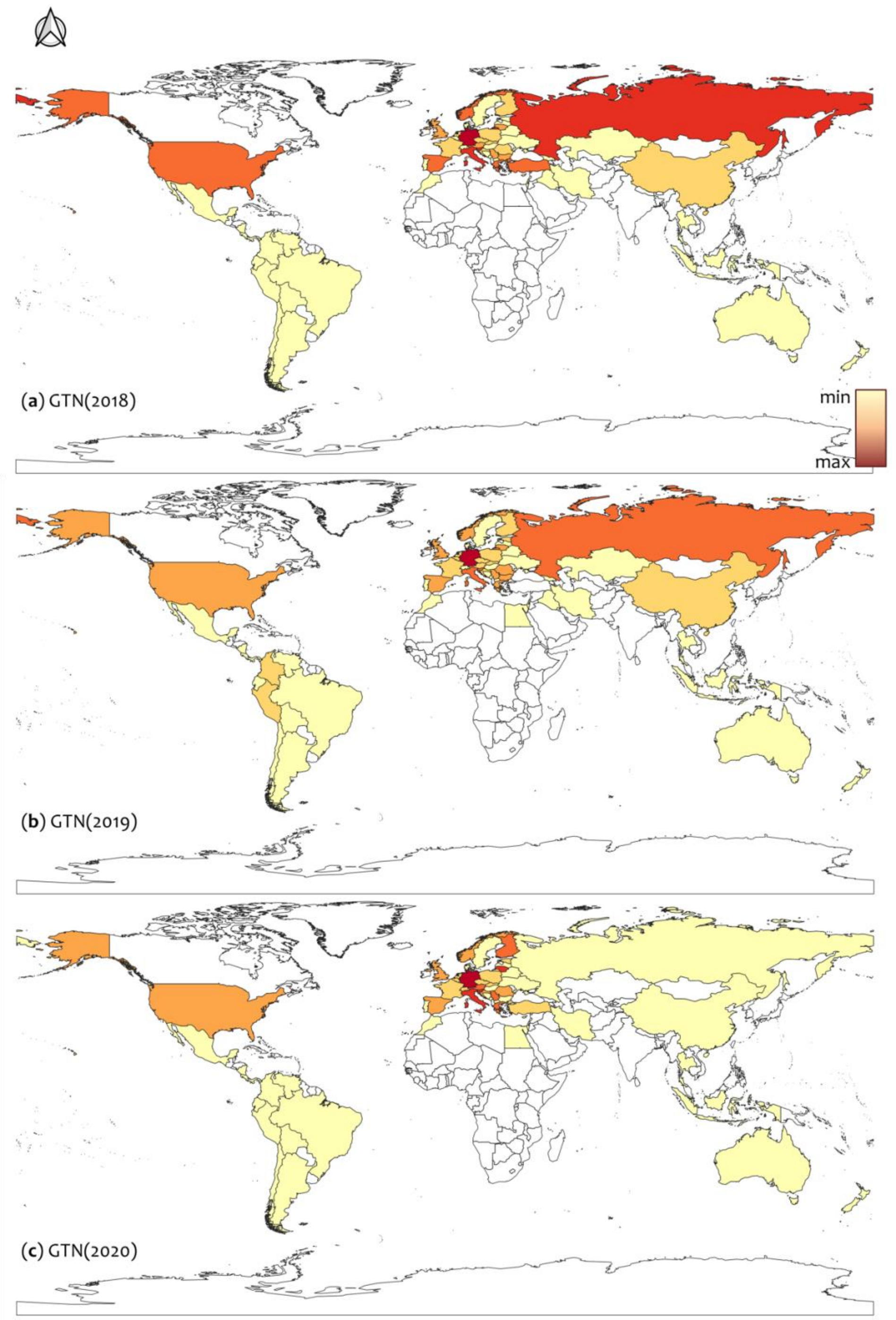

FIGURE 5 - SPATIAL DISTRIBUTION OF THE GTN'S BETWEENNESS CENTRALITY IN 2018, 2019, AND 2020 (SOURCE: OWN ELABORATION)

In the year 2020, the value distribution ranges reveal a less dense and connected network, as the concentrations at high measure values have become smaller. Compared to the first two years, the ranking changed in the year of the pandemic, with the top five countries consisting of Denmark, Luxembourg, Malta, Portugal, and Belgium. Next, the spatial distribution of betweenness centrality for the first two years in Figure 5 shows a similar pattern to the degree distribution. The highest intensity of values occurs in

Europe and individually in Russia, Turkey, and the USA, and especially in 2019 the values of the six highest-ranked nodes increase. Germany's clear advantage is also confirmed in this measure for each year.

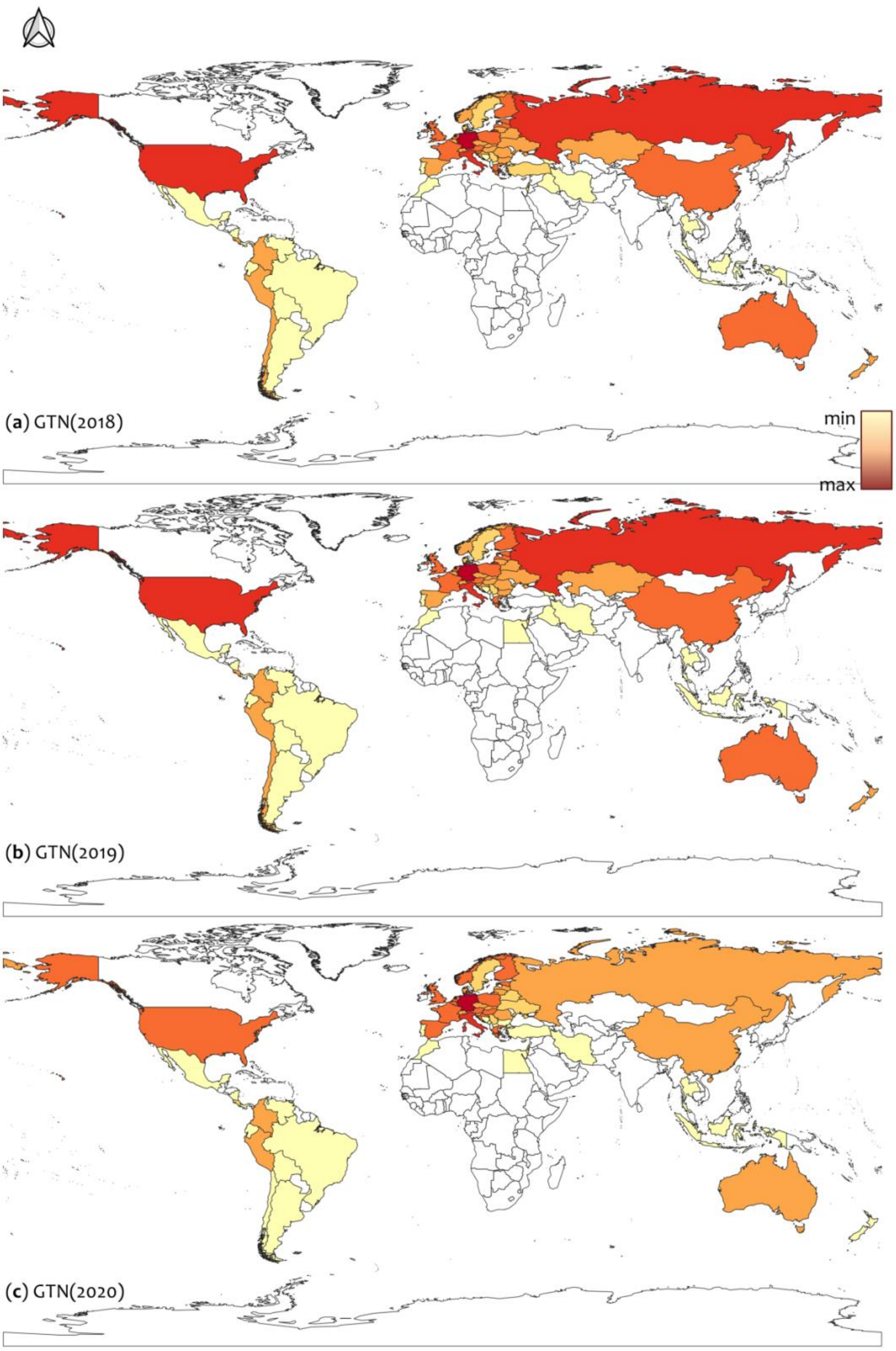

FIGURE 6 - SPATIAL DISTRIBUTION OF THE GTN'S CLOSENESS CENTRALITY FOR THE YEARS 2018, 2019, AND 2020 (SOURCE: OWN ELABORATION)

Continuing with the spatial distribution of closeness centrality, the pattern does not change in the first years, except for the decrease in the values of the maximum nodes, but without losing their position in the descending ranking. The dominant countries in this measure are Germany, Russia, Italy, Italy, the USA, and France, indicating the good connectivity of these nodes and their neighbors. In the year 2020, Russia is absent from the top ranking, which in combination with the above findings, reflects a weakening of the tourism market. On the contrary, and despite the quantitative decline, there is a strengthening of the role of the markets of Italy, France, Greece, the Netherlands, and Poland, while Austria is falling in the ranking.

4.2. Pattern recognition

Pattern recognition of the GTN builds on examining the degree distribution, along with the omega index and diagonal distance indicators. The annual degree distributions for the GTN are shown in Figure 7, where the annual coefficients of determination R^2_{2018} =0.8534, R^2_{2019} = 0.8873, and R^2_{2020} = 0.8141 first indicate that this model can satisfactorily highly (> 80%) describe the variation of the GTN's degree distribution data for each year. Previous studies, have generally shown that the tourism network is governed by social and economic network characteristics (Miguens and Mendes, 2008; Seok et al., 2021) and the distributions of the input and output degree exhibit a power-law pattern (Lozano and Gutierrez, 2018). In this analysis, the inequality in the power-law exponents $|\gamma_{2019}| < |\gamma_{2018}| < |\gamma_{2020}|$ implies that the COVID-19 pandemic drove the GTNs into a better hierarchical structure (scale-freeness) than this of the previous years. This observation complies with a previous finding about the local reduction of the GTN peripherality, illustrating that the increase in the network's scale-freeness is more a matter of neighborhood connectivity.

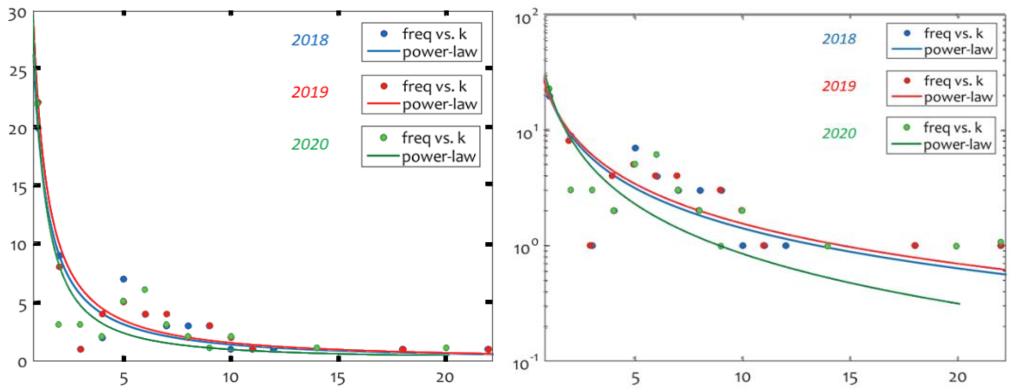

FIGURE 7 - THE GTN DEGREE DISTRIBUTION (*K*, *N*(*K*)) FOR THE YEARS 2018 (γ_{2018}= –1.152), 2019 (γ_{2019}= –1.153), AND 2020 (γ_{2020}= –1.407), SHOWN IN (LEFT) METRIC AND (RIGHT) SEMI-LOG SCALE (SOURCE: OWN ELABORATION)

Next, Table 2 shows an approximate pattern recognition analysis of the GTN based on the omega index and diagonal distance indicators. As can be observed, the GTN topology became more latticed due to the pandemic at the expense of the small-world property. The lattice-like characteristics captured are in line with the finding about the distance (average path length and network diameter) increase of the GTN, interpreting an increase of local activity in the tourism market that is attributed to the restriction of traveling and weakening of visiting global destinations because of the pandemic and, in general, to the breakdown of the complex connectivity resulting from the changes in travel. In addition, this transformation in network topology means that the network has become more regional, and regional markets dominate. The emergence of this behavior is attributed to limitations in travel variety and choice and the creation of a more local and constrained network, with an emphasis on domestic and short-distance travel rather than long-distance travel.

TABLE 2 - RESULTS OF THE APPROXIMATE PATTERN RECOGNITION ANALYSIS OF THE GTN

Size	GTN 2018	GTN 2019	GTN 2020
Ω-index*	-0,041	-0,111	-0,428
Indication	Small-world	Small-world	Lattice like
dd**	0.7417	0.7226	0.5596
Interpretation Range	~0.25n ← (K_{62}: 15.5; K_{61}: 15.75; K_{62}: 14.75)		→0 (self-connected topology)

*. Based on Telesford et al. (2011)
**. Based on Tsiotas (2019); Calculations applied to a multiplex matrix structure (63×63) across the layers
(Source: own elaboration)

In terms of the diagonal distance indicator, Table 2 shows that the GTN topology became more self-connected due to the pandemic. This self-connection increase interprets the emergence of more regional markets in the GTN, which is in line with the finding about the increase of network distance and modularity. Further, to the extent that link concentration close to the main diagonal indicates a lattice topology, the result of the diagonal distance computation implies higher participation of GTN due to the pandemic, as previously detected by the omega index assessment. Overall, this shift in network behavior may enjoy an interpretation in the context of NEG (Krugman, 1991), according to which an increase in transportation cost (generally in spatial impedance) obstructs the concentration of activities in geographical space and favors the emergence of centrifugal forces driving to peripheral markets' development. In the context of GTN, social distancing causes limitations in travel variety and choice that consequently drove the creation of a more local and constrained network, with an emphasis on domestic and short-distance travel rather than long-distance travel.

4.3. Community Detection

Community detection analysis resulted in six communities in the 2018 and 2020 networks and five communities in 2019. The spatial distribution and a node-proportional topological layout of the communities' composition are shown respectively in Figure 8 and Figure 9. First, the results in Figure 8 highlight geographical proximity as a major force in the community (market) configuration of the GTN in

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the period 2018-2020, which is likely related to the propensity of travelers to choose shorter-distance trips due to the emergence of the pandemic. However, a study on global tourism travel (Lozano and Gutierrez, 2018) highlighted that the structural sharing of the tourism network stems from commercial and cultural factors in addition to geographical ones. In the case of GTN, this is evident in the year 2018 where three almost pure hub communities are identified that include an admixture of South America with North America, the Nordic countries, and the Balkans.

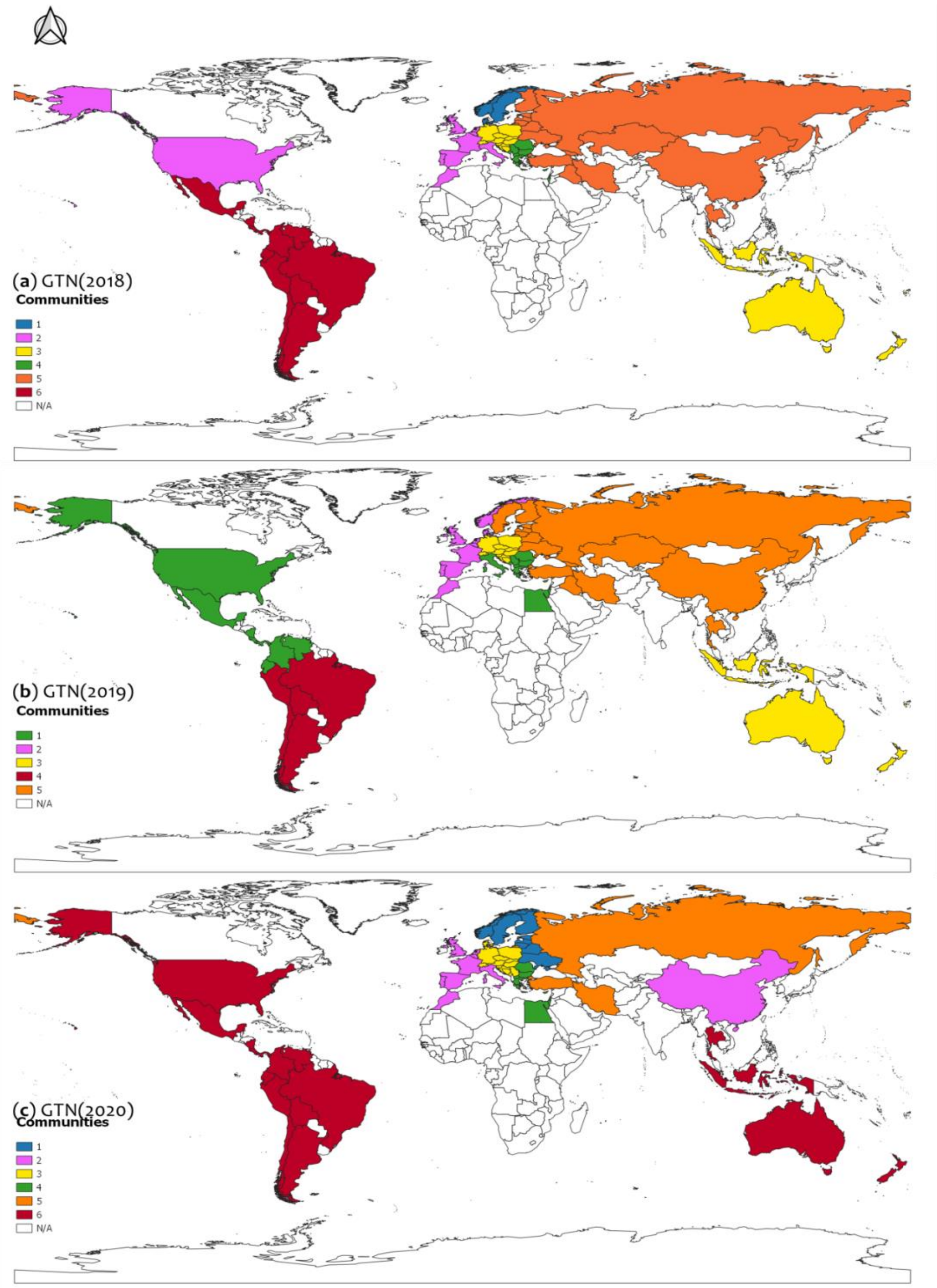

FIGURE 8 - SPATIAL DISTRIBUTION OF GTN'S MODULARITY CLASSIFICATION FOR THE YEARS 2018, 2019, AND 2020 (SOURCE: OWN ELABORATION)

In the year 2019, we can observe an overlap between central and regional countries in the network. Countries in the center of the network perform better on measures of centrality as they attract more tourists than other countries and some of these countries have a regional position in the network. The clearest community is that of South American countries, but losing many of the countries that made up the community in the previous year. A new community was created bringing together countries from the Mediterranean, the Balkans, and North America. An interesting observation is that the Nordic countries have been divided into two distinct communities, each with common linguistic-cultural characteristics and geographical proximity.

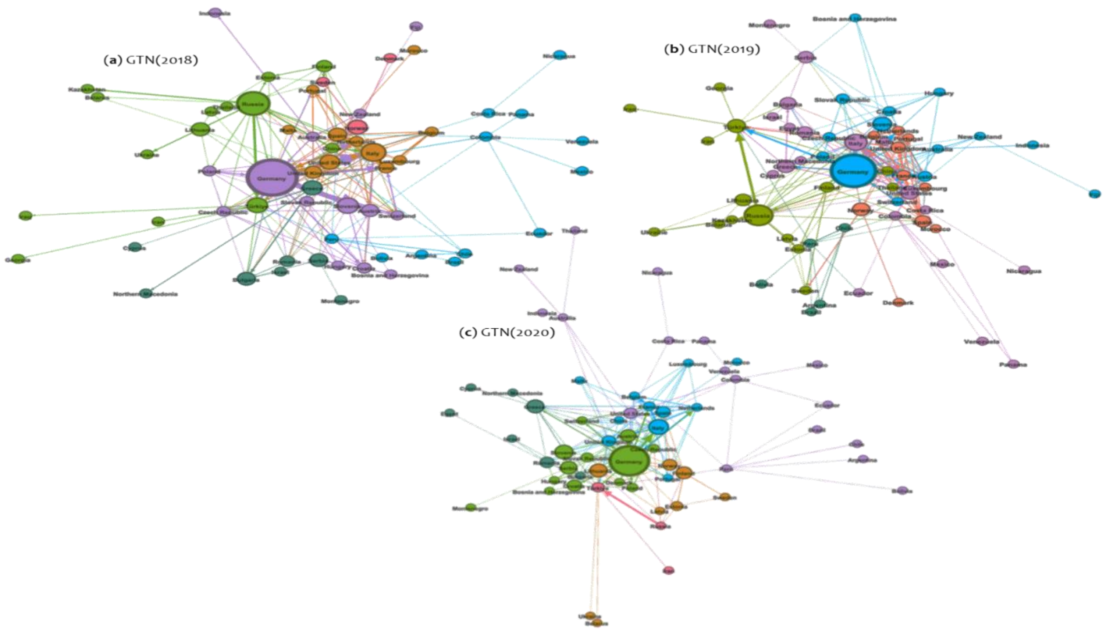

FIGURE 9 - GTN'S COMMUNITY LAYOUT PROPORTIONALLY TO NODE DEGREE FOR THE YEARS (A) 2018, (B) 2018, AND (C) 2020 (SOURCE: OWN ELABORATION)

In the year of the pandemic, the clustering pattern of hub countries into communities shows remarkable relevance to the profile of the countries included in each group. Moreover, it is confirmed in many cases that short-distance travel is favored. The factor of cultural similarities also plays an important role in this case and countries with linguistic similarities are integrated into a common group. A group with evidence of proximity includes countries such as Austria, many countries of Yugoslavia, Germany, Hungary, and others and reveals a tendency for short-distance travel. Another community with many common features includes Balkan and Mediterranean countries, which is a consistent pattern of grouping in all the years considered, as can be also observed in Figure 9. Similarly, Russia, Iran, and Turkey make up a common group and these are countries that are either strategic allies or have very close trade and economic relations. What is concluded about the form of network clustering is that cultural similarity and affinity an important factors in travel choices and in the year of the pandemic this conclusion is strengthened. In

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2020, the network is grouped with similar rules and patterns as in the previous years and the group compositions argue for a preference for covering shorter distances, but also for the conclusion that the way the communities are segregated shows the highest relevance of the three years in terms of node mixing.

Amongst the communities that resulted from the analysis, one group includes countries of the former Soviet Union and Scandinavia allocated to support close movements. A second community includes countries with a long tradition of tourism mobility, such as China and the United Kingdom, European countries with good economic growth the Iberian countries, Morocco, and Malta, which has strong tourism relations with Italy and the United Kingdom. A third community shows a clear geographical and social correlation with countries in Yugoslavia and Central Europe. A fourth community includes neighboring countries of the Balkans and the Mediterranean. A fifth community, although smallest in size, includes countries with geographical proximity and good diplomatic relations. A final community is composite and includes countries from South and North America and Oceania. Taking into account the changes in communities' composition, the greatest homogeneity can be seen in the community with Balkan and Mediterranean countries and the community with the Iberian countries, the United Kingdom, Malta, Morocco, and economically developed countries.

4.4. Discussions

In the year of the pandemic, the first studies dealt with the short-term effects of the pandemic on tourism activity (Ioannides and Gyimothy, 2020; Gossling et al., 2020). Changes in tourists' preferences and patterns were found in their decision to travel due to fear of infection (Chhabra, 2020) and the pattern of short-distance and short-haul tourism was developed (Goodnow and Mackenzie, 2020). Still, the COVID-19 crisis created a travel pattern in the preferences of tourists, who indeed chose to move closer to their country of residence. This travel behavior also emerged from the homophily property, where it is assumed that tourists are motivated by geographical proximity, low costs, time savings, and social factors, such as shared culture and common language elements. This paper highlighted the exogenous pressure and spatial friction of the pandemic, which necessitated less travel and avoidance of social networking (Wieckowski, 2021), in addition to cost and social integration to the stimuli that determine the mode and psychology of travel. The results revealed reduced linkages between the GTN countries each year and a more sparse structure, while the average distance covered by tourists showed an increasing trend and the network acquired a more regional structure. The role that a country has played, retained, or lost in GTN can be indicative of the development of tourism, the impact of global change, the stringency of health policies, and its ability to compete. The core country network was composed of countries that have also been identified by recent literature as central hubs for the global tourism flow system (Lozano and

Gutierrez, 2018). In each year, Germany was the main hub in both inbound and outbound tourism, while Italy, which recorded the worst pandemic outcomes globally (Musumeci, 2021), maintained high positions in all centrality measures, and Russia was submitted to the greatest weakening in the year of the pandemic. Also, many countries were intermediate-hub bridges for tourist flows before and after the pandemic, this phenomenon was even more pronounced and the countries in this role were in Europe. In the first two years before the pandemic, both the US and Turkey were hubs with significant influence and connections in the global tourism network, but in the year of the pandemic, this status was suspended. More generally, countries that generally performed best were European, whereas Africa and South America were low in the ranking. An interesting result regards the resilience of some destinations after the pandemic, such as France, Austria, and Spain, which lost few or no connections. A similar resistance is observed in France, Greece, and the Netherlands.

Another finding regards the spatial friction that the pandemic has created in tourists' willingness to travel. Until recently, the notion of distance (both objective and subjective) was a factor in potentially inhibiting travel (Lin et al., 2022). However, during the pandemic, containment measures, concern for personal safety, and the psychological need for detachment prompted many people to change or even terminate their travel plans (Chua et al., 2021). As a result, travel patterns have changed and, as Lin et al. (2022) report, tourists showed a tendency towards destinations with cultural and environmental diversity and a moderate caution about the economic costs of travel. The analysis in this paper also showed a tendency to group neighbor countries that belong to the same continent and have strong diplomatic relations. This outcome is in line with empirical knowledge stating that network segmentation is largely determined by geographical factors (Barthelemy, 2011; D'Agata et al., 2018) and strengthens the conclusion of movement simplification. The revealed topological patterns appeared particularly representative of the structural changes detected in the GTN. The small-world property of GTN was in line with previous works (Miguens and Mendes, 2008; Lozano and Gutierrez, 2018). Differences detected in the 2020 GTN's annual layer indicate that the network becomes more linear and transforms into a more regional structure. Beyond geographical distance and transport costs, in the theory of travel incentives theory, the necessity of limiting travel due to the pandemic intrudes. The change in travel patterns based on the available data did not, however, indicate a radical change in travel patterns. Travel to peripheral areas of the network did not appear to increase in proportion to the reduction of flows to major and central destinations and in the context of the study.

The limitations raised in the paper primarily relate to the paucity of available data. There is a need to retrieve more data on tourism flows, not only at the level of top markets and destinations, to implement a more systematic approach with a thorough investigation of more nodes and more connections. An important research addition will be to count more years after 2020 to analyze the network dynamics, the new travel patterns created, the promotion of different markets, and the role of alternative destinations after more waves of the pandemic. In addition, the importance of vaccination, and the narrative of immunity in the determination to travel can be studied and the reason for travel beyond the tourist incentive can be integrated into the analysis. In addition, transport modes, the discourse of destination choice, the economy of the countries, and tourism incentives may be useful parameters. This research can also be specialized at the national or regional level to analyze the diversity of travel patterns, but it can also delve deeper into the analysis of specific periods when the pandemic was at its peak. Future work could analyze the overall functionality of the network by assessing country profiles individually and then taking into account the subjective criteria that drive travelers to travel.

5. CONCLUSIONS

Tourism activity, mobility, and tourism patterns are constantly changing, as the travel choices of tourists can change all the time. In this paper, we applied network analysis to detect the patterns of tourist movements and how they change outside the context of absolute data values such as arrivals. The results revealed heterogeneity in the global network of tourist flows (GTN) and distinguished between central and peripheral areas. The number of tourism flows and spatial connectivity reduced in GTN, implying a simplification of the macroeconomic travel behavior. The emergence of the pandemic did not cause disconnectedness to the GTN but hub connectedness decreased, although the main tourism hubs overall appeared resilient in performance, shaping, and a distinctive core-periphery network structure. The pandemic outbreak caused a topological shift to the GTN, from small-world to lattice-like network characteristics, and the network became more diffused and divisible favoring the scenario that domestic tourism increased due to the pandemic. The GTN expanded in geographical space and larger peripheral markets emerged, however, this expansion was accompanied by an increase in local hierarchy (as it was captured by average clustering coefficient and degree distribution), interpreting that local tourism markets became more central due to the pandemic. Moreover, a revisit of the pattern of the new economic geography emerges: the pandemic of COVID-19 introduced a new spatial (social distancing) friction, that of social distancing, resulting in the creation of centrifugal forces in the network. The topological pattern of the network in the first two years before the pandemic was coherent, while in the year of the pandemic, a statistically significant change was observed, showing regional specificity and the spread of its regional markets. The analysis revealed that the Balkan and Mediterranean countries showed greater sympathy and coherence in all three study years and the same resilience was evident in the community with Iberian countries, the UK, Malta, Morocco, and economically developed countries. Overall, this paper contributes to a better understanding of the response of tourism mobility to the pandemic.

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APPENDIX

TABLE A - NETWORK SPACE AND TOPOLOGY MEASURES USED FOR THE ANALYSIS OF GTN

Measure	Description	Mathematical formula
Graph density - Graph density (ρ)	The ratio of existing network connections to the maximum number of connections that can be formed. The graph density operates as an index of the total connectivity of the GTN and represents the probability of a connection occurring between two random nodes.	$\rho = \frac{m}{n(n-1)/2}$
Node Degree (k)	The number of total edges adjacent to a network vertex representing the connectivity of the network	$k_i = k(i) = \sum \delta ij,\ j \in V(G)$
Average Degree $\langle k \rangle$	The mean value of all node degrees of the network set (ki) for the set of vertices V(G) of the network.	$\langle k \rangle = \frac{1}{n} \cdot \sum_{i=1}^{n} k(i)$
Degree centrality - In-degree ki^{in} *and Out-degree* ki^{out}	Alternative name for the node degree. In a directed network there is an in-degree and an out-degree. In this paper, the in-degree represents the connections received by one country and the out-degree represents the connections generated by one country to another.	$ki^{out} = \sum_{j=1}^{N} a_{ij}$ $ki^{in} = \sum_{j=1}^{N} aji$
Closeness Centrality C_i^c	The inverse average length of the minimum paths that start from a given node. It represents the accessibility of this node to other nodes in the network The measure of closeness centrality expresses the average distance that a node has against the set of the other nodes of the network, calculated in the network's metric space. It computes the total distance $d(v_i, v_j)$ along the shortest paths from a given node v∈V(G) to all the others vi∈V(G) in the network, within a bond (connected) component (local measure), expressing the node's reachability or general accessibility cost of overcoming spatial separations among	$C_i^c = \frac{1}{\sum_{j=1}^{N} d_{ij}}$
Betweenness Centrality C_k^B	The ratio of the number of of the minimum number of paths in the network, which include a given vertex k, to the total number σ of paths in the network. The measure expresses the property of a node to act as a bridge for other nodes. In the case of the paper, the intermediate centrality indicates that a country without centrality can act as a bridge for other unconnected countries.	$C_k^B = \sum_{j,k \in I} \frac{\sigma(j,k\|i)}{\sigma(j,k)}$
Clustering Coefficient C_υ	The ratio of the number of connected neighbors E(n) of the vertex to the number of total triplets formed by that vertex.	$C_\upsilon = \frac{triplets(v)}{triangles(v)} = \frac{E(v)}{k_v \cdot (k_v - 1)}$
Modularity (Q)	Objective function expressing the potential of a network to be subdivided into communities. In the mathematical formula, g_i is the community of node i∈V(G), $[A_{ij} - P_{ij}]$ is the difference of the actual minus the expected number of edges falling between a particular pair of vertices i,j∈V(G), and δ(gi,gj) is an indicator function returning 1 when $g_i = g_j$. In this paper, the measure of modularity is used to separate distinct communities in the network based on the strength of relationships between node countries.	$Q = \frac{\sum_{i,j} [Aij - Pij] \cdot \delta(gi, gj)}{2m}$
Average path length $\langle l \rangle$	The average length of the shortest paths in the network between all pairs of nodes in the network.	$\langle l \rangle = \frac{\sum_{v \in V(G)} d(v_i, v_j)}{n \cdot (n-1)}$
Omega index ω	Small-world property detection index. Values close to zero indicate the existence of a small-world network, negative values indicate lattice-like, and positive values indicate a random-like network.	$\omega = \left(\frac{\langle l \rangle_{rand}}{\langle l \rangle} \right) - \left(\frac{\langle c \rangle}{\langle c \rangle_{latt}} \right)$
Diagonal distance DD	Measure of the average distance from the main diagonal of the non-zero elements in the adjacency matrix of a graph.	$DD = \frac{1}{\sqrt{2 \cdot n^2}} \sum_{(i,j) \in E} \|i - j\|$

Sources: Koschutzki et al. (2005); Barthelemy (2011); Fortunato (2010); Telesford et al. (2011); Tsiotas (2019)

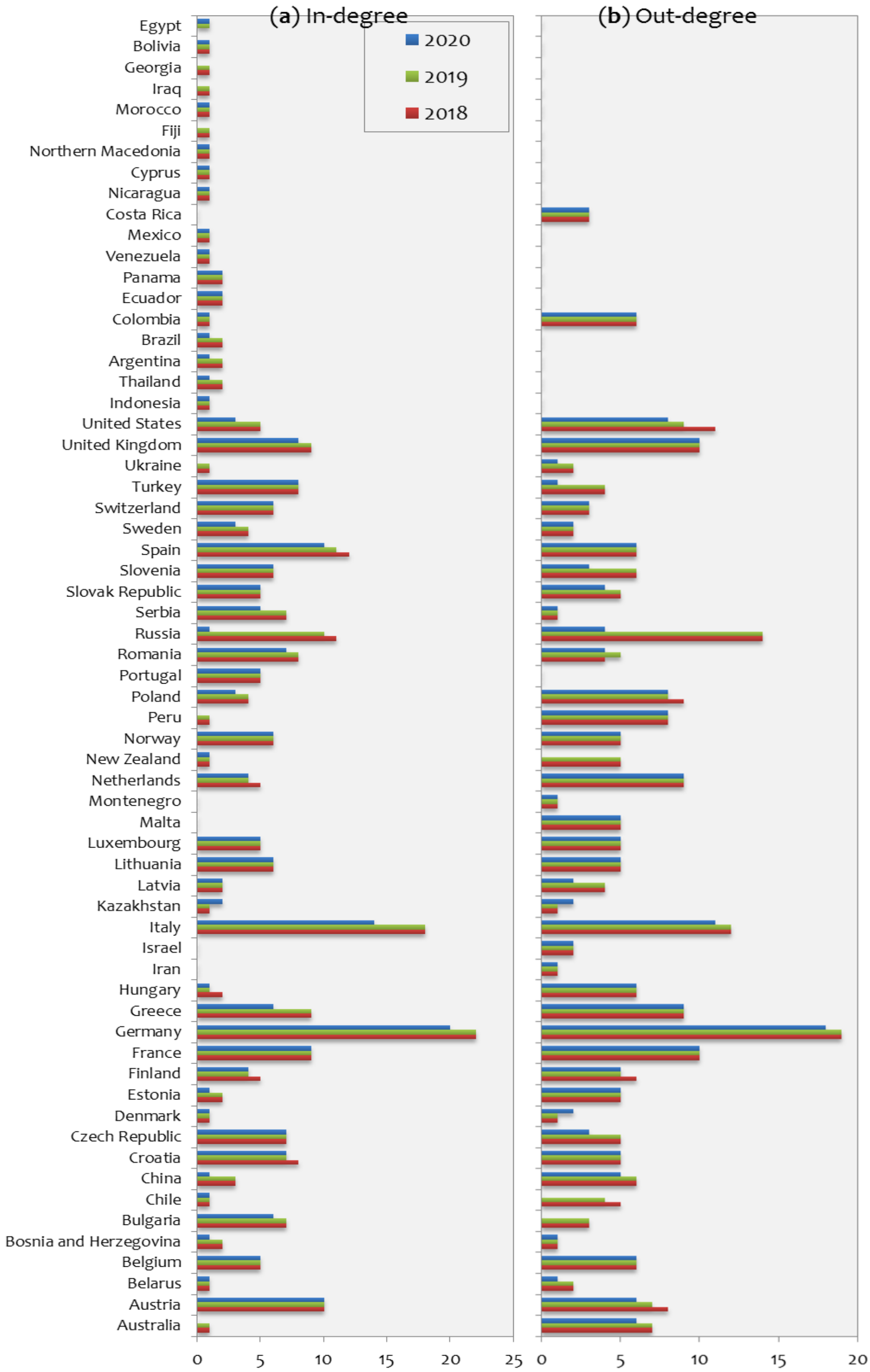

FIGURE A1 - (A) IN-DEGREE AND (B) OUT-DEGREE OF THE GTN, FOR THE YEARS 2018, 2019, AND 2020 (TOP LEFT AND RIGHT, BOTTOM CENTER RESPECTIVELY) (SOURCE: OWN ELABORATION)

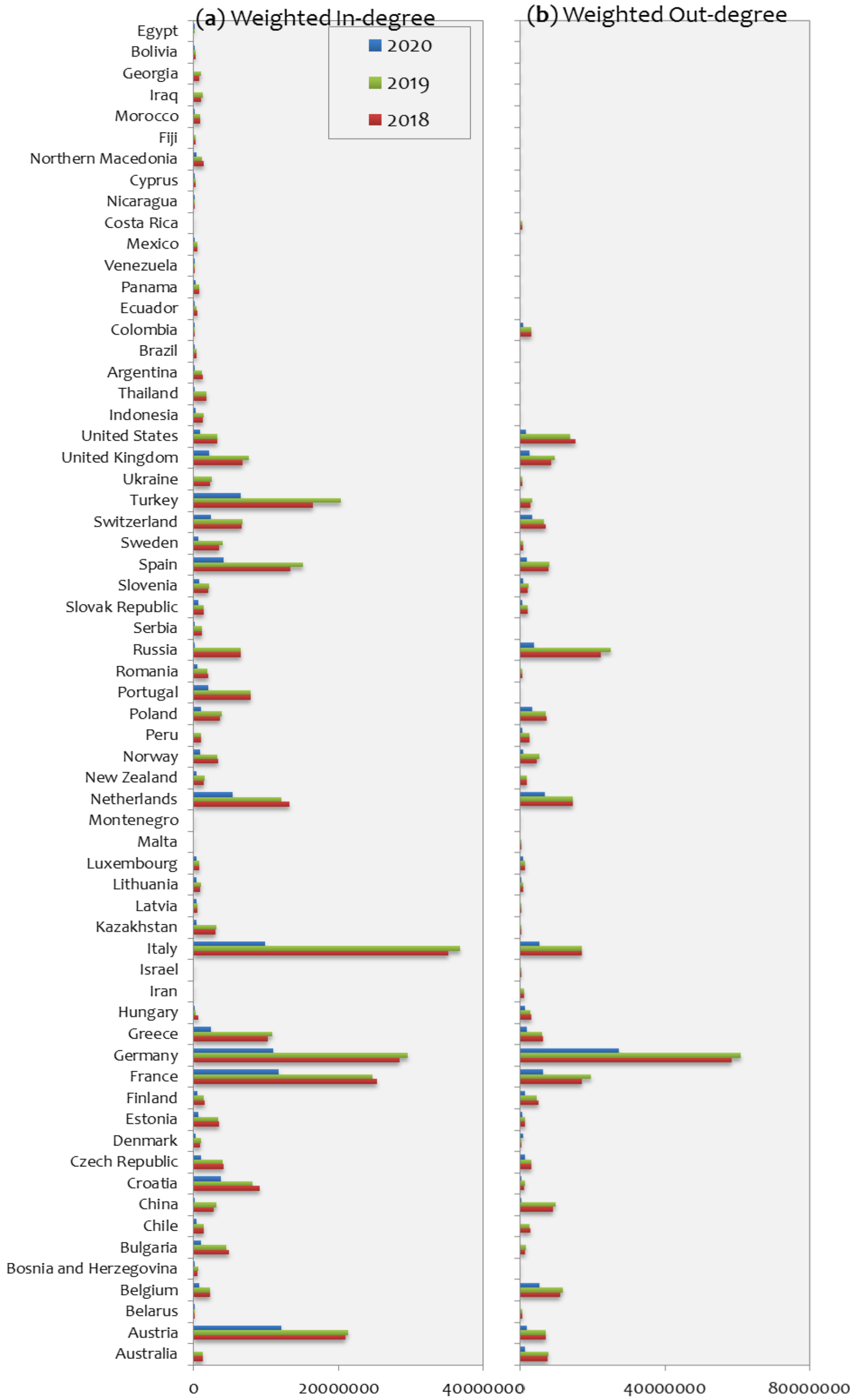

FIGURE A2 - (A) WEIGHTED IN-DEGREE AND (B) WEIGHTED OUT-DEGREE OF THE GTN, FOR THE YEARS 2018, 2019, AND 2020 (TOP LEFT AND RIGHT, BOTTOM CENTER RESPECTIVELY) (SOURCE: OWN ELABORATION)