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Network science to correlate COVID-19 and tourism indicators in Mexico

Ciencia de redes para correlacionar COVID-19 e indicadores del turismo en México

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Abstract

In this paper we analyze tourism as complex system susceptible to external perturbations, like COVID-19 public health emergency. The research objective is to confirm pertinence of using transdisciplinary tools such as complexity approach and network analysis to understand and represent tourism occupancy dynamic. We used network science methodology to introduce an analysis that integrates two Mexican tourism industry indicators: Tourist Destinations occupancy rates and Hospitality-Gastronomy jobs; correlated with COVID-19 in Mexico pandemic indicator: Confirmed cases. The analysis results are based on centrality measures used to describe organizational patterns in tourism dynamic, besides we identified some

Resumen

En este artículo analizamos al turismo como un sistema complejo suceptible a perturbaciones externas, como la contingencia de salud COVID-19. El objetivo es confirmar la pertinencia de usar herramientas transdisciplinares de complejidad y análisis de redes para entender y representar la dinámica de ocupación turística. Utilizamos una metodología con ciencia de redes para presentar un análisis que integra dos indicadores de la industria turística mexicana: Tasas de ocupación en destinos turisticos y Empleos de hospitalidad y gastronomía; correlacionados con el indicador de pandemia COVID-19 en México: Casos confirmados. Los hallazgos obtenidos se basan en medidas de centralidad usadas para describir los patrones de organización en la dinámica turística,

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generic properties of tourism occupancy distribution.

Keywords: Correlation, Data analysis, Network analysis, Systems engineering, Tourism.

y se identificaron algunas propiedades genéricas de distribución de la ocupación.

Palabras clave: Correlación, Análisis de datos, Analisis de Redes, Ingeniería de sistemas, Turismo.

Introduction

We applied network science field published in Science, 1999 and Nature, 2000 by Barabási; pertinent to analyse tourism (Scott et al., 2007); (Baggio, 2017); (Provenzano et al., 2018); (Arenas et al., 2019). Considering no published study has constructed yet complex networks that correlate:

- Mexican tourist destinations occupancy rates.
- Mexican Hospitality and Gastronomy Jobs.
- and Mexican COVID-19 statistics.

We justify network science application to analyse COVID-19 impacts on Mexican tourism, based on definition of complex systems as those with many interrelated compounds with difficulty to derive their collective behavior from an isolated knowledge of their components (Barabási, 2016).

Another complex network approach published on Nature by Albert et al. (2000) provides us with reasons to justify our subject belongs to complex systems order. To contribute understanding of tourism as complex system, susceptible to perturbations like COVID-19, having direct implications for destinations occupancy rates and jobs, enabling understanding from interacting components perspective; pertinent to consider significant tourism contribution with 8.7% of Mexico's GDP (Gobieno de Mexico, 2019) and according to National Survey of Occupation and Employment (ENOE from its Spanish initials) first trimester 2019 employed population in tourism sector reached 4 million 246 thousand direct jobs, meaning 8.7% of total employment nationwide ratifying tourism industry importance in mexican economy (Gobieno de Mexico, 2019).

In each section of the article, the reader will find:

- In Literature Review, the main trends and gaps in existing literatura
- In Methodology the description of networks following Power-Law mathematical formalism, the software used, analysis of each network, limitations of the method and technique used
- Results and Discussion about metrics for tourist destinations occupancy distributions; hospitality and gastronomy jobs; COVID-19 confirmed cases and implications.
- Conclusions describe research contribution, limitations and future directions.

Literature Review

We contribute with tourism data analytics using network science, emphasizing correlations among different databases. Proposing interdisciplinary approach for tourism studies. Network science, according to Barabási (2016) is possible because fast data sharing methods and cheap digital storage that made viable creation of network maps to describe behaviour of complex systems consisting of multiple interacting components. Since the size of most networks of practical interest have huge amount of data behind them; we consider tourism indicators can be mapped as a network.

Table 1.
Literature

Application	Authors
Social networks	(Barabási, 2016)
Web search advertising in Google, Facebook, Twitter, Linkedin, Cisco, Apple, Akamai	(Barabási, 2016)
Health	(International Human Genome Sequencing Consortium, 2001) (Venter et al., 2001) (Hopkins, 2008) (Gulbahce, Barabási, & Loscalzo, 2011)
Biology	(Oltvai & Barabási, 2004)
Medicine	(Gulbahce, Barabási, & Loscalzo, 2011)

Terrorism-military	(Do Valle et al., 2021) (Wilson, 2010) (Arquilla & Ronfeldt, 2001)
Epidemics	(Balcan et al., 2009) (Hufnagel, Brockmann, & Geisel, 2004) (Wang, Gonzalez, Hidalgo, & Barabasi, 2009)
Neuroscience	(Oh et al., 2014) (Sporns, Tononi, & Kötter, 2005)
Management	(Wu et al., 2008)
Tourism	(Scott, Cooper & Baggio, 2007) (Baggio, 2017) (Provenzano, Hawelka & Baggio, 2018) (Arenas et al., 2019)

Personal elaboration.

In summary, the main trends existing in network science literature relate to health, biology, medicine, epidemics and neuroscience; which give the context that physical systems are more frequently analyzed with network science, followed by technological applications; gaps remain on social complexity considering new drivers like employment, economic indicators, type of destinations that represent future research opportunities to broad current examples of network science applied to tourism that remain on state of the art, analyzing research lines, topics, authors, countries, to get the main trends in academic tourism research; instead we see pertinence and huge potential on analyzing with network science tourist routes, travel patterns, market segments, occupancy indicators, and elements that could provide inferences and be more illustrative of tourist consumption behaviour, travel decisions and consumer markets preferences that nowadays remains limited yet on network science applications.

Methodology

We applied network analysis based on graph theory (Barabási, 2002; Barabási & Albert, 1999; Watts, 2004; Watts & Strogatz, 1998); our results are representative to scale free networks theory that defines networks whose degree distribution follows a power law that persists in different network sizes (Barabási, 2016). Another theoretical argument congruent with our results is that in networks with power law degree distribution most nodes have only a few links, these numerous small nodes are held together by a few highly connected hubs (Barabási, 2016). In that way, the identification of those hubs in our results show the important role some states and tourist destinations have: driving strong sustained travel demand; their contribution to Hospitality and Gastronomy jobs and COVID19 confirmed cases ranges (COVID.GOB, 2020).

Description of research methodology used begins creating architecture of the networks we want to analyse, then identify their organizing principles and express mathematical formalism behind them to contribute understanding of tourism as complex system.

Our networks model P(k)=ck^(-γ) follows empirical nature, focusing on data, function and utility; describing system's properties and behavior; like power law distribution (Barabási, 2016) revealing key information based on quantitative characterization; deepen in our case into occupancy rates, jobs and COVID-19 confirmed cases distributions on Mexican destinations (COVID.GOB, 2020), towards characterization of pandemic impacts on Mexican tourism industry dynamic.

Our networks distributions are represented by $P(k) = ck^{-\gamma}$ for $k_0 \leq k \leq K$ where:

- c is an appropriate normalization factor.
- γ is the exponent of connections distribution.
- k_0 is the minimum grade of any given node.
- K the cut degree depending on the network size.

To prove usefulness of the used method, in Table 2 we compare two main networks models; emphasizing power-law pertinence for our study given its advantages.

Table 2.
Comparison Power-Law vs Poisson

Model	Advantages	Disadvantages
Power-Law	1. Clusters or hubs. Reveal key elements to understand the complex system behavior. That lead to identify: * Occupancy levels that replicate the most between destinations * Which destinations concentrate bulk of tourism, i.e., drive strong sustained travel demand * States classification according to Hospitality and Gastronomy employment ranges * States by COVID-19 confirmed cases ranges * States by employment and COVID19 confirmed cases ranges 2. Topology with numerous small degree nodes coexisting with highly connected nodes. That in our study ratify cluster presence. 3. Size of each node proportional to its degree. Lead to identify robust tourist destinations that constantly ensure relevant tourist consumption for Mexico and COVID-19 decreasing occupancy effects in tourist destinations. 4. Many nodes with only few links. Lead to identify states and tourist destinations with low level ranges of: * Hospitality Gastronomy employment * COVID-19 confirmed cases 5. Few clusters with more links. Lead to identify states and tourist destinations with high level ranges of: * Hospitality and Gastronomy employment * COVID-19 confirmed cases 6. Lack scale characteristic, congruent with most networks representative of socio economic complex systems 7. Number of links a node can have is not restricted, consistent with most real socio economic networks in which elements have multiple interactions.	1. Fragility in network topology when removing clusters. For our study purposes, this “disadvantage” works in our favor as it confirms our results regarding the important role some tourist destinations have, that we might consider to better understand Mexican tourism industry dynamic.
Poisson or Random networks	1. Robust network topology to random elimination of nodes. Contrary to our study purposes of identifying most important states and tourist destinations in terms of occupancy, hospitality and Gastronomy employment as well as COVID-19 confirmed cases.	1. Most nodes have same number of links which is not consistent with our created networks 2. Restricted to a characteristic scale, which is not consistent with most real socio economical networks. 3. Hubs absence, meaning not having highly connected nodes denying roles importance between states and tourist destinations. 4. Limits the number of links a node can have. Contrary to our findings in tourist networks.

Personal elaboration.

Since network science emphasizes correlations and interactions among different databases, to describe behaviour of tourism as complex system, we elaborate network maps about:

1. *Mexican tourism industry indicators:*

   1.1 *Destinations occupancy rates*
   1.2 *Hospitality and Gastronomy jobs*

2. *COVID-19 in Mexico indicator:*

   2.1 *Confirmed cases*

We used Netdraw Ucinet software to elaborate network maps (Borgatti et al., 2002) having links between nodes to indicate existent interactions.

UCINET for Windows is a software package for the analysis of network data. It was developed by Lin Freeman, Martin Everett and Steve Borgatti on 2002. It comes with the NetDraw network visualization tool, that we used to create and analyze our networks.

1. Networks about *mexican tourism industry indicators*:

   1.1. *Destinations occupancy rates*. First interaction is about tourist destinations and their occupancy rate registered on certain date. Figure 1.

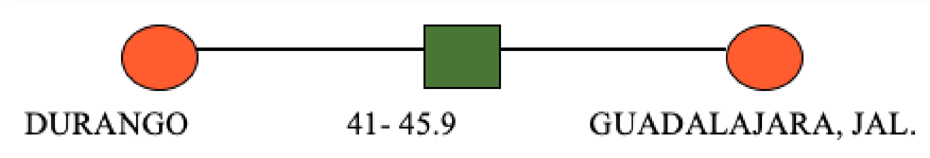

Figure 1. Tourist destinations and its occupancy rate.
Personal elaboration.

Second type: occupancy rates clusters on certain dates, and tourist destinations belonging to those clusters. Figure 2.

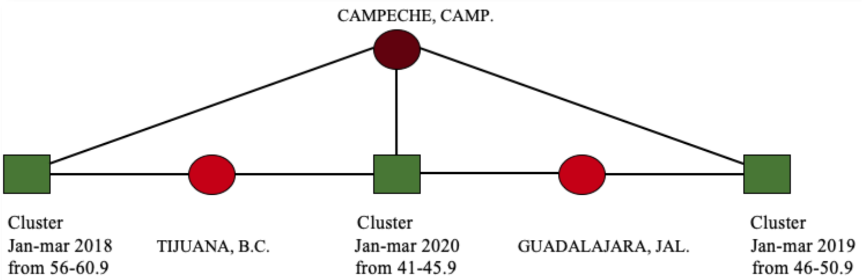

Figure 2. Tourist destinations by occupancy rates clusters.
Personal elaboration.

For indicators: *Hospitality and Gastronomy jobs* as well as *COVID-19 Confirmed cases*, given INEGI (2020) and COVID.GOB (2020) data sources are displayed by state; Figure 3 specifies correspondence between states and tourist destinations.

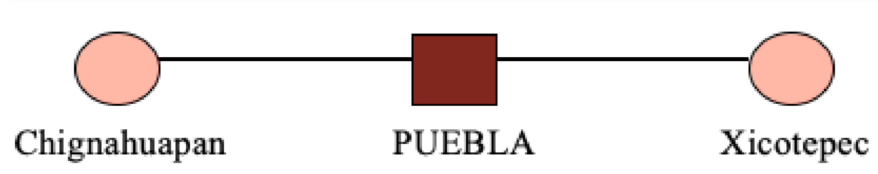

Figure 3. Tourist destinations by state.
Personal elaboration.

1.2. *Hospitality and Gastronomy jobs*. Figure 4 about states and their employment range to April 21st 2020.

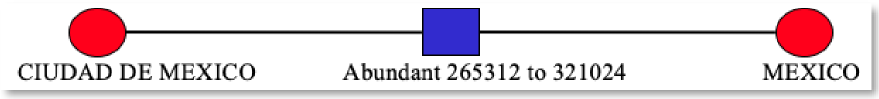

Figure 4. States and their employment range.
Personal elaboration.

2. For *COVID-19 indicator*:

2.1 Confirmed cases. Figure 5. States by confirmed cases ranges 11th June 2020.

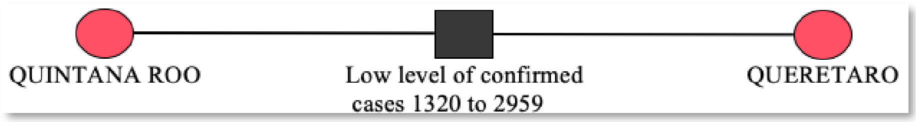

Figure 5. Confirmed cases range by state.
Personal elaboration.

For integral perspective Figure 6 integrates both jobs and confirmed cases ranges, with their corresponding states.

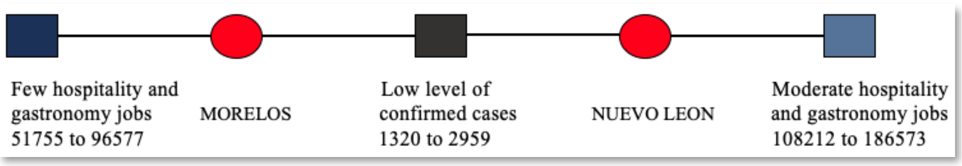

Figure 6. States by jobs and confirmed cases ranges.
Personal elaboration.

Limitations of the method and technique

Relies on accurate data to build the networks, real data may be incomplete, uncertain, or non available; another challenge is to choose indicators or drivers that enable accurate analysis; specifically time consuming and demanding to prepare relational data to interpret causality.

Results and Discussion

Since the contribution of network maps is to describe the detailed behaviour of a system consisting of various interacting components. The findings for each indicator are as follows.

Figure 7 offers structure of analysis findings.

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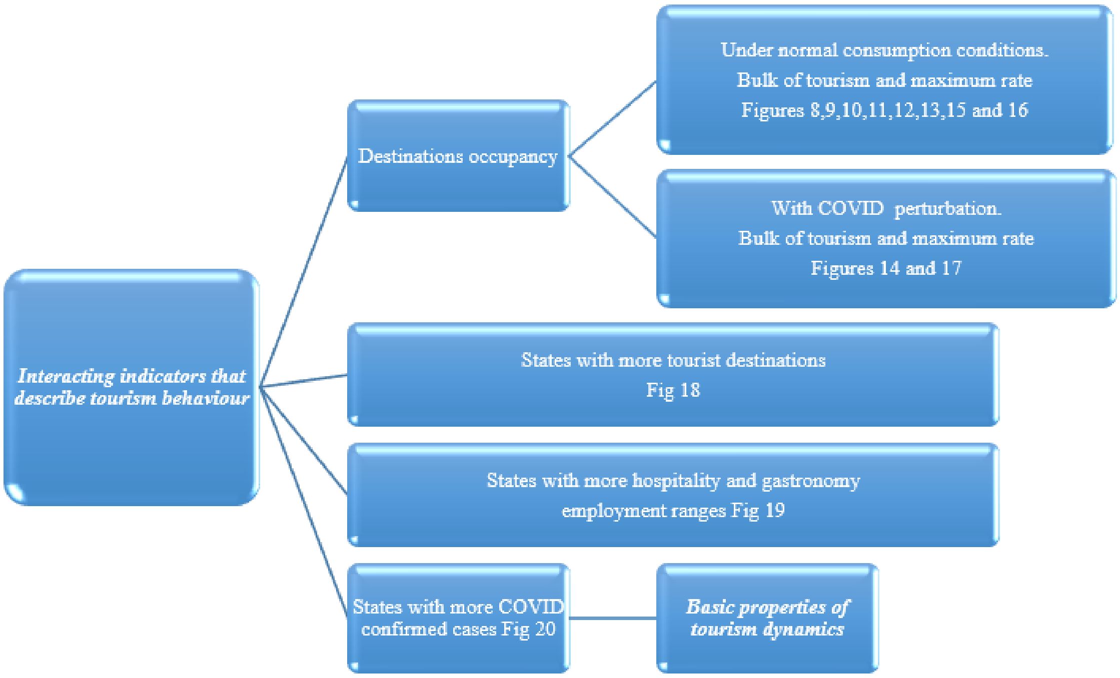

Figure 7. Results.
Personal elaboration.

Results:

1. On networks about *mexican tourism industry indicators*:

1.1. Destinations and occupancy rates. Bipartite networks (Figure 1) which first set of nodes are 70 mexican tourist destinations; and second set occupancy rates each destination had from January-May 2020, 2019 and 2018 (DATATUR, 2020, 2019, 2018).

Considering in Mexico flight suspensions, self-isolation and quarantine began entirely on april 2020, first graphs for this research illustrate January-March accumulated rates in 2018, 2019 and 2020 (Figures 8-10) to evidence how mexican tourist destinations registered occupancy rates under normal consumption conditions without COVID-19.

After running Analytic Technologies Harvard software on 2-Mode Centrality (Borgatti et al., 2002) results found Highest Degree Centrality for occupancy rates between 51-60.9 on January toMarch 2018 (Figure 8).

That degree centrality identified in Figure 8 with blue circles is important because it shows from January-March 2018, under normal consumption conditions, occupancy rates that replicate the most between destinations are 51-60.9 per cent concentrating bulk of tourism on 20 destinations: Los Mochis, Sin; Salamanca, Gto; Veracruz Boca del Rio, Ver; Acapulco, Gro; Manzanillo, Col; La Paz, B.C.S; Durango, Dgo; San Juan del Río, Qro; Irapuato, Gto; Oaxaca, Oax; Hermosillo, Son; Ciudad Juarez, Chih; Campeche, Camp; Mazatlan, Sin; Loreto, B.C.S; Zona Corredor Los Cabos; León, Gto; San Miguel de Allende, Gto; Tijuana, B.C and Mexicali, B.C. that registered referred occupancy.

Another observation is that maximum occupancy rate for same period was 86-90.9 registered by two destinations: Playacar, Q. Roo and Puerto Vallarta, Jal. (Figure 8).

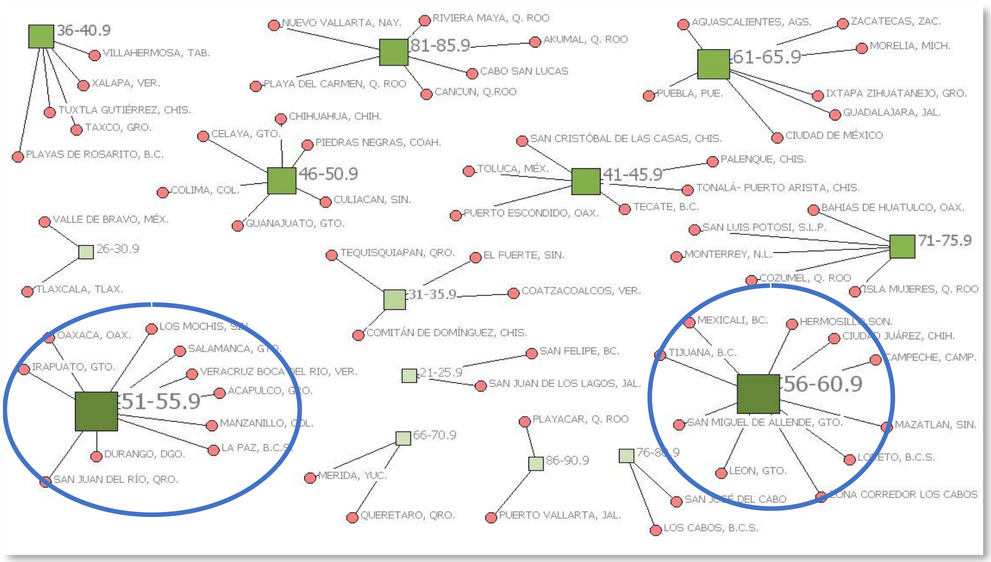

Figure 8. Degree centrality for accumulated occupancy January-March 2018. Personal elaboration.

On 2-Mode Centrality analysis (Borgatti et al., 2002) January-March 2019 we found Highest Degree Centrality for occupancy rates between 46-50 .9 (Figure 9).

Deegree centrality circled in blue, Figure 9 on January-March 2019 under normal consumption conditions, 12 destinations replicate occupancy rates between 46-50.9 concentrated bulk of tourism in: Villahermosa, Tab; San Juan del Rio, Qro; Campeche, Camp; La Paz, B.C.S; Culiacan, Sin; Durango, Dgo; Acapulco, Gro; Guadalajara, Jal; Chihuahua, Chih; Los Mochis, Sin; Oaxaca, Oax and Loreto, B.S.C. And having maximum occupancy for the same period 86-90.9 registered by Nuevo Vallarta, Nay (Figure 9).

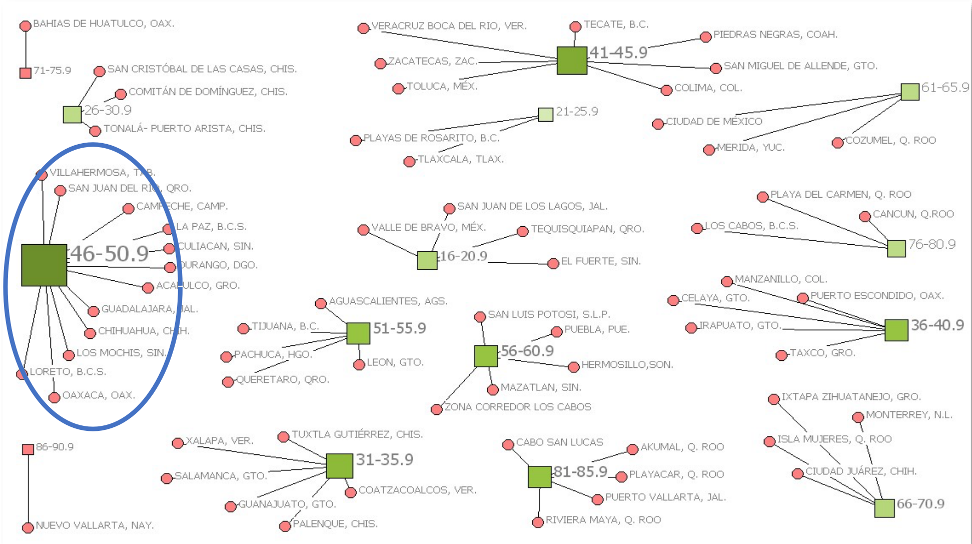

Figure 9. Degree centrality for accumulated occupancy January-March 2019. Personal elaboration.

On 2-Mode Centrality analysis (Borgatti et al., 2002) January-March 2020 COVID decreasing occupancy effects in mexican destinations became visible, given flight suspensions and measures including self-isolation were applied in Mexico's travel market sources like United States and European countries; thus Highest Degree Centrality for occupancy rates was 36-45.9 (Figure 10) on 22 destinations: Taxco, Gro; Puerto Escondido Oax; San Juan del Río, Qro; Chihuahua, Chih; Toluca, Mex; Loreto, B.C.S; Xalapa, Ver; Piedras Negras, Coah; León Gto;

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Manzanillo, Col; Zacatecas, Zac; Durango, Dgo; Tijuana, B.C; San Luis Potosi, S.L.P; Queretaro, Qro; Aguascalientes, Ags; Veracruz Boca del Rio, Ver; Villahermosa, Tab; Guadalajara, Jal; Culiacan, Sin; Oaxaca, Oax; and Campeche, Camp.

COVID-19 decreasing occupancy effects is confirmed again in Nuevo Vallarta, Nay; that in same period of previous year registered maximum occupancy 86-90.9 (Figure 9) decreasing 10 percent by January-March 2020 with maximum occupancy 76-80.9 (Figure 10).

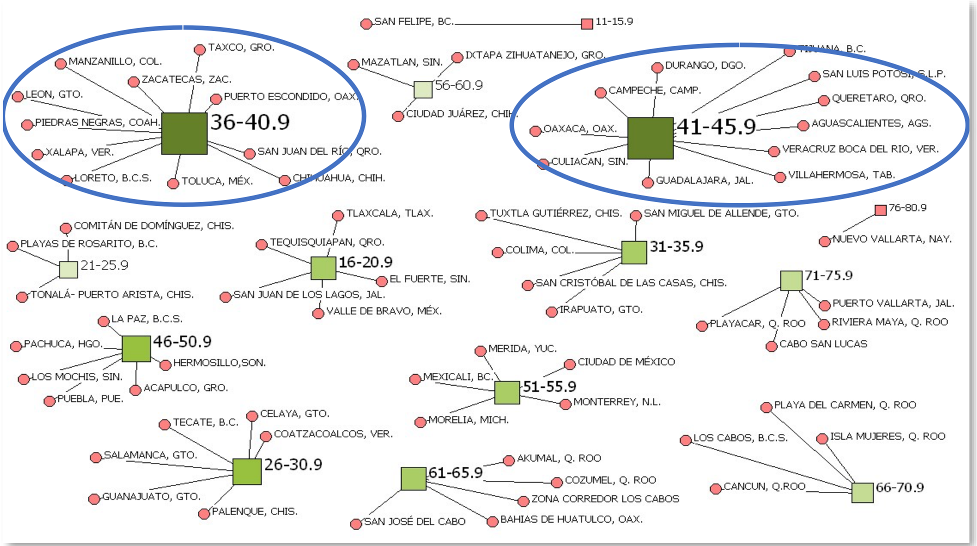

Figure 10. Degree centrality for accumulated occupancy January-March 2020. Personal elaboration.

Deepening analysis January-March accumulated rates 2018, 2019 and 2020 (Figures 8-10) a fourth network map (Figure 11) was built from second type of interaction represented in Figure 2 focusing on destinations that concentrated bulk of tourism in three periods:

- 20 destinations January-March 2018
- 12 destinations January-March 2019
- 22 destinations January-March 2020

Finding that destinations represented with red circle nodes, but mostly: Loreto, B.C.S; Campeche, Camp; San Juan del Río, Qro; Oaxaca, Oax and Durango, Dgo. represented with brown circle nodes are robust destinations that constantly ensure relevant tourist consumption for Mexico (Figure 11).

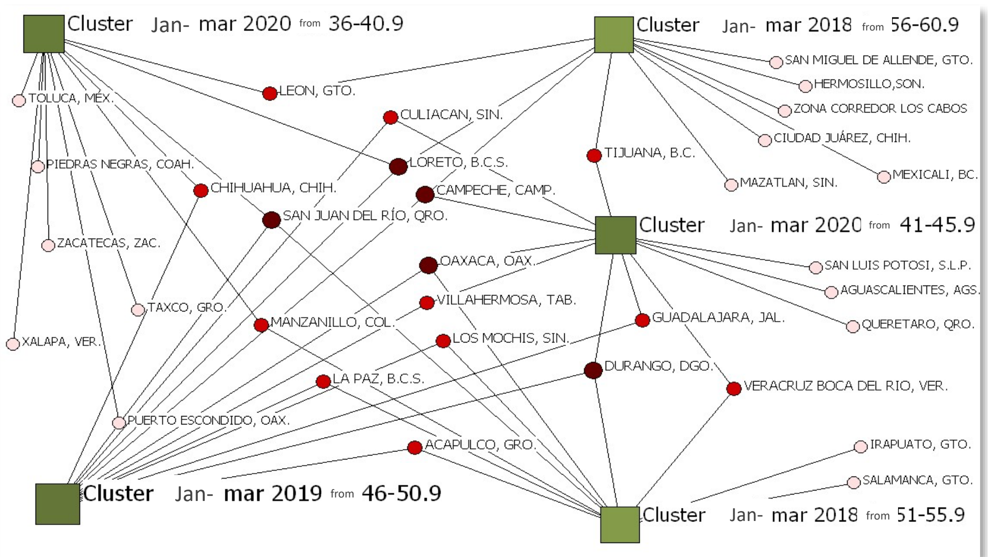

Figure 11. Destinations that concentrated bulk of tourism January-March 2018, 2019, 2020. Personal elaboration.

April and May analysis was done separately to get information about COVID-19 decreasing occupancy effects; considering in Mexico during those months in 2020 measures including flight suspensions, self-isolation and quarantine prevailed throughout whole country territory.

Figure 12 corresponds April 2018 analysis for previous occupancy rates registered by destinations under normal consumption conditions without COVID-19. Finding Highest Degree Centrality for occupancy rates 46-55.9; concentrated greater amount of tourism flow on 20 destinations: Chihuahua, Chih; Acapulco, Gro; Xalapa, Ver; La Paz, B.C.S; Campeche, Camp; Celaya, Gto; San Juan del Rio, Qro; Colima, Col; Oaxaca, Oax; Culiacan, Sin; Tijuana B.C; Guadalajara, Jal; Cozumel, Q. Roo; Manzanillo, Col; Zona Corredor Los Cabos; Salamanca, Gto; Los Mochis, Sin; Durango, Dgo; Toluca, Mex and Irapuato, Gto. And maximum occupancy rate 91-95.9 registered on Akumal, Q.Roo.

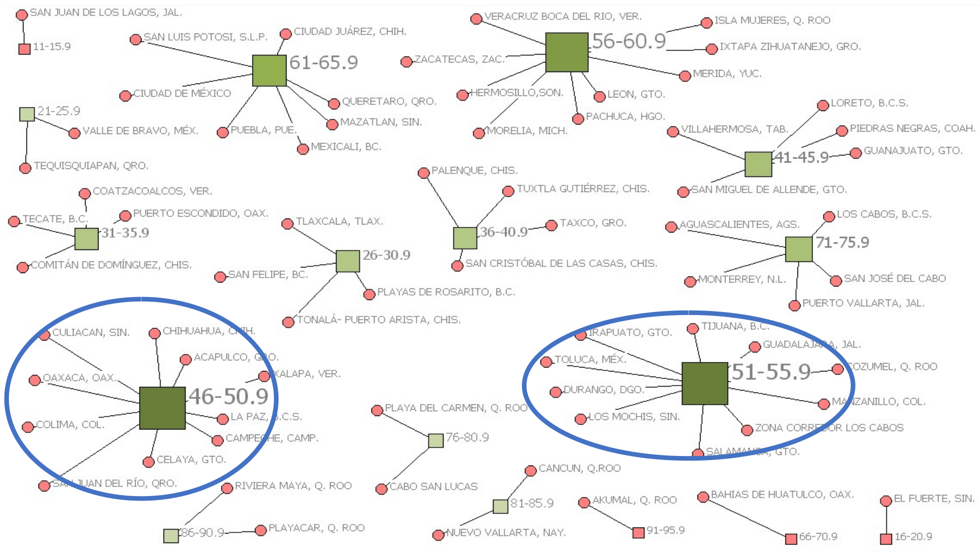

Figure 12. Degree centrality April 2018.
Personal elaboration.

Likewise, Figure 13 corresponds to April 2019 analysis for previous occupancy rates registered by destinations under normal consumption conditions without COVID-19. Having found Highest Degree Centrality for occupancy rates 41-45.9 and 61-65.9; i.e having concentrated greater amount of tourism flow on 21 destinations: Mexicali, B.C; Zacatecas, Zac; San Jose del Cabo; Queretaro, Qro; Ciudad de Mexico; Merida, Yuc; Loreto, B.C.S; Durango, Dgo; Bahias de Huatulco, Oax; Aguascalientes, Ags; Isla Mujeres, Q.Roo; Culiacan, Sin; Tecate, B.C; Comitan de Dominguez, Chis; Tuxtla Gutierrez, Chis; Puerto Escondido, Oax; Piedras Negras, Coah; Taxco, Gro; San Cristobal de las casas, Chis; Guanajuato, Gto and San Miguel de Allende Gto. And maximum occupancy rate 86-90.9 registered in Playacar, Q.Roo

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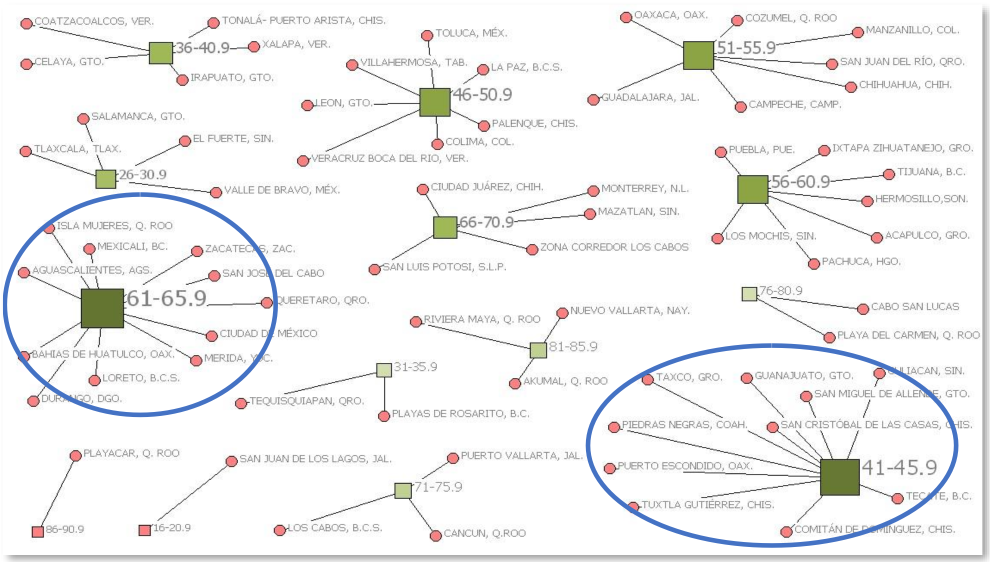

Figure 13. Degree centrality April 2019.
Personal elaboration.

2-Mode Centrality analysis (Borgatti et al., 2002) for April 2020 COVID-19 decreasing occupancy effects in destinations is clearly visible, having Highest Degree Centrality for occupancy rates 0-5.9 in most destinations; an unprecedented situation with highest occupancy rate registered by Mazatlan, Sin. 16-20.9 (Figure 14).

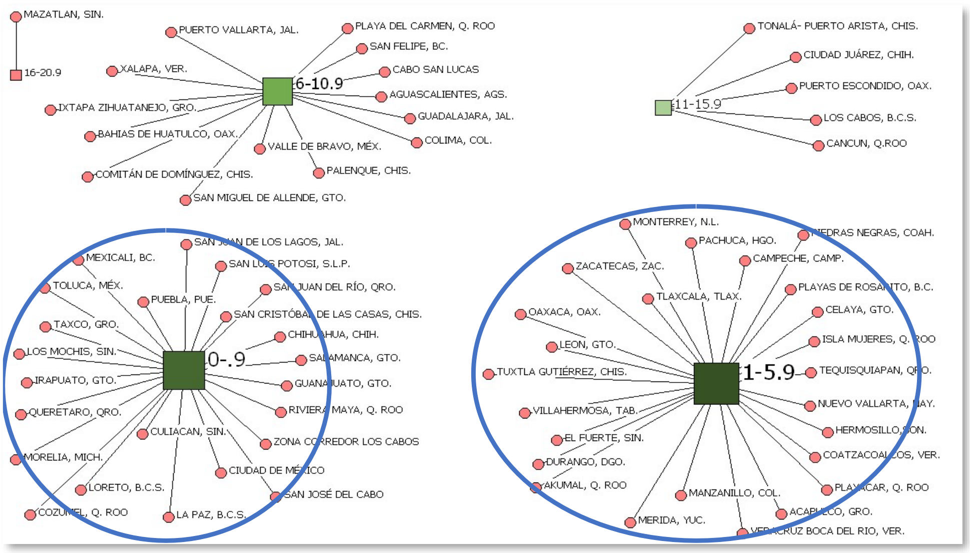

Figure 14. Degree centrality on April 2020.
Personal elaboration.

May analysis was done separately to get information about COVID-19 decreasing occupancy effects in destinations.

Figure 15 corresponds to May 2018 analysis refering previous occupancy rates registered under normal consumption conditions without COVID-19. Having found Highest Degree Centrality for occupancy rates 41-45.9 and 51-55.9; i.e concentrated greater amount of tourism flow on 19 destinations: Zona Corredor Los Cabos; Manzanillo, Col; Villahermosa, Tab; Salamanca, Gto; San Juan del Río, Qro; Acapulco, Gro; La Paz, B.C.S; Celaya, Gto; Irapuato, Gto; Leon, Gto; Pachuca, Hgo; Mazatlan, Sin; Guadalajara, Jal; Isla Mujeres, Q.Roo; Cozumel, Q. Roo; Bahias de Huatulco, Oax; Veracruz Boca del Rio, Ver; Culiacan, Sin and Zacatecas, Zac. With the maximum occupancy rate from 86 to 90.9 reported by 2 Q. Roo destinations: Playacar and Akumal.

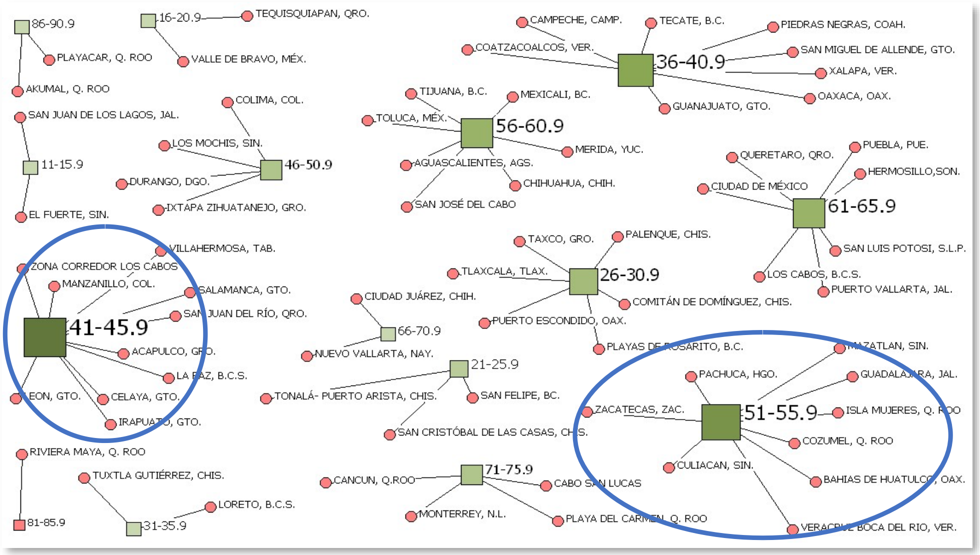

Figure 15. Degree centrality on May 2018.
Personal elaboration.

Figure 16 corresponds to May 2019 analysis refering previous occupancy rates under normal consumption conditions without COVID-19. Having found Highest Degree Centrality for occupancy rates 51-55.9 and 61-65.9; concentrating greater amount of tourism flow on 19 destinations: Piedras Negras, Coah; Manzanillo, Col; Los Mochis, Sin; Villahermosa, Tab; Zacatecas, Zac; Loreto, B.C.S; Guadalajara, Jal; San Jose del Cabo; Pachuca, Hgo; Culiacan, Sin; Tijuana, B.C; San Lis Potosi, S.L.P; Zona Corredor Los Cabos; Durango, Dgo; Aguascalientes, Ags; Queretaro, Qro; Mazatlan, Sin; Puebla, Pue and Mexicali, BC. With the maximum occupancy rate 81-85.9 reported again by 2 Q. Roo destinations in the same month of previous year: Playacar and Akumal.

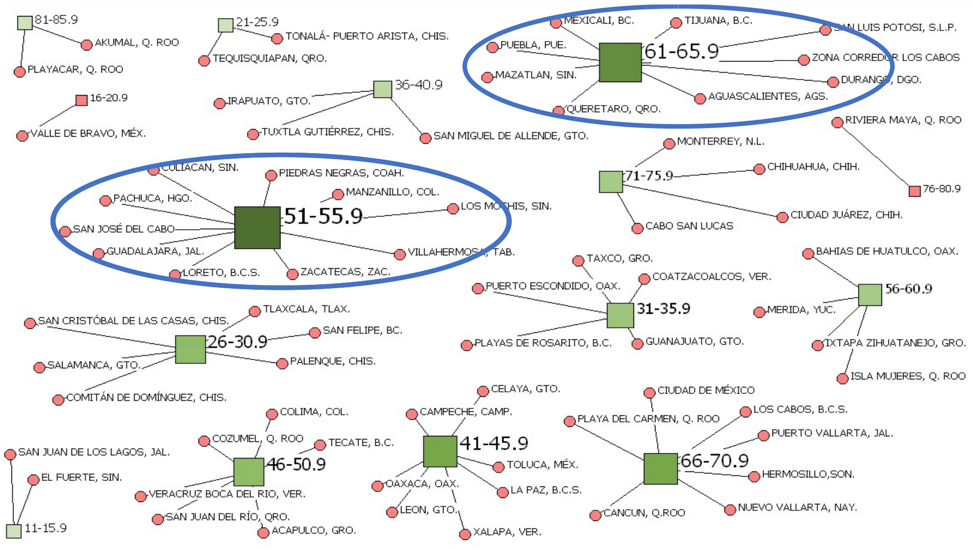

Figure 16. Degree centrality on May 2019.
Personal elaboration.

For May 2020 COVID-19 pandemic decreasing occupancy effects were exacerbated, nullifying tourism activity in most destinations and registering Highest Degree Centrality for occupancy rates 0-5.9 in 7 destinations: Toluca, Mex; Oaxaca, Oax; San Juan de los Lagos, Jal; Bahias de Huatulco, Oax; Guanajuato, Gto; Puerto Escondido, Oax and Valle de Bravo, Mex. With maximum occupancy 11-16 on Celaya, Gto and Ciudad Juarez, Chih (Figure 17).

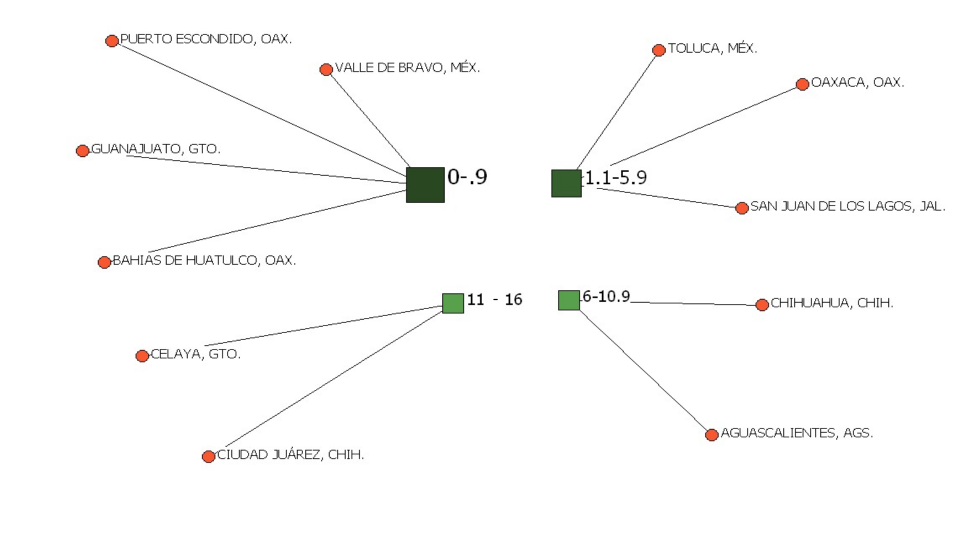

Figure 17. Degree centrality on May 2020.
Personal elaboration.

The most important metric for our research purpose is Highest Degree Centrality for occupancy rates in figures 8-17, given we looked for destinations that concentrated bulk of tourism and maximum occupancy levels registered. We generated those data using Analytic Technologies Harvard software on 2-Mode Centrality (Borgatti et al., 2002). The analysis generated other 4 metrics that support our metric of interest, which is degree centrality (Table 3).

Table 3.
Metrics for tourist destinations that concentrated bulk of tourism january-march 2018, 2019 and 2020

Cluster	Occupancy range	Degree	2-Local	Eigenvector	Closeness	Betweeness
jan-mar 2020	36-40.9	0.157142863	0.024693878	0.281663418	0.838709652	0.088587321
jan-mar 2020	41-45.9	0.157142863	0.024693878	0.486292988	0.787878811	0.063163474
jan-mar 2019	46-50.9	0.171428576	0.029387757	0.648508668	0.939759016	0.079402491
jan-mar 2018	51-55.9	0.142857149	0.020408165	0.463044554	0.772277236	0.049962241
jan-mar 2018	56-60.9	0.142857149	0.020408165	0.221835926	0.838709652	0.08558818

Personal elaboration using Ucinet (Borgatti et al., 2002).

Degree, consists of the sums of ties values, meaning most common occupancy level registered by destinations across all periods analysed is 46-50.9%. Complementary metrics: 2-Local represents our mode network as bipartite graph with balanced incoming and outgoing links. Eigenvector, calculates eigenvector of the largest positive eigenvalue as measure of centrality, ratifying robustness. Closeness is a metric that gives the overall network closeness centralization and is useful to measure distance by sums of the lengths of all the paths or all the trails; a metric that can be thought as an index of the expected time-until-arrival for things flowing through the network via optimal paths. Betweennes is a measure of information control. Highest values in all metrics support our finding that destinations represented with brown circle node linked to jan-mar 2019 cluster, are robust destinations that constantly ensure tourist consumption for Mexico; represented in tourism behavioral dynamic (figure 11).

Although it is necessary to carry out more in-depth analysis integrating other indicators to quantify correlations degree; as well as verifiable effective incentives application; both are beyond this research paper scope. However, we have identified some essential characteristics and destinations that concentrate bulk of tourism that might be considered when focusing marketing intelligence initiatives and public-private partnerships.

Having concluded analysis for the first Mexican tourism industry indicator: Destinations occupancy rates (Figures 8-17); before continuing with the rest indicators Hospitality and Gastronomy jobs and COVID-19 Confirmed cases, given INEGI and COVID.GOB primary data sources are displayed by state; Figure 18 was built following type of interaction in Figure 3. To specify correspondence between states of the republic and tourist destinations; even though in Figures 8-17, names of the corresponding states were abbreviated after name of tourist destination.

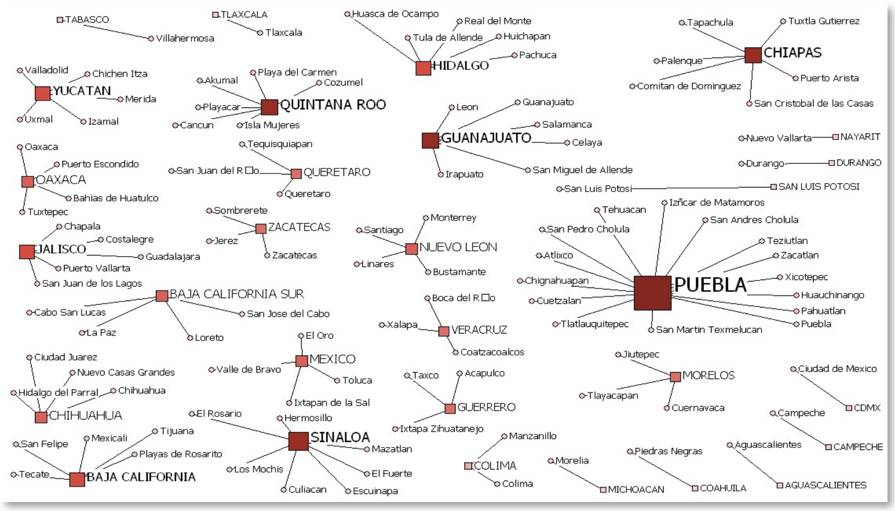

Figure 18. Correspondence between states of the republic and tourist destinations.
Personal elaboration.

Analysis for states of the republic reveals highest degree for Puebla, supporting is the state with most tourist destinations (Table 4).

Table 4.
Correspondence degree between states and tourist destinations

State	Degree
Aguascalientes	0.009346
Baja California	0.046729
Baja California Sur	0.037383
Campeche	0.009346
Coahuila	0.009346
Colima	0.018692
Chiapas	0.056075
Chihuahua	0.037383
CdMx	0.009346
Durango	0.009346
Guanajuato	0.056075
Guerrero	0.028037
Hidalgo	0.046729
Jalisco	0.046729
Mexico	0.037383
Michoacan	0.009346
Morelos	0.028037
Nayarit	0.009346
Nuevo Leon	0.037383
Oaxaca	0.037383
Puebla	**0.140187**
Queretaro	0.028037
Quintana Roo	0.056075
San Luis Potosi	0.009346
Sinaloa	0.065421
Tabasco	0.009346
Tlaxcala	0.009346
Veracruz	0.028037
Yucatán	0.046729
Zacatecas	0.028037

Personal elaboration using Ucinet (Borgatti et al., 2002).

Identify States of the Republic with more tourist destinations, is useful to propose focalized restart of tourism after COVID-19.

The next mexican tourism industry indicator for this research analysis is:

Hospitality and Gastronomy jobs. Bipartite: states-employment ranges network was built to connect data following type of interaction in Figure 4.

After running Analytic Technologies Harvard software 2-Mode Centrality (Borgatti et al., 2002) for Hospitality and Gastronomy jobs in Mexican territory by April 21st 2020, five employment ranges were identified from Scarce to Maximum; finding considerable number of states and therefore tourist destinations classify on Few employment range 51755-96577 in contrast Maximum range 883776 hospitality and gastronomy jobs reported by Baja California state (Figure 19) with its 5 tourist destinations: Tecate, San Felipe, Mexicali, Tijuana and Playas de Rosarito.

Our Network analysis allows sizing and graphically represent number of Hospitality and Gastronomy jobs affected in Mexico by COVID-19.

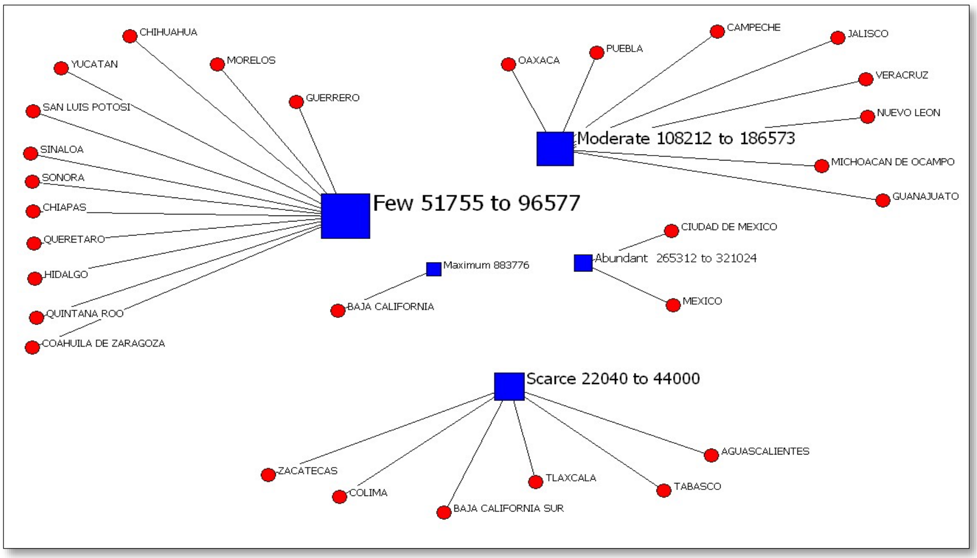

Figure 19. States by Hospitality and gastronomy employment ranges.
Personal elaboration.

Our finding about most states classifying on Few employment range is supported by software metrics with .40 degree, .16 on 2-mode local linkage and 1 eigenvector robustness.

Table 5.
Metrics for states by hospitality and gastronomy employment ranges

Employment	Degree	2-Local	Eigenvector
Maximun 883776	0.033333335	0.001111111	0
Abundant 265312 to 321024	0.06666667	0.004444445	0
Moderate 108212 to 186573	0.266666681	0.071111113	8.27E-08
Few 51755 to 96577	0.400000006	0.160000026	1
Scarce 22040 to 44000	0.200000003	0.040000003	6.76E-16

Personal elaboration using Ucinet (Borgatti et al., 2002).

Having concluded mexican tourism industry indicators; the last set analyzed is COVID-19 indicator:

Confirmed cases. Bipartite: states-confirmed cases ranges network was built to connect data following type of interaction in Figure 5.

After running software 2-Mode Centrality (Borgatti et al., 2002) for COVID-19 confirmed cases in Mexico by 11th June 2020, four ranges were identified from Scarce to Maximum; finding that considerable number of states and therefore tourist destinations classify on Low level range of confirmed cases 1320-2959 compared to Maximum range 21631-34077

COVID-19 confirmed cases reported by Mexico state and Ciudad de Mexico (Figure 20) and their corresponding 5 tourist destinations: El Oro, Toluca, Ixtapan de la Sal, Valle de Bravo and CDMX. Useful information for responsible tourism restart having identified the most and the least infected destinations, crucial to restoring trust and confidence in the sector focalizing promotional campaigns and tourism product development initiatives.

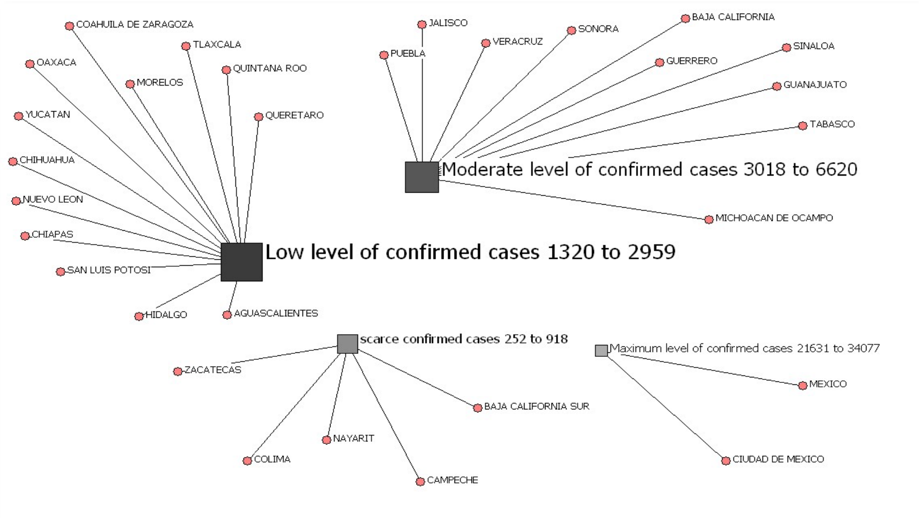

Figure 20. States by COVID-19 confirmed cases ranges. Personal elaboration.

Our finding about most states classifying Low level confirmed cases is supported by software metrics with .43 degree and .18 on 2-mode local linkage. Consistent with early stages of pandemic in Mexico.

Table 6.
Metrics for states by COVID-19 confirmed cases ranges

Range	Degree	2-Local
Maximum level of confirmed cases 21631 to 34077	0.06666667	0.004444445
Moderate level of confirmed cases 3018 to 6620	0.333333343	0.111111097
Low level of confirmed cases 1320 to 2959	0.433333337	0.187777787
Scarce confirmed cases 252 to 918	0.166666672	0.02777778

Personal elaboration using Ucinet (Borgatti et al., 2002).

Deepen into findings for Mexico's Hospitality and Gastronomy jobs and COVID-19 Confirmed cases (Figures 19 and 20); network map on Figure 21 was built to have integral perspective considering type of interaction in Figure 6 regarding both jobs and confirmed cases ranges, with their corresponding states.

Findings confirm COVID deep negative impacts particularly for Mexico and Ciudad de Mexico CDMX, having maximum level of confirmed cases and abundant hospitality and gastronomy jobs affected. However, outcomes for overcoming pandemic are observed on Campeche that corresponds to moderate hospitality and gastronomy jobs and scarce COVID confirmed cases; also Nuevo Leon and Oaxaca with moderate employment and low confirmed cases; likewise Baja California reporting moderate confirmed cases and maximum hospitality and gastronomy jobs; furthermore most states and destinations report low level COVID confirmed cases (Figure 21). Besides occupancy pattern in Oaxaca and Campeche evidencing their role as generators of sustained tourism flow (Figure 11). In fact, on June 22nd Campeche obtained the Safe Travel Stamp from the World Travel and Tourism Council (WTTC) because of sanitary protocols standardization in hotels, restaurants, tour operators and other tourism service providers; hence the first POSTCOVID Corridor in Latin America was inaugurated in Mexico integrated by Campeche, Yucatan and Quintana Roo destinations (Mexico desconocido, s.f).

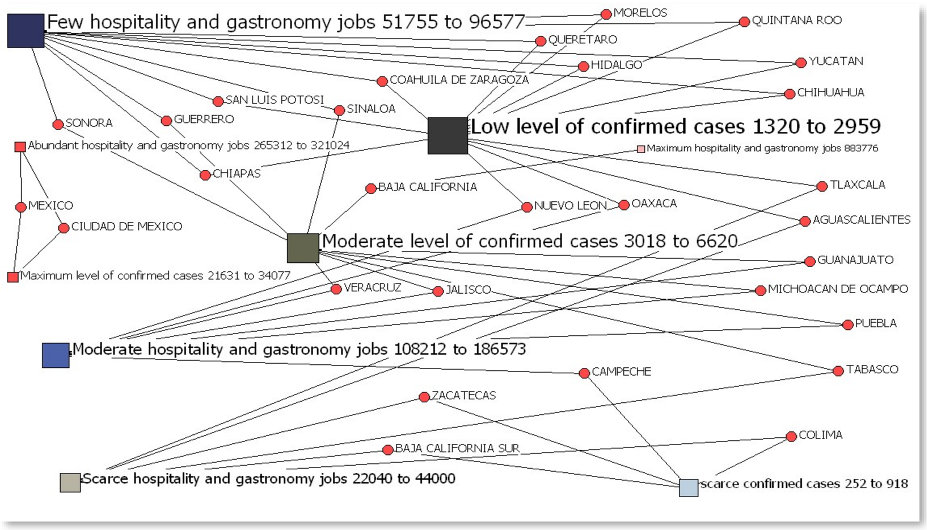

Figure 21. States by employment and COVID19 confirmed cases ranges.
Personal elaboration.

Most states according to software analysis classified Low level of confirmed cases and Few hospitality and gastronomy jobs with degree metrics .43 and .40; as well as .18 and .16 on 2-mode local linkage. Probing correlation between confirmed cases and employment rate; verifiable on lowest degree and 2-Local metrics for Maximum hospitality and gastronomy jobs as well as confirmed cases; finding there are more cases per capita in densely populated areas.

Even though it is out of scope of this paper, some insights for most affected areas providing emergency economic assistance through monetary measures like credit lines at reduced rate or exemption/reduction of social security contributions, wage subsidies or special support mechanisms for hospitality and gastronomy jobs might be helpful.

Table 7.
Metrics for States by employment and COVID19 confirmed cases ranges

Range	Degree	2-Local
Maximum level of confirmed cases 21631 to 34077	0.06666667	0.004444445
Moderate level of confirmed cases 3018 to 6620	0.333333343	0.111111097
Low level of confirmed cases 1320 to 2959	0.433333337	0.187777787
Scarce confirmed cases 252 to 918	0.166666672	0.02777778
Maximum hospitality and gastronomy jobs 883776	0.033333335	0.001111111
Abundant hospitality and gastronomy jobs 265312 to 321024	0.06666667	0.004444445
Moderate hospitality and gastronomy jobs 108212 to 186573	0.266666681	0.071111113
Few hospitality and gastronomy jobs 51755 to 96577	0.400000006	0.160000026
Scarse hospitality and gastronomy jobs 22040 to 44000	0.200000003	0.040000003

Personal elaboration using Ucinet (Borgatti et al., 2002).

To complement our study we support our findings with quantitative characterization of our networks, given networks distributions reveal information towards better understanding of tourism mobility dynamic during analyzed periods.

We analyzed occupancy levels on different months and years. Finding that under normal conditions without COVID-19 visited destinations that concentrate bulk of tourism behave according to power law.

$$P(V > v) = 1 — F(V \le v) = \left(\frac{M}{v}\right)^{\propto} \qquad (1)$$

Conserving same statistical distribution regardless year or month of the information (Figure 22).

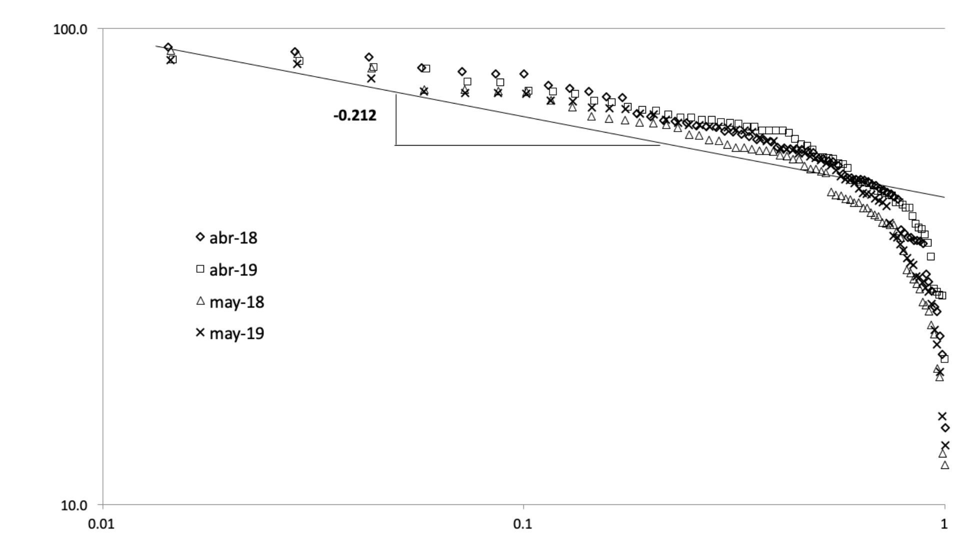

Figure 22. occupancy levels distributions in Mexico. Personal elaboration.

Regardless each destination conditions, we found statistical similarity of visitors distribution among different periods. Which supports two generic properties seen in social networks: alien to single characteristic scale and high clustering degree. Implying small destinations are organized hierarchically into larger groups, maintaining free-scale topology, following power law distribution.

$$P(k) = ck - \gamma\ k0 \leq k \leq K \qquad (2)$$

Our interpretation of scale free and scale invariance generic properties found is that tourism occupancy is preserved regardless period or destination type; another finding is that distributions confirm tourism occupancy is not random. And we consider it is one of the firsts steps to understand underlying dynamic of tourism as complex system.

On Figure 23 we analyzed correlation between confirmed cases and reduction in tourism, finding by may 2020 moderate level of confirmed cases prevailed among destinations with reduction in tourism occupancy from 1-5.9 level. Identifying that Puebla state occupancy, was the most affected.

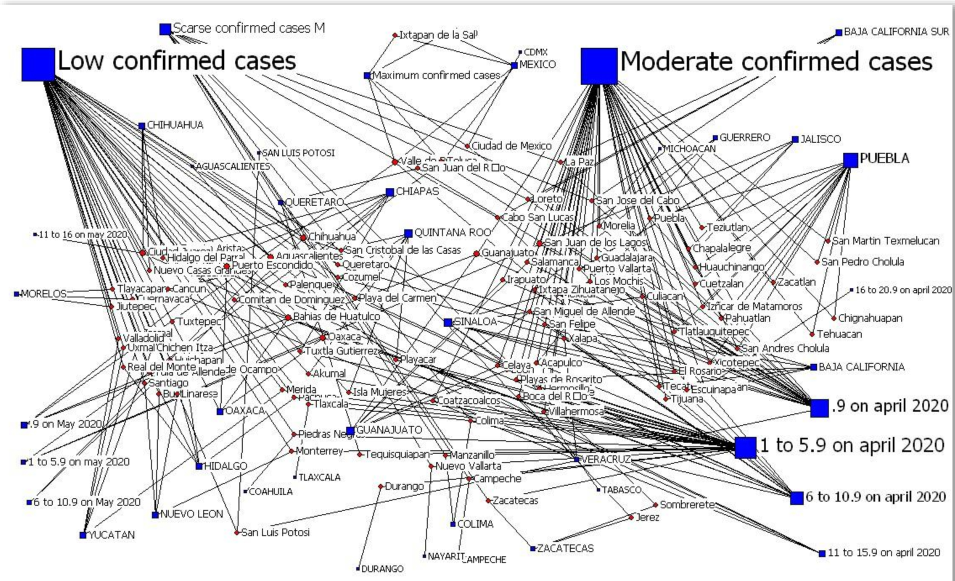

Figure 23. COVID-19 confirmed cases and occupancy reduction. Personal elaboration.

Highest degree measures found by software: .42 for moderate confirmed cases; .23 for 1-5.9 occupancy and .14 for Puebla (Table 8).

Table 8.
Degree measures COVID-19 confirmed cases and occupancy reduction

	Degree
Aguascalientes	0.009345794
Baja California	0.046728972
Baja California Sur	0.037383176
Campeche	0.009345794
Coahuila	0.009345794
Colima	0.018691588
Chiapas	0.056074765
Chihuahua	0.037383176
CdMx	0.009345794
Durango	0.009345794
Guanajuato	0.056074765
Guerrero	0.028037382
Hidalgo	0.046728972
Jalisco	0.046728972
Mexico	0.037383176
Michoacan	0.009345794
Morelos	0.028037382
Nayarit	0.009345794
Nuevo León	0.037383176
Oaxaca	0.037383176
Puebla	**0.140186921**
Queretaro	0.028037382
Quintana Roo	0.056074765
San Luis Potosi	0.009345794
Sinaloa	0.065420561
Tabasco	0.00945794
Tlaxcala	0.009345794
Veracruz	0.028037382
Yucatán	0.046728972
Zacatecas	0.028037382
.9 on may 2020	0.037383176
1 to 5.9 on may 2020	0.028037382
6 to 10.9 on may 2020	0.018691588
11 to 16 on may 2020	0.009345794
	0
9 on april 2020	0.196261689
1 to 5.9 on april 2020	**0.233644858**
6 to 10.9 on april 2020	0.130841121
11 to 15.9 on april 2020	0.037383176
16 to 20.9 on april 2020	0.009345794
Low confirmed cases	**0.392523378**
Moderate confirmed cases	**0.429906547**
Scarse confirmed cases	0.102803737
Maximum confirmed cases	0.046728972

Personal elaboration using Ucinet (Borgatti et al., 2002).

If it follows from this example to give continuity to complexity approach for tourism, in further research we recommend to develop models that integrate more indicators that allow quantify correlations degree between variables. By now, our power law occupancy distribution networks model contributes finding and representing generic properties of tourism occupancy dynamic as pertinent alternative to understand tourism from transdisciplinary perspective.

Implications

From this research, academics can model other tourist networks as we have confirmed some essential characteristics of tourism dynamic can be projected.

Conclusions

This is an attempt to confirm network science pertinence to analyse tourism dynamics, useful to provide quantitative characterization for our understanding of tourism organization principles and some underlying patterns behind this activity.

Our research contributes:

- With verifiable application of network science to tourism análisis.
- Representing tourism dynamic in terms of centrality measures.
- Expressing mathematical formalism behind tourism organizing principles.
- Identifying generic properties of tourism occupancy distribution.
- Modeling tourism and pandemic indicator in tourist destinations.
- Approaching tourism as complex system with interacting elements and susceptible to external perturbations.
- As example of future tourism data analytics using network science.
- With detailed descriptions of tourism complex Dynamic.
- Modeling tourist occupancy in Mexico under normal consumption conditions.
- Modeling tourist occupancy in Mexico affected by COVID-19.
- Identifying destinations that concentrate bulk of tourism and maximum occupancy rates registered, useful to consider when focusing marketing intelligence initiatives and public-private partnerships.
- Identify Mexican states with more tourist destinations, useful to propose focalized tourism restart after COVID-19.
- As alternative to correlate indicators that capture tourism dynamic complexity.
- Confirming mexican tourism destinations occupancy have same trend regardless month/year.

Perhaps our findings don't have capacity to influence tourism decision makers, still our metrics results add value to project some characteristics of tourism dynamic, and are congruent with reality having strong correlation between confirmed cases and employment rate in densely populated areas; confirming correlation between confirmed cases and reduction in tourism.

This paper shows network science pertinence in tourism; and usage of transdisciplinary tools.

Discussion on the limitations of the study

Scope in terms of considered indicators remains limited yet, in tourism network analysis real demanding phase is to acces and then gather representative elements of the tourism complexity, and foresee connections between those elements; being careful on the data classification; unveil constantly changing and evolving dynamics over seasons and destinations; such as the possible lack of generalization of the results in this research case to other countries or contexts linked to other sociodemographic characteristics. It is also important to have in consideration several different patterns that might arise from the network analysis given tourism inherent complexity according to market segments and tourist offer; in that way depending on the type and intention of the network designed making sense out of the relational data analyzed for enhanced predictability of tourist indicators as well as their practical significance and visualization as a complex system.

Future directions for research

In future works we can do similar analysis in other countries for degree distribution and organization principles comparison purposes; to be able to make generalizations. And to consider the analysis of other variables like marketing strategies, consumer segments, tourist preferences, currency flows, flights availability, classification of natural, cultural tourist attractions, destinations internet access, sustainability indicators, demographic impacts derived from tourism activity and also perturbations or elements that affect and limit tourist activity like insecurity, emitted warnings for certain destinations, visa restrictions, adverse political environment or considerable cultural differences between visitors and host communities. Still network science to analyse tourism susceptible to external perturbations like COVID-19 in this paper; is pertinent to reveal some tourism dynamic basic properties, providing evidence to develop understanding of tourism complexity.

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