Supplementary Material

Introduction

The interest around climate services, their operational value and use has been increasing since their first appearance in early 2000s (Bruno Soares and Buontempo, 2019). The concept itself expanded and embraced perspectives derived from climatology and physical sciences, as well as economics and social disciplines. This allowed the investigation of technical aspects required to build science-based services (Dekker *et al.*, 2018; Troccoli *et al.*, 2018; De Felice *et al.*, 2019), as well as research on users' needs (Buontempo *et al.*, 2017; Christel *et al.*, 2018) and market and non-market dynamics that should be in place to boost their uptake (Bremer and Meisch, 2017; Webber and Donner, 2017; Damm *et al.*, 2019). Despite these efforts, a 'usability gap' (Dinku *et al.*, 2014; Kirchhoff, Lemos and Kalafatis, 2015) between providers of climate information and their potential users is still in place. Reasons for this are imputed to the existence and co-occurrence of multiple factors: inefficient underutilization of climate models as tools to support robust decision-making in a complex reality (Weaver *et al.*, 2013), poor inclusion of insights from social sciences to fully understand users' needs (Vaughan *et al.*, 2016), a good-dominant logic that fails at including users' experiences and perspectives in the co-production and co-generation process (Alexander and Dessai, 2019), as well as timeliness in meeting expectations (Ford, Knight and Pearce, 2013; Webber, 2017) among others.

The implicit assumption behind this literature is the complete knowledge of what climate services are. However, there is no agreement on their definition (Vaughan and Hewitt, 2018; Bruno Soares and Buontempo, 2019) and this poses challenges in identifying what they are. In this paper, we consider "climate services" those innovations translating climate science into a user-tailored, decision-relevant tool. Examples of operational climate services are provided in Table 0S.

Table 0s. Examples of climate services

Climate service	Description	URL
IRRICLIME	Spatially-explicit, open-source tool providing short- and medium-term water budget forecasts to the target user.	https://gecosistema.com/climate-services-and-tools/
CLIME	Offers a multi-model approach to integrate high-resolution post-processed climate data, uncertainty evaluations from national to local level with the purpose of supporting decision-making.	https://www.dataclime.com/en/dataclime-en/
MAREX SPECTRON	Offering to commodity traders the "Global Seasonal Weather Outlook" to help managing risks related to soft commodities	https://climate.copernicus.eu/marex-spectron
Africa Hydromet program	A partnership of development organisations working to improve weather, water and climate services to boost local economies in Africa.	http://www.worldbank.org/en/programs/africa_hydromet_program
AgroClimas	Historical analysis, monitoring services and climate forecasts developed to support local farmers in Colombia under threat of food insecurity	https://ccafs.cgiar.org/es/agroclimas#.XQIXCYgzZPY

Materials and methods.

Framework.

Data. We used Scopus web-portal (www.scopus.com), the largest abstract and citation database of peer-reviewed literature, with almost 70 million items and 1.4 billion cited references dating back to 1970. We run a specific query[1] in the database specifying to look for any type of document. We found 358 records at January 23rd 2019 (Table 1S). We cross-checked the initial results launching the same query to Web of Knowledge (www.webofknowledge.com) under "Topic". In this case, the sample included records from 1985 to present. Hence, the time series differed. Scopus reported a significantly larger collection (358 vs 243 records). We exported the dataset in *.bib* format to perform data cleaning on multiple software (Mendeley and TeXMaker).

[1] "climate service*" AND NOT "service* climate". We also run an alternative query ("climate services" AND "Climate Services" AND "climate service" AND "Climate Service" AND NOT "service* climate") to check on the validity of our first search. The two gave the exact same results.

Table 1S. Main information

Variable	
Documents	358
Sources	173
Keywords Plus (ID)	1788
Author's Keywords (DE)	770
Period	1974-2018
Average citations per documents	14.32
Authors	1427
Author appearances	1729
Author of single-authored documents	56
Authors of multi-authored documents	1371
Single-authored documents	82
Documents per author	0.251
Authors per document	3.99
Co-authors per document	4.83
Collaboration Index	4.97

We included only peer-reviewed publications in English language. English is the universal language for peer-reviewed literature. Hence, despite the existence of French and Spanish written works, we feel our sample successfully represents official literature. Many projects have produced or are still producing material often included under “grey literature” label. This corpus comprises project deliverables, milestones, press releases, communication records, workshop and meeting reports. Given the novelty of the field, their exclusion from the sample may drive the results towards well-established and purely research-oriented actors. Furthermore, private firms and institutions are rarely involved in the peer-review process and do not take credit for publications or dissemination of their innovation actions. Despite this limitation, we restricted our analysis to scientifically recognized works for two main reasons: *(i)* projects funded under public schemes (i.e. Horizon2020, FP7, FP6, multilateral funds and bilateral agreements) are normally developed by a consortium of partners, where research institutions may cover a portion of the workflow. However, they are normally assessed against a set of criteria that necessarily involve a peer-review process. Therefore, outcomes of projects can be reflected in scientific works and co-authorship networks capture variety of authors involved. *(ii)* Ideas, methodologies and concepts published through a peer-review mechanism are useful tools to backup the strengths behind some of the most promising and cutting-edge innovations. Hence, they serve as proxies of the most prominent topics and areas of work. The distribution of publications considered in the sample is presented at continuation (Table 2S).

Table 2S. Distribution of records per source type

Source Type	
Article	221
Article in press	6
Book	8
Book chapter	26
Conference paper	55

Editorial	3
Erratum	1
Letter	1
Note	14
Review	21
Short survey	1

Climate services have been formally defined only in 2001. Therefore, the steady growth of research (Figure 1S) around this topic is justified by the lack of a shared vision and a still not existent action plan. Despite the novelty of the concept, we believe the query launched on Scopus is fully valid. One could argue that every document published before 2001 should not be included in the sample of interest. However, we claim that the broad scope of "climate services" definition allows for their inclusion because it does not constitute a limitation under any circumstance. The growth rate of the overall period is 16.81%.

Bibliometrics. Bibliometrics, Scientometrics and Infometrics share the same theory and methods, but differ for fields of application and usage (Figure 2S). Bibliometrics has been widely employed in Engineering and Science (Tian, Wen and Hong, 2008; Larivière *et al.*, 2013), Social Sciences (Archambault and Gagné, 2004) and others (Thomson Reuters, 2008; Zare-Farashbandi, Geraei and Siamaki, 2014). We used the *"bibliometrix"* package of R software (Aria and Cuccurullo, 2017). Despite the existence of several tools for bibliometric and science mapping tools, the use of *bibliometrix* R-package is justified by two reasons: *(i)* it works in R, an open-source environment, fully accessible to the research community; *(ii)* it allows to download data and its associated metadata from two bibliographic sources (Scopus and Clarivate Analytics WoS) and to convert them into a data frame to facilitate data mining.

Bibliometrics can provide quantitative estimates of the scientific production ina given field, but presents some frawbacks: it is not able to provide insights about the properties that interactions and collaboration patterns show, failing in considering the individual agent as part of the complex systems where microscopic dynamics affect the emergence of meso and macroscale phenomena. Bibliometrics also struggles with three additional challenges: *(i)* outcomes are often extrapolated out of context and may not reflect the quality of an individual; *(ii)* performance of authors are often not fully comparable; *(iii)* the sample size affects the reliability of the results (Belter, 2015; Ball, 2017; Suebsombut *et al.*, 2017; Martín-Martín, Orduna-Malea and Delgado López-Cózar, 2018). Therefore, it provides a partial vision of the actual success of a scholar, institution or country and requires additional and complementary tools.

First, we computed descriptive statistics for the co-authorship networks of individuals, affiliations of the main author and country of the institution they work for. Co-citation networks were explored only in a dynamic framework: we addressed the most 20 cited manuscripts throughout our sample to derive implications around the conceptual evolution of the field. For visualization purposes, we used a combination of *ggplot2* and *igraph* packages' libraries.

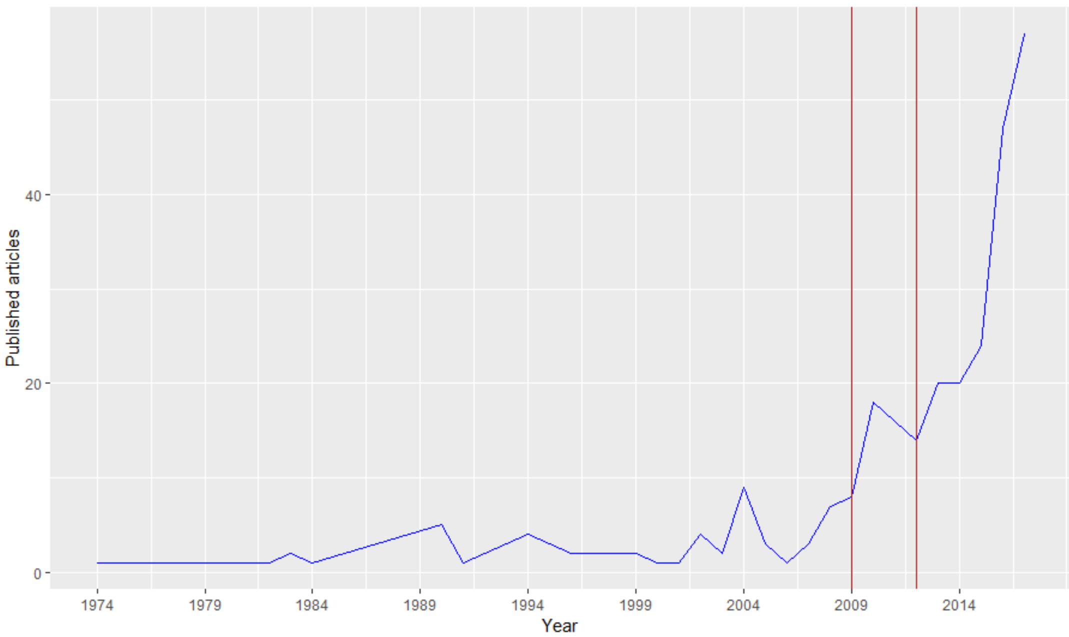

Figure 1S. Scientific production

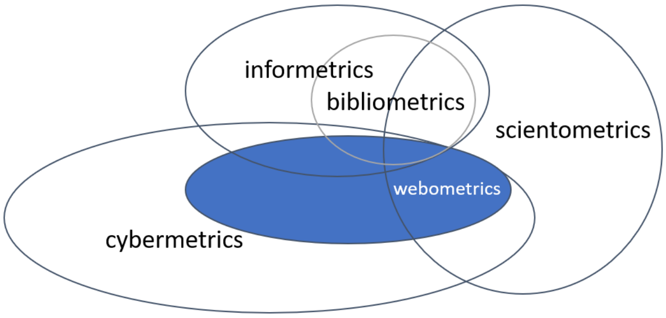

FIG 2S. Information science: scientific domains

We also checked the validity of the Lotka's Law of Scientific Productivity in the case of Climate Services to see whether regularities can be found. Given a set of publications (x), the relative frequency of researchers with n publications (y) and k as a field-specific constant, the Lotka's Law takes the following form:

$$x^n y = k$$

The Law states that the number of authors contributing x to the overall sample in a given timeframe is a fraction of those making a single contribution, following an inverse-quadratic form of the type $1/x^{\alpha}$, with $\alpha \approx 2$. The higher the number of articles in a given field, the less frequent the number of authors publishing that amount of publications. Given the heterogeneity of disciplines, the actual ratios – expressed as a function of α – changes. We first checked whether the Lotka's Law can be used to predict publication productivity in the field of Climate Services, examining the goodness-of-fit of the empirical distribution of our publication sample and a theoretical one using the Lotka's formula (1926). We limited our analysis to the number of publications. We obtained the goodness-of-fit from a Kolmogorov-Smirnov (K-S) two sample test, which is used to compare the functions of the two distributions and check if structural differences between the two exist. The estimation of the constant is equal to 0.58. This figure indicates that the proportion of authors publishing a single item in the field of Climate Services is almost 58%, which is slightly higher than the one predicted by Lotka. However, results from the K-S test give a goodness-of-fit of 0.95 and a p-value of 0.164, which means that no significant differences exist between the two distributions and that Lotka's Law can be adopted to predict the evolution of research on Climate Services (Figure 3S).

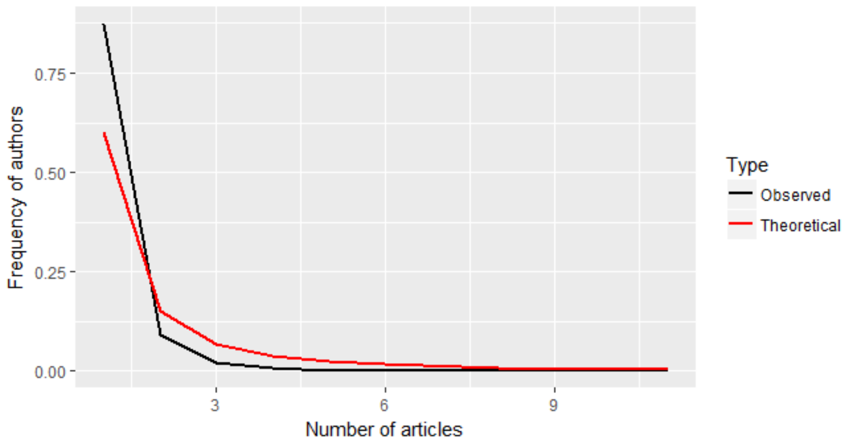

Figure 3S. Scientific productivity (Lotka's Law)

We ranked the top scholars, institutions and countries based on the quantity of publications produced and published (Figure 4S). Despite the significant presence of European entities, the United States are still largely dominating the field. Overall, national weather offices, well-established research institutions and international organisations are shaping research with their contributions. Multi-country collaborations are enhancing the existing stock of knowledge by allowing inputs to travel beyond borders.

As stated in the article, the sample under study is not taking into account any contribution belonging to the so-called "grey literature". This may possibly lead to a biased result in favor of universities and Research Performing Organisations (RPOs), which are – by mandate – required to produce scientific contributions. However, we are confident that advancements in the field of climate services are representative of the efforts made at global level: public-private partnerships are often the most appropriate frameworks where research and innovation are pursued. This holds for European-funded schemes, where representatives of both domains are asked to merge their competences and skills in order to win projects and initiatives. Nevertheless, the bibliometric results hereby presented are important to stimulate reflections about the uneven coverage of research on climate services, which appears skewed in favour of English-speaking countries and established institutions.

We run a specific analysis on the author-scientific production to explore productivity patterns (Table 5S), while also measuring the research impact (*quality*) through bibliometric indicators (Table 3S). Authors are ranked on the Dominance Factor (DF), which is a ratio indicating the fraction of papers of a given author in which she appears as first author over the total amount of papers of that author (Kumar Surendra Kumar and Kretschmer, 2008). Within the top 20 authors, 35 percent are US-based, 30 percent are working in UK institutions and 20 percent is currently in Spain. The remaining 15 percent is allocated in Indonesia, The Netherlands and South Africa. Despite the role of productivity in assigning a relative importance to authors, the research impact is signaling how appreciated are the produced works. Based on the *h-index*, Lowe R. is ranked first, followed by Hewitt C. and Buontempo C.. Given the *h-index* does not average the number of citations received, we ranked authors on their *g-index*: the top three authors are Hewitt C. (11), Buontempo C. (7) and Lowe R. (6), Vaughan C. (6) and Thomson MC. (6). The *m-index* provides the research impact of any individual scholar over their professional career in a given field of interest: Golding N. (1), Lowe R. (0.83) and Bruno-Soares M. (0.75) are the first three authors listed. Results from the bibliometric analysis also provide insights on the main subjects tackled by the top 20 scholars: Earth and Planetary Sciences (20), Environmental Sciences (20) and Social Sciences (17) are the dominant research areas. This distribution reflects the global one of the overall sample of publications considered.

Table 3S. Authors' ranking by productivity patterns and research impact

Author	**DF**	**h-index**	**g-index**	**m-index**
CARR ER	1	2	3	0.5
WINARTO YT	0.8	2	2	0.4
BRUNOSOARES M	0.75	3	4	0.75
VINCENT K	0.75	2	4	0.5
VAUGHAN C	0.66	3	6	0.5

ASRAR GR	0.66	3	3	0.37
BETT PE	0.66	2	2	0.66
BRÖNNIMANN S	0.66	1	2	0.5
GUIDO Z	0.6	3	5	0.42
LOWE R	0.57	5	6	0.83
DUNSTONE N	0.5	3	4	0.75
GOLDING N	0.4	3	4	1
THOMSON MC	0.33	3	6	0.33
BALLESTER J	0.33	3	3	0.6
DOBLAS-REYES FJ	0.25	4	4	0.57
RAY AJ	0.25	3	4	0.75
TALL A	0.25	2	4	0.22
TROCCOLI A	0.25	0	0	0
BUONTEMPO C	0.23	4	7	0.66
HEWITT C	0.18	4	11	0.5

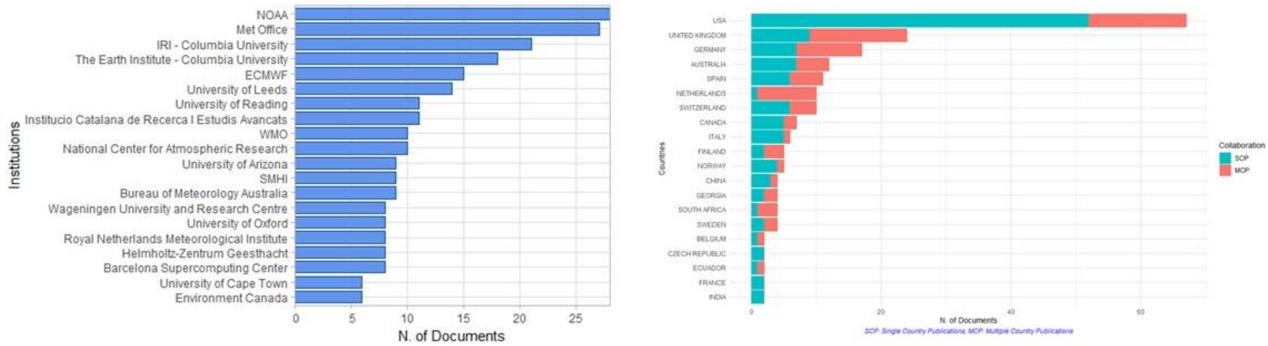

Figure 4S. Bibliometric results. The left-hand side reports the top institutions in the sample; the right-hand side shows the most productive countries differentiating between multi-country and single-country publication records.

Conceptual structure. The conceptual structure of our global map of climate services includes the assessment of exploration of the most relevant topics covered by the sample of authors and institutions and their temporal dynamics. We extracted the abstracts of each publication record and we computed the most frequent terms overtime. We applied two main restrictions: (i) we accepted only terms mentioned at least 5 times (quantity); (ii) we computed a “relevance score” of the so-obtained collection, including only those with score greater than 60 percent. The relevance score is automatically obtained from the software VOSViewer: the score is lower in case the co-occurrence of terms with other phrases follow a random pattern. The score increases in case the co-occurrence of certain words occur primarily in a limited set of sentences.

The top 10 words of our sample present all a significantly steep curve, especially in recent times (Figure 5S). Interest has shifted from a global to a more regional and localized perspective, hence leading to a significant turn towards adaptation. This is also confirmed by the dynamic snapshot of the network of concepts (Figure 6S). Research has progressively moved away from a mitigation-centered and carbon-related focus in favor of a user-centric view where decision-making becomes central. The observation of links between different concepts reinforce once more this transformation: “emission” and “mitigation” were strictly connected to “agriculture” and “land” between 2010 and 2012. Since 2014-2016, our results show an intensified connection between “farmer”, “risk management” and “adaptation”.

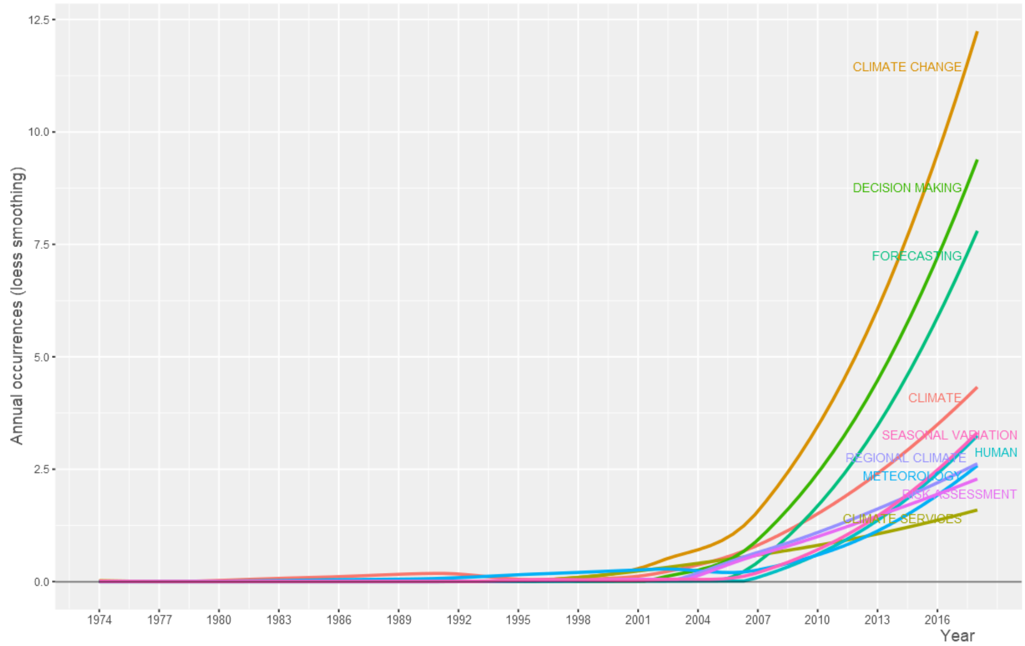

Figure 5S. Word growth graph: evolution of top mentioned keywords in abstracts

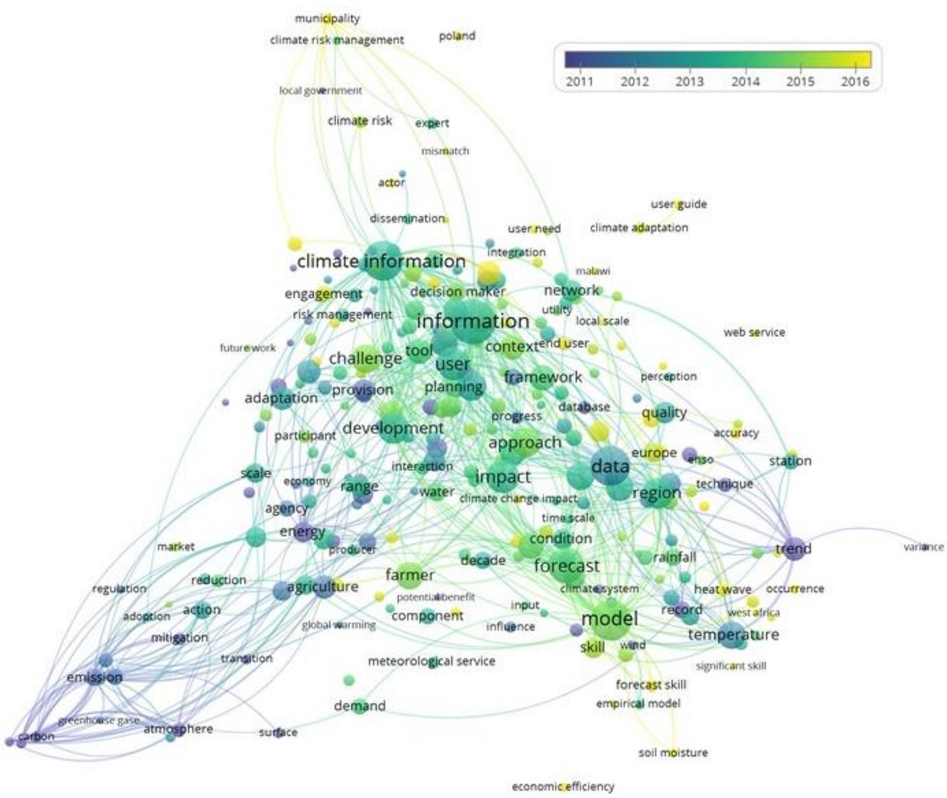

Figure 6S. Network of abstract keywords co-occurrence

Network Analysis. We used Social Network Analysis to uncover four main aspects: similarities, relations, interactions and patterns. The fundamental axiom behind the choice of this methodology is that "structure matters" (Otte and Rousseau, 2002; Borgatti *et al.*, 2009). We performed the analysis using a combination of *igraph*, *statnet*, *itergraph* and *sna* R packages on undirected graphs. For visualization purposes, we also used Gephi (https://gephi.org/) and VOSViewer (http://www.vosviewer.com/). We extracted the Giant Component of each sub-graph and we assigned the following names: $N_{ind}, N_{countr}, N_{inst}$ for individuals, countries and institutions respectively. Then, we computed the following:

1. Graph density
2. Degree distribution and average degree
3. Average path length and diameter
4. Clustering coefficient

Density is an indicator of cohesion within a graph. It gives the number of ties in a network, as a proportion of the total possible ties (which describe the case of complete graphs, where density =1). Density of N_{ind} is 0.026, which indicates a loosely connected graph. Degree distribution (Figure 8S) is the simple count of the number of nodes presenting each possible degree realization. High-degree nodes are typically influential within a network and have potentially more power in influencing the information flows.

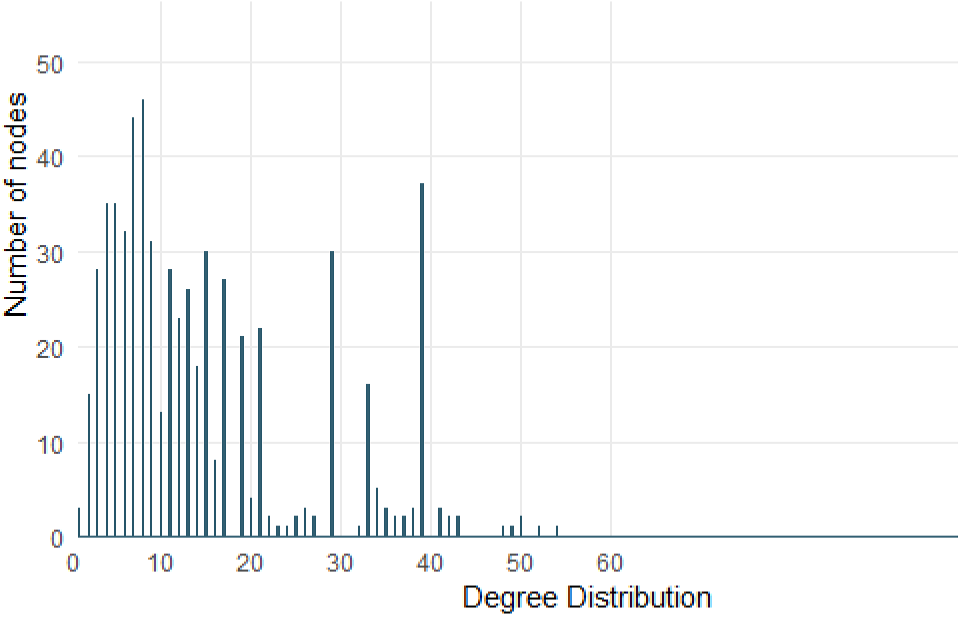

FIG 8S. Degree Distribution

The average degree is 15.093 and represents the average number of links touching upon a node. The average path length of the giant component of out network of individual scholars is mathematically expressed as:

$$\langle L \rangle = \frac{1}{n(n-1)} \sum_{i \neq j} d_G(v_i, v_j)$$

where $d_G(v_i, v_j)$ is the distance between two vertices, meant as the amount of edges in the shortest path running between v_i and v_j.

Equally connected to the edge dimension, the clustering coefficient estimates the probability of two neighbors of a given node to be connected to each other. The average clustering coefficient is given by

$$\bar{C} = \frac{1}{n} \sum_{i=1}^{n} C_i$$

where $C_i = \frac{number\ of\ edges \in N_i}{\frac{k_i(k_i-1)}{2}}$ is a vertex-specific (local) clustering coefficient. Local clustering coefficients represent the number of cliques to which a given node belong over the maximum number of triangles the same node could be part of.

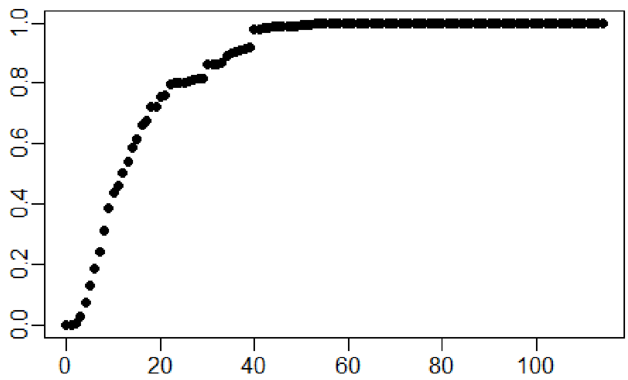

Figure 9S. Cumulative degree distribution function

Centrality measures. Literature on complex networks has proved them to share three main features: the "small world" property, the "scale free" effects and the "clustering" trait. A network typically displays short distances between the nodes ("small world"), which scales following a logarithmic scale with the total number of nodes (Latora and Marchiori, 2001). The second effect prescribes the existence of "hubs": few nodes with high degree and many nodes with low degree, following a power-law distribution (Boccaletti *et al.*, 2006). Finally, clustering property forecasts that each pair of nodes will be linked to a third one, forming at least a triangular shape (Estrada and Rodríguez-Velázquez, 2005). Other subgraph functional forms ("network motifs") are actually proved to be significant and they indicate patterns occurring in a graph far more frequently than in a random network with the same degree sequence (Milo *et al.*, 2002).

Centrality measures are useful numerical characterization of networks. The most common is *Degree centrality*, which quantitatively assesses the scale-free feature and broadly represents the number of links each node has with other nodes. *Degree centrality* is a measure of "popularity" of a given actor. It is expressed as the sum of all the actors directly connected to the node of interest:

$$d(i) = \sum_j m_{ij}$$

where $m_{ij} = 1$ if there is a link between two authors and $m_{ij} = 0$ otherwise.

In the context of social networks, *Betweenness Centrality* is also very common. It measures the number of times an individual connects a pair of other actors:

$$b(i) = \sum_{j,k} \frac{g_{jik}}{g_{jk}}$$

where g_{jk} is the number of shortest paths from j to k passing through i $(with\ j, k \neq i)$. Betweenness allows the information to circulate smoothly within their neighborhoods and, ultimately, the overall network. Therefore, authors with larger values of betweenness centrality are facilitators of knowledge flows. Whenever in presence of connected networks, it is possible to measure *Closeness centrality*, which is equal to the total distance of a given node from all the others:

$$c(i) = \frac{1}{\sum_i d_{ij}}$$

where d_{ij} represents the number of ties in the shortest path from i to j. Comparison between nodes of different sizes is possible via normalization (the average length of the shortest possible path).

The three measures emphasize different aspects, but they all depend on the graph size. Freeman (1979) pioneered in the analysis of "the effects of network size" and solved the issue introducing the point-centrality, an absolute measure allowing for interpretation of the values with respect to a [0,1] scale. In contrast with point-centrality, node-centrality is any $nc(v_i)$ function, which assigns a real value to every node of an undirected and connected graph $G = (V, E)$ with $|V| = n$. We can say that $nc(v_i)$ is a node-centrality of a node v_i if

$(i)\ nc(v_i)\ \in\ [0,1] \qquad for\ every\ v_i \in V,$ and

$$(ii)\ nc(v_i) = 1 \qquad iff\ G = S_{1,\ n-1}\ amd\ i = 1$$

Eigenvector centrality is also related to connected components of the graph. It provides the most appropriate simulation of a case where each node has simultaneous effect on its neighborhood. It is mathematically expressed as “the principal or dominant eigenvector of the adjacency matrix A” (Estrada and Rodríguez-Velázquez, 2005) representing the considered connected subgraph:

$$x_v = \frac{1}{\lambda} \sum_{t \in M(v)} x_t \quad = \quad \frac{1}{\lambda} \sum_{t \in G} a_{v,t} x_t$$

where $G \coloneqq (V, E)$ is a given graph defined over a set of vertices and edges; $A = (a_{v,t})$ is the adjacency matrix; $M(v)$ is the set of all the neighbors of v and λ is a constant. Note that $a_{v,t} = 1$ if vertex v is linked to vertex t, and $a_{v,t} = 0$ otherwise. Eigenvector centrality can be interpreted as an extension of degree centrality. Throughout the past 50 years, multiple centrality measures have been computed and used for a variety of complex networks. Table 4S provides a list of the most commonly observed, with their relative mathematical formulation and their interpretation.

Table 4S. Centrality measures used in this work

Measure	Definition	Mathematical formulation	Explanation	Source
Average distance	Average distance of node u to the rest of the nodes in the network	$C_{AV}(u) = \frac{\sum_{w \in V} d(u,w)}{n-1}$	The measure requires strongly connected networks. It is the inverse of closeness centrality.	(Del Rio, Koschützki and Coello, 2009)
Barycenter centrality	The inverse of total distance between a given node and all the others. Running these scores require to rank one subgraph at a time.	$\frac{1}{d(v, all\ other\ vertices)}$	Closeness scores are calculated on the average distance between a vertex and all the others. Barycenter scores use the total. More central nodes in a connected subgraph will present overall shortest paths.	(Ashtiani *et al.*, 2017)
Betweenness centrality	The number of times an individual connects a pair of nodes.	$b(i) = \sum_{j,k} \frac{g_{jik}}{g_{jk}}$ where g_{jk} is the number of	In co-authorship networks, the measure gauges the extent to which a node facilitates the flow of information in the network. Therefore, it is a	(Otte and Rousseau, 2002; Estrada and Rodríguez-Velázquez, 2005)

		shortest paths from j to k passing through i $(with\ j,k \neq i)$.	measure of potential control in a graph.	
BottleNeck centrality	A tree T_v of shortest paths is drawn from node v; n_v is the number of shortest paths included in T_v. Extract all nodes s in T_v, such that more than $\frac{nv}{4}$ meet at node s. Nodes extracted in this way are "bottlenecks" of T_v.	$$BV_v = \sum_{s \in V} P_s(v)$$ with T_s be the tree of shortest paths rooted at node s; $P_s(v) = 1$ if more than $\frac{\lvert V(T_s)\rvert}{4}$ paths from node s to other nodes in T_s meet at v and $P_s(v) = 0$ otherwise.	The high-betweenness characteristic of nodes that tend to share similar functions and find themselves as "between" highly interconnected subgraph clusters. Removing these edges could partition the network.	(Yu *et al.*, 2007)
Closeness centrality (Freeman)	An inverse measure of centrality, equal to the total distance of a given node from all the others). It is computed as the inverse of the sum of distances to all other nodes	$$c(i) = \frac{1}{\sum_i d_{ij}}$$ where d_{ij} represents the number of ties in the shortest path from i to j.	How far each actor is located from all the others. It often interpreted as either an indication of efficiency or of independence. It is related to betweenness because they are both expressed as function of the shortest path and they conceptually share a duality in terms of dependency:	(Ruhnau, 2000; Otte and Rousseau, 2002; Brandes, Borgatti and Freeman, 2016)
Closeness centrality (Latora)	Expressed as the sum of the inversed distances to all other nodes.	$$\sum_{i \neq j} \frac{1}{d_{ij}}$$ where d_{ij} represents the number of ties in the shortest path from i to j.	Variant of the Freeman algorithm, suitable for networks with disconnected components.	(Latora and Marchiori, 2001; Crucitti, Latora and Porta, 2006; Opsahl, Agneessens and Skvoretz, 2010)
Closeness vitality	The change in the sum of distances between all node	$$C_{CV}(x) = I_W(G) - I_W(\frac{G}{\{x\}})$$	It requires a strongly connected network and	(Brandes, Erlebach and Gesellschaft

	pairs when excluding a given node. It requires the computation of the Wiener Index	where $I_W(G)$ is the Wiener Index: $$I_W(G) = \sum_{v \in V} \sum_{w \in V} d(v, w)$$	denotes how much will the relationship change in an all-to-all communication if a given element x is removed form the graph	für Informatik., 2005)
ClusterRank	A measure inspired by PageRank and LeaderRank capable of accounting for the number of neighbors, neighbors' influences and clustering coefficient of a given node.	$$s_i = f(c_i) \sum_{j \in \Gamma_i} (k_j^{out} + 1)$$ where $f(c_i)$ includes the effects of the local cluster of *i*, while the +1 term results from the contribution of the j node itself. The clustering coefficient of a directed network is: $$c_i = \frac{\left\|\{e_{jk} \| j, k \in \Gamma_i\}\right\|}{k_i^{out}(k_i^{out} - 1)}$$ with k_j^{out} is the out-degree of i, which represents the number of followers of node *i* and Γ_i if the set of followers of I, $\{e_{jk} \| j, k \in \Gamma_i\}$ is the set of links connecting two of *i*'s followers.	Typically applied to directed networks, it can be used in undirected graphs where ClusterRank is significantly higher than degree centrality and k-core decomposition.	(Chen *et al.*, 2013; Wang *et al.*, 2017)
Clustering coefficient	Local clustering coefficient of a node n_i is a measure of the cliquishness of n_i neighborhood. Global clustering coefficient is the average of local clustering coefficients.	$$c_i = \frac{y_i}{\binom{d_i}{2}}$$ where y_i is the number of links between the neighbors of n_i and d_i is its degree.	The local clustering coefficient can be viewed as a local density measure in the neighborhood of a node i. In the case of undirected graphs, the global clustering coefficient is the number of closed triplets over the	(Hernández and Mieghem, 2011; Fouss, Saerens and Shimbo, 2016)

		$$C = \frac{1}{N}\sum_{i\in N} c_i$$	total number of closed triplets.	
Current-Flow Closeness Centrality	Alternative measure of distance between two nodes, treated as differentiated electric potential in the case of an electric network.	$$C_u = \frac{n}{\sum_{v\in V}(v_{uv}(u) - v_{uv}(v))}$$ with $u \neq v$; $v_{uv}(u)$ is the absolute potential of vertex u, based on the power supply from vertex u to vertex v; $(v_{uv}(u) - v_{uv}(v))$ is an alternative measure of distance or, in the case of an electric network, the effective resistance measured in voltage.	Appropriate t measure critical nodes in the network. Current-Flow closeness measures how easily others can access a node and viceversa. Limit: the measure cannot assess which nodes impact more on the total network current-flow efficiency once a node fails.	(Li *et al.*, 2018; Liu and Yan, 2018)
Communicability Betweenness centrality	Let $G = (V, E)$ be an undirected graph and be A the adjacency matrix of G. Let $G(r) = (V, E(r))$ be the graph obtained by removing all edges connected to node r, but not r itself. The adjacency matrix becomes A+E(r), where E(r) has nonzero values in row and column r.	$$\omega_r = \frac{1}{C}\sum_p\sum_q \frac{G_{prq}}{G_{pq}},$$ $$p \neq q, p \neq r, q \neq r$$ whit $G_{prq} = (e^A)_{pq} - \left(e^{A+E(r)}\right)_{pq}$ is the number of random walks involving vertex r; $G_{pq} = (e^A)_{pq}$ is the number of closed walks starting at p and ending at q; $C = (n-1)^2 - (n-1)$ is a normalization factor. The measure takes values [0,1].	Derived from the concept of shortest path, it takes into account the shortest path between nodes and all the paths between nodes.	(L.D and Raj, 2017)
Community centrality	The sum of local influence zones of all network edges and nodes, including the one under study.	$$C_C(i) = \sum_{i\in j}^{N}(1 - \frac{1}{m}\sum_{i\in j\cap k}^{m} S(j,k))$$ where the main sum is expressed over the total N communities to which node i belongs to; m is the number of	A community is ultimately a subgraph depicting a set of interacting agents. The measure uses the pairwise similarity between detected communities as weights for the number of communities a given node belongs	(Kalinka and Tomancak, 2011; Konstantinidis, Papadopoulos and Kompatsiaris, 2017)

		communities paired with community j and to which node i jointly belongs; $S(j,k)$ is computed using the Jaccard coefficient for the number of shared nodes between community j and k.	to.	
Dangalchev Closeness Centrality	It is a variation of closeness centrality.	$$C(i) = \sum_{j \neq i} \frac{1}{2^{d(i,j)}}$$ where d(i,j) is the distance between two nodes.	It is aimed at assessing the network's resistance after the removal of individual links or nodes.	(Dangalchev, 2006a)
Decay centrality	Based on proximity between a given node and every other weighted by a decay.	$$\sum_{y \in V(G)} \delta^{d(x,y)}$$ where δ is a parameter taking values [0,1]	The prerequisite is the existence of a strongly connected network.	(Tsakas, 2017)
Degree centrality	Number of ties a node has	$$d(i) = \sum_{j} m_{ij}$$ where $m_{ij} = 1$ if there is a link between two authors and $m_{ij} = 0$ otherwise.	In co-authorship networks, degree expresses the number of authors in the graph with whom she has co-authored at least one article.	(Otte and Rousseau, 2002)
Diffusion Degree	The cumulative distribution score of the node itself and its neighbors	$$C_{DD}(v) = C'_{DD}(v) + C''_{DD}(v)$$ $$= \lambda_V * C_D(v) + \sum_{i \in neighbors(v)} C'_{DD}(v)$$ $$= \lambda_V * C_D(v) + \sum_{i \in neighbors(v)} \lambda_i * C_D(i)$$ where $C'_D(v)$ represents the contribution of node v in the diffusion process; $C''_{DD}(v)$ is	Differently from other measures, Diffusion degree considers neighbors' contributions in addition to the degree of a given node. Furthermore, DD works accurately with not uniform propagation probability distributions.	(Pal, Kundu and Murthy, 2014)

		the total contribution of neighbors of v; λ is the propagation probability of a given node to activate another node		
DMNC – Density of Maximum Neighborhood Component	Ratio between the number of edges of the Maximum Neighborhood Component of a given node v and the number of nodes elevated to a given parameter, conveniently set to describe the number of communities in the neighborhood sub-network of v.	$\frac{\lvert E(MNC(v))\rvert}{\lvert V(MNC(v))\rvert^{\varepsilon}}, 1 \leq \varepsilon \leq 2$	Neighborhood-based measure, capable of undercovering unrecognized hubs within a given network	(Chin and Samanta, 2003; Lin *et al.*, 2008)
Eccentricity centrality	The greatest distance between vertex v and any other vertex in the network.	$C_E(v) = \frac{1}{\max\{dist(u,v): u \in V\}}$	An eccentricity with high values implies a greater node proximity. If eccentricity is low, there is at least one node far from node v.	(Hage and Harary, 1995; Hernández and Mieghem, 2011; Takes and Kosters, 2013)
Eigenvector centrality	The principal or dominant eigenvector of the adjacency matrix A of the connected subgraph	$x_v = \frac{1}{\lambda}\sum_{t\in M(v)} x_t = \frac{1}{\lambda}\sum_{t\in G} a_{v,t}x_t$ where $= (a_{v,t})$ is the adjacency matrix; $M(v)$ is the set of all the neighbors of v and λ is a constant. Note that $a_{v,t} = 1$ if vertex v is linked to vertex t, and $a_{v,t} = 0$ otherwise	Eigenvector centrality can be interpreted as an extension of degree centrality.	(Ruhnau, 2000; Estrada and Rodríguez-Velázquez, 2005; Fletcher and Wennekers, 2018)
Entropy centrality	Centrality of nodes is measured depending on their contribution to the entropy of the graph.	$H_{ce}(G) = -\sum_{i=1}^{n}\gamma(v_i) \times \log_2 \gamma(v_i)$ where	The measure provides information on the degree of centrality for a node in the graph	(Nie *et al.*, 2016)

		$\gamma(v) = \frac{paths(v_i)}{paths(v_1, v_2, \ldots, v_M)}$ represents the total number of geodesic paths from node v to all the others over the total number of geodesic paths M existing across all nodes.		
EPC – Edge Percolated Component	Assign a removing probability p to every edge of a connectivity network G. G' is the realization of a random edge removing from G. If two nodes v and w are connected within G', then $d_{vw} = 1$ and 0 otherwise. The percolated connectivity of v and w, c_{vw}, is the average of d_{vw} over realisations. The EPC is the size pf the percolated component.	$EPC(v) = \frac{1}{\lvert v \rvert} \sum_{k=1}^{1000} \sum_{t \in V} \delta_{vt}^{k}$ where $\delta_{u,v} = \begin{cases} 0\ if\ (u,v) \notin E' \\ 1\ if\ (u,v) \in E' \end{cases}$ is the Kronecker delta function defined on the set of initial edges	A proportion of edges are randomly removed from the graph. The measure shows the impact of removing communication channels between individuals	(Dokas *et al.*, 2017)
Geodesic K-path centrality	The number of geodesic paths up to length k emanating from a given node	$C^K = W'$ where W is a matrix in which w_{ij} is the number of paths of length k or less from node i to j.	It is the measure of direct involvements that a given node has within the geodesic structure of the network.	(Borgatti and Everett, 2006; Agneessens, Borgatti and Everett, 2017; Dokas *et al.*, 2017)
Harmonic centrality	It is the sum of all the inversed distances between every pair of distinct nodes.	$\sum_{i \neq j} \frac{1}{d(i,j)} = \sum_{d(i,j)<\infty, i \neq j} \frac{1}{d(i,j)}$	It is an extension of closeness centrality. Instead of using average distances, harmonic centrality employs harmonic mean of all distances. Hence, it accounts also for nodes j that cannot reach nodes i. It can be applied to not weel	(Boldi and Vigna, 2014)

			connected graphs, too.	
Hubbell Index	Based on the Leontief's input-output model.	$C_{Hubb} = E + WC_{Hubb}$ Where E is an exogenous input and W is a weight matrix derived from the adjacency matrix A.	The measure requires connected and free loop networks.	(Hubbell, 1965)
Information centrality	The relative drop in network efficiency originated by the removal form the graph of the edges incident in node *i*.	$C_i^I = \frac{\Delta E}{E} = \frac{E[G] - E[G']}{E[G]}$ where G is a graph of N nodes and K edges and G' is the graph with N nodes and $K - k_i$ edges. Efficiency of G (E[G]) is: $E[G] = \frac{1}{N(N-1)} \sum_{i,j \in G, i \neq j} \frac{d_{ij}^{Eucl}}{d_{ij}}$	The measure relates the importance of a given node to the capacity of the network to react to the deactivation of the node. Network performance is assessed through an indicator of efficiency.	(Crucitti, Latora and Porta, 2006; Ferreira *et al.*, 2016; Das, Samanta and Pal, 2018)
K-core decompositio n	A subgraph $H = (C, E\|C)$, induced by a subset of vertices $C \subseteq V$ is a k-core or a core of order k iff $\forall v \in C: degree_H(v) \geq k$ and H is the maximum subgraph with this property	$k_i = \sum_j^N d_{ij}$ where k_i is the node degree of i and j is the number of nodes connected to i. Note that: $\begin{cases} d_{ij} = 1 \; if \; i \; and \; j \; connected \\ d_{ij} = 0 \; otherwise \end{cases}$	The measure allows the identification of particular subsets of the graph, named k-cores, each of which is obtained removing all the vertices of degree $\leq k$, until the degree of those left is equal to k.	(Alvarez-Hamelin *et al.*, 2005; Al-garadi, Varathan and Ravana, 2017)

Katz Centrality	Weighted count of the number of walks starting or ending at a given node.	$$x_i = \alpha \sum_j A_{ij} x_j + \beta$$ Where A is the adjacency matrix with eigenvalues λ; β controls the initial centrality and $\alpha < \frac{1}{\lambda\_max}$	It measures the number of immediate neighbors (first degree) plus all other nodes in the network that connect to the node through the first degree ones.	(Borgatti and Everett, 2006; Fletcher and Wennekers, 2018)
Kleinberg's centrality scores	The authority score at node i, x_i^a, is equal to the normalized (weighted) sum of hub scores of all nodes pointing to i. The hub score of a node i is equal to the (weighted) sum of the authority scores that hub node i links to.	$$x^h = AA^T$$ $$x^a = A^T A$$	Hubs and authorities should intuitively hold two properties: (a) a good hub is a page cited by many authorities. The larger the number of authorities and the highest their quality, the larger is the hub score; (b) a good authority is being cited by many (large hub score). Therefore, the larger the number of hubs and their quality, the larger the authority score.	(Kleinberg, 1998; Fouss, Saerens and Shimbo, 2016)
Laplacian centrality	The centrality of a given vertex v is characterized as a function in terms of its Laplacian energy, a measure capturing the ability of the network to respond to the deactivation of that vertex from the graph.	$$C_L(v_i, G) = \frac{(\Delta E)_i}{E_L(G)}$$ where $(\Delta E)_i = E_L(G) - E_L(G_i)$ is the variation of Laplacian energy and must be nonnegative.	It requires weighted networks and allow a better evaluation of "intermediate" information around a vertex. The Laplacian centrality method values both the number of connections a vertex has and the importance of those nodes to which a given vertex is connected to.	(Qi *et al.*, 2012, 2013)

Leverage centrality	Measure to count the difference of degree between a node and its neighbors. In the average case, positive and high values implies a higher influence of a node on s neighbors.	$l_i = \frac{1}{k_i}\sum_{N_i}\frac{k_i - k_j}{k_i + k_j}$ where k_i is the degree of a given node and k_j is the degree of its neighbors. The measure is then averaged by the number N of all neighbors.	The measure allows the identification of the most relevant nodes within their own neighborhood ("critical network nodes")	(Joyce *et al.*, 2010; Dokas *et al.*, 2017)
Lin centrality	The normalized closeness centrality measure (considered as the inverse of the average distance in the graph) multiplied by the square of the number of reachable nodes.	$\frac{\{y\|d(y,x) < \infty\}\|^2}{\sum_{d(y,x)<\infty} d(y,x)}$ For a nonempty reachable set.	Used in the specific case of graphs with infinite distances. Nodes with larger reachable sets are more important. However, given that the average distance is the same, the measure is re-multiplied by the number of reachable nodes.	(Boldi and Vigna, 2014)
Load centrality	It weights shortest paths according to their probability of being selected in a random walk on a directed graph of shortest paths from node I to node k.		Alternative measure to betweenness and optimal for the analysis of flow structures operating below their capacities. Given an input of flow x arriving at v with destination v', v splits x in equal parts among all neighbors of minimum geodesic distance to the target.	('Package "sna": Tools for Social Network Analysis', 2016)
Lobby Index (Centrality)	The largest integer k such that a node x has at least k neighbors with a degree of at least k.	$l(x) = \max\{k\colon \deg(y_k) \geq k\}$ where $\deg(y_k)$ is the degree of x's neighbors y_i with	The lobby index is closer to closeness centrality, betweenness and eigenvector centrality measures.	(Korn, Schubert and Telcs, 2009; Campitelli *et al.*, 2013)

		$\deg(y_1) \geq \deg(y_2) \ldots$		
MNC – Maximum Neighborhood Component	The neighborhood of a given node v, expressed as nodes adjacent to v, induces a subnetwork N(v). The MNC score of a node v is defined by the size of the maximum connected component of N(v)	$MNC(v) = \lvert V(MC(v)) \rvert$		(Lin *et al.*, 2008; Kabir *et al.*, 2017)
Markov Centrality	The average of the average Mean first-passage time (MFPT) in the Markov chain.	$C_M(v) = \frac{n}{\sum_{s \in V} m_{sv}}$ where $m_{st} = \sum_{n=1}^{\infty} n f_{st}^{n}$ is the MFPT, or the expected number of steps starting at node s taken until the first arrival at node t.	The measure requires directed and weighted networks. It uses the concept of random walks through the graph and it uses the MFPT as a measure of how tight the connection between a given node and every other vertex of the network is. Random walks reach quicker well-connected vertices. Therefore, this method helps measuring distances, that can eventually be used as ranking between nodes.	(Boldi and Vigna, 2014)
Radiality Centrality	The shortest path between node v and all other nodes in the graph. The value of each path is removed by the value of the maximum possible distance between nodes (diameter)	$C_{rad}(v) = \frac{\sum_{w \in V}(\Delta G + 1 - dist(v, w))}{n - 1}$	If the shortest paths are short, the radiality centrality will be high – given that they are subtracted by the maximal possible distance (the diameter). Overall, if radiality has high	(Cueno and Imai, 2018; Ivanov, Gorlushkina and Ivanova, 2018)

	+1. Resulting values are summed together and so obtained numerical value is divided by the total number of nodes -1.		values, with respect to the diameter, the node is closer to other nodes. If radiality is low, then the node is peripheral. Results are meaningful when compared to the average of graph.	
Residual closeness centrality	Be $d_k(i,j)$ be the distance between i and j, originated from the original graph where all links of node k are deleted. Using the definition of closeness, we can derive a modified version.	$$C_k = \sum_{i} \sum_{j \neq i} \frac{1}{2^{d_k(i,j)}}$$ The vertex residual closeness is $$R = \min_{k}\{C_k\}$$ The link residual closeness is $$R = \min_{(k,p)}\{C_{(k,p)}\}$$	More sensitive than other measures, because it is able to capture the effects of a node removal even if this does not produce any disconnected components.	(Dangalchev, 2006b; Chen *et al.*, 2013)
Semi local centrality	The measure considers the nearest and the next nearest neighbors of node, which introduces a trade-off between low-relevant degree centrality and other consuming measures.	$$Q(u) = \sum_{w \in \Gamma(u)} N(w)$$ $$C_L(v) = \sum_{u \in \Gamma(v)} Q(u)$$ Where Γ(u) is the set of all the nearest neighbors of node u; N(w) is the number of the nearest and the next nearest neighbors of node w.	High performing measure in low computational complexity	(Chen *et al.*, 2013)
Shortest-Paths Betweenness Centrality				

Stress centrality	Stress is computed as the measure of the shortest paths passing through a node.	$C_s(v) = \sum_{s \neq t \neq v \in V} \rho_{st}(v)$ Where $\rho_{st}(v)$ is the number of shortest paths passing through v. The same definition applies to links: $c_s(e) = \sum_{s \in V} \sum_{t \in V} \sigma_{st}(e)$ where $\sigma_{st}(e)$ denotes the number of shortest paths containing edge e.	A node is highly stressed if it is transversed by a high number of nodes. The measure itself does not automatically imply that node v is a critical one to maintain communications within the graph	(Scardoni, Petterlini and Laudanna, 2009; Zheng *et al.*, 2017)
Subgraph centrality	The sum of closed walks of different lengths in the network that starts and ends on vertex i.	$C_S(i) = \sum_{k=0}^{\infty} \frac{\mu_k(i)}{k!}$ where $\mu_k(i) = \left(A^k\right)_{ii}$ are the local spectral moments defined as the ith diagonal entry of the kth power of the adjacency matrix **A**.	The measure characterizes nodes according to their participation in structural subgraphs of G. Contribution of walks decreases as the length of the walk increases (due to the “small world” property).	(Estrada and Rodríguez-Velázquez, 2005)
Topological coefficient	Number of neighbors shared between a pair of nodes, n and m, plus one if there exists a direct link between the two, divided by the number of neighbors of node n.	$T_n = \frac{avg\big(J(n,m)\big)}{k_n}$ Where $J(n,m)$ is defined for all the nodes sharing at least one neighbor with n.	It is a relative measure of the extent to which a node shares neighbors with other nodes.	(Deng, Zhu and Huang, 2016)

Principal Component Analysis

The 42 centrality measures listed in Table 4S were detected automatically via the R package CINNA. Depending on the topology of the network under study, a specific function detects the optimal number of metrics to be used. We launched a PCA on the 42 measures and then we assessed their correlation and their contribution to each factor.

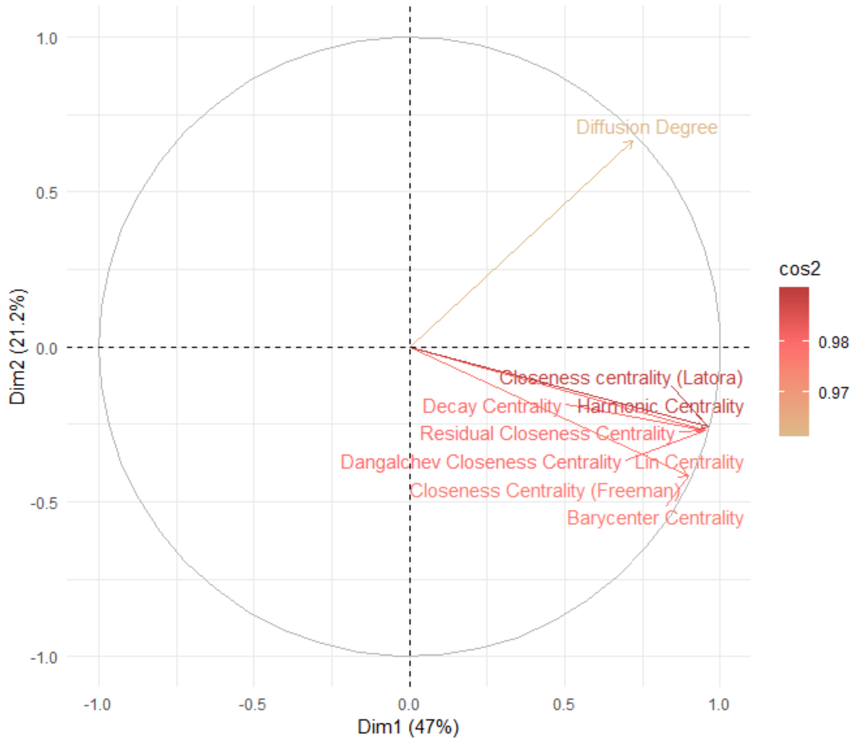

Figure 10S. Most correlated centrality measures as expressed by $\cos^2$

Community detection. Communities are groups of nodes strongly connected within themselves and poorly linked to each other (Barabasi, 2016). They play a significant role in understanding the spread and diffusion of epidemics (Johnson, de Roode and Fenton, 2015), economic inequality (Nishi *et al.*, 2015), diversity in social networks (Becker, Brackbill and Centola, 2017; Han *et al.*, 2017) and consensus (Baronchelli, 2018). Knowledge about the structure of the network and the groups offers the opportunity to predict where critical connectors are, hence the chance to manipulate the graph. This "power" can be very helpful in driving and increasing the efficiency of processes. Real word networks often present structured groups: there exists a wealth of algorithms to perform community detection, but the main methods still remain hierarchical clustering. Therefore, the main question lies in the optimality of the algorithm used to perform community detection. In fact, the challenge lies in the speed of the Bell number: the number of ways allowing the partition in communities grows faster than exponentially with the size of the graph (Barabasi, 2016). Community detection is a major field of investigation in network science: Scopus reports 5320 documents, 41.6% in the Computer Sciences domain[2].

Graph clustering algorithms may be: *(i)* hierarchical methods; *(ii)* spectral methods; or *(iii)* modularity-based methods. Each solution presents advantages and bottlenecks and it may be more appropriate for certain networks, rather than generically applicable to every type. Hierarchical clustering methods comprise agglomerative or divisive procedures. The former populates an empty graph of nodes with edges, ranging from "stronger" to "weaker" connections. Conversely, the latter removes links from a complete graph in every iteration, recomputing at every step the weights assigned. We computed four community detection algorithms: the Newman-Girvan, the Greedy Community, the Spectral Community and the Louvain method. In order to

[2] The query "community detection" was launched in January 21st 2019

assess their performance and choose between the available outcomes, we used the modularity criterion.

Modularity is a structural measure in network science. It is "the fraction of the edges that fall within the given groups minus the expected fraction if edges were distributed at random" (Li and Schuurmans, 2011). It is mathematically expressed as a difference between two ratios:

$$Q = \sum_{i=1}^{k} (e_{ii} - a_i^2)$$

where e_{ii} is the percentage of edges falling under module i and a_i^2 is the probability that a random edge falls into module i. Extending the above mathematical formula, modularity is defined as:

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta(C_i, C_j)$$

where A_{ij} is the adjacency matrix, k_i *and* k_j are degrees of nodes i and j, m is the number of edges, C_i is the community to which node i belongs and $\delta(.)$ is the Kronecker function that takes values 1 if $C_i = C_j$ and 0 otherwise. Modularity has useful properties that may be used to check the quality of the partitioning: *(i)* high values of modularity implies a better portioning, given $Q \in [-1,1]$; *(ii)* $Q = 0$ when the network is observed as a single community. For values $0.3 < Q < 0.7$ the community structure is significantly valid. The community structure with maximal modularity is the optimal one. We are hereby presenting the characteristics of each of them and discussing further the outcome and comparing their performance.

The Newman-Girvan algorithm. The Newman-Girvan algorithm (Newman and Girvan, 2004b) is a divisive community detection method. It builds upon edge betweenness, a value that equalizes edge weights to the number of shortest paths crossing the edge. It is an extension and generalization of central vertex betweenness that provides the quantification of the influence of a given node on the others. Edge betweenness is mathematically expressed as:

$$eb(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Where the numerator represents the number of shortest paths from s to t including v and the denominator includes all the shortest paths from s to t. The algorithm:

(i) starts with one node

(ii) computes edge betweenness for every edge of the network

(iii) removes the edges with highest edge betweenness and

(iv) recomputes edge betweenness with the remaining ones.

Steps are iteratively repeated until every edge is removed. Given the order in which edges with highest weight is not defined, the implementation of the algorithm may produce different results. Therefore, the best partition is provided by modularity.

The Greedy community algorithm. The Greedy algorithm is the first modularity-maximisation algorithm ever conceived (Newman, 2004). It is built on the "Maximal Modularity Hypothesis", which states that "for a given network, the partition with maximum modularity corresponds to the optimal community structure" (Barabasi, 2016). The algorithm works iteratively according to the following steps:

(i) each node constitutes a community on its own for the total amount of N communities of N single nodes

(ii) compute the modularity difference ΔM for each pair of connected communities, obtained as outcome of a merging procedure. Identify the pair for which ΔM is higher and merge them

(iii) repeat the second step until all the nodes form a single community

(iv) select the partition with the maximal value of M

This is a hierarchical agglomerative method: the outcome is – as in the N-G case – a dendrogram where different cuts provide alternative partitions.

The Spectral community method. This algorithm builds on the eigenvectors of the normalized Laplacian matrix (Newman, 2013). The Laplacian is normalized by the size of identified clusters. Modularity is expressed as:

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta_{g_i} \delta_{g_j}$$

where $\delta = 1$ if i and j are in the same community.

For simplicity, we consider only two clusters. We introduce the Ising spin variable that takes values $s_i = 1$ if i belongs to the first group and $s_i = -1$ if included in group 2. The Kronecker function can be conveniently rewritten as $\delta_{g_i} \delta_{g_j} = \frac{1}{2}(s_i s_j + 1)$. Hence, the modularity assumes the form:

$$Q = \frac{1}{4m} \sum_{ij} [A_{ij} - \frac{k_i k_j}{2m}](s_i s_j + 1)$$

We substitute $B_{ij} = A_{ij} - \frac{k_i k_j}{2m}$ to rewrite the modularity as $Q = \frac{1}{4m} \sum_{ij} B_{ij} (s_i s_j + 1) = \frac{1}{4m} \sum_{ij} B_{ij} s_i s_j$.

As the Ising sping variable takes discrete values, the modularity maximisation becomes a combinatorial problem. To simplify the computation, the algorithm relaxes the assumption of discreteness and allows s_i to take real values, under the constraint of a "spherical model", i.e. $\sum_i s_i^2 = n$, that is $-\sqrt{n} \leq s_i \leq \sqrt{n}$.

The maximisation problem becomes:

$$maximise_s Q = s^T B s \quad s.t. \left| |s| \right|_2 = 1$$

Which is a spectral matching problem, where the global optimum corresponds to the leading eigenvector of matrix B. The solution of the maximisation problem is provided by the derivative of the Lagrangian function.

The Louvain method. The Louvain Method (Blondel *et al.*, 2008) is a multi-level aggregation technique based on modularity optimization. It consists of two phases: *i)* it locally optimizes modularity and observes the potential gain generated by moving one node from its original community to another; *ii)* it aggregates nodes belonging to different communities. The two steps are applied repeatedly and sequentially. The first run typically results in smaller communities, while subsequent ones generate bigger ones as an outcome of the aggregation process. The Louvain method algorithm is highly efficient, mainly due to the fact that the potential modularity gains generated in phase one are easily computed as:

In the undirected case, the gain of modularity is easily computed as:

$$\Delta Q = \left[\frac{\sum_{in} + d_i^C}{2m} - \left(\frac{\sum_{tot} + d_i}{2m} \right)^2 \right] - \left[\frac{\Sigma_{in}}{2m} - \left(\frac{\Sigma_{tot}}{2m} \right)^2 - \left(\frac{d_i}{2m} \right)^2 \right] = \frac{d_i^2}{2m} - \frac{\sum_{tot} \cdot d_i}{2m^2}$$

where d_i^C is the degree of agent i in community C; Σ_{in} is the number of links belonging to community C, while

Σ_{tot} is the number of links globally incident to community C. The algorithm runs up to maximal modularity is found.

Detecting key players. This step requires the punctual and explicit identification of actors exerting such a significant influence that their removal may cause a drop of cohesion or even a collapse of the network. The problem of influential agents has been widely discussed in literature: link deletion approaches (Valente and Fujimoto, 2010) are similar to node removal techniques (Borgatti, 2006), but they conceptually differ. While the former is exploring changes in cohesion as effect of manipulation of edges, the latter focuses on the consequences of modifications at node level.

We computed fragmentation centrality, which measures how fragmented the network becomes as effect of a node removal. The metric is mathematically expressed as:

$$F_i = 1 - \frac{\sum_{j,k \neq i} d_{jk}^{-1}}{d \cdot (n-1)(n-2)}$$

where d_{jk} is equal to the shortest path between nodes two nodes j and k once node i has been removed; d is the maximal of d_{jk}^{-1}. We obtained the set of key players that are crucial in not altering cohesion of the graph.

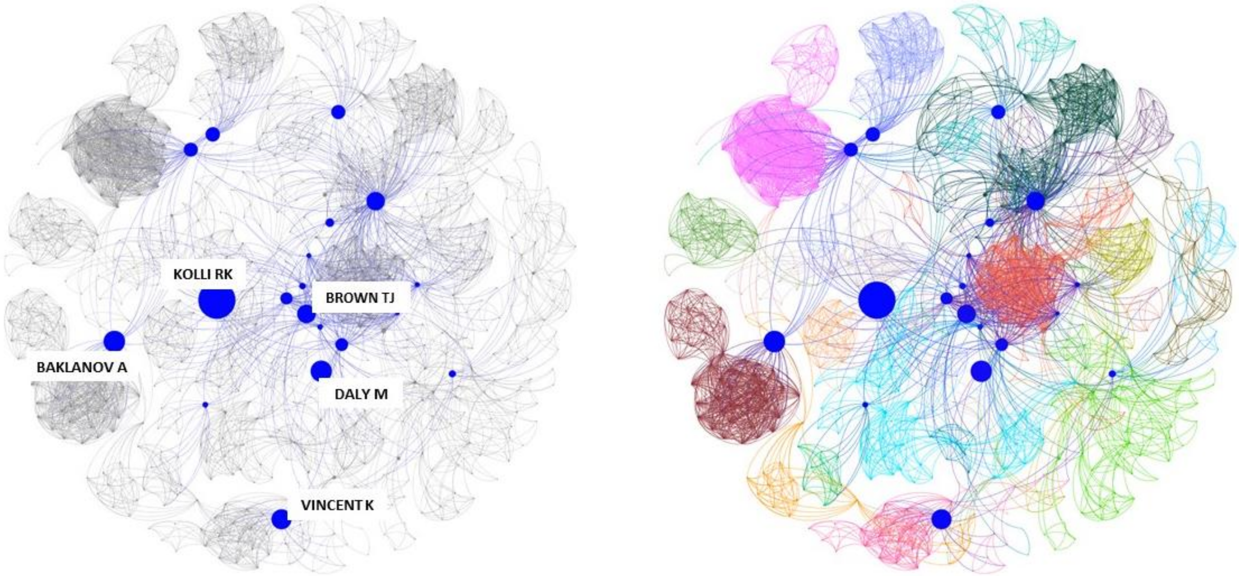

Figure 12S. Identification of key players in the network of individual scholars and their position within communities

We evaluated the performance of the four community detection algorithms by comparing their modularity score (Table A). The algorithms generate different community sizes and heterogeneous number of partitions. The top performer is the Louvain Method.

Algorithm	Communities	Modularity
Newman-Girvan	21	0.8313877
Greedy community	16	0.7897702
Spectral community	17	0.7905254
Louvain method	19	0.8395771

Table A. Comparison between community detection algorithms and their modularity scores

Results

Table 5S. Top 20 authors ranked per productivity (#articles)

Author	Score
Buontempo C.	13
Hewitt C.	11

Doblas-Reyes F.	9
Dessai S.	8
Lowe R.	7
Rodò X.	6
Thomson M.C.	6
Vaughan C.	6
Golding, N.	5
Guido Z.	5
Jacob D.	5
Winarto Y.T.	5
Bruno Soares M.	4
Dunstone N.	4
Kumar A.	4
Mason S.	4
Ray A.J.	4
Scaife A.A.	4
Tall A.	4
Troccoli A.	4

The most productive authors are ranked on the number of published articles in the sample. Hence, productivity is a simple metric of quantity. Authors are also ranked according to their centrality score (Table 6S), as derived from the Principal Component Analysis (PCA) of the available centrality measures. The score reflects the contribution of each agent to the first five dimensions. These explain approximately 86% of the total variance of the sample, which was deemed a significant threshold. Distance between scholars is progressively reduced along the ranking.

Table 6S. Top 20 authors ranked per centrality

Author	Score
Buontempo, C.	5.059
Kumar A.	1.692
Wintzer J.	1.256
Hewitt C.	1.153
Webb R.S.	1.091
Schulz J.	0.999
Kjellström E.	0.715
Jack C.	0.710
Zebiak S.E.	0.640
Brönnimann S.	0.639
Jourdain S.	0.615
Ray A.J.	0.614
Brown T.J.	0.613
Doblas-Reyes F.	0.597
Blaschek M.	0.539
Dahlgren P.	0.539
Vidard A.	0.538
Haimberger L.	0.537
Weaver A.	0.537
Valente M.A.	0.536

Table 7S. Top 20 institutions per centrality score

Affiliation	Score
Columbia University	4.358
University of Reading	3.687
University of Oxford	1.476

Desert Research Inst.	1.422
University of East Anglia	1.404
University of Helsinki	1.234
Observatori de l'Ebre	1.128
University of Florida	0.899
University of Chile	0.852
Barcelona Supercomputing Center	0.850
Sorbonne Université	0.838
University of Belgrade	0.837
Karlsruhe Institute of Technology	0.803
Spanish Meteorological Agency	0.792
Pacific Marine Environmental Laboratory	0.792
Izaña Atmospheric Research Center	0.788
Physikalisch-Meteorologisches Observatorium Davos	0.788
National Observatory of Athens	0.788
Max Planck Institut for Meteorologie	0.788
Naval Research Laboratory	0.786

Computation of the bridging properties at author and institution level offers a new perspective on the power of nodes included in the sample. The ranking provided below are the top 20 agents based on their role in reducing fragmentation in the network. These are the "brokers" of the graph: they reduce distances and facilitate the flow of information and knowledge.

Table 8S. Set of key authors

Author	Score
Kolli R.K.	0.773
Baklanov A.	0.756
Daly M.	0.756
Vincent K.	0.754
Brown T.J.	0.753
Buontempo C.	0.752
Grimmond C.S.B.	0.748
Jacob D..	0.747
Schulz J.	0.747
Kumar A.	0.746
Ray A.J..	0.745
Soubeyroux J-M	0.741
Jack C.	0.740
Vaughan C.	0.739
Vautard R.	0.738
Hewitt C.	0.738
Kjellström E.	0.737
Coughlan de Perez E.	0.737
Guido Z.	0.736
Zebiak S.E.	0.736

Table 9S. Set of key institutions

Affiliation	Score
University of Nairobi	0.605
Joint Research Centre	0.600
Met Office	0.599
Institució Catalana de Recerca i Estudis Avançats	0.592
National Center for Atmospheric Research	0.591

Desert Research Institute	0.590
University of Reading	0.590
NOAA	0.590
University of Chile	0.589
Royal Belgian Institute for Space Aeronomy	0.588
ECMWF	0.588
Columbia University	0.588
University of Leeds	0.588
Swedish Meteorological and Hydrological Institute	0.587
University of Helsinki	0.586
University of Oxford	0.586
Barcelona Supercomputing Center	0.586
Royal Netherlands Meteorological Institute	0.586
London School of Hygiene and Tropical Medicine	0.586
Deutscher Wetterdienst	0.586

Country-network

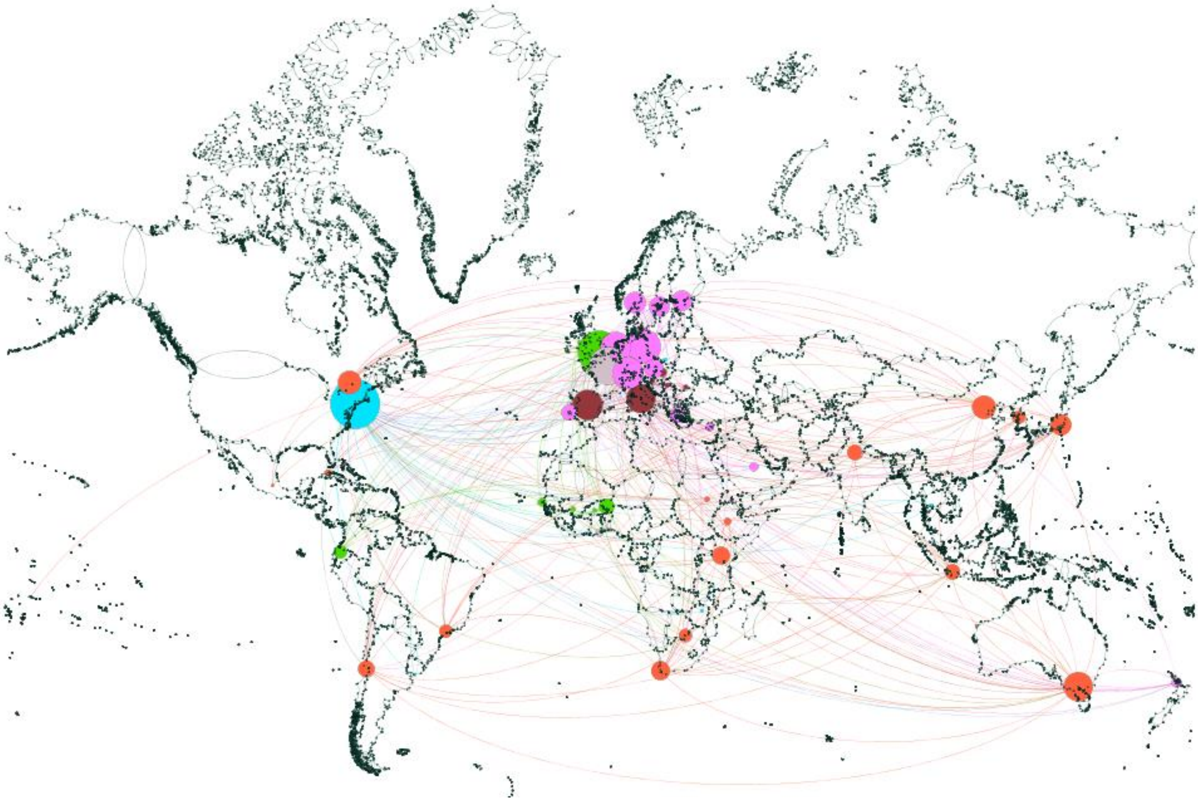

Figure 13S. Centrality as derived from the PCA. Different colors correspond to different clusters as extracted from the Louvain Method

Table 10S. Set of top central countries

Country	Score
USA	44
United Kingdom	38
France	33
Germany	30
Switzerland	28
Spain	27
The Netherlands	27
Italy	26
Australia	26
China	21
Canada	21
Norway	19
Japan	19
Sweden	18
Finland	17
South Africa	17
Austria	16
Kenya	15
Chile	14
Portugal	14

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