1 Mapping the landscape of Climate Services

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Abstract

Climate services are technology-intensive, science-based and user-tailored tools providing timely climate information to a wide set of users. They accelerate innovation, while contributing to societal adaptation. Research has explored the advancements of climate services in multiple fields, producing a wealth of interdisciplinary knowledge spanning from climatology to social sciences. The aim of this paper is to map the global landscape of research on climate services and to identify patterns at individual, affiliation and country level and the structural properties of each community. We use a sample of 358 records published between 1974 and 2018 and we quantitatively analyse them. We provide insights on the main characteristics of the community of climate services through Bibliometrics and we complement these findings with Network Science. We computed the centrality of each actor as derived from a Principal Component Analysis of 42 different measures. By exploring the structural properties of the networks of individuals, institutions and countries we derive implications on the most central agents. Furthermore, we detect brokers in the network, capable of facilitating the information flow and increasing the cohesion of the community. We finally analyse the abstracts of the sample via Content Analysis. We find a progressive shift towards climate adaptation and user-centric visions. Agriculture and Energy are the top mentioned sectors. Anglophone countries and institutions are quantitatively dominant, and they are also relevant in connecting different sides of the network of scholars, by building on established partnerships. We find that nodes facilitating the diffusion of information flows (the brokers) are not necessarily the most central, but they have a high degree of interdisciplinarity facilitating interactions of different communities.

Social media abstract

#WhoisWho in #climateservices? A comprehensive map of research in #Europe and beyond

1. Introduction

Social and technological innovation is a vital part of adaptive capacity (Cohen et al., 2016). Innovation embedded in, or pursued by means of, climate services is conducive to a better management of climate risks (Brooks, 2013). Climate services entail “transformation of climate-related data into customized products such as projections, forecasts, information, trends, economic analysis, assessments (including technology assessment), counselling on best practices, development and evaluation of solutions and any other service in relation to climate that may be of use for the society at large” (EC, 2015). Several European and international initiatives have stimulated vibrant community: Third World Climate Conference (in 2009), the Climate Services Partnership (in 2011), the International Conference on Climate Services (in 2011), the Global Framework of Climate Services (in 2012), the European Roadmap for Climate Services (in 2015), and the Climate Services for Resilient Development Partnership (in 2017). Climate services can improve efficiency and speed innovative methods and processes in agriculture (Amisah-Arthur, 2003; Stigter, 2008; Lechthaler and Vinogradova, 2017; Li, Giuliani and Castelletti, 2017), food security (Vogel and O’Brien, 2006), disaster risk reduction (van den Hurk et al., 2016), urban planning (Jones et al., 2017; Lindberg et al., 2018), health (Goddard et al., 2010; Bruno Soares, Alexander and Dessai, 2017), tourism (Scott and Lemieux, 2010; Scott, Lemieux and Malone, 2011), and other climate-sensitive sectors.
Climate services (i) are technology-intensive and draw on coding, protocols, systems and devices; (ii) employ action-driven research, connecting science, business and policy; (iii) share processes and workflows for climate-smart decisions. It is important not only trace the wealth of research outputs such as publications or patents, but also collaboration networks that have jointly produced these outputs. Co-authorship is a proxy of joint innovation and cooperation between institutions and experts. Hence, network analysis is useful to explore centrality and power relation driving innovation. Content analysis (CA) on the other hand sheds light on most salient concepts.

In this paper we map the research on climate services. We explore productivity patterns, time-evolution of fields of interest, and structural properties of co-authorship networks at individual, organisation and country level. We use a sample of 358 bibliographic records published between 1974 and 2018 and retrieved from the Scopus database in January 2019. We characterise the interactions of individual scholars and institutions combining Bibliometrics, Network Analysis and Content Analysis. This work contributes to existing literature in two ways. First, it provides a comprehensive mapping of actors and topics in the domain of climate services and, hence, climate innovation. Second, it offers an original methodological approach to study node centrality and combine bibliometrics and network science. The work is organised as follows. Section 2 describes the framework, data and methods used. Section 3 presents the results (i) giving insights on the conceptual structure through bibliometrics; (ii) elaborating about the social structure of interactions within the network of individuals, institutions and countries; (iii) assessing the most relevant concepts of the fields of interest over the considered timeframe. Section 4 concludes with the limitations of our approach and provides reflections on future extension.

2. Materials and methods

2.1. Data and methods

Our framework combines bibliometrics, network and content analysis in a consistent approach. It aims at uncovering the conceptual and social structure of the network in which research is produced. The stepwise procedure allows to check and validate at multiple stages the quality of the analysis and the correctness of the results (Figure 1).

Bibliographic sample was retrieved from Elsevier’s Scopus (www.scopus.com) querying a combination of keywords1. The same query run on Web of Science (www.webofknowledge.com) resulted in lower number of records. The query yielded records from 1974 until 2019. Non-relevant records were removed from the sample (see Supplementary Material).

We used bibliometrics to describe the corpus of publications. Network Analysis and Content Analysis were, instead, deemed the most appropriate tools to assess the social and conceptual structure of the records included. Bibliometrics has been used to study the evolution of a given field, as well as to characterize the polarization of different topics and institutions. In climate change domain, a recent analysis based on 222,060 papers published between 1980 and 2014 identified an exponential increase and a strong presence of vulnerability and adaptation-related concepts among the most cited documents (Haunschild, Bornmann and Marx, 2016).

Research on impacts of climate change that goes beyond the natural sciences domain has intensified since 2005 (Haunschild, Bornmann and Marx, 2016). Furthermore, bibliometrics is often deemed appropriate to assess the role of interdisciplinarity in fostering the creation of new ideas, by looking in-depth at the

1“climate services” AND “Climate Services” AND “climate service” AND “Climate Service”. We also run an alternative query (“climate service*”) to check on the validity of our first search.
composition of research teams and at their expertise (Ma, Mondragón and Latora, 2015), as well as the exchanges between disciplines (Youngblood and Lahti, 2018).

Figure 1 | A stepwise method to map research on climate services. The framework combines Bibliometrics, Network Analysis and Content Analysis and offers opportunities to revise and verify the process.

To study the social structure of co-authorship, we derived co-authorship relationships at individual and institutional level and performed a network analysis. A network is a catalog of components \( V(.) \) – the nodes or vertices – interacting within a system and connected through links or edges \( E(.) \). It is mathematically represented as a graph that can describe the complexity behind the individual node’s behavior and the interaction between different nodes (Barabasi, 2016). NA has been successfully applied to study the drivers of social consensus (Baronchelli, 2018), as well as in analyzing social sciences (Borgatti et al., 2009) and the emergence of social dynamics (Castellano, Fortunato and Loreto, 2009). We characterized agents on their “importance” (centrality), by exploring the giant component of each network. This is the highest connected portion of the general graph. Given the wealth of existing centrality measures, we performed a Principal Component Analysis (PCA) on 42 metrics. We reduced the dimensionality to five and four main components, which explain more than 80% of the total variance (see Supplementary Material) in the individual scholar and institution and country case respectively. Moved by the idea that “structure matters” (Newman, 2003; Newman and Girvan, 2004a; Barabasi, 2016), we aimed at detecting communities - meant as groups or clusters of nodes connected to each other than to nodes belonging to different groups – to understand how science and research on climate services move within the network of actors involved.

Community detection is vital when studying the structural features of a network. First, highly connected nodes could share interests or shared preferences. Second, agents within the same community may have a privileged access to information and opportunities. Therefore, the investigation of structural properties at network level can reveal some important information about the mechanisms behind collaboration and diffusion patterns. There is no single unambiguous definition of what communities are. This has important implications: climate services employ knowledge from climatology and physics, but also information sciences, economics, business and sociology. Communities are nested and interlinked – often overlapping. The study of their structure offers insights about the research on climate services: insights from different disciplines are combined. The relevance
of community detection has produced a wealth of algorithms and methods to facilitate the identification of different groups. We performed the Newman-Girvan algorithm, the Spectral community algorithm, the Greedy algorithm and the Louvain method separately obtaining different community partitions (see Supplementary Material). Hence, we compared their performance using modularity as criterion. This measure represents the “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). We employed the community structure with maximal modularity among the four computed algorithms.

Finally, we characterized individual based on their capacity to influence the network they are embedded in. We aimed at detecting brokers that allow research insights on climate services to travel within the network. These “connectors” act through two channels: (i) if removed from the network, their absence cause a significant drop in the cohesion of the graph; (ii) they are seeds for the diffusion of habits, methods, ideas and information (Borgatti, 2006). Hence, key players may be more efficient in spreading novelties rather than highly central nodes. We implemented the greedy search algorithm to look for the optimal number of key players and to overcome computational challenges. The algorithm selects an initial set of nodes as seeds. By continuously and iteratively swapping between selected and unselected nodes, the protocol computes if and how much group centrality increases (details in Supplementary Material).

We further investigated the thematic evolution of climate services combining two approaches. We performed Content Analysis on the set of abstracts and titles included in the database. Content Analysis transforms non-numerical material into quantitative information. It is the systematic analysis of textual, visual and audio inputs to identify regularities and patterns in a corpus of matters (Krippendorff, 2004). The output of this effort consisted in the dynamic characterization of top mentioned terms throughout the timeframe. Content Analysis also served as input for co-word analysis. This methodology links science mapping and bibliometrics to grasp connections in textual material (Cobo et al., 2011) and provides a thematic map that spatially allocate topics on a 1:2 plane.

The integration of different disciplines – from scientometrics to content analysis – represents an original feature of this work. By including tools from network science to a bibliometric database, we assess the social structure of individual scholars, institutions and countries. Finally, we move beyond existing metrics of success of a scholar (e.g. h-index, m-index, productivity) and we analyze both the power (centrality) of each node and the influence this has in driving the information flow.

3. Results
3.1. Bibliometric analysis

Our sample includes a corpus of 363 bibliometric records, published between 1974 and 2018 in 187 sources (journals and books) by 1351 authors from 234 institutions in 72 countries. Research articles (54.54 percent), conference proceedings (44.18 percent), reviews (5 percent) and book chapters (5 percent) represent the majority of records. Research on climate services has grown in numbers with an annual growth rate of 14.67 percent, with a sizeable acceleration between 2005 and 2010. The peak (Figure 1S) coincides with the World Climate Conference 3 (2009) and launch of the Global Framework for Climate Services (in 2012). In-between, the first International Conference on Climate Services (2011) marked an important milestone: the conference launched the Climate Service Partnership (CSP) to boost development of climate services. Earth and Planetary Sciences (35.3%) and Environmental Sciences (28.9%) are dominating the sample and are also the most time-consistent disciplines across time. Social Sciences (12.6%), Agricultural and Biological Sciences (4.6%) and Engineering (3.1%) follow suit. Economics, Econometrics and Finance (1.0%) are represented starting from 2010. Anglophone authors and institutions dominate the sample. Multi-country collaborations are prevalent: while the authors from United States mostly publish alone, the overall trend is a collaborative research across borders (Figure 4S). The most productive authors per number of published records are more diverse: 20% have
a background in Environmental Sciences, 20% in Social Sciences and the remaining 60% in Physical Sciences. Despite the heterogeneous cohort of actors involved, climatologists, physicists, and numerical modellers are widely recognised as the most central when it comes to climate services.

3.2. The conceptual structure

The science of climate services has roots in climatology and meteorology but as the innovation has become more user-centric oriented, social science disciplines are more represented and the articles pay more attention to clients’ knowledge requirements and the value unleashed by climate services. Literature has responded to this trend by exploring the barriers and opportunities from multidisciplinary angles. The historical citation analysis documents this shift: the most cited articles belong to a more recent body of research (Miles et al., 2006; Hewitt, Mason and Walland, 2012; Vaughan and Dessai, 2014) addressing co-design and co-development of national climate services (Figure 2).

Most frequent keywords (Figure 5S) include ‘climate change’ (365), ‘decision making’ (236) and ‘forecasting’ (214) display a fairly steep trajectory since 2001 onwards. Future-oriented keywords dominate, whereas ‘observations’ or ‘reanalysis’ are not among the first 100 concepts. ‘Seasonal forecasts’ gained on popularity, especially in the past eight years. ‘Multidisciplinarity’ and ‘adaptation’ have received progressively more attention: the temporal analysis of abstracts shows that ‘carbon’ and ‘emission-related’ topics were more popular in early 2010s, while ‘user-tailored’, ‘forecast skills’ and sector-specific topics nowadays prevail. ‘Adaptation measures’ are strongly related to ‘risk management’ and ‘decision making’ and require ‘climate modelling’ and sector-specific studies. Instead, articles related to meteorology and climatology contribute to scientific advancements of the services, but they are still tightly linked to essential climate variables (Figure 2a).
3.3. The social structure

We transformed the bibliographic records in undirected graphs (or networks) of co-authorship ($N_{\text{ind}}$), collaborating organizations ($N_{\text{aff}}$) and countries ($N_{\text{co}}$). The network has a small-world property with tightly interconnected clusters of nodes and most nodes can be reached from any other node through few steps (Mehlhorn and Schreiber, 2013) ($SM_{\text{index\_ind}} = 7.91 > 3$). The giant component contains 613 nodes and 4326 edges. The network is loosely connected ($density = 0.024$). On average, each author is connected through 15.093 links (i.e. average degree) to 4.55 scholars (i.e. average path length). The probability of two adjacent nodes to be connected (i.e. clustering coefficient) is 82.26%. We performed a Principal Component Analysis (PCA) on 42 standardised centrality measures. The first five components (Figure 4a) explain 86.1% of the total variance. Buontempo C. happens to be the central agent, directly connecting 21.70% of the nodes and 29.25% edges. He is also connecting some of the most productive scholars per number of papers.
Figure 4 | a) Representation of eigenvalues.. The percentages represent the portion of variance contained in the data explained by components; b) centrality measures included in the PCA are represented according to the degree of correlation with the different dimensions. Dark blue colors are higher correlation measures included in the PCA.

The community detection protocol produced four different partitions – each per algorithm performed. We compared the modularity scores and we chose the Louvain method (Table 1), obtaining 19 communities.

The network of individuals is a set of complex interactions. Nodes’ size is equal to the contribution of each agent to the first five dimensions of the PCA and colors correspond to communities as derived from the Louvain method. The most central authors (Figure 5a) are located in five communities, which (the largest in size). Only three (Buontempo C., Hewitt C. and Kumar A.) are listed among the most productive authors (per number of papers) . Hence, quantity is not an automatic predictor of the “power” of agents, but rather a complementary feature. Two big communities are polarizing the network. The central group (orange) is deeply connected: authors are linked through a number of publications, one of which contributed to the scientific knowledge around sub-seasonal forecasts (White et al., 2017). The purple cluster (community 1) embraces authors involved and bounded in a European project ERA-CLIM2, under the Seventh Framework Program (Buizza et al., 2018).

Figure 5 | a) The individual scholars’ network. Colors represent communities as deducted by the Louvain method. Node sizes gives the centrality of each author, as derived from the PCA; Buontempo C (412) is the most central, followed by Kumar A. (614), Wintzer J. (494), Webb RS. (881), Schulz J. (295), Kjellström E. (623), Jack C. (939), Zebiak SE. (636), Brönniman S. (249), Jourdain S. (256), Ray AJ. (317), Brown TJ. (630), Doblas-Reyes F. (8) and Blaschek M. (275). b) The keyplayers represented with their own communities. The top 20 are (ranked in decreasing order): Kolli RK. (366), Baklanov
We measured the contribution of each node to maintain the cohesiveness of the graph, as suggested by Borgatti (2006). Top influential nodes (key players) do not entirely correspond to the most central ones (Figure 5b). Indeed, the set of key players includes some “bridging” scholars: they link different communities co-authoring with well-known and highly recognized authors. The key players are mostly involved in advancing numerical models, predictions and physical sciences, but they are also active in providing inputs about decision-making and user engagement. Hence, they do not just connect distant communities, but they also embody the conceptual framework in which climate services have been developed. They are “brokers” of knowledge generated throughout the network: by working as bridges both in physical and content level, they facilitate the information flow.

The institutional network \(N_{\text{inst}}\) contains 234 nodes and 1578 edges. The network is more cohesive than the individual one \(N_{\text{ind}}\) with density equal to 0.057. Nodes are also closer (diameter = 6). The average degree is 13.487 and each affiliation is linked to 2.750 (i.e. average path length). The average clustering coefficient is very high: 85.80% (higher than \(N_{\text{ind}}\)). We followed the same methods as for \(N_{\text{ind}}\) to detect centrality, community structure and degree of influence. Centrality is the contribution of each institutions to the first four dimensions, which explain 86.8% of the total variance of the sample. The top institution is Columbia University, with a centrality score of 4.358 (21.79% of the overall network and 28.14% of the overall edges), followed by University of Reading (3.867), University of Oxford (1.476), Desert Research Institute (1.422), University of East Anglia (1.404) and University of Helsinki (1.234). As for \(N_{\text{ind}}\), the Louvain method has the highest modularity. The algorithm found 13 communities: the biggest (community 6) has 31 members, while the smallest (community 1, 3 and 8) have only 7. The geographical location of institutions included in the sample appear in \(N_{\text{inst}}\) is relevant: African universities are clustered in the same group as the Chinese research institutes. German speaking and Belgian institutions have a tight connection. English-speaking (UK and USA-based) affiliations are cooperating with a heterogeneous set of actors: Columbia University is clustered together with other American institutes, but also co-publishes with the London School of Economics (LSE) and the Swedish Meteorological and Hydrological Institute (SMHI). The University of Reading has, instead, a strong European basin of co-publications, but the community it belongs to also includes the NASA Goddard Institute for Space Studies and Colorado State University.

The set of key players in the network is, as for \(N_{\text{ind}}\), different from the most central ones and provides the ground for some insightful considerations. The most influential node happens to the University of Nairobi, which acts as connector of extra-EU countries mainly located in Africa or China, with European and American institutions. Reasons for this may be related to the IGAD Climate Prediction and Applications Centre, where teams of researchers work on short, medium and long-term products and applications. Also, the Joint Research Center has a role in bridging knowledge around climate services produced in different areas of the world facilitates the diffusion of information and reduces distances in the network, increasing cohesiveness. Given the widespread collaborations that the UK Met Office has, its influence in spreading knowledge on climate services increases exponentially if compared with the centrality metrics. Not surprisingly, other well-established research institutions are listed among the top ten influential of the network (the National Center for Atmospheric Research and ECMWF). The top ones are not just providers of climate information services, but they are also producers of climate data. Furthermore, interactions seem to strongly depend on the level of economic development: African, South American and Asian institutions have tight bonds. Our analysis delivers a polarized picture that is possibly driven by project funding and calls for deeper analysis.
Conclusions

In this article we map the research on climate services by analysing a sample of articles published between 1974 and 2018. Results provide an overview of the most relevant topics explored by the pool of scholars and institutions, as well as the social interactions that shape co-authorship. Scientific production on climate services is higher than expectations: the interest has been stimulated by the launch of multiple international initiatives. Their action-driven component allowed climate services to progressively shift from mitigation towards adaptation. Hence, they are used as science-based tools capable of supporting decision-making by building on interdisciplinary expertise.

We found there is no perfect match between productivity (quantity) and centrality as derived from the PCA. Despite the high degree of interdisciplinarity, only one author has a background outside physical sciences (Wintzer J.). At institutional level, universities are more represented than research centers. Our analysis also provides details about bridging agents in the network: these actors are crucial in brokering information and speed the diffusion of information, reducing fragmentation in the network. At author level, the set of key players produce knowledge about physical sciences and decision-making. Hence, they contribute in filling the gap between provider and users with their scientific production. Institution-wise, the highest the geographic and field heterogeneity within a single publication, the stronger the influence within the network. Hence, interdisciplinarity is an asset to promote the reception of ideas, especially when it comes to user needs, value of the information, risk assessment and sector-specific adaptation. Institutes that provide inputs to build fully operational climate services are among the most influential (University of Nairobi, Joint Research Center, Met Office).

Our paper entails several novel contribution. First, we combine bibliometrics, network and content analysis in a consistent framework, making it possible to explore conceptual and social structure of the networks of individual and institutional actors. Second, we analyse structural properties of the field.

We acknowledge some limitations. Our query drives our bibliographic sample. First, climate services are not univocally defined, and they have formally received attention since 2011, while we included documents.
published from 1974 onwards. However, their definition has always been voluntarily broad: the keywords we
used to perform the query allow for maximum heterogeneity and are aligned to the flagship initiatives
promoted to unleash climate services’ potential (Barron, 2001; World Meteorological Organisation, 2009;
Street et al., 2015). Second, bibliographic databases – such as Scopus – are biased towards English-based
records. Also, our sample is populated by peer-reviewed material only, leaving nationally-relevant reports,
protocols and regulations out. Third, climate services often include other products and platforms, such as
decision-support systems, hydro-meteorological services and even weather services. We deemed “climate
services” as the most general and policy-oriented term, capable of capturing the whole period under study, but
strongly related to the recent initiatives. Finally, we acknowledge that our sample is is entirely focused on
peer-reviewed scientific records and excludes other initiatives and development. Hence, our contribution is not
meant to be exhaustive and calls for further research to complement the global mapping.

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