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Published in:
Research Evaluation

DOI:
10.1093/reseval/rvae005

Published: 01/01/2024

Document Version
Publisher's PDF, also known as Version of record

Research Evaluation, 2024, **00**, 1–13
https://doi.org/10.1093/reseval/rvae005
Article

OXFORD

Organizational changes and research performance: A multidimensional assessment

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Abstract

This paper analyzes the research performance evolution of a scientific institute, from its genesis through various stages of development. The main aim is to obtain, and visually represent, bibliometric evidence of the correlation of organizational changes on the development of its scientific performance; particularly, structural and leadership changes. The study involves six bibliometric indicators to multidimensionally assess the evolution of the institution's performance profile. For a case study, we selected the Renewable Energy Institute at the National Autonomous University of Mexico, created 35 years ago as a small laboratory, then it evolved to a research center and finally to a formal institute, which over the last 8 years changed from the traditional departmental structure to a network-based structure. The evolution of the multidimensional performance profiles is analyzed, and graphically represented, using a novel artificial intelligence-based approach. We analyzed the performance profiles evolution yearly, using Principal Components Analysis, and a self-organizing neural network mapping technique. This approach, combining bibliometric and machine learning techniques, proved to be effective for the assessment of the institution's evolution process. The results were represented with a series of graphs and maps that clearly reveal the magnitude and nature of the performance profile evolution, as well as its correlation with each of the structural and leadership transitions. These exploratory results have provided us data and insights into the probable effects of these transitions on academic performance, that have been useful to create a dynamical model.

Keywords: research performance assessment; scientific institutions; organizational development; multidimensional performance profile; self-organizing neural network.

1. Introduction

Scientific institutions, like any organization, experience changes throughout their existence that allow them to constantly adapt to the environment in which they operate, as well as to develop their resources and capabilities to achieve the goals for which they have been created. Structural and leadership changes constitute two of the most frequent transformations carried out in these entities. However, many related questions may emerge after these transformations from the viewpoint of research evaluation: To what extent administrative-structural changes have an impact on the institutional research performance? What are the effects on productivity of substituting a departmental structure by a network-like flexible structure? Do these changes affect the way researchers collaborate or the nature of their production?

This study explores these questions from a scientometric perspective. The effect that organizational and leadership transitions might have on the evolution of a research group is the main issue addressed. We assess quantitatively the performance using bibliometric indicators looking for correlations with leadership and organizational changes. We use a multidimensional approach to characterize the performance profile in terms of a battery of bibliometric indicators. For the visual analysis of the evolution of the research group's multidimensional performance profile, we introduce a novel graphical technique, powered by an artificial neural network.

Using these approaches and techniques, our study contributes elements and data to evaluate the policy of the Universidad Nacional Autónoma de México (UNAM) for the development of research units. The laboratories at the UNAM follow a road map for creating and developing research institutes. UNAM has been evaluated many times globally in various university rankings; however, there is no study of how its research policy at critical organizational units fosters productivity. As a case of study, we have selected a laboratory that evolved to become a scientific institute, experiencing deep changes in its organizational structure, which involved the substitution of a hierarchical academic model, by a more complex network-like adaptable structure.

2. Background

The specialized literature has addressed the previous questions using different approaches. Many authors have focused on the factors that drive productivity of scientific institutions, how these factors evolve, and which of them has a major effect. These factors have been used to classify institutions according to their typology and performance, thus serving as a decision-making tool for research policies (Carayol and Matt 2004). Different possible approaches depending on the level of aggregation (institutions, individual researchers, or research groups) have been studied (Carayol and Matt 2006; Braam and van den Besselaar 2010; Verbree et al. 2015; Sandström and van den Besselaar 2019), considering several parameters in each case. Individual determinants are commonly age, gender, and position in the institution, while collective determinants could be the size of the institution, financial support, or the number of associated postdoctoral researchers (Carayol and Matt 2006; Zharova, Tellinger-Rice and Härdle 2018). The nature and the evaluation of research impact is another consideration that has been analyzed from various points of view (Penfield et al. 2014).

Other authors have been studying how the scientists work, considering the research group as a fundamental unit, part of higher-level units, such as laboratories or research centers (Braam and van den Besselaar, 2010). They argue that the evolution of a scientific institution, no matter the knowledge domain involved, is strongly related to the behavior of these research groups, their relationships with internal and external conditions, and their interactions, which are conditioned by different types of leaderships and organizational changes (Braam and van den Besselaar, 2010, 2014; Verbree et al. 2015). Particularly, Braam and van den Besselaar (2010) hypothesized a basic life cycle pattern for research groups. In the first stage of its life cycle, the group formulate and/or internalize its mission and find a strategic pattern of activities in domains that are suitable for realizing its mission. If a group succeeds in this phase, it will reach the next phase of robust equilibrium. In the second stable phase, change comes only if it is forced upon the group (i.e. a change of a group's mission or strategy). Deviations from this expected standard pattern allowed the authors to identify basic dynamics and changing conditions. They found that their case study fits the hypothetical model in its first period of existence, thus fulfilling a first life cycle. Later, a boost in activities marked the beginning of a new life cycle (Braam and van den Besselaar, 2010).

Following the same line, Verbree et al. (2015) developed a model to demonstrate the interrelationships between academic leadership and scholarly performance considering multiple contextual factors. They showed how the organizational strategies may affect the performance in various dimensions. A typical organizational change is the selection of a new director, or the modification of the hierarchical structure or work styles derived from this new leadership, several aspects considered by our current research. In fact, the correlation of the life cycles of institutes with the life cycle of the directors is an issue that we considered in the present paper.

More recently, Wu, Wang and Evans (2019) examined the composition of research teams analyzing 65 million papers, patents, and software products. They concluded that large teams develop, while small teams disrupt science and technology. In the same line of analysis, previously Mote et al. (2016) had investigated the impact of organizational size in the case of six federally funded institutions and concluded that a too large size of the research team could have a negative influence on the innovation process.

In this context, leadership has been one of the most studied factors associated with institutional performance. Some authors claim that organizational culture is deeply influenced by different styles of leadership (Bass 1985; Bass and Avolio 1994; Schein 2010), considering it as a key factor to achieve organizational effectiveness. These types of studies have been focused on the impact of transformational and transactional leaders (Jandaghi, Matin and Farjami 2008; Van der Voet 2014), the determinants of institutions' success (Yıldırım and Birinci 2013), and the stability of organizational structures (Meyer 1975). Van der Voet (2014) observed the limitations that bureaucratic organizational structures caused on transformational leaders, while Eva et al. (2018) studied the mechanism through which servant leadership affects organizational performance, demonstrating that there is a moderate relationship between both elements.

From a quantitative perspective, multiple bibliometric studies have analyzed leadership related topics (Garcia 2020; Gümüş et al. 2020; Samul 2020; Scheffler and Brunzel 2020; Vogel et al. 2020), the effect of changes in national science policies (Önder et al. 2008), and other determinants of productivity (Carayol and Matt 2004, 2006). A large number of bibliometric techniques and indicators have been used to characterize the performance of researchers (Verbeek et al. 2002; Van Leeuwen 2003), to identify trends in their productivity (Garner et al. 2018), to determine the research fronts they have developed (Gutiérrez-Salcedo et al. 2018), to evaluate the scope and prestige of publication biases they have chosen (Lariviere and Sugimoto 2019), to analyze the strength of their collaboration links (Liang and Liu 2018), to measure interdisciplinarity of research communities (Marres and de Rijcke 2020), and even to predict the impact of research from the dynamics of citations received by the work they have done (Abramo, D'Angelo and Felici 2019).

However, there is a lack of research focused on the structural changes which scientific institutions undergo (Coccia and Rolfo 2007; Tiberius, Rietz and Bouncken 2020); and particularly, in how these structural changes have been reflected on the dynamics of scientific activity, the development of institutional networks, and the diversity of pipelines and outputs (Zitt 2005), which is also a relevant issue analyzed here by us.

3. Multidimensional approach based on bibliometric mapping and artificial intelligence

A clear statement emerges from previous literature: scientific performance should not be measured by a one-dimensional metric since it is a multi-dimensional phenomenon (Schmoch et al. 2010). Therefore, to assess the academic performance of scientific institutions, it is convenient to consider multiple indicators to holistically capture the various dimensions of the scientific activity and products. However, dealing with multidimensional data is not a common practice. We are used to one dimensional measures and comparisons (e.g. rankings). This is because one dimensional data comparison is very simple, since they can be ordered in a line segment. On the contrary, n-dimensional data are more difficult to compare and it is impossible to visualize them when $n > 3$ (because human intuition in an euclidean space of more than three dimensions does not operate).

To characterize academic performance, it is desirable to use several indicators that encompass, in a multidimensional performance profile, various dimensions of the academic endeavor. But multidimensional profiles, composed of more than three indicators, inhabit abstract mathematical spaces where we do not have geometrical intuition, so we have to resort to sophisticated processing and visualization techniques (Ràfols 2019), to automatically compare them; or posed in a more general way, to discover patterns or regularities in sets of multidimensional data.

Even a more ambitious challenge is to picture the evolution of multidimensional data, because it adds the temporal dimension. We show here that Principal Component Analysis (PCA) and certain types of Neural Networks, are well suited to carry out this type of analysis, providing us with an elegant and friendly, visual representation of performance profile evolution in a 2-D knowledge map. This is possible because the neural network has the capability of synthetically representing, in just one figure, a display of the institution's multidimensional profile evolution, as a curve transiting through a set of clusters representing a sequence of different performance profiles. Without this resource just plotting in a dashboard, the individual time evolution of each of the indicators, does not provide a holistic view of the academic performance profile evolution as a multidimensional phenomenon, because the profile in any given moment of time is separately represented with its components in the individual temporal courses graphs.

The research method we apply in the present investigation is based on three main elements: (1) multidimensional characterization of institutional performance profiles; (2) bibliometric mapping, and (3) the use of Principal Component Analysis and artificial neural networks technology to analyze and visualize the evolution of multidimensional data. We remark that the neural network is used here in a novel way to carry out multidimensional temporal analysis.

In the context of analyzing sets of multidimensional profiles, during the last two decades mapping methodologies based on artificial intelligence have gained prominence, as they allow not only to carry out the analysis but to visually represent the space distribution of multidimensional profiles sets. The Self-Organizing Map (SOM) neural network (Kohonen 2013) has proved to be useful in bibliometric studies for visualizing and comparing multidimensional performance profiles. White, Lin and McCain (1998) were the first to show that SOM neural networks produce similar results to those obtained with multidimensional scaling (MDS) to create maps of intellectual domains, with the advantage of requiring less computational effort. Later, this view was reinforced by Moya-Anegón, Herrero-Solana and Jiménez-Contreras (2006). They showed that SOM and MDS are complementary methods which provide representations of the same reality from different analytical points of view (Moya-Anegón, Herrero-Solana and Jiménez-Contreras 2006). In Latin America, Sotolongo-Aguilar and Carrillo-Calvet applied the SOM to the analysis of co-occurrence matrices (e.g. co-cites, co-words and co-authorship networks) using case studies from biomedical domains (Sotolongo-Aguilar et al. 2001; Sotolongo Aguilar, Guzmán Sánchez and Carrillo-Calvet 2002; Guzmán-Sánchez et al. 2010). Meanwhile, Polanco and colleagues in 2001 presented multi-SOM, a modified version of the SOM algorithm, to hierarchically organize scientific and technological information (Polanco, François and Lamirel 2001).

Later, Skupin, Biberstine and Börner (2013) demonstrated the capabilities of the SOM to process large volumes of bibliometric data. More recently Villaseñor, Arencibia-Jorge and Carrillo-Calvet (2017) developed a SOM based method for performance profiles assessment. With this new bibliometric application of SOM, fundamentally different from co-occurrence matrix analysis, the authors laid down a framework for visualizing and comparing multidimensional performance profiles in any kind of scientific units (Arencibia-Jorge et al. 2016; Villaseñor, Arencibia-Jorge and Carrillo-Calvet 2017; Ruiz-Coronel, Jiménez Andrade and Carrillo-Calvet 2020), which is a pioneer approach to analyze the evolution of multidimensional performance profiles. These studies proved the power of the neural network technique, not only to discover knowledge in large sets of multidimensional data, but also to provide graphical scenarios to represent it in a friendly way. However, to the best of our knowledge, the problem of analyzing the evolution of multidimensional performance profiles has never been tackled, which is another point in favor of the methodology proposed in this study.

4. The Renewable Energy Institute as a case study

The genesis of scientific institutions within universities encompasses diverse processes and development stages. At the UNAM there is a well-established track by which a small group of researchers could organize and create first a *Research group* or *Laboratory*—'the laboratory level' explored by Latour and Woolgar (1986)—, to grow later into a *Research Center* which after a maturity evolution could acquire the status of a *Research Institute*, if they fulfill certain standards. During these transitions various academic and administrative figures operate, implying different levels of resources and support. Besides the transition cycles, another temporal characteristic is the 4-year cycles that UNAM follows to change leadership in Centers and Institutes, and even the university's Rector, with only a single possible reelection.

UNAM is the most important public university of Mexico, with several campuses distributed around the country. The Renewable Energy Institute (IER, *Instituto de Energías Renovables*) was born as a small Solar Energy Laboratory (LES, *Laboratorio de Energía Solar*) in 1985. It was established in Temixco, Morelos, a territory that receives a substantial amount of solar radiation throughout the year. The lab belonged to the Institute of Materials Research (IMM, *Instituto de Investigaciones en Materiales*) of UNAM, but it became independent as a research center in 1996, when it was transformed to the Center of Energy Research (CIE, *Centro de Investigación en Energía*). Finally, in 2013 it was promoted to become an Institute.

The IER has focused on the development of renewable energies. Research at this institution deals with actions covered by the Sustainable Development goal 7 (Affordable and clean energy) and the Glasgow agreement (United Nations 2022, March). The strategy of this agreement aims to empower civil society for boosting an alternative plan of action (inventory and climate agenda), without waiting for governments and international institutions to do so. This initiative reinforces the Paris Agreement (United Nations 2015, December), promoting renewable energies around the world, which is a fundamental pillar in the science policy agendas of many countries. The selection of this institute also considered the increasing number of bibliometric studies related to institutions specialized on this topic (Sanderink 2020; Sanderink and Nasiritousi 2020).

The IER has a multicultural and a multiethnic composition as it is opened for international calls. It has hosted many foreign visitors on short stays and sabbaticals, and it has trained foreign students, mostly from Latin America. One important aspect to achieve promotion from being a center to becoming an institute is the human resources training, and the IER proved this skill by fostering a Master program on solar energy and solar design, which has evolved into a PhD program on energy engineering. More recently the Institute has also created undergraduate studies in renewable energies engineering within its premises. Because energy is a transdisciplinary subject the institute is multidisciplinary, mainly composed of physicists, chemists, and engineers. The staff has increased during these 36 years with a goal of including women and young researchers (see Supplementary Appendix 1, Table A1). Recently, it has also opened to social studies.

The IER has grown not only in researchers and students, but in buildings, laboratories and equipment. Through all this time the Institute experienced different organization schemes. In Figure 1 the blue timeline displays the moments of structural changes, while the orange timeline shows the leadership changes.

The laboratory had five research groups: photovoltaic systems; mass and energy transfer; applied thermodynamics; passive systems and construction materials and systems. This last group disappeared as such but the interest in bioclimatic architecture remained (CIE 2010). It is important to mention that the computing support was very scarce at the beginning and an incredible amount of work has been done since the turn of the century to fix that. The CIE took the usual organization scheme: departments, with different research groups (see Supplementary Appendix 1, Fig. A1). The departments were: Solar Materials, Energy Systems and Thermo-sciences. It also had a Teaching Coordination and included a Technological Transfer unit. The center was also a step forward to do research in other renewable energy sources, besides solar energy. It is important to highlight geothermal energy, which is a relevant source of energy in Mexico.

The CIE had three general directors. The first one (A) oversaw its creation, and the second one (B) started the process to become an Institute. The third one (C), the first woman in charge of the institution, coordinated the work during the months needed to finish the promotion process. In the transition from Center to Institute, which also implied a change of leadership, a big step was given. As a center, the CIE had a conventional hierarchical structure, based on departments. As an Institute, with its first director (D), the organization changed to a flexible network structure, based in projects self-organized by academics, without hierarchical relations among them, and with three main continuous improvement goals: research, teaching, and innovation (see Supplementary Appendix 1, Fig. A2). The motivations on the organizational changes were supported in the need to include new research problems, improving the institutional productivity with quality, interdisciplinarity, and without a substantial increase in the number of academics and in budget. Currently, one challenge is to understand and assess the effects of this new transversal organization.

It is an interesting example of academic growth in an isolated environment that has changed its organization rather drastically through a 34 year period. Although there are conclusions that might be considered local, the analysis of the production evolution of this Institute, and its correlation with the sequence of events it had been through, may help to assess the relevance that organizational changes might have on the development of a research group, affecting productivity, as well as other variables such as collaboration or the multidisciplinarity character of research.

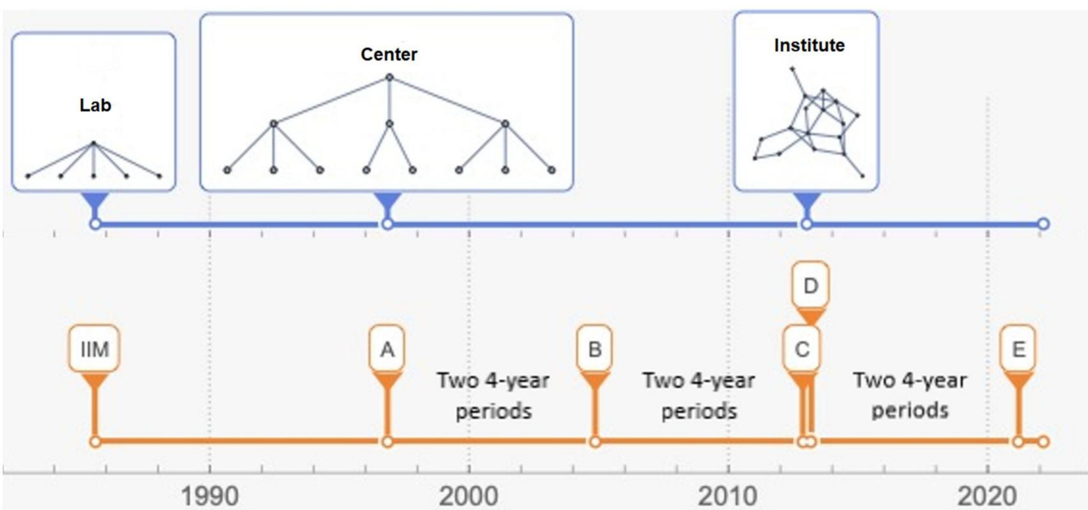

Figure 1. Structural timeline of the Renewable Energy Institute. The blue timeline marks the three main structural organizations as Laboratory (LES), Center (CIE) and Institute (IER). The orange timeline represents the leadership changes, the leaders of the first period were not directors but lab chefs, while being part of the Institute of Materials Research (IIM) and we do not specify them here. In the CIE period there were three directors (A, B, C) and two directors (D, E) in the final institute stage. Director C served only during a short transition appointment.

5. Materials and methods

5.1 Data source

Web of Science Core Collection (WoS), currently developed by Clarivate Analytics, was used as the data source, including the following information resources: Science Citation Index Expanded (SCIE); Social Science Citation Index (SSCI); Arts and Humanities Citation Index (AHCI); Conference Proceedings Citation Index–Science (CPCI-S); Conference Proceedings Citation Index–Social Science and Humanities (CPCI–SSH); Book Citation Index–Science (BKCI-S); Book Citation Index–Social Sciences and Humanities (BKCI-SSH); Emerging Sources Citation Index (ESCI). This database contains articles indexed under internationally accepted quality criteria covered by the most prestigious serial publications in all areas of knowledge (Anselmo, Rodrigues and Karpinski 2020). Datasets were available through the UNAM's digital library.

5.2 Search strategy, data retrieval and disambiguation process

The search strategy considered different queries to identify the name of the institution from its foundation as laboratory to 2020. Using the *Advanced Search* functionality at WoS, 24 queries were constructed (see Supplementary Appendix 2), targeting the address (AD), country (CU) and organization (OG) fields. The obtained records in each query were merged using the logical operator OR. Records were downloaded and processed year by year.

Author name disambiguation process was semi-automatically developed in an *ad hoc* database and using a registry of institutional researchers and collaborators provided by the Academic Secretary of IER. This registry was the result of a systematic work of data normalization carried out for the annual reports of the institution. New orthographic and spelling variants, spelling errors and duplication of authors' names identified in the most recent articles were directly corrected in the database, and a .ris file was exported to identify groups of collaborating authors (Research Teams).

5.3 Indicators

A battery of bibliometric indicators was considered to analyze six variables: productivity, collaboration, internationalization of collaboration, multidisciplinarity, research teams and research fronts. We assume that high values of these indicators, with a balanced distribution, can be associated with a positive institutional performance.

5.3.1 Productivity

The ability to systematically publish research results, in correspondence with the number of the researchers on staff, is always considered by research evaluation exercises (Pudovkin et al. 2012). The Annual average number of documents per researcher (**Doc/Res**) was the indicator selected to operationalize this variable, which is a size-independent measure that shows the efficiency of the institutional staff.

5.3.2 Collaboration

In this study, the average number of authors per document is used as a Collaboration Indicator (**C**). We use this indicator to estimate the size of research teams.

5.3.3 International collaboration

International co-authorship is an element that enhances the visibility of research beyond national borders, frequently analyzed in institutional evaluations (Bookstein, Moed and Yitzahki 2006). Here, we use the percentage of institutional articles with at least one international author (%**IC**) as indicator, which can reveal both the level of international linkage and the dependence on this linkage for the development of research.

5.3.4 Multidisciplinarity

The increasingly complex nature of research problems demands the integration of knowledge from various scientific disciplines to their solution (Van den Besselaar and Heimeriks, 2001). Renewable energy as a knowledge domain is a good example. Here, it was important to correlate the multidisciplinary nature of the field with the level of specialization of papers generated by the institute, as a performative dimension. There are many diversity measures available, most of them based on the Web of Science classification scheme. Here, we use a Thematic Dispersion Index (**TDI**) which has been applied to study the Artificial Intelligence evolution since its emergence (Arencibia-Jorge, Vega-Almeida and Carrillo-Calvet 2021). It is obtained from the formula $\mathrm{TDI} = \sqrt{(\mathrm{TCp} * \mathrm{TCc})}$, where TCp, the thematic concentration of production, is the minimum number of WoS subject categories covering 80% of cited documents, and TCc, the thematic concentration of citation, is the minimum number of WoS subject categories covering 80% of citing documents. Thus, this indicator considers the most important thematic categories of the WoS journal classification scheme in which the institution generates knowledge, as well as those where it had the greatest impact.

5.3.5 Research teams and research fronts

Also, in this study we are interested in analyzing the variation of the number of Research Teams and Research Fronts during the 34 years of the institution's evolution. For this we define two indicators by calculating the number of communities in two different networks.

The network used to identify research groups is a network of authors linked by co-authorship; the weight of each link is proportional to the number of documents in which the authors share authorship. Clusters in this network are interpreted as a community of authors that collaborate in some theme or subject. Thus, we define the indicator 'Research Groups (**RG**)' as the number of clusters in this network. The identification of research groups by detecting communities in an author's network is an idea previously applied by other authors (Calero et al. 2006; Perianes-Rodríguez, Olmeda-Gómez and Moya-Anegón 2010; Zhao et al. 2019).

The determination of communities or clusters is a classic problem in network theory that has been approached in a wide variety of ways (Fortunato and Hric, 2016). Among community detection methods in networks, optimization algorithms have received the greatest attention in the literature. To identify clusters in the authors network, we use an optimization technique developed and implemented in a software system (VOSviewer v1.6.15) by researchers of the Center for Science and Technology Studies at the University of Leiden (Van Eck and Waltman 2010). We determined the number of clusters on each of the networks using the VOSviewer default parameters of attraction (2), repulsion (−1) and resolution (1.00). The VOSviewer's algorithm optimizes a clustering quality measure based on the most popular modularity algorithm introduced by Newman (2004). Further details on the VOSviewer's clustering algorithm can be found in Waltman and Van Eck (2013).

Similarly, to identify the number of research fronts, we consider a network of documents that are linked, when their bibliographies have a non-empty intersection. The weight of the links is the number of elements in the intersection set of these two bibliographies. This relationship between two documents is known as 'bibliographic coupling' (Kessler 1963). In this network of documents we look for bibliographic coupling clusters, and interpret each of them as a research front. Again, the clusters are obtained and displayed using VOSviewer, with default parameters. The indicator that estimates the number of research fronts (counting the number of bibliographic coupling clusters) is then denoted: **Bibliographic Coupling Groups** of documents (**BCg**).

5.4 Multidimensional performance profiles evolution with artificial intelligence

In this study we are multidimensionally characterizing the scientific performance profile of the IER using the six indicators described above. These variables were chosen because they encompass several aspects commonly prioritized in research policies. They also have the advantage of not necessarily increasing as the number of researchers grows, avoiding the effect of the number of academics working in different periods. Our goal was to analyze the profile evolution using yearly data spanning from 1986 to 2020. Since multidimensional data analysis is a complex task for the human mind, we resort here to the use of two dimensionality reduction techniques. Firstly, we use Principal Component Analysis (PCA), a multivariate data technique (Paul, Suman and Sultan 2013) to identify periods of the profile evolution qualitatively differentiated. Secondly, we apply an artificial neural network technique to picture the details of the multidimensional profile evolution.

PCA is aimed to reduce dimensionality of datasets; it can be used to visualize multivariate data by projecting the n-dimensional dataset into two or three dimensional spaces which explain most of the variability observed in the original data, minimizing in this way information loss. The plane on which to project the data is determined by new axes chosen so that the first axis (first principal component, PC1) is in the direction of maximal variability in the original data; then, a second perpendicular axis is chosen so that it explains the maximal variance, not explained by PC1.This process can be repeated to obtain a third axis, and so on, till n new perpendicular axes are obtained (Krzanowski 2000). If the original variables differ in such a way that data can be grouped accordingly, successively maximizing variability will allow us to visualize these groups. Each new variable is a linear combination of all original ones. How many PCs should be used depends on the amount of variability explained by them (Ringnér 2008).

Posing mathematically the requirements of maximization of variance and orthogonality, reduces to finding eigenvectors and eigenvalues of the covariance matrix of the original data. When original variables have different measurement scales, each variable is standardized by subtracting its mean value and dividing by its standard deviation. In this case eigenvectors and eigenvalues are obtained from the resulting correlation matrix. Matlab was used to perform PCA.

The artificial intelligence method, used to analyze and visually represent the multidimensional performance profile evolution, is powered here by the self-organizing map (SOM) neural network (Kohonen 2013). This network processes data using a non-supervised training process and produces knowledge maps over a 2-D hexagonal grid, picturing performance dynamics. In this grid, each hexagon is associated with an artificial neuron of the network. The neural network algorithm automatically identifies similar data (in our case data points are annual performance profiles) and produces a no linear projection into close locations (hexagons) of the 2D neural grid.

From a mathematical point of view, the set of the IER'S annual performance profiles (1985–20), characterized by six performance indicators, constitute a time series of multivariate data that can be pictured as a trajectory evolving in a six-dimensional Euclidean space. The main task performed by the SOM neural network technique that we are applying in this article, is to represent in a 2D map this performance profile trajectory by means of a nonlinear projection to a plane in which the profile evolution is easily interpretable.

The neural network also provides information about the time intervals in which the institution had similar profiles, allowing us to appreciate the transition years, in which a significant profile change occurs. These features facilitate the profile evolution analysis, otherwise we would be forced to carry out a difficult analysis in a dashboard of the six temporal courses that exhibit the evolution of each individual variable, that forms part of the multidimensional performance profile.

The neural network processing was executed in LabSOM, a software program created at the non Linear Dynamics Laboratory, Faculty of Sciences, UNAM (Jiménez-Andrade, Villaseñor-García and Carrillo-Calvet 2019), with the basic version of the SOM's training algorithm (Kohonen 2013). Temporal sequences were pre-processed using a 5-year exponential centered moving average, to diminish data volatility. Afterwards indicators were scaled dividing by the maximum value (Milligan and Cooper 1988) to get rid of scale disparity. Curve trajectories are automatically drawn in the 2D maps by the software with spline interpolation. The hyperparameters used were: number of iterations: 3500, initial value of sigma: 8.25 (parameter of the gaussian neighborhood function), and the initial value of alpha = 0.3 (the learning factor).

6. Results

6.1 Time history of the case of study

From 1985 (foundational year) to 2020 an amount of 2218 documents developed by IER's authors were identified in WoS. In general, with some variations, a growing trend of scientific production was observed (Figure 2). However, each institutional stage shows its own characteristics.

Initially, the annual number of documents was in growth until 2001, when a stable behavior over the 80 annual documents started. Then, a new growing trend was observed up to the last 3 years, when the scientific production was stable between 120 and 140 published documents (Figure 2). It was clear that research at the laboratory stage (LES) was constantly growing, leading to the creation of the center (CIE). During this new stage, the research was consolidated and began to show stable patterns. Later on, from the new change in the structure that happened with the creation of the institute (IER), the growing trend of scientific production was recovered, reaching a peak in 2018.

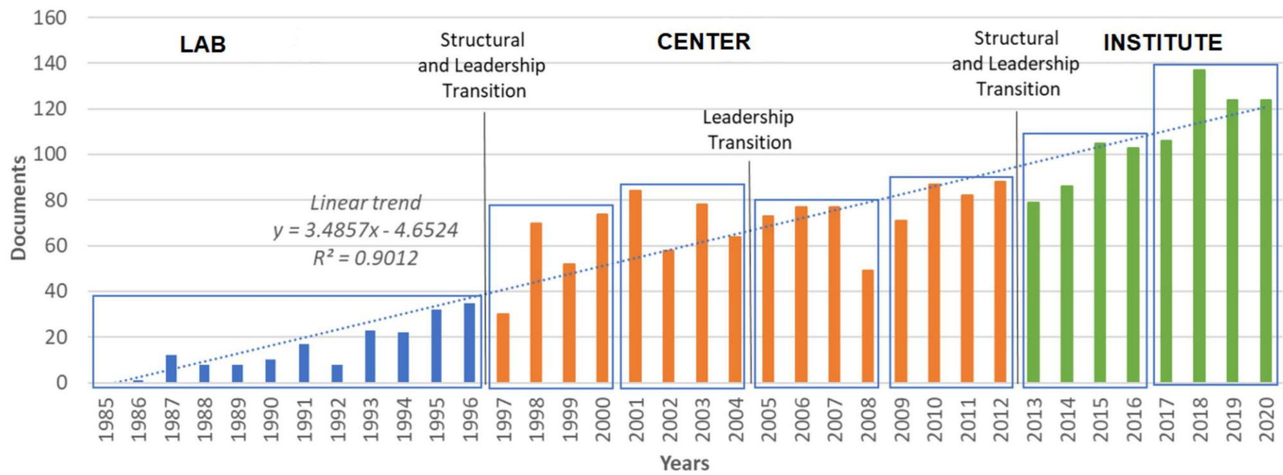

Figure 2. Scientific output of the Renewable Energy Institute, 1985–20. From 1985 to 1996 the laboratory was part of the of the Institute of Materials Research (IIM) and had several Laboratory chiefs that we are not marking off in the figure.

6.2 Multidimensional performance profile analysis

As previously mentioned, six indicators reflecting Productivity (Doc/Res), Collaboration (C), Internationalization (%IC), Research teams (RG), Multidisciplinarity (TDI) and Research Fronts (BCg) were selected to characterize the institution's multidimensional profiles (see Supplementary Appendix 3).

6.2.1 Principal component analysis

As a first multivariate approach, a principal component analysis (PCA) was performed to analyze research profiles, during the evolution from Laboratory to Center, and then to Institute. The first two principal components obtained are:

$$PC1 = 0.415 * Doc/Res + 0.389 * C + 0.319 * \%IC + 0.440 * RG + 0.414 * TDI + 0.458 * BCg$$
$$PC2 = 0.115 * Doc/Res - 0.549 * C + 0.750 * \%IC - 0.297 * RG + 0.146 * TDI - 0.043 * BCg$$

They explain 74% and 12% of data total variability, indicating that the two-dimensional plot in Figure 3 loses little information when original data are projected using these two components as axes.

In this Figure 3 we clearly observe three clusters of performance profiles, which interestingly correspond to three stages of the institution: LES (second and third quadrant), CIE (first quadrant) and IER (fourth quadrant). The year 1986 may be considered as an outlier. This is because only one article was published this year, therefore we will exclude it from the following neural network analysis.

The two exceptions of years apparently misclassified (first year of CIE in LES's cluster and the last year of CIE in IER's cluster) could be related with the time delay for structural changes to take effect. However, it could also be the result of a projection effect, which must be further confirmed by neural network analysis.

The spread of the clusters gives us information about profile development. For example, the clear separation between the initial and last years of IER, indicates the changes of research profiles during those last years. Contrastingly, the relative compactness of CIE's cluster reflects lesser performance changes during that stage. Regarding the laboratory stage it must be considered that, during the first 7 years, the number

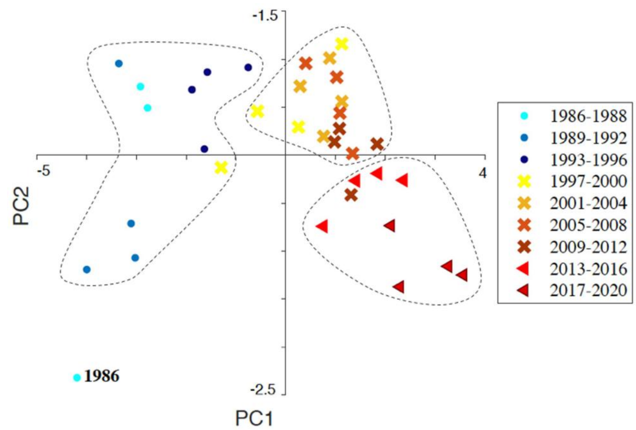

Figure 3. First two principal components plot. Circles correspond to the laboratory stage (LES), cross correspond to the center stage (CIE), triangles correspond to the institute stage (IER). Each point represents 1 year.

of publications fluctuated between 1 and 17 (see Supplementary Appendix 2), thus the high-profile variability, reflected in Figure 3 as a rather broad cluster.

Loadings (i.e. weights assigned to each original variable) of the first component are positive and quite similar. Therefore, negative values in the PC1 axis correspond to indicator values under their mean along the years. Similarly, values above the average are on the positive side of the abscissa. Figure 3 shows that the six variables increased from 1986 to 2020. The Laboratory stage measurements are below the average. They increased to close to average and positive values during the CIE period and continue to increase in the IER period.

In the second component (PC2 axis) loadings for Doc/Res, %IC and TDI are positive, while loadings for C, RG and BCg are negative. Consequently, we see in Figure 3 that the main difference between the center stage and the institute stage is due to an increment in local collaboration (C and RG) and in the number of research fronts (BCg).

6.2.2 Neural network analysis

A self-organizing neural network-based visualization technique was used to obtain a detailed description of the institution's scientometric performance dynamics. This method has the advantage over other analysis methods, that provides detailed results, that are easily interpretable, and allow us to picture in just one figure, the qualitative features of the multidimensional performance profile evolution of the institution during the 34 years of the period 1987–20.

With the neural net we clustered the performance profiles corresponding to the 34 years of the period 1987–20 according to similarity, and we show the clusters' map in Figure 4a. Accordingly, each cluster represents a characteristic performance profile which is shared by all the years in it contained.

In Figure 4a we have also drawn a path of black segments, indicating the flow of time from 1987 to 2020. The structural transitions: LES–CIE, CIE–IER are indicated as red segments in the profiles' evolutionary path. The various colors of the year numbers identify leadership changes (different directors of the institution). Thus, the cluster structure and the evolutionary path obtained with this technique allowed us to correlate profile changes with both structural, and 4-years leadership changes.

Figure 4b shows six heat maps corresponding to the indicators used to multidimensional characterize the institution's bibliometric profile. We can trace profile changes using the graded chromatic bar under these maps. Green indicates lowest values and red highest values.

The earliest stage (profile of C1 cluster) is characterized by the lowest values of the six indicators (green color in the map). The next profile (C2) characterizes the last 3 years of the LES with a small improvement in all indicators (slightly higher growth in productivity, multidisciplinarity and internationalization). Interestingly, the profile of the first year of the CIE also belongs to C2, indicating some kind of profile inertia: it took 1 year for the newborn center to start developing its new profile, through the emergence of the transition profile of cluster C3. This cluster represents a transition profile occurring between the laboratory stage and the emerging research center structure. Notice that the neural network coincides with PCA, in that 1997's CIE's profile is similar to those of the last 3 years of laboratory stage (1994–6), confluently establishing that the first structural change correlates with performance from the second year on.

Cluster C4 represents the mature profile acquired through the metamorphosis LES–CIE. In this cluster the predominance of orange or red colors, in most of the indicator maps, is a clear improvement sign. New research groups and research fronts were created, but productivity and multidisciplinarity were the most benefited profile dimensions. Observe that the CIE's profile evolution reached its ultimate form during 2004, the last year of the 8-years leadership of the first center director (characterized by a new profile). Actually, 2004's profile was relatively preserved during the following 8-years period of the second CIE director, meaning that the institution reached a stable profile without forces that could promote more profile changes. This C5 profile reached the highest values of internationalization (>30%) for the 34 years of analysis, and it prevailed until in 2013, when the second structural transformation CIE–IER happened. In this case the new structure manifested itself immediately, adopting the new profile of cluster C6.

C6 marks a qualitative change in the profile. The path jump from C5 to C6, coincides with the transition from center to institute and a new leadership with a director who transformed the classical hierarchical-departmental structure of the institute into a flexible and horizontal network structure. It was expected that this new institutional organization propelled a positive effect on performance. In fact, we see in the transition from cluster C5 to cluster C6 a manifest increment in Collaboration (C), Research teams (RG) and Research Fronts (BCg), and productivity (Doc/Res). It is very clear that, during the last period of the study, cluster C7, the institution exhibited by far, the best of all the profiles sequence (it is red in all indicators, except international collaboration).

A general conclusion that we can derive from Figure 4 is that, although there was a certain degree of variability in some indicator values, the institution's evolutionary path showed a considerable performance profile improvement.

6.2.3 Radar charts

Once the neural net identified that the institution transitioned through seven performance profiles (clusters), during the 34 years period, we can now use radar charts to obtain a visual representation of each profile (see Figure 5). With this technique

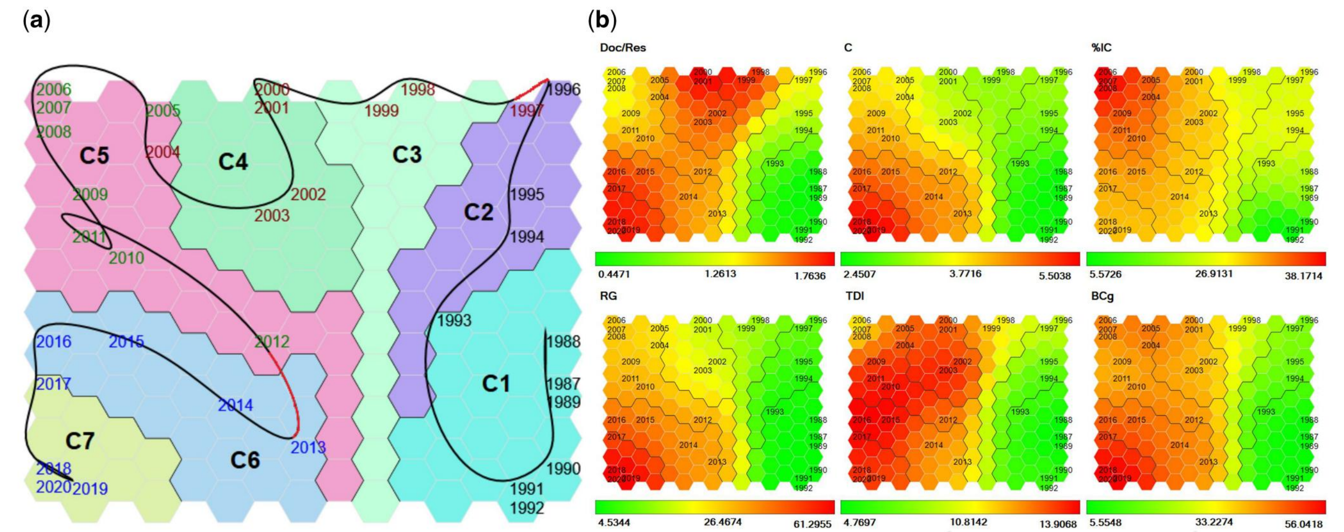

Figure 4. Graphic representation of bibliometric profile evolution from 1987 to 2020. (a) Clustering Map and performance trajectory. A cubic spline interpolation is connecting profiles of each year. (b) Indicators maps: Productivity (Doc/Res); Collaboration (C); Internationalization (%IC); Research teams (RG); Multidisciplinarity (TDI) and Research Fronts (BCg).

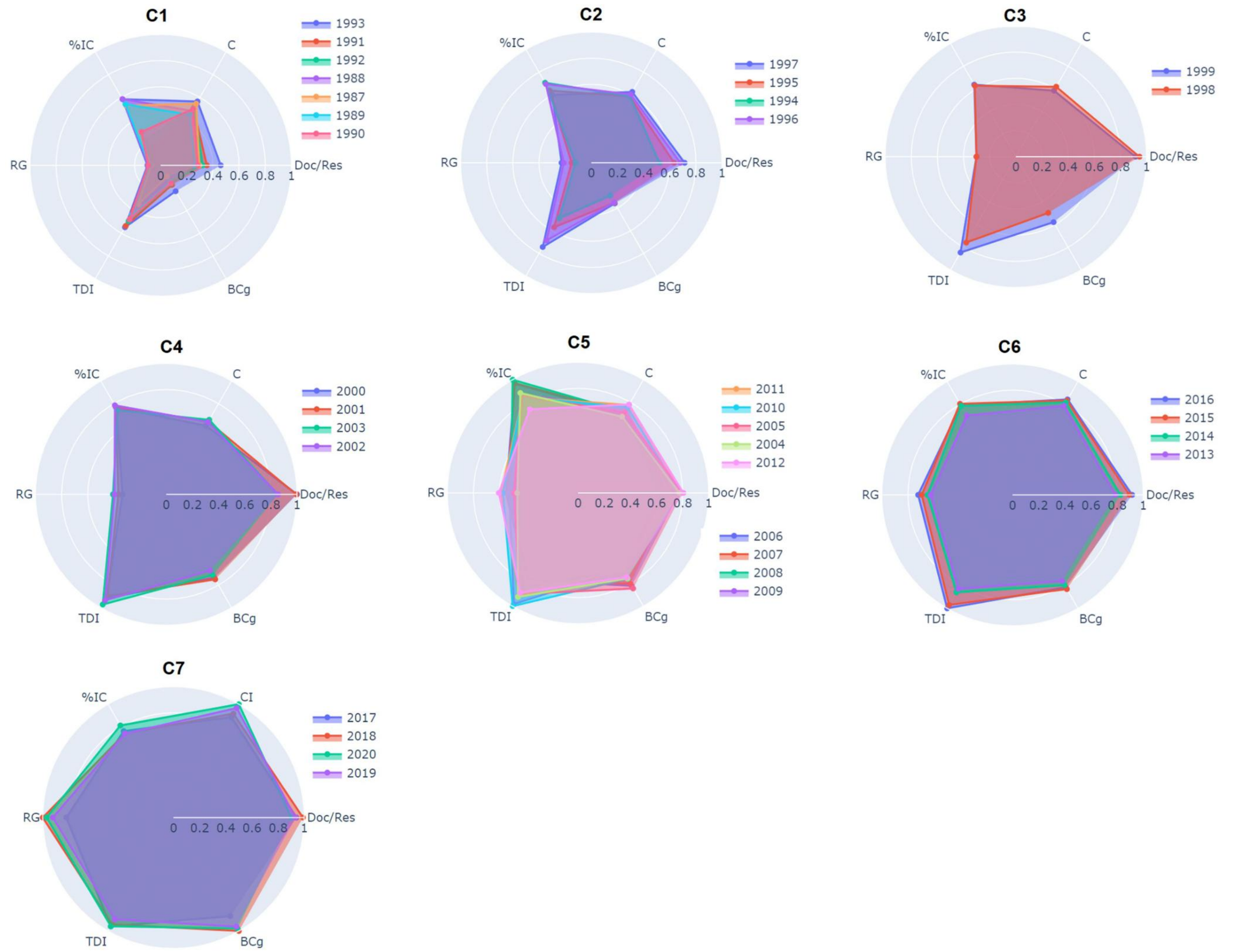

Figure 5. Geometric representation of the multidimensional performance profile. Each profile is represented by a hexagone and we can observe that: (1) Hexagons areas grow progressively from cluster C1 to C7; (2) with the exception of cluster C1 there is a considerable degree of shape similarity among the hexagons in each cluster.

each profile is characterized with a geometrical shape (an irregular hexagon). These charts also serve as a validation of the correctness of the cluster organization because it is easy for the human mind to compare geometric figures and therefore appreciate the profile similarity among the elements of each cluster, as well as the degree of improvement achieved in each step of the seven profiles sequence, due to area growth. The comparison of these 'geometrical profiles' allows us to appreciate both quantitative and qualitative changes.

The transformations experimented by the geometric figures provide information about the nature of the profile change: if the figure only grows without changing its shape, there is a quantitative change, but if shape changes, we could consider it a qualitative change.

In each radar chart we clearly see the similarity among all the performance profiles which belong to the same cluster. In the sequence of radars, we can also appreciate the profile's qualitative evolution.

7. Discussion and conclusions

We have analyzed the scientific production evolution of the research group of this institution, observing and comparing its performance with the series of structural, organizational and leadership changes it has been through during 34 years. Using six bibliometric indicators, data allowed us to conclude that these changes correlate with certain changes in scientific performance patterns, related to productivity, multidisciplinarity, collaboration, networks development, and the diversification of research topics. Analyzing these data, various development stages of the institution were identified, and its correlation with structural, organizational or leadership changes were noticed.

It can be considered that the first stage of development of the founder group started with the foundation of the Solar Energy Laboratory, which in the overall perspective was characterized by low values of almost all considered scientometric performance indicators. This might be interpreted as an experimental stage, during which the young researchers group created capacities and conditions to jump to a higher level of development.

We consider that the second stage started with the transformation of the laboratory into a Research Center. As it could be expected, during the first directorship (A, December 1996–November 2004), the CIE thematically diversified itself from the original focus on solar energy, and incremented its productivity: new research lines related with energy were developed during this stage, and postgraduate programs on renewable energy were established, in a social context characterized by a growing awareness of the impact on the environment, of various energy sources. Later, under the second directorship period of the center (B, December 2004–November 2012), main advances were observed in the size of research teams and international collaboration.

Conceptualizing this process in the ‘life cycles’ theoretical framework hypothesized by Braam and van den Besselaar (2010), these two stages as laboratory (LES) and center (CIE) could be considered as a first phase of the institution’s life cycle, in which, agreeing with these authors theory, ‘the group will formulate and/or internalize its mission and it will find a strategic pattern of activities in domains that are suitable for realizing its mission’. After two 8-years directorship periods, this mission was fulfilled, and the research group was ready to initiate the second phase of its life cycle.

A second phase of the life cycle commenced when the institution achieved the status of a research institute. This stage is still in course at the present time. Its characteristics agree with those of the phase of ‘robust equilibrium’ characterized by Braam et al., in which the research group was capable of functioning in a stable way and showed relatively better performance, with respect to the previous life cycle, in almost all bibliometric indicators. After this consolidation phase of the institution and 34 years of growing activity and productivity of the research group, it could be expected a downturn in activity (saturation growth) to follow a S-shaped growth curve (de Solla Price 1963). Also according to the life cycle pattern of evolutionary development of Braam et al., it might be expected that research activity follows a third phase of relative decline, triggered by internal (e.g. aging) or external conditions changes (budget, salaries, competition). However this may not be the case, if stimulating factors emerge. For instance, data suggest that organizational change operating during the last directorship period of the institute fostered collaboration and the creation of more multidisciplinary research groups.

It was during this period that the institute changed from a vertical structure to a network one, with the intention to promote collaboration. Correlating this change with the indicators that characterize the performance profile, we see a clear increment in average number of authors per document and the number of research groups, but no relevant change in the international collaboration.

Our first approximation to map the evolution of the multidimensional performance profiles, was to linearly project the institution’s multidimensional profiles to a 2D plane using a PCA method. This technique allowed us to visually identify three clusters that correspond to the different ways in which the research group was institutionalized: Laboratory, Research Center and Research Institute.

Complementary, the SOM neural network revealed a finer structure within the three PCA clusters, identifying seven stages of the institution’s development well correlated to leadership and structural transitions. In each of these stages the institution had different scientometric performance profiles that were represented in a map of seven clusters. This map results from carrying out a nonlinear projection from the multidimensional data space (6D) to a 2D plane. The heat maps served to characterize the seven corresponding performance profiles, and the radar charts to geometrically picture its qualitative differences. In these radars we clearly see the profile similitude of the members of each cluster. Finally, an evolutionary path was depicted on the cluster map, exhibiting the sequence of performance profiles transitions through the whole period of analysis (Figure 4). This figure was obtained with the neural network and has the advantage that it synthesizes a lot of knowledge about the multidimensional scientometric performance profile evolution that otherwise would have to be deducted from several plots.

The National Autonomous University of Mexico has a research development policy according to it, in a first stage, researchers may get support to group themselves in a laboratory or in a department. In a second stage of development, once they have acquired a certain mass and expertise, they may create a research center. The final and highest level in this development path is reached when the group consolidates its expertise, so the center transforms into a research institute. In the present case the developmental sequence implied thematically transitioning from a Solar Energy Laboratory, to a more general Center of Energy Research that ended as a more specialized Institute of Renewable Energy. This Institute is just one example of multiple entities that today form a constellation of research institutes operating within the university.

The combination of multiple bibliometric measures, the analysis by periods and transitions, and the use of artificial neural networks, have proved to be convenient for visualizing the evolution of the IER’s scientific performance.

From a methodological point of view, it would be desirable to include other variables in the analysis like: teaching activities, graduate students and postdocs, the number of projects executed, the funding for each project, and even variables related to the knowledge domain of our case study (renewable energy), such as evidence of knowledge transfer, technical advice, and community exchange. To consider these kinds of elements is a pending issue in many scientometric studies (Abramo 2018), and undoubtedly constitutes a great challenge to undertake in further research, considering that social impact is a priority element in the current national science, technology, and innovation policy in Mexico (Vargas Meriño and Zúñiga-Rodríguez 2021). In spite of these limitations, the methodological approach presented in this study has been useful to observe patterns in this research group evolution and its correlation with structural, organizational and leadership changes. This type of analysis provides insights on research groups development and might be useful to analyze research groups dynamics of other institutions. In fact, this study has provided insights and data that have been useful to create a dynamical model (García-Rodríguez et al. 2023).

Supplementary data

Supplementary data are available at *Research Evaluation Journal* online.

Acknowledgments

This research is a result of the program ‘Scientometrics, Complexity, and Science of Science’, at the Complexity Science Center of the National Autonomous University of Mexico (UNAM). We want to thank Dr Ricardo Ruiz Sánchez for his support during the data disambiguation processes.

Funding

This work was supported by the National Council for Science and Technology [CONACYT 283279 to R.A.B.] and the National Autonomous University of Mexico [PAPIIT-IG200121 to R.A.B.].

Conflict of interest statement

The authors have no conflict of interests related to this publication.

Data availability

Data available at https://doi.org/10.6084/m9.figshare.17131808.v1.

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