Exploring indicators for monitoring sociotechnical system transitions through portfolio networks

Penna, C.C.R.; Goyeneche, Oscar Yandy Romero; Matti, Cristian

DOI
10.1093/scipol/scad015

Publication date
2023

Document Version
Final published version

Published in
Science and Public Policy

Citation (APA)
Penna, C. C. R., Goyeneche, O. Y. R., & Matti, C. (2023). Exploring indicators for monitoring sociotechnical system transitions through portfolio networks. *Science and Public Policy*, *50*(4), 719-741. https://doi.org/10.1093/scipol/scad015

Science and Public Policy, 2023, **00**, 1–23
DOI: https://doi.org/10.1093/scipol/scad015
Article

OXFORD

Exploring indicators for monitoring sociotechnical system transitions through portfolio networks

Caetano C.R. Penna[1,*], Oscar Yandy Romero Goyeneche[2,*] and Cristian Matti[3]

[1]Department of Values, Technology and Innovation, Delft University of Technology, Building 31, Jaffalaan 5, Delft 2628 BX, The Netherlands, [2]Centre for Global Challenges, Utrecht University, Janskerkhof 2-3a, Utrecht 3512 BK, The Netherlands and [3]EIT Climate-KIC 7, Rue Guimard, Brussels 1040, Belgium

*Corresponding author. E-mail: c.c.r.penna@tudelft.nl; o.y.romerogoyeneche@uu.nl

Abstract

In this paper, we propose a method for tracking the evolution of sociotechnical niches supported by sustainability-focused project portfolios. Based on social network analysis (SNA), this method can be used to evaluate and monitor funding initiatives that seek to advance sociotechnical transitions. It is an important area of study because there is currently a lack of tools for measuring the success of efforts to promote transformative innovation. Conceptually, our approach is based on existing sociotechnical transition research and offers insights into how project networks evolve. We applied this method to a specific portfolio of food system projects that the European Institute for Innovation and Technology Climate-KIC supported. Our results show that SNA can provide a proper visual representation of the infrastructure that supports programme-based investment and can help us understand how specific network structures can support niche development and protect it from external pressures.

Key words: sociotechnical transitions; transformative innovation policy; ST&I indicator frameworks; social network analysis; portfolios.

1. Introduction

In this paper, we explore the use of alternative indicators of science, technology, and innovation (ST&I) to monitor public funding programmes (project portfolios) that aim to support transformative innovation. ST&I indicators serve different yet interrelated purposes (Table 1): to gain insights into the nature of the ST&I process, to inform the formulation and execution of corporate strategies, and to provide evidence for public policies (their design, implementation, monitoring, and evaluation). Such ambitions led to the development of a series of innovation indicators, which guide and standardise data collection and their application, with the Organisation for Economic Co-operation and Development (OECD) indicator frameworks—such as the Frascati (OECD 2015 [1963]) or Oslo (OECD and Eurostat 2019 [1992]) manuals—providing the basis for measuring scientific, technological, and innovative activities. Although widely adopted, new types of indicators and frameworks are needed for assessing innovation (development, policy, and strategy) concerning transformational objectives.

The evolution of ST&I indicators reflected and influenced the evolution of innovation policies and innovation process models (Viotti 2003). Table 2 provides an overview of three 'frames' of innovation policy (Schot and Steinmueller 2018): the period when each emerged; their focuses, rationales, and strategy implications; underlying heuristic models of the ST&I process; and, finally, the indicator frameworks developed by the OECD that reflect these models. On a fundamental level, ST&I indicator frameworks have been influenced by two objectives: supporting R&D activities and developing the innovation system. However, a third emerging frame of innovation policy—transformative innovation policy—still lacks an indicator framework for monitoring its objectives. Although conceptually important, this gap represents a barrier to implementing effective policy programmes that seek to support innovative niches with the potential to transform sociotechnical systems.

Therefore, there is a need for indicator frameworks that allow for monitoring, learning, and improvement of transformative innovation programmes, for example, investment portfolios of niche projects. This need is scantily covered by existing ST&I indicator frameworks that do not capture the *directional* and *transformational* aspects of transition processes, nor do they account for the complex nature of sociotechnical systems. As Sovacool et al. (2020: 13) suggest: 'future research should explore how different [transformative innovation policy] experiments evolve in distinctive contexts and socio-technical systems … and further advance in the development of tools and indicators that can guide this process'. More specifically, there is a growing need for indicator frameworks that address monitoring, formative evaluation, and learning processes for research and innovation (R&I) agencies that manage programme-based R&I investments to foster transitions through a portfolio of projects (Alvial-Palavicino et al. 2021; Hill 2022; OECD 2022; UNDP 2022).

To address this gap, this paper proposes a methodology,[1] based on network analysis, for (formative/mid-term) monitoring the evolution of sustainability-oriented project portfolios as an indicator of sociotechnical transition processes. By

Table 1. Why do we need ST&I indicators?

Scientific reason: evidence on the ST&I process	Business reason: evidence for corporate strategies	Political reason: evidence for public policies
(1) Relationship between basic research, applied research, experimental development, and innovation (2) Determinant factors of innovation (also diffusion/absorption) (3) Relationship between technical change and economic growth (4) Characteristics of innovative companies (5) Impacts or risks of technological advances in social welfare and the environment	(1) Monitoring trends and identifying technological opportunities (2) Monitoring the process of technical change of competitors, suppliers, and buyers ('benchmarking') (3) Support investment decisions	(1) Monitoring the technological capacity of companies/sectors/regions/countries (2) Identification of limitations and potentials of the ST&I system (3) Inform the policy debate (4) Formulation, monitoring, evaluation, and improvement of policy programmes and investment portfolios, including accountability
Additionally: assessing innovation (development, policy, and strategy) concerning transformational goals		

Source: based on Viotti (2003).

Table 2. Three frames of innovation policy, associated models of the ST&I process, and OECD indicator frameworks.

Dominant period	Frame 1: research and development 1960s–19780s	Frame 2: innovation systems 1980s–2000s	Frame 3: transformative innovation Emerging 2010s–2020s
Focus	Market incentives for generating scientific knowledge	Commercialisation of knowledge and gap between discovery and application	Mobilising the innovation potential to address societal challenges
Rationale	Fixing market failures (associated with positive externalities such as public goods)	Fixing systemic failures (associated with network externalities)	Fixing transformational failures (associated with negative externalities)
Strategy	Knowledge generation: boosting public investments in R&D	Knowledge utilisation: boosting learning and absorptive capacity, propensity to innovate, and entrepreneurship	Knowledge and innovation directionality: boosting purpose to address societal challenges
Model(s)	Linear model of innovation	Systems of innovation (macro) and chain-linked model (micro)	Multi-Level Perspective and strategic niche management
Indicator framework(s)	Frascati, Technology Balance of Payments	Canberra (Human Resources), Oslo	SDG global indicator framework

Source: Based on Viotti (2003); Schot and Steinmueller (2018).

applying this framework to a portfolio of innovation projects funded by public agencies, we can better understand how such investments contribute to and facilitate the development of sociotechnical niches. In so doing, the paper seeks to answer two research questions:

(1) How can we monitor and evaluate transformative processes of niche development supported by policy programmes and investments?
(2) What programme/investment mechanisms foster systemic transformations?

To answer these questions, we draw on existing research on sociotechnical transitions to develop a set of propositions about how project networks evolve as a transition process unfolds. We then test these propositions by constructing networks based on the European Institute for Innovation and Technology (EIT) Climate-KIC programme-based portfolio of food system projects. Through this approach, we aim to better understand where we are in the systemic transformation process from a niche development perspective and thus provide insights that can be used to inform funding agencies' programmes and policy practices in this area.

This paper is organised into five other sections. In Section 2, we consider the theory of sociotechnical transitions to outline the roles programme-based investment portfolios can play in generating 'transformative outcomes' (TOs; Ghosh et al. 2021) to advance such a process. This conceptualisation is the basis for our proposal of an indicator framework for sociotechnical transformations, for which, in Section 3, we discuss methodological and conceptual choices, drawing also on complex system theory. Section 4 describes the methodology and data (EIT Climate-KIC food system project portfolio) used to test our propositions through a portfolio network analysis. In Section 5, we present and discuss our results. Section 6 concludes, highlighting limitations of the analysis and areas for future research.

2. Sociotechnical transitions, TOs, and programme-based investment portfolios

Sociotechnical transitions to sustainability are transformations in sociotechnical *systems*: the configurations of technical elements (e.g. technologies and infrastructures, among others) and socio-institutional elements (actor networks, laws, and regulations, among others) that all together fulfil societal functions such as the provision of energy, food, mobility, health care, or housing (Geels 2004). A sociotechnical transition is, therefore, a process of changing or transforming one system configuration to another: for instance, the transition from horse-driven carriages to internal-combustion engine automobiles (Geels 2005) or the ongoing decarbonisation transition in the energy system (McDowall 2014).

Systemic sociotechnical changes are complex non-linear phenomena with multiple causal factors, feedback loops, and spatial and temporal dynamics. A helpful heuristic framework to analyse such a complex process is the *multi-level perspective* (MLP) (Geels 2002), which deconstructs the sociotechnical transition process into three levels: the niche, the regime, and the landscape. We briefly explain each of the levels (drawing on the synthesis by Alvial-Palavicino et al. 2021) to then concentrate on niche processes, which is the focus of this paper:

(1) At the *landscape* level, occur macro processes and trends that actors cannot substantively or directly influence and therefore change slowly—for example, climate change, cultural transformations, macroeconomic cycles, or geopolitical developments. Landscape processes may exert pressure on or create opportunities for the other two levels.
(2) The *sociotechnical regime* comprises the mainstream institutions of a sociotechnical system: relatively stable rules and norms that guide action by actors such as established firms, consumers, or regulators. The use of dominant technologies is facilitated by those institutions so that innovation may occur but tends to follow incremental trajectories. A sociotechnical transition is thus the process of transforming a regime by means of the emergence and diffusion of radical innovations.
(3) Sociotechnical *niches* are protected spaces where radical innovations, new institutions, and new behaviours emerge. Detached from the influence of regime institutions and actors, a niche is a locus for experimentation and learning.

Considering these three analytical levels, how does the MLP explain the sociotechnical transition process? The first aspect to consider is (complex) system theory (Geels 2010): changes happen due to multidimensional factors (cultural, economic, political, technological, social, scientific, and ecological) that occur across levels and at different timings, creating feedback mechanisms and cumulative processes. Due to this complexity, different transition 'pathways' were identified with the aid of the MLP (Geels and Schot 2007). However, in all different pathways, niches for radical innovations—their formation, building, and consolidation—are essential for the success of a transition.

Based on the MLP's stylisation of sociotechnical transition processes, Ghosh et al. (2021) identify three core transformative processes in sociotechnical transitions: (1) *building and nurturing niches*, (2) *expanding and mainstreaming niches*, and (3) *opening up and unlocking the incumbent regime*. Associated with each process are distinctive capacity- and capability-related 'TOs'. We present those associated with niches ((1) and (2)) and discuss them concerning a programme-based investment portfolio (understood as an instrument for inducing niche-building processes that we will present in detail in Section 3).

(1) *Building and nurturing niches* offer protected spaces (physical and institutional) for innovative practices (niches) to emerge. The process entails the creation of new capacities and capabilities, which are TOs of this process: *shielding* niches from regime pressures and competition; *learning* about the niches, so that niche actors may improve them and change their own perceptions about potential uses and associated opportunities; *aligning expectations* in order to promote convergence of perceptions and interests; and establishing networks (*networking*) as places for the exchange of actor experiences (that in turn can contribute to learning, shielding, and alignment of expectations). In the scope of a R&I programme addressing transformative change, shielding is granted not only through dedicated funding (financial resources) but also (and notably) through soft measures that allow for network formation around shared goals and visions to promote learning and alignment of expectations. In this sense, a programme-based investment portfolio creates the seeds of niche formation through project funding and soft measures.
(2) *Expanding and mainstreaming niches*: a sociotechnical transition requires a second process, which is expanding niches and stabilising their design standards and rules until they are normalised and mainstreamed (consolidation). Expansion of niches can happen through the creation and accumulation of specific capacities/capabilities, resulting in other TOs: vertical growth or *upscaling*, that is, a given niche increases in size in its original geographical location; horizontal growth or *replicating*, when a niche is emulated in a different geographical location; *circulating* resources and practices, for instance, knowledge about the niche flowing to other geographies or rules being adopted in other niches; and *institutionalising*, when the norms and rules under which the niche operates become stable, resulting in a dominant configuration among several niches (that were upscaled, circulated, and replicated), and the niche is then able to compete with the incumbent regime on equal footing. A programme-based investment portfolio contributes to upscaling and replication by increasing the number of funded projects and sharing (circulating) lessons about the experience with successful and failed projects that may strengthen already-funded projects and help to consolidate niche rules. While it is unlikely that a programme-based investment portfolio will lead to niche institutionalisation at the regime level, it can induce cohesion of actors around projects and thus contribute to niche maturing and consolidation through purposive action that strengthens project–partner networks.

TOs synthesise sociotechnical transitions research by identifying specific facts that emerged from empirical (historical) evidence. These stylised facts indicate the intermediary outcomes of a transition process and, therefore, essential signals for whether the process is unfolding in the right direction. Our methodological approach links selected TOs with network characteristics.

3. Towards an indicator framework for sociotechnical transformations

Indicator frameworks have in common their ambition to give structure and meaning to data and to inform their intended use, such as learning, monitoring, or evaluation exercises. Sonntag (2010) discusses the uses of (sustainability) indicator frameworks and explains that

> … the general purpose of frameworks is to help clarify what to measure and what actions are needed to foster a positive direction of change as measured by the indicators. However, the "how and what" of frameworks are embedded in particular worldviews of what is seen as meaningful and effective… The selection of a framework reflects differences among the needs and interests of multiple stakeholders, including the target users and the indicators' developers.…

The development of new indicator frameworks depends on a structured worldview of the processes that the indicators seek to illuminate and the intended uses of the indicators. This worldview is structured through models or theories. However, there is often a lag between the emergence and consolidation of a model or theory and its translation into an indicator framework, particularly in the social sciences. This is the case with sociotechnical transitions research, which has evolved in the last two decades into models and 'middle-range theories' (Geels 2007) that are mature enough to call for the development of indicator frameworks to inform their uses (Köhler et al. 2019; Sovacool et al. 2020)—including for testing of theories and models themselves, but, also importantly, to provide evidence for strategic action and policies in support of transitions. This paper aims to contribute to developing a practical indicator framework based on the sociotechnical transitions theory that can assist in the guidance of transformative innovation policy (investment) programmes.

In practice, indicator frameworks can serve two purposes: learning about a process or measuring progress towards a goal. The first purpose leads to the development of positive or descriptive indicators, which provide information about a situation or change process without being tied to a specific goal. These indicators are instrumental in monitoring programme-based R&I investments because they can provide a snapshot of the situation at a given time. The second purpose leads to the development of normative or performance indicators, which provide quantitative metrics for measuring progress towards a specific goal or objective over time. Descriptive frameworks are not uncommon to be used as performance metrics and vice versa. In this paper, we will develop and pilot a descriptive indicator for sociotechnical transitions (systemic transformations) by creating network snapshots at different moments to infer how a transition process is unfolding concerning its transformational goals.

Integrating concepts from complex system theories to develop an indicator framework for systemic transitions is challenging because certain concepts are not easily operationalisable. Nevertheless, it is crucial to consider the properties of such complex systems because sustainability transitions or transformative processes are complex phenomena that occur at the sociotechnical *system* level. We draw on Selomane et al. (2019), who propose five properties of complex systems for evaluating the Sustainable Development Goal (SDG) global indicator framework (Ghosh et al. 2021)[2]: (1) feedback loops between the ecological and socio-economic systems, (2) resilience, (3) heterogeneity, (4) non-linear dynamics, and (5) spatial and temporal cross-scale dynamics.

In developing the practice-based prototype for systemic transformations (i.e. sociotechnical transitions), we operationalise two properties of complex systems: resilience and heterogeneity (the other properties, except for (1), are indirectly considered when discussing our results). Resilience depends on a system's absorptive, adaptive, and transformative capacities, while heterogeneity refers to the diversity or differentiation of a system's components (including spatial or multilocation dynamics). We operationalise these properties through modular networks, complex structures important for mobilising social and financial resources and avoiding small perturbations or disruptions in transformative processes. The way a modular network evolves provides insights for monitoring sociotechnical transformation processes.

4. Methodology

4.1 Empirical context: the EIT Climate-KIC systemic transformation strategy and portfolio of projects in the food sociotechnical system

Before we detail our analytical strategy for operationalising niche-related TOs, we present our empirical case (the EIT Climate-KIC food project portfolio) because our methodological discussion will refer to the case's characteristics. The EIT is an agency of the European Union (EU), established in 2008 in the context of Horizon 2020 (the EU's eighth *Framework Programme for Research and Innovation*) to strengthen Europe's ability to innovate.

Our focus is on the EIT Climate-KIC, which supports a portfolio of projects and programmes that help society mitigate and adapt to climate changes by promoting interactions in multi-actor, cross-sectoral arenas and covering a wide range of geographical spaces. In contrast to other KICs that focus on economic competitiveness, Climate-KIC defines its purpose and mandate in a broader sense (Dierks 2017), positioning itself as a cross-sectoral and cross-regional initiative that goes beyond (Frame 1) innovation policy for competitiveness. It, therefore, adopts a systemic approach to innovation (Frame 2) aimed at sociotechnical transformation (Frame 3), as outlined in its most recent (2018) strategy document, 'Transformation, in Time' (EIT Climate-KIC 2018). This strategy targets systemic transformational change and is implemented through a portfolio approach aimed at accelerating change across various industrial sectors and throughout society.

An essential part of its activities is orchestrating an investment architecture for systemic transformation projects through various programmes addressing multidimensional aspects of innovation systems and different stages of the innovation process—from ideation and prototyping to the more mature stage of demonstrating products, services, and business models. To this end, the EIT Climate-KIC creates thematic portfolios of projects to leverage private funding in support of climate innovation. These portfolios are tracked in terms of progress and outcomes to promote learning and insights and maximise impacts. Figure 1 depicts the structure of EIT Climate-KIC portfolios, which includes a range of specific programmes that aim to incubate, scale up, and mature social and technological innovations that address climate change mitigation and adaptation.

In the context of the EIT Climate-KIC, a portfolio can be defined as a group of projects that share common resources such as partners, funding schemes, and knowledge assets. In this regard, a subgroup of projects under a programme can contribute to expected outputs and outcomes. The EIT Climate-KIC macro portfolio comprises five programmes

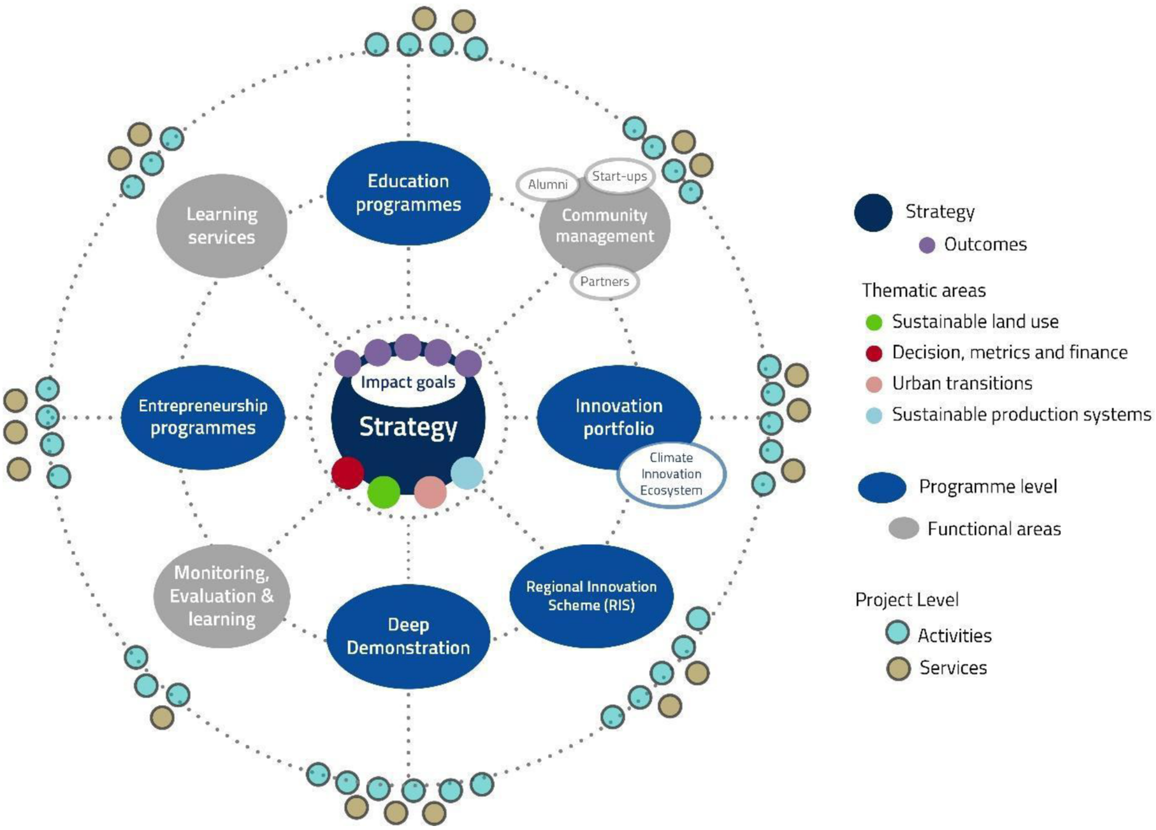


Figure 1. EIT Climate-KIC's portfolio structure.

that enable knowledge production, technological development, and supporting ideas into marketable innovation. For instance, the education programme includes graduate-level education, summer schools, and learning hubs; meanwhile, entrepreneurship supports startups and businesses at different stages. Overall, the portfolio encompasses a network of organisations across multiple locations. Therefore, through this portfolio approach, EIT Climate-KIC seeks to create positive impacts on multiple sociotechnical systems such as water, food, mobility, and energy. Note that this rationale on innovation portfolios applies to EIT Climate-KIC and other innovation agencies, as in the case of OECD's Observatory of Public Sector Innovation (OPSI) (OECD 2022), Vinnova (Hill 2022), or the United Nations Development Programme (UNDP)'s Regional Innovation Centre (UNDP 2022).

Our analysis focuses on the food system, which is nested under the 'Innovation Portfolio' category. However, to consider intersections between food with other EIT Climate-KIC programmes, our analytical strategy searched for projects related to food in *all* funded projects from 2016 to 2020. This strategy permits us to consider multiple portfolio dimensions such as thematic areas (conceived initially as strategic programmes): Sustainable Land Use, Decision, Metrics and Finance, Urban Transitions, Sustainable PRoduction Systems, and concrete programmes addressing interactions in multiple areas, such as the Climate Innovation Ecosystem and the Regional Innovation Scheme (RIS). In turn, the strategy leads to a representative case of the EIT Climate-KIC portfolio on one specific sociotechnical system (i.e. food).

Figure 1 also shows the layers of the portfolio, starting with the strategy core and moving to programmes and projects that work across different thematic areas. Programmes and projects are implemented through activities that produce tangible outputs such as technologies, products, or digital items (e.g. websites), as well as services ranging from design facilitation and community management (e.g. networking events) to system mapping, capacity-building, and targeted communication. As those outputs seek to contribute to EIT Climate-KIC's impact goals of transforming sociotechnical systems in the context of a sociotechnical transition, they are critical inputs for niche formation and evolution, providing the link between the portfolio of projects and niche dynamics.

Based on social network analysis (SNA), in the following subsection, we develop the argument that a dynamic portfolio of projects (and associated outputs)—or what we call a portfolio network—enables niche evolution and, thereby, the emergence of resilient and cost-efficient structures characterised by modular structures where interactions across social groups trigger the consolidation of niches (Pan and Sinha 2009a,b; Safarzynska et al. 2012; Pinheiro et al. 2019). Complex system literature has referred to modular structures as the dynamic selection processes at the group level. In other words, modular structures may favour niche development to increase resilience and facilitate diversification or heterogeneity across the modules. Social groups, or modular structures, favour shared vision, beliefs, and closer ties among diverse actors (Geels and Raven 2006; Schot and Geels 2008; Safarzynska et al. 2012; Giurca and Metz 2018). Thus, we further assume that in the mature niche stage, a programme-based project portfolio's network structures will have a modular architecture that is resilient, is cost-efficient, and reduces internal selection pressures. By means of network visualisation techniques and metrics, using indicators derived from the EIT Climate-KIC portfolio, we can infer the portfolio's development stage.

4.2 SNA in the context of a portfolio of projects for sociotechnical transitions

To operationalise selected TOs (namely, niche building and expanding) into monitoring and formative evaluation indicators of the systemic, transformative change that underlies sociotechnical transitions, we use insights, techniques, and theories from SNA, a method used to study the structure and function of social networks, which are complex systems composed of multiple interconnected entities. SNA uses visualisation and mapping techniques to represent interactions between entities and analyse the structure and function of these interactions (Freeman 2004; Bellotti 2015).

Analysing structural patterns in complex networked systems that occur in biological, social, technological, and sociotechnical contexts has been vital for understanding the evolution of adaptive systems (Guimera et al. 2007; Wen et al. 2015; Pinheiro et al. 2019). It has also been used in sustainability transition research to analyse niche dynamics (Hermans et al. 2013; Giurca and Metz 2018; Dias and Ramirez 2021). In Science and Technology Studies, a broad multidisciplinary field that examines the social, cultural, and political aspects of science and technology, including how complex system dynamics influence these phenomena, researchers often use SNA as a method to study the relationships between individuals or organisations within a social network and to understand the impact of these relationships on the diffusion of scientific and technological knowledge and innovation. For example, broad and brokered network structures have been studied to understand how new knowledge and technologies are produced (Rafols and Meyer 2010; Rudnick et al. 2019). In socio-ecological studies, Ernstson (Ernstson 2011) employed SNA to describe network-level mechanisms that underpin transformative collective action.

In the field of sociotechnical transitions, a few contributions employed SNA techniques to study transformative change (mostly related to niche dynamics), which served as an inspiration to our contribution. Morone and Lopolito 2010; Lopolito et al. 2011 present a method of studying innovation niche formation using SNA, proposing a taxonomy of different niche development statuses based on three social network indicators (density of sharing relations index, in-degree network centralisation index, and density of knowledge flows). Giganti and Falcone (2021) adopt a similar approach to study the European niche for virtual and augmented reality technologies. Imbert et al. (2019) study the actor (knowledge) networks underlying the transition towards a bio-based economy (bioplastics), considering four network indicators (density, inclusiveness, clustering coefficient, and network centralisation). In Giurca (2020), SNA serves as a background technique to build a network of actors working on Germany's wood-based bioeconomy (originally built in Giurca and Metz 2018), but the core of the contribution is to map the 'network discourse' through discourse analysis techniques. Finally, Boillat et al. (2022) use SNA to investigate the impact of transnational links on the empowerment potential of the agroecology niche in Senegal, building a network composed of different organisation types (nodes) and different link types (resources, knowledge, membership, and advocacy).

Hermans et al. (2013) *draw on* strategic niche management theory to investigate the dynamics of a collaborative innovation network, linking macro-level network dynamics to micro-level niche processes. The authors describe a method for constructing longitudinal two-mode affiliation networks, composed of actors and events (represented by both projects and organisations), which is similar to our approach (see Section 4.3), but Hermans et al. analyse different network indicators and do not consider the network topology in terms of modules. Thus, despite the different uses of SNA to indicate a transformative change in transitions, the implications of more complex network structures—such as modular structures, nested architectures, or small-world networks—have not been fully considered in the ST&I nor the sociotechnical transitions literature, which are the fields to which this paper seeks to contribute.

Modular networks are complex structures where entities are highly interconnected in groups, and these groups have few links to other groups (Pan and Sinha 2009a,b). They form, therefore, subnetworks or networks of networks. Those links are vital for keeping cross-pollination between groups—the circulation and exchange of knowledge and experiences—contributing to building common visions and trust in the whole network (Geels and Raven 2006; Schot and Geels 2008; Safarzynska et al. 2012; Giurca and Metz 2018, see also Ramirez et al. 2020). Figure 2 shows a network graph characterising four types of networks (a high modularity network appearing in the centre) and their relationship with complex properties: resilience, cost, and efficiency:

(1) *Resilience*: Modular and broad networks are characterised by high levels of resilience due to their ability to absorb and adapt to perturbations or disruptions. This is because modular networks are composed of multiple interconnected modules or subnetworks, which can continue to function independently even if one or more modules are disrupted. In contrast, chain and brokered networks are less resilient because they rely more on a single, linear flow of information or resources, or on a central node acting as an obligatory passage point, and are thus more vulnerable to disruptions. Heterogeneity, or diversity, within a network, can increase its resilience by providing multiple paths for information or resources to flow and allowing the network to continue functioning even if one or more components are disrupted. Non-linear dynamics, or the complex and unpredictable nature of interactions within a network, can also increase its resilience by making it more difficult for external perturbations or disruptions to propagate throughout the network.

(2) *Cost*: Modular networks are generally more efficient and cost-effective than chain and broad networks because they allow for multiple, parallel flows

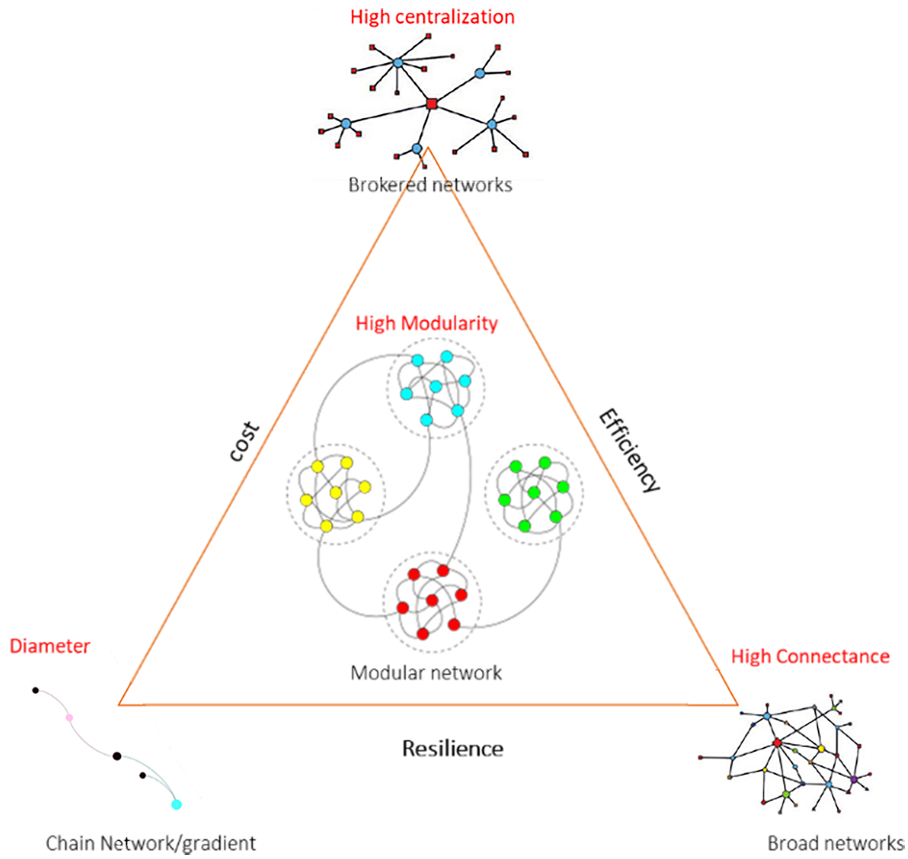


Figure 2. Modular networks or a 'network of networks'.

of information and resources within the network. This allows for more efficient use of resources, while also reducing the need for intermediaries or brokers, which can increase the cost of the network. In contrast, chain and brokered networks are typically less efficient and more costly due to their reliance on a single flow of information or resources and the need for intermediaries or brokers. Note that heterogeneity and non-linear dynamics can affect the cost of a network by requiring more resources for managing diverse components or by making it more difficult to predict and control the flow of information or resources within the network. However, the result of the interaction between the complex system properties and the cost of the network will depend on its empirical type.

(3) *Efficiency*: Modular networks are generally more efficient than chain and broad because they allow for more flexible and adaptive responses to changing conditions. This is because modular networks are composed of multiple interconnected modules or subnetworks, which can be reconfigured or reorganised in response to changing conditions. In contrast, chain networks are less efficient than modular networks because they are more rigid and less adaptable to changing conditions (one could argue that brokered networks are also less *dynamically* efficient). Heterogeneity within a network can increase efficiency by allowing for multiple, parallel flows of information and resources and reducing the need for intermediaries or brokers. Non-linear dynamics can also increase a network's efficiency by allowing for more flexible and adaptive responses to changing conditions.

We further elaborate on these characteristics, considering the early niche dynamics of a sociotechnical transition and the role of investment portfolios. The creation of modular network structures in the context of a project portfolio strategy is relevant to sociotechnical transitions because they permit diversification or heterogenisation[3] of multiple niche experiments yet keep cohesion across social actors engaged in connected experiments (within modules), thus enabling the production of new outputs and reducing selection pressures over (or shielding) those niches. When modular structures emerge, they signal the maturing of the network around a niche, thus being an indicator to monitor potential system transformation.

Modular networks are essential in mobilising social and financial resources (Bellotti 2015) while avoiding small perturbations or disruptions (Pan and Sinha 2009; Pinheiro et al. 2019). In other words, modular networks have been shown to have high levels of cost-efficiency and resilience because they are formed of several subnetworks, each scoring higher in two of those characteristics. Resilience has been characterised as the ability to maintain the communications between entities in a network even in the face of disruptions (if one connection is broken, two nodes in the network may still communicate following a different path). Disruption can be understood as the consequence of selection pressures: resilience in the context of a sociotechnical transition means not only that a niche may withstand competition from the regime but also that it can survive adverse shocks from the landscape or will not disintegrate due to adverse internal developments (such as disagreements between niche actors and early fragmentation).

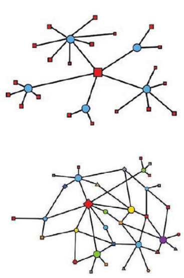
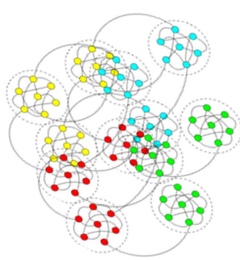
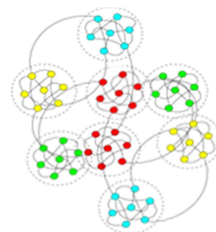
Cost in the context of a network refers to the number of resources needed to maintain a connection, while efficiency is the time needed for communication between two nodes to happen (Pan and Sinha 2009). Thus, cost-efficiency is related to the capacity to reduce the cost of information diffusion. Resilience and cost-efficient processes are therefore relevant for niche development because they enable diversification and knowledge circulation while shielding the niche from selection pressures.

The dynamics of transformation imply building and upscaling niche structures, and these processes do not happen at once. Therefore, we consider a more dynamic—or evolutionary—approach to changes in niche structures. Based on Wen et al. (2015), we expect to find four sequential types of networks related to four stages of niche building (see Ghosh et al. 2021; Safarzynska et al. 2012): (1) incubation, (2) replication, (3) diversification, and (4) maturing. Table 3 details the expected network characteristics (metrics) for these four phases of niche development, which we associate with specific TOs. The table's last row provides a hypothetical graphic example of how the network architecture should look.

With a programme's transformative goals providing directionality, programme-based investment portfolios can generate the necessary conditions and resources to foster a niche incubation process. The incubation phase thus creates a safe space for pioneer social entities to explore and develop new niches through network building and economic support, which programme managers allocate to a few targeted organisations and thematic areas in line with the programme's transformative goal. These dynamics are essential for forming resilient and efficient networks supporting niche development. We associate these dynamics with the shielding process of niches in systemic transformations (sociotechnical transitions) and with the initial formation of networks that contribute to niche building. In this phase, we, therefore, expect to find (Proposition 1) *low diversity of partners and projects and broad or brokered networks, which are characterised by having low levels of resilience (brokered) or low-cost-efficiency structure (broad networks).*

The second and third phases are characterised by two complementary processes: replication and diversification (heterogenisation). We associate these processes with the transformative dynamics of moving from the initial niche incubation stage to the stage of scaling up and diversifying niches. In the context of a programme-based investment portfolio, replicating successful topics and/or incorporating new partners lead to a diversified network architecture. Diversification (a specific type of scaling a niche project) has been characterised as highly relevant in sociotechnical transition processes, as it represents the build-up and inclusion of multiple voices in the niche consolidation process (Kemp et al. 1998; Smith 2007; Hermans et al. 2013). Nevertheless, diversification can also lead to a reduction of cohesion between projects and partners. Therefore, to avoid the lack of cohesion, *modular structures*

Table 3. Niche evolution dynamics and network metrics expected.

Phase	Incubation	Replication	Diversification	Maturing
Description	Pioneers start working on new niche development projects (brokered or broad networks)	After niche projects are successful, other actors replicate them (growth of the network)	New and old actors add variants to their development (modular network)	Shared vision, technical agreements, and trust developed (cohesive modular network)
Associated key niche-related TOs[a]	Networking, shielding, learning, and aligning expectations	Replicating, circulating, and [learning]	Upscaling (diversifying), [replicating], and [circulating]	Consolidation [institutionalisation], [upscaling], realignment of expectations
Number of actors (project–partner)	Few	High	High	Medium
Diversity entities	Few	Medium	High	Medium
Degree centralisation	High	Low	Low	High
Betweenness centralisation	High	Low	Low	High
Diameter	Small	High	High	Medium
Number of modules	Few	High	High	Medium
Connectance	Medium	Low	Low	Medium
Multilocation	Low	Medium	High	Medium
The expected architecture of the network				

Source: authors' construction.
[a]Many (if not all) outcomes may happen in more than one phase (which we indicate with brackets), but we expect them to have a centre of gravity in a specific phase.

should start to emerge in Phase 2 (and continue in Phase 3) to keep actor groups cohesive, reduce selection pressures, and enable cohesive diversification (Proposition 2). A programme-based investment infrastructure motivates new investments in projects similar to the initial ones (be them successful or not) and attracts other social organisations: *this process leads in Phase 3 to the circulation of knowledge and ideas beyond the initial project, resulting in increased adoption (replication)* (Proposition 3). The critical difference between Phases 2 and 3 is related to the *diversity and location of entities: both should be higher in Phase 3 than in Phase 2* (Proposition 4).

The fourth phase of niche maturing consolidates niche practices: *in this phase, we expect to see a reduction in the number of groups and a closer interaction across these groups* (Proposition 5). This will enable building trust and sharing of visions, thus realigning expectations (Giurca and Metz 2018). In so doing, the investment portfolio promotes the selection of successful niche clusters (modules), increases the share of projects between organisations, and induces 'cross-pollination' between modules. In terms of the sociotechnical transition dynamics, at this stage, we would expect to see mainstream regimes opening to niches, which become empowered (Schot and Geels 2008). Yet, we do not investigate whether these dynamics should be confirmed by looking at other indicators external to the portfolio network logic, for example, the increasing share of resources being dedicated to niches vis-à-vis regimes.

When analysing this mature stage, Hermans et al. (2013) initially expected to find brokered networks: high-degree centralisation because of coordinating processes. However, they could not find evidence of this; indeed, they found very low levels of centralisation. By contrast, we suggest that coordination processes happen *across* modules rather than through endogenous social capital development led by a few social actors (network centralisation). In the scope of a programme-based project portfolio, brokering, decentralisation, and coordination (or 'orchestration') happen not through the network structure but through the actions of programme managers at the programme level. Therefore, *we expect low levels of centralisation and a reduction of modules in Phase 4* (Proposition 6). In other words, *the network should develop more complex structures than brokered networks in mature stages, showing a more cohesive modular structure (lower number of modules than in Phases 2 and 3)* (Proposition 7). This is an important indicator that the system incorporates cohesive, diversified niches.

In summary, we propose that niche building from a programme-based investment infrastructure perspective involves constructing and orchestrating portfolios to support resilient structures that enable transformations. This is accomplished by keeping cohesive groups focused on shared goals and visions (i.e. provided by the programme). In these network dynamics, the sociotechnical transformation processes of niche incubation, shielding, building, learning, replicating, upscaling, circulation of ideas and knowledge, and consolidation can all be observed through network analysis. In Table 3, we have tentatively allocated these transformative processes and outcomes to specific phases. This tentative allocation forms the basis of our framework for monitoring and evaluating the stage of niche evolution. Using network mapping and visualisation techniques, we can answer the question of where we are in the systemic transformation process from a niche development perspective. This contributes to monitoring how systemic innovations are unfolding at the niche level and whether they are moving towards the transformative direction embedded in a programme's goal and vision.

4.3 Analytical strategy (methodological steps)

Our analytical strategy followed eight steps, described in detail in Appendix 1, which also explains the rationale behind each of those methodological steps:

(1) We conducted an analysis of the EIT Climate-KIC portfolio dataset to identify projects related to the food system, which required addressing issues related to missing information about the focus areas and goals of projects by collecting descriptive information on all projects and standardising focus areas from 2016 to 2020.
(2) We used a vocabulary with ninety-four terms to identify food system projects and identified 221 projects and 178 partners between 2016 and 2020.
(3) We defined time windows (TWs) according to the EIT Climate-KIC investment strategy and programme logic.
(4) We then plotted, for each TW, two-mode networks (composed of two elements/nodes: projects and partners), which represent the governance behind the EIT Climate-KIC portfolio based on a social coalition of partners framed by several R&I programmes.
(5) We then calculated, for each network, metrics such as modularity, connectance, degree centrality, and betweenness centrality for each network and used Simpson's diversity index to identify diversification within each group of partners and projects. These metrics bring detail to network structures and therefore allow us to identify if these networks are brokered, broad, linear, or modular. We justify the choice of indicators and bring further information about their operationalisation for two-mode networks in Appendix 2.1.
(6) Altogether, these metrics allow us to test the propositions stated in Section 4.2: we compare the empirical indicators of the networks and diversity with the conceptual definition of networks to identify the phase of niche development.
(7) We conducted a non-linear correlation analysis to study the effects of the EIT Climate-KIC investment portfolio on network development and develop an indicator of the frequency of interactions to identify partners' influence on network connectivity.
(8) We study the co-occurrence of partners in projects between 2016 and 2020 to evaluate whether partners interacting in many projects have more opportunities to arrive at late stages of niche development, using a non-parametric test to evaluate connectivity differences between actors at mature network stages.

To reiterate, our analytical strategy to trace niche evolution using SNA is based on the generation of the coalition at the group level. It has been shown that technological and social change occurs by clusters (groups) of radical innovation forming successive and distinct developments that facilitate system change (Meunier et al. 2010; Smaldino 2014; Buskell

Table 4. A summary of network metrics in each TW.

Network metrics	TW1	TW2	TW3	TW4
Number of partners	56	96	109	102
Number of projects	47	97	118	76
Edges	115	188	288	221
Connectance	0.043693	0.021907	0.022367	0.030959752
Network asymmetry	0.087378	−0.00518	−022026	0.146067
Diameter	4	15	16	16
Degree centralisation	0.203598	0.041073	0.037445	0.046911699
Betweenness centralisation	0.711753	0.317896	0.225908	0.181609002
Modularity (Newman Mode 2)	0.676375	0.763035	0.768911	0.71113
Number of modules	4	11	11	6
Average path length	4.23136	6.407256	6.050677	5.828039169

Source: authors' elaboration.

et al. 2019). In this regard, our analysis goes beyond a linear analysis of the increased investment, programmes, projects, or partners associated with the EIT Climate-KIC innovation ecosystem. In other words, our understanding of niche evolution goes beyond network growth to fully understand the structural properties of the networks that facilitate social and technical coalitions. In this regard, we first aim to identify the formation of modules or clusters in the network and its association with the diversity of programmes, partners, and regions involved in niche building. In addition, we evaluate to what extent the co-investment facilitates network resilience. Lastly, we analyse the permanence of partners in the network to identify long-term interactions, which can foster the further development of sociotechnical niches. To conclude, our methodological approach considers multiple dimensions of networks, and we associate network metrics with the evolution of sociotechnical niches, as presented in Table 1.

5. Results and discussion

5.1 Evolution of portfolio networks as an indicator of niche building for sociotechnical transformation

Table 4 summarises the characteristics (metrics) of two-mode networks during each of the TWs, while Figs 3–6 depict our results throughout the periods of interest.

In the early TW (Fig. 2), the (project–partner) network focused extensively on topics related to the Climate-KIC thematic programme 'Sustainable Land Use', which implies a low diversity of topics. Furthermore, highly connected partners are associated with research and businesses, while cities, regions, and non-governmental organization (NGO) partners have a more peripheral position in the network (Fig. 3). During this phase, we identified a brokered network (high-degree and betweenness centralisation) (Table 4), where one project enables the connectivity and flow of information (intermediation). This type of network has a highly cost-efficient structure but is not very resilient, as explained in Section 2. This result is in line with Proposition 1: the incubation phase is characterised by a *low diversity of partners and projects, forming broad or brokered networks with low levels of resilience (brokered) and low cost-efficiency structure (broad networks).*

In the second (2017–8) and third (2018–9) TWs (Figs 4 and 5), the networks showed an increase in the number of partners and projects and the diameter of the network, indicating network growth (Table 4). The second TW (2017–8, Fig. 4) is characterised by the emergence of the multilocation programme 'Climate Innovation' as a critical enabler of interconnectivity and flow of information together to 'Sustainable Land Use', thus promoting the circulation of knowledge and ideas around across niches and locations. Furthermore, Fig. 4 shows that partners associated with higher education are highly interconnected in the network, having a central position in the portfolio network. The results imply that—together with EIT Climate-KIC's programme staff—partners connect projects from the 'Sustainable Land Use' thematic area and the Climate Innovation Programme.

In the third TW (2018–9, Fig. 5), we identify the emergence of new projects related to other thematic programmes, such as 'Decision Metrics and Finance' and 'Urban Transitions', which points to a further diversification process induced by the EIT Climate-KIC programmatic logic. Small and medium business enterprise (SMEs), research, and higher education partners contribute to building bridges across different thematic areas (Fig. 5), showing that coherence is induced by the agency's programmatic strategy and the network's structure (diverse partnerships).

We also find the emergence of modular networks during the second and third TWs[4] (high modularity and the number of modules) (Table 4). These results are in line with Propositions 2–4. As explained in Section 2, these networks are vital in enabling the cohesive diversification of networks and contributing to consolidation (early institutionalisation and higher resilience). The diameter of the network is very high (>10), but the average path length does not increase significantly (Table 4). This underscores the notion that the portfolio network is growing but cohesive, further indicating resilient consolidation that may lead to upscaling.

In the final TW in our study (2019–20, Fig. 6), a new modular network emerges, but with fewer modules. This result suggests a selection process of modules rather than of projects or partners. We identified that 58.87 per cent of the partners in the final TW participated in projects before (2016–8). This significant number of diverse (heterogeneous) partners working together over the four TWs indicates the possibility of long-term interactions being built, where trust and a shared vision often emerge, which are transformative processes. Note that, from a probabilistic point of view, all actors in the network would have the same *ex ante* probability of

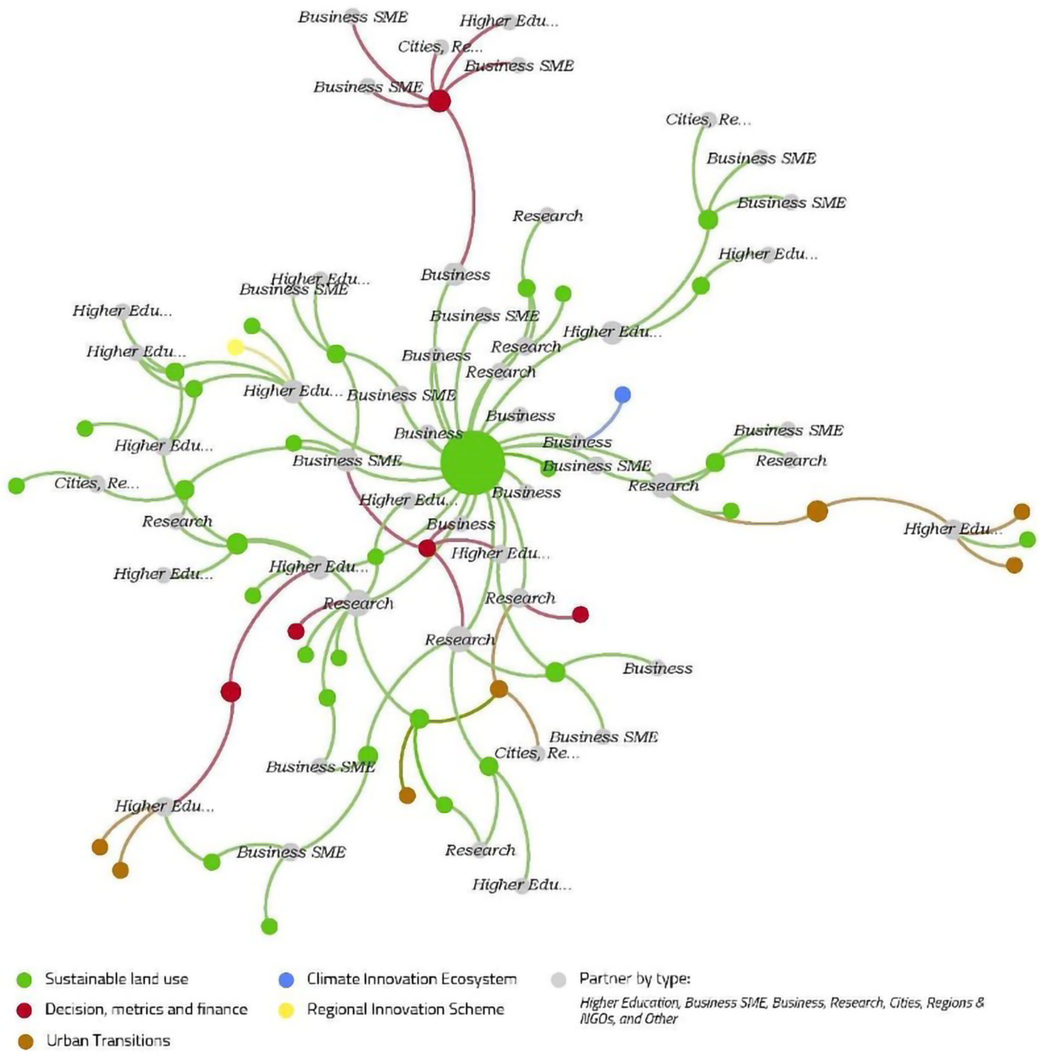


Figure 3. Project–partner networks in the first TW (2016–7).

Obs.: In this and the following figures, dots sizes indicate the nodal betweenness centrality (intermediaries in the network): the bigger the size, the higher the betweenness centrality. lso, we only plotted the great component (network with the highest number of dots) in every time window, which in our case, contains more than 95 percent of the nodes in each time window.

continuing to work in/with EIT Climate-KIC projects. Our interpretation of the *ex post* result is that better-connected actors are thus more likely to continue working in/with EIT Climate-KIC projects because they are more deeply embedded in the niche (Granovetter 1985). This interpretation would further suggest the initial consolidation and empowerment of the niche network, allowing for the alignment of expectations and eventually upscaling.

During the last TW, the portfolio network does not have any project or partner attribute that is extendedly more frequent than the others (low dominance) (results reported in Appendix 2.2). Modules, on the other hand, have higher dominance than the network, suggesting that diversification happens at the network level and cohesion at the group level. The diversity of partners' attributes did not vary during the period studied, although the networks showed a significant transformation over the fourth TW. By contrast, the diversity of projects increases significantly from TW 2, suggesting that the diversity of projects may influence the evolution of the portfolio network. According to Pinheiro et al. (2019), a high diversity of resources (projects in our case) generates modular systems by increasing global diversity but keeping cohesion at the module level. These results suggest the importance of having a diverse programmatic portfolio, enabling multilocation and partner-type diversity. Therefore, the findings about the fourth TW seem congruent with Propositions 5–7.

5.2 Networks quality and investment

Our results also show that the unilateral investment of EIT Climate-KIC (the network orchestrator), guided by a strategic goal and driven by the programme-based infrastructure and the network-building-related activities, characterises the very early stage of the network (first TW). This infrastructure enables a critical mass of projects under the investment portfolio, which may shape the network's connectivity. We found a significant Spearman's rank correlation (R_s) between EIT Climate-KIC's investment and network connectivity (nodal degree[5]); meanwhile, partners' investment did

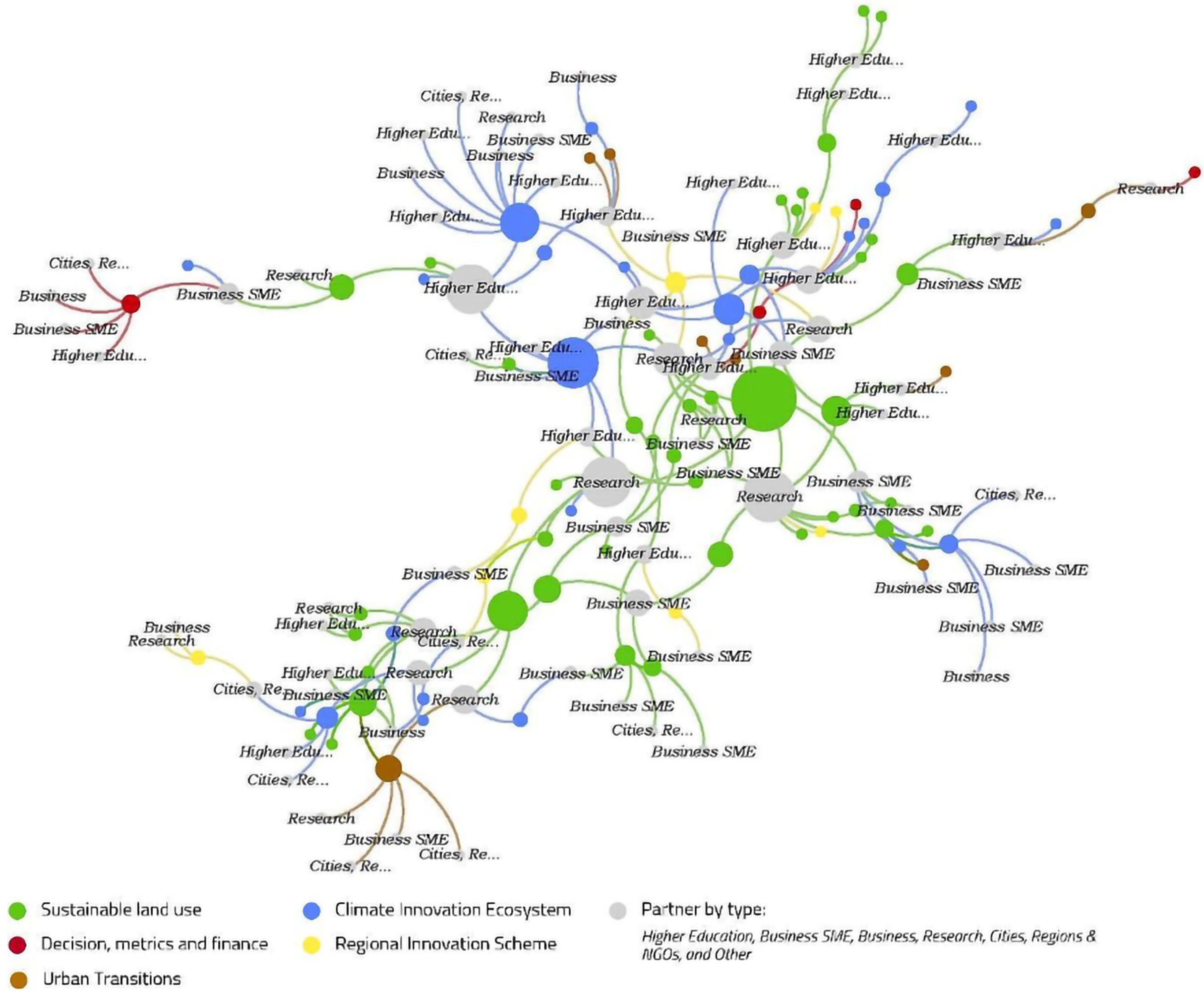


Figure 4. Project–partner networks in the second TW (2017–8).

not seem to influence their connectivity[6] (results reported in Appendix 2.3). We did not find that either EIT Climate-KIC's investment or partners' investment has a significant association with their positions as intermediaries in the network (see Appendix 2.3). These results suggest that EIT Climate-KIC may play a key role in inducing and incubating pioneer projects, likely creating expectations around them in the early stages. In this regard, EIT Climate-KIC's investment following a programmatic logic might influence the network connectivity and therefore shape the development of the network in the early stages. In terms of transition theory, this finding seems to underscore the importance of an intermediary organisation such as R&I agencies (in our case, EIT Climate-KIC) in shielding and incubating initial networks to create opportunities for mutual learning via the circulation of knowledge and practices, inducing replication and eventually alignment of expectations and leading to upscaling and institutionalisation in later stages of network development.

The results also show that the evolution of the network implied more equal investment shares between the EIT Climate-KIC and its partners. To foster this investment architecture, the directionality provided by the programmes' goals, the creation of expectations, and the demonstration of successful projects (and learnings from less successful ones) seem of high importance as incentives for new partners to participate and invest in these projects. As neither the agency's investment nor the partners' investments directly influence network connectivity, the results highlight that a programmatic strategy directed by shared transformative goals is more than financial instruments: they bring community management and capacity-building elements that support a process for setting collective expectations. These are indeed crucial processes in the system's transformation dynamics.

However, both the partners' investment and the projects' investment have significantly influenced their connectivity and role as intermediaries from the second TW to the fourth TW (results reported in Appendix 2.3). Our results show that more mature niche development stages are significantly associated with the programmatic investment logic of EIT Climate-KIC and its partners; an equal investment interaction also indicates the active participation of partners and the possible alignment of expectation and vision. Furthermore, the association (correlation R_s) increased in every TW (from a moderate correlation to a strong correlation; see Appendix 2.3), suggesting that the evolution of the networks might be influenced

Figure 5. Project–partner networks in the third TW (2018–9).

by the original logic of EIT Climate-KIC's programme-based investment and their partners. This finding is in line with complex system theory, which posits that initial system states and perturbances have a lasting effect on the system's evolution (i.e. may lead to path dependency).

To evaluate how the relationship between EIT Climate-KIC's projects and partners' investment can influence their interaction, we study the frequency of interactions between one partner and one project (*dyads*) (results reported in Appendix 2.4). As mentioned earlier, in the early stages, the interaction between a project and a partner depends mainly on EIT Climate-KIC's programme-based investment infrastructure and the shared goals induced by it. From the second to the fourth TW, a higher frequency of interactions between the partner and the project is more related to higher EIT Climate-KIC's investment than to each partner's investment (see Appendix 2.4). The agency's partners increased their investment compared with early-phase networks. However, EIT Climate-KIC invested in the most frequent dyads one-quarter more than each partner or double of each partner (0.25–0.5) (see Appendix 2.4). Note that EIT Climate-KIC can invest more than every partner in every interaction (*dyad*), but the total amount of partners' investment can be higher than EIT Climate-KIC's investment.

These results reinforce the evidence of the active partners' role in investing in more mature stages of network development and their possible influence on shaping the network's structure, which could suggest both learning and empowering processes. However, EIT Climate-KIC orchestrates during the niche maturing stage by making the programme

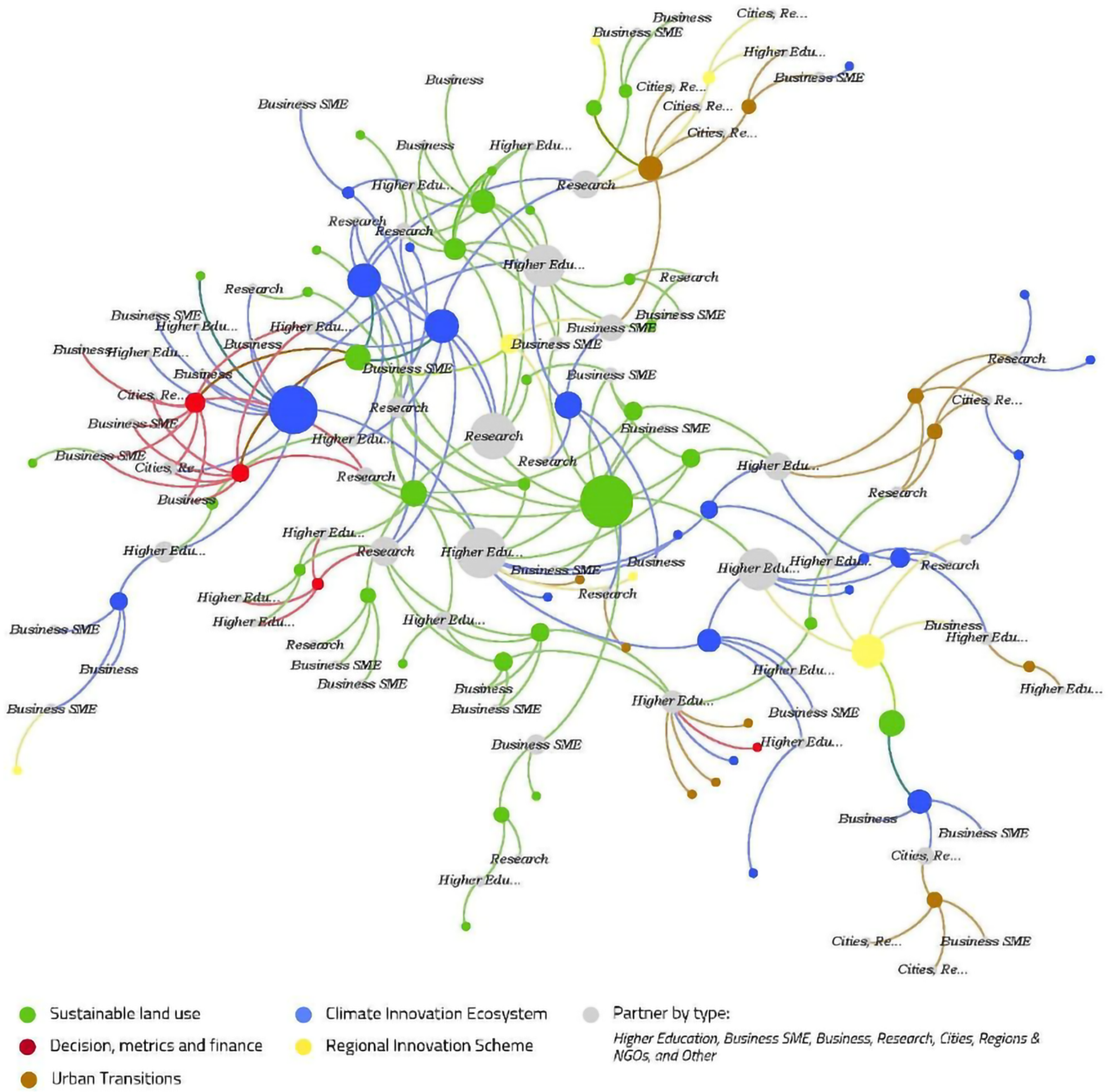


Figure 6. Project–partner networks in the fourth TW (2018–9).

infrastructure instrumental for investing and creating links across partner groups (modules). Such findings have implications for how a challenge-led R&I funding agency may structure the disbursal of its resources over time in the future.

5.3 The role of long-term interactions

Long-term interactions are critical in niche-building and consolidation (maturing) processes, mainly when guided by shared goals (as provided by a common programme or related programmes that share a vision) that confer directionality to the process. In this respect, we study the permanence of partners due to their connectivity across projects, that is, several partners interacting across a programme-based investment infrastructure towards the same direction through a portfolio of projects. Previously, we identified a significant reduction of projects and partners in the last TW. We proposed that this happens in the maturing phase when around 58 per cent of the partners involved in EIT Climate-KIC projects in the previous TWs remain in the last TW, indicating higher levels of resilience and institutionalisation. Moreover, interactions between partners and projects are influenced by the programme-based investment strategy of EIT Climate-KIC, whose infrastructure is shared by/with partners.

Figure 7 shows the recurrence of partnerships over time: two partners are connected due to their mutual participation in EIT Climate-KIC projects. The red dots indicate that these actors remained from the first TW through to the last TW. The blue dots in the first three TWs (2016–7, 2017–8, and 2018–9) indicate that these partners do not continue working in the last TW. The blue dots in the last TW (2019–20) indicate that they are new partners, which were then integrated into the niche network. Note that actors in the network's core or that are more deeply interconnected have a red colour. The great

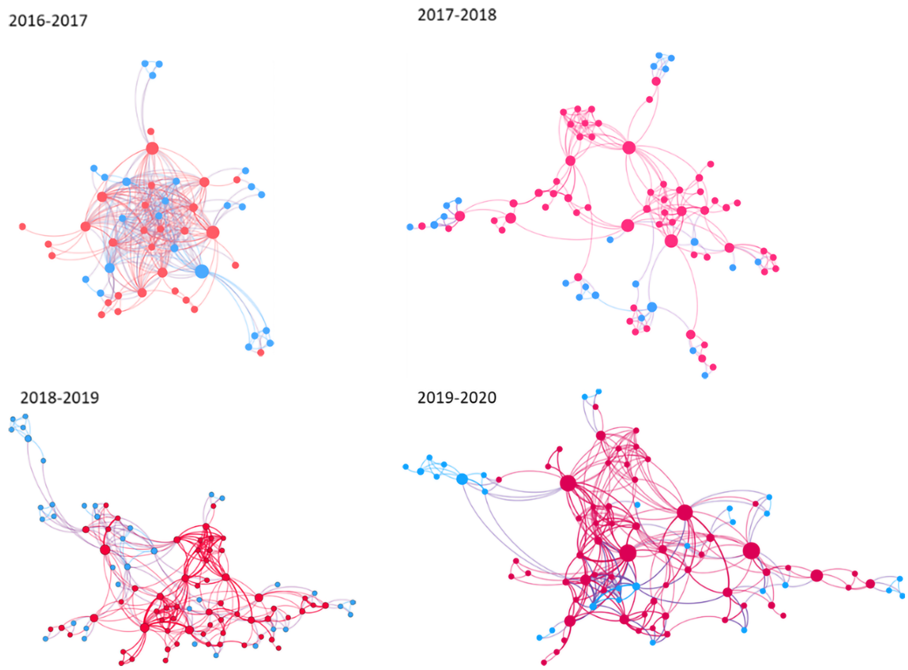


Figure 7. The partner–partner network.

network component in each TW was only analysed, which contains more than 95 per cent of the nodes in each TW.

We undertook a Mann–Whitney *U* test to analyse whether the remaining actors had a significantly higher nodal degree than actors (nodes) that disappeared (results reported in Appendix 2.5). We did not find any significant difference during the network evolution's first window. This result indicates that partners' connectivity during the early stage did not significantly influence their possibility of arriving to mature stages of network evolution. By contrast, over the growing phase (TWs 2 and 3), we find a significant difference between the connectivity of remainder and non-remainder actors, as the mean connectivity of those that continue in the network is significantly higher than the actors who leave the network[7] (see Appendix 2.5).

This significant difference in the connectivity between remaining and non-remaining actors in the growing stages indicates that actors more closely interconnected might have more possibilities to remain in the development of the niche. This result might also indicate that selection forces might act more strongly on groups of nodes not profoundly interconnected in the network (indicating path dependency and lack of resilience). Therefore, selection forces may concentrate at the between-group level rather than at the partner level. This result is in line with the other results of modular networks, which are characterised by reduced selection pressure within the groups but concentrating selection at the between-group level. This also indicates the relevance of building long-term relationships (strong ties) and close interactions across partners. These long-term interactions are essential for institutionalising niches and consolidating trust and shared visions. Relationship building and institutionalisation processes are fundamental for the implementation of ST&I policies. The results show that a programme-based investment infrastructure can play an instrumental role for an innovation agency such as EIT Climate-KIC to enable stable interactions by setting a safe space, strategic direction, and availability of financial resources and related networking activities. These results further indicate that the network evolution process was quantitative and qualitative: the network transformed itself over time.

In summary, our overall result confirms that certain structural properties of networks reveal the formation of sociotechnical niches in the context of a programme-based investment infrastructure. Our indicator framework took into account multiple dimensions of networks, and we used network metrics to better understand the evolution of sociotechnical niches. It captured the formation of modules or clusters within the programme-based portfolio network, which seems to contribute to both niche building and consolidation. Our findings provide insights into the mechanisms by which investment-supported networks facilitate the development of sociotechnical niches and can inform the work of public funding agencies in supporting sustainability transitions.

6. Conclusion

This paper proposed a methodology based on SNA to depict the early evolution of sustainability-oriented investment portfolios. Our goal was to use this methodological framework as a tool for the monitoring and formative evaluation of a key process in sociotechnical transitions: the formation and consolidation of sociotechnical niches. The proposed framework sought to address a gap in ST&I studies, which is the lack of 'Frame 3' (transformative innovation) indicators, especially for practical application by public agencies promoting projects and activities that shall contribute to systemic change. The paper showed that transformative processes of niche incubation and development can be monitored by looking at actor–project network evolution, guided by a goal-oriented investment programme and its programmatic infrastructure.

The proposed visual indicator prototype based on network mapping techniques accounted for the characteristics of transformative innovation policy and complexity aspects of systemic dynamics, namely, purpose and directionality (as stated in the programmatic logic and associated goals/visions behind the investment strategy), resilience (connected not only to the building of the network and its governance but also to how the partner–project relationships shield them from adverse selection), and heterogeneity (multiple themes and subthemes, actors, and localities). By incorporating in the prototype methodological considerations of complex system dynamics, our results reveal how purposively orchestrated networks—through active support from policy programmes and public investment portfolios—contribute to the dynamics of niche incubation, formation, shielding, and consolidation, by inducing resilience through cohesive heterogeneity.

Combining those considerations with findings from the sociotechnical transitions literature, we put forth propositions on project network evolution as a transition process evolves, which were confronted with empirical networks formed by the EIT Climate-KIC programme-based investment portfolio of food system projects. Considering the EIT Climate-KIC programmatic investment logic and infrastructure, with programmes guided by transformative goals and sharing a common transformative vision, funded projects represent seeds for niche formation and consolidation. Our contribution therefore adds to the emerging literature that shows how SNA can complement sustainability transitions. SNA is a valuable visual indicator to map niche development: it allows for studying the complexities of co-evolution processes within niches and understanding how certain network structures can contribute to reducing selection pressures, thus shielding niches.

The proposed visual indicator prototype composed of network mapping techniques allowed for the identification of phases of niche development, from emergence to consolidation. Doing so allows the analysis of simultaneous cross-sectoral, multilocation programmes implemented under a common orchestrated portfolio. While we recognise that the niches developed through a portfolio of investments represent a small sample of the many niches that contribute to a transition process (and one could argue that these portfolios operate at a substructural niche level), we argue that our prototype still indicates the early evolution of a transition process.

Networks play a critical role in facilitating the formation of sociotechnical niches, which are crucial for driving sustainability transitions. Networks provide the structural basis for the formation of social and technical coalitions, which are essential for the development and deployment of new technologies and practices. Through the formation of modules or clusters within networks, diverse programmes, partners, and regions can come together to collaborate and support the growth and evolution of sociotechnical niches. Additionally, the resilience of these networks can be enhanced through co-investment, and long-term partnerships within the network can foster further development of sociotechnical niches. In summary, networks are an important factor in the formation and evolution of sociotechnical niches, and understanding their evolutionary structures can inform the work of public funding agencies in supporting sustainability transitions. In conclusion, our visual indicator prototype is a tool especially relevant for innovation and funding agencies acting through a programmatic logic and facing the challenge of orchestrating several simultaneous programmes and action lines.

The proposed methodology goes beyond existing studies that combine SNA with sociotechnical transition theory, by focusing on modular networks, which might emerge in more mature stages of niche development. In the case under analysis, these modular networks seemed to result from an equal investment share between an intermediary organisation (EIT Climate-KIC) and partners and of long-term partners' interactions in (EIT Climate-KIC) programme-driven projects. A high percentage of EIT Climate-KIC's partners interact intensively and are deeply associated with their participation and investment in EIT Climate-KIC's projects. However, some results should be taken as indicative, and further qualitative research may study, for example, programme-based investment infrastructures as enabling mechanisms behind the emergence of shared vision and trust within the modules in our study case, that is, how strong the relationships actually are.

The quantitative (network/visual) analysis of the portfolio of investments to identify early TOs should, therefore, be combined with a qualitative assessment of the projects being supported (types of niches, technologies, social innovations, skills, and capacities/capabilities). This analysis is beyond the scope of the paper but is critical for a nuanced understanding of the niche development process beyond the investment portfolio dynamics. More work is also necessary on relating other TOs to niche development phases and exploring how to include regime-related outcomes in the framework.

Future research should aim to replicate this method of analysis using other programme-based investment portfolios, such as those managed by the EIT Climate-KIC or other R&I and funding agencies. While it should be noted that the framework presented in this study has limitations, including a requirement for familiarity with network analysis (concepts and software packages) and access to detailed data on the project (standardised description and classification according to the SDGs) and actor characteristics (role in the innovation system and classification as the regime or niche actor), we believe that the visual indicator framework has potential for use in the monitoring and formative evaluation of transformative innovation policy initiatives. This framework could potentially be applied to other cases of agencies that utilise a portfolio approach in the pursuit of goals related to fostering transformative change and sustainability transitions, such as the Swedish innovation agency Vinnova, the UNDP's Regional Innovation Centre, or the OECD's OPSI.

Conflict of interest statement. None declared.

Notes

1. The methodology was developed through the PROPORTION project (which ended in December 2020), funded by the EIT Climate-KIC as part of its *Transition Hub* activities, and draws from the work on 'transformative outcomes' (Ghosh et al. 2021) developed in a second EIT Climate-KIC project, MOTION (ending in December 2021).
2. The authors find limited use of complex system's theoretical constructs in the design of the SDG global indicator framework.

3. When referring to networks, we use heterogeneity and diversity interchangeably.
4. Note that we identify a high level of modularity but very few modules during the early stage; however, we identify high modularity and the number of modules in the second and third timeframe windows.
5. Number of links of each node.
6. Note that we use a non-parametric statistic test (non-linearity) because our data do not have a normal distribution; therefore, neither could we undertake a regression analysis.
7. The mean normalise degree for remainder actors was 0.011; meanwhile, 0.003777 was the mean normalise degree for non-remainder actors in TW 2. A very similar result was found in TW 3: the mean normalised degree for remainder actors was 0.010 and the non-remainder was 0.0029.
8. Further improvements of this dataset imply characterising partners' attributes in terms of transitions' literature: niche actors, regime actors, and landscape actors. These categorisations will permit one to access the niche–regime interaction dynamic.
9. This vocabulary was double-checked and improved by EIT Climate-KIC staff to align it with the terms used by the organisation in its projects.
10. We did a manual check of all projects.
11. Further qualitative research may be necessary to verify these assumptions; therefore, our analysis and conclusions in this regard should be taken as tentative.
12. Thematic areas: Sustainable Land Use, Decision, Metrics, and Finance and Urban Transitions, Sustainable Production Systems. Geographical programmes: Climate Innovation Ecosystem and the RIS.
13. Type of partners: higher education, research, business, business SME, and NGOs.
14. We calculated other indicators of disparity: Gini and Shannon Evans indicators. We did not find significant differences between them; therefore, we only report Simpson's results.
15. The network diameter is the longest of all the calculated path lengths. In other words, the network diameter is the longest distance between two nodes in the network. The longest distance indicates the growth of the network and possible disaggregation. This measure is not standardised; therefore, the diameter values need to be interpreted by comparing networks. In our case, we compare the four TWs. To identify possible disaggregation, we also calculate the average path length. This metric provides a contrasting point of the networks' growth (an increase of network's diameter) and networks' aggregation. For instance, the diameter may increase, but the average path length may not change, indicating the growth and cohesion of the network.

References

Alvial-Palavicino, C., Matti, C., and Witte, J., eds (2021) *MOTION Handbook: Developing a Transformative Theory of Change*. Brighton: Transformative Innovation Policy Consortium.

Barber, M. J. (2007) 'Modularity and Community Detection in Bipartite Networks', *Physical Review E*, 76: 066102.

Bellotti, E. (2015) *Qualitative Networks: Mixed Methods in Sociological Research*. New York: Routledge.

Boillat, S., Belmin, R., and Bottazzi, P. (2022) 'The Agroecological Transition in Senegal: Transnational Links and Uneven Empowerment', *Agriculture and Human Values*, 39: 281–300.

Borgatti, S. P. and Halgin, D. S. (2011) 'Analyzing Affiliation Networks', in J. Scott and P. J. Carrington (eds) *The Sage Handbook of Social Network Analysis*, pp. 417–33. London: Sage.

Borgatti, S. P., Mehra, A., Brass, D. J., et al. (2009) 'Network Analysis in the Social Sciences', *Science*, 323: 892–5.

Buskell, A., Enquist, M., and Jansson, F. (2019) 'A Systems Approach to Cultural Evolution', *Palgrave Communications*, 5: 1–15.

Dias, M. F. P. and Ramirez, M. (2021) 'Niche Evolution, External Circumstances, and Network Transformation: From Butiá Technical Niche to Butiá Socio-technical Niche', *Revista Brasileira de Inovação*, 19.

Diercks, G. (2017) 'Transformative Innovation Policy: Assessing Discourse Institutionalisation of an Emerging Policy Paradigm', in *Centre for Environmental Policy, Faculty of Natural Sciences*. London: Imperial College London.

Dormann, C. F., Fründ, J., Blüthgen, N., et al. (2009) 'Indices, Graphs and Null Models: Analyzing Bipartite Ecological Networks', *The Open Ecology Journal*, 2: 17–24.

Dormann, C. F. and Strauss, R. (2014) 'A Method for Detecting Modules in Quantitative Bipartite Networks', *Methods in Ecology and Evolution*, 5: 90–8.

EIT Climate-KIC (2018) *Transformation, in Time: EIT Climate-KIC Strategy 2019-2022*. Brussels: EIT Climate-KIC.

Ernstson, H. (2011) 'Transformative Collective Action: A Network Approach to Transformative Change in Ecosystem-based Management', in B. Örjan and P. Christina (eds) *Social Networks and Natural Resource Management: Uncovering the Social Fabric of Environmental Governance*, pp. 255–87. Cambridge University Press.

Freeman, L. C. (2004) *The Development of Social Network Analysis: A Study in the Sociology of Science*. Empirical Press.

Geels, F. W. (2002) 'Technological Transitions as Evolutionary Reconfiguration Processes: A Multi-level Perspective and a Case-Study', *Research Policy*, 31: 1257–74.

——— (2004) 'From Sectoral Systems of Innovation to Socio-technical Systems—Insights about Dynamics and Change from Sociology and Institutional Theory', *Research Policy*, 33: 897–920.

——— (2005) 'The Dynamics of Transitions in Socio-technical Systems: A Multi-level Analysis of the Transition Pathway from Horse-Drawn Carriages to Automobiles (1860–1930)', *Technology Analysis & Strategic Management*, 17: 445–76.

——— (2007) 'Feelings of Discontent and the Promise of Middle Range Theory for STS—Examples from Technology Dynamics', *Science, Technology & Human Values*, 32: 627–51.

——— (2010) 'Ontologies, Socio-technical Transitions (to Sustainability), and the Multi-level Perspective', *Research Policy*, 39: 495–510.

Geels, F. W. and Raven, R. (2006) 'Non-linearity and Expectations in Niche-Development Trajectories: Ups and Downs in Dutch Biogas Development (1973-2003)', *Technology Analysis and Strategic Management*, 18: 375–92.

Geels, F. W. and Schot, J. (2007) 'Typology of Sociotechnical Transition Pathways', *Research Policy*, 36: 399–417.

Ghosh, B., Kivimaa, P., Ramirez, M., et al. (2021) 'Transformative Outcomes: Assessing and Reorienting Experimentation with Transformative Innovation Policy', *Science & Public Policy*, 48: 739–56.

Giganti, P. and Falcone, P. M. (2021) 'Socio-technical Transitions and Innovation Niches: The Case of the Virtual and Augmented Reality in Europe', *Aims Energy*, 9: 755–74.

Giurca, A. (2020) 'Unpacking the Network Discourse: Actors and Storylines in Germany's Wood-based Bioeconomy', *Forest Policy and Economics*, 110: 101754.

Giurca, A. and Metz, T. (2018) 'A Social Network Analysis of Germany's Wood-based Bioeconomy: Social Capital and Shared Beliefs', *Environmental Innovation and Societal Transitions*, 26: 1–14.

Goyeneche, O. Y. R., Ramirez, M., Schot, J., et al. (2022) 'Mobilizing the Transformative Power of Research for Achieving the Sustainable Development Goals', *Research Policy*, 51: 104589.

Granovetter, G. (1973) 'The Strength of Weak Ties', *American Journal of Sociology*, 78: 1360–80.

——— (1985) 'Economic Action and Social Structure: The Problem of Embeddedness', *American Journal of Sociology*, 91: 481–510.

Guimera, R., Sales-Pardo, M., and Amaral, L. A. N. (2007) 'Module Identification in Bipartite and Directed Networks', *Physical Review E*, 76: 036102.

Harrison, D. A. and Klein, K. J. (2007) 'What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations', *Academy of Management Review*, 32: 1199–228.

Henrich, J. (2004) 'Cultural Group Selection, Coevolutionary Processes and Large-Scale Cooperation', *Journal of Economic Behavior & Organization*, 53: 3–35.

Hermans, F., van Apeldoorn, D., Stuiver, M., et al. (2013) 'Niches and Networks: Explaining Network Evolution through Niche Formation Processes', *Research Policy*, 42: 613–23.

Hill, D. (2022) *Designing Missions: Mission-Oriented Innovation in Sweden—A Practice Guide by Vinnova*. Stockholm: Vinnova.

Imbert, E., Ladu, L., Tani, A., et al. (2019) 'The Transition Towards a Bio-based Economy: A Comparative Study Based on Social Network Analysis', *Journal of Environmental Management*, 230: 255–65.

Kemp, R., Schot, J., and Hoogma, R. (1998) 'Regime Shifts to Sustainability through Processes of Niche Formation: The Approach of Strategic Niche Management', *Technology Analysis and Strategic Management*, 10: 175–95.

Köhler, J., Geels, F. W., Kern, F., et al. (2019) 'An Agenda for Sustainability Transitions Research: State of the Art and Future Directions', *Environmental Innovation and Societal Transitions*, 31: 1–32.

Lopolito, A., Morone, P., and Sisto, R. (2011) 'Innovation Niches and Socio-technical Transition: A Case Study of Bio-refinery Production', *Futures*, 43: 27–38.

McDowall, W. (2014) 'Exploring Possible Transition Pathways for Hydrogen Energy: A Hybrid Approach Using Socio-technical Scenarios and Energy System Modelling', *Futures*, 63: 1–14.

Meunier, D., Lambiotte, R., and Bullmore, E. T. (2010) 'Modular and Hierarchically Modular Organization of Brain Networks', *Frontiers in Neuroscience*, 4: 1–11.

Morone, P. and Lopolito, A. (2010) 'Socio-technical Transition Pathways and Social Networks: A Toolkit for Empirical Innovation Studies', *Economics Bulletin*, 30: 2720–31.

Newman, M. E. J. and Girvan, M. (2004) 'Finding and Evaluating Community Structure in Networks', *Physical Review E*, 69: 26113.

OECD (2015 [1963]) *Frascati Manual 2015*. Paris: OECD.

——— (2022) *Tackling Policy Challenges Through Public Sector Innovation*. OECD.

OECD and Eurostat (2019 [1992]) *Oslo Manual 2018*. Paris: OECD.

Pan, R. K. and Sinha, S. (2009a) 'Modular Networks with Hierarchical Organization: The Dynamical Implications of Complex Structure', *Pramana—Journal of Physics*, 71: 331–40.

——— (2009b) 'Modularity Produces Small-World Networks with Dynamical Time-Scale Separation', *EPL (Europhysics Letters)*, 85: 68006.

Piepenbrink, A. and Gaur, A. S. (2013) 'Methodological Advances in the Analysis of Bipartite Networks: An Illustration Using Board Interlocks in Indian Firms', *Organizational Research Methods*, 16: 474–96.

Pinheiro, R. B. P., Felix, G. M. F., Dormann, C. F., et al. (2019) 'A New Model Explaining the Origin of Different Topologies in Interaction Networks', *Ecology*, 100: e02796.

Rafols, I. and Meyer, M. (2010) 'Diversity and Network Coherence as Indicators of Interdisciplinarity: Case Studies in Bionanoscience', *Scientometrics*, 82: 263–87.

Ramirez, M., Estevez, J. H. G., Goyeneche, O. Y. R., et al. (2020) 'Fostering Place-based Coalitions between Social Movements and Science for Sustainable Urban Environments: A Case of Embedded Agency', *Environment and Planning C: Politics and Space*, 38: 1386–411.

Reinders, M. (2011) 'The Role of Social Networks: Mark Granovetter', in Vellema S (ed.) *Transformation and Sustainability in Agriculture*, pp. 49–56. Wageningen: Wageningen Academic.

Rudnick, J., Niles, M., Lubell, M., et al. (2019) 'A Comparative Analysis of Governance and Leadership in Agricultural Development Policy Networks', *World Development*, 117: 112–26.

Safarzynska, K., Frenken, K., and van den Bergh, J. (2012) 'Evolutionary Theorizing and Modeling of Sustainability Transitions', *Research Policy*, 41: 1011–24.

Schot, J. and Geels, F. W. (2008) 'Strategic Niche Management and Sustainable Innovation Journeys: Theory, Findings, Research Agenda, and Policy', *Technology Analysis & Strategic Management*, 20: 537–54.

Schot, J. and Steinmueller, W. E. (2018) 'Three Frames for Innovation Policy: R&D, Systems of Innovation and Transformative Change', *Research Policy*, 47: 1554–67.

Selomane, O., Reyers, B., Biggs, R., et al. (2019) 'Harnessing Insights from Social-ecological Systems Research for Monitoring Sustainable Development', *Sustainability*, 11: 1190.

Smaldino, P. E. (2014) 'The Cultural Evolution of Emergent Group-Level Traits', *Behavioral and Brain Sciences*, 37: 243–95.

Smith, A. (2007) 'Translating Sustainabilities between Green Niches and Socio-technical Regimes', *Technology Analysis & Strategic Management*, 19: 427–50.

Somerfield, P. J., Clarke, K. R., and Warwick, R. M. (2008) 'Simpson Index', in S. E. Jorgensen and B. D. Fath (eds) *Encyclopedia of Ecology*, pp. 3252–5. Oxford: Elsevier.

Sonntag, V. (2010) 'Designing Sustainability Indicator Frameworks for Information Flow: A Case Study of B-Sustainable', *Applied Research in Quality of Life*, 5: 325–39.

Sovacool, B. K., Hess, D. J., Amir, S., et al. (2020) 'Sociotechnical Agendas: Reviewing Future Directions for Energy and Climate Research', *Energy Research & Social Science*, 70: 101617.

Stirling, A. (2007) 'A General Framework for Analysing Diversity in Science, Technology and Society', *Journal of the Royal Society Interface*, 4: 707–19.

UNDP (2022) *System Change: A Guidebook for Adopting Portfolio Approaches*. Bangkok: UNDP.

Viotti, E. B. (2003) 'Fundamentos e evolução dos indicadores de CT&I', in E. B. Viotti and M. D. M. Macedo (eds) *Indicadores de ciência, tecnologia e inovação no Brasil*, pp. 41–87. Campinas: Editora da Unicamp.

Wen, B., van der Zouwen, M., Horlings, E., et al. (2015) 'Transitions in Urban Water Management and Patterns of International, Interdisciplinary and Intersectoral Collaboration in Urban Water Science', *Environmental Innovation and Societal Transitions*, 15: 123–39.

Zar, J. H. (2005) 'Spearman Rank Correlation'. In: Armitage, P. Colton, T. (eds.) *Encyclopedia of Biostatistics*.

Appendix 1 Detailed analytical strategy—methodological steps and rationale

The following steps were adopted in our analysis:

(1) The portfolio data set is a collection of programme-based projects undertaken by the EIT Climate-KIC within the scope of one of its strategic programmes. The EIT Climate-KIC anonymised this data set to protect partners' identities. However, from 2020 projects do not have information about the focus areas due to the readjustment of EIT Climate-KIC's programme structure. Besides this, EIT Climate-KIC's projects did not have a description of the activities and goals. The first step was to address these issues: the co-author affiliated with the EIT Climate-KIC did a significant job collecting descriptive information on all projects. Subsequently, we could standardise the focus areas from 2016 to 2020 using the project description, allowing us to identify food system projects.[8]

(2) Based on the thesaurus developed by Goyeneche et al. (2022) for studying the SDG, the second step was to generate a vocabulary[9] with ninety-four terms to identify projects related to food system (roughly corresponding to SDG 2). Subsequently, we used these terms to search in the title and description of the EIT Climate-KIC portfolio. We identified 221 projects[10] and 178 partners between 2016 and 2020.
(3) In the third step, TWs were defined according to the EIT Climate-KIC investment strategy and programme logic. Multiple simultaneous R&I programmes provide conditions and resources for selected projects to operate for 1–3 years, depending on the type and maturity of the targeted innovation addressed in the project. To capture the portfolio's temporal dynamics, we use 2-year TWs. Following the EIT Climate-KIC strategic logic, time frames of individual projects within programmes may overlap, which allows us to study transformation in a smooth manner rather than in a discrete way.
(4) Subsequently (Step 4), for each TW, we plotted two-mode (or bipartite) networks, which are networks composed of two different elements (nodes in the network): in our case, projects and partners. The ties between them are the co-occurrence of a partner in a project. While methodologically, two-mode networks may lead to higher modularity, this effect would impact every TW so that changes in modularity between periods would still be significant for the analysis. Therefore, we use two-mode networks to represent better the governance behind the EIT Climate-KIC portfolio, which is based on a social coalition of partners framed by several R&I programmes.
(5) We then calculated the following metrics for each network: *modularity* (the strength of division of a network into node clusters or modules), *connectance* (the proportion of existing connections concerning all possible connections for that network, which is a measure of resilience), and *degree centrality* (the average number of links of each node) and *betweenness centrality* (the average shortest distance between the two nodes). These metrics bring detail to network structures and therefore allow us to identify if these networks are brokered, broad, linear, or modular. We justify the choice of indicators below and bring further information about their operationalisation for two-mode networks in Appendix 2.1.
(6) Then, in Step 6, we calculate Simpson's (or Herfindahl–Hirschman's) diversity index (1D): the probability that two nodes taken at random from the network represents the same type—in our case, the same thematic area and the same type of partner. To identify diversification, we calculate this diversity indicator for the whole network and within each group of partners and projects (modules).
(7) The seventh step was to study the effects of the EIT Climate-KIC investment portfolio on network development (*connectivity* and *intermediation*), employing a non-linear correlation analysis. To complement this step, we develop an indicator of the frequency of interactions due to common investment between EIT Climate-KIC projects and partners. This indicator permits us to identify if partners play a more active role investing in Climate-KIC projects and influencing the network's connectivity.
(8) Finally, in Step 8, we study the co-occurrence of partners in projects between 2016 and 2020. We evaluate whether partners interacting in many projects have more opportunities to arrive at late stages of niche development. We use a non-parametric test to evaluate the connectivity difference between actors arriving at mature network stages. This strategy permits the study of the consolidation of niches.

Altogether, these metrics from Steps 4 and 6 allow testing the propositions stated in Section 4.2: we compare the empirical indicators of the networks and diversity with the conceptual definition of networks to identify the phase of niche development.

We further explain the rationale behind these steps. We divided the 221 projects related to the food system and 178 partners working on these projects into four TWs—2016–7; 2017–8; 2018–9, and 2019–20—to identify the evolution of portfolio networks. We studied the structure of each network by considering the EIT Climate-KIC programme–based investment infrastructure as a directed (towards the programme's transformative goals) safe space enabling relational events between partners and projects. Relational events are short-term interactions (Freeman 2004; Borgatti et al. 2009; Bellotti 2015); therefore, we consider the occurrence of a partner in a project as an event. While we cannot identify empirically strong ties (such as friendship, trust, or shared vision links) that amount to long-term interactions (Granovetter 1973, 1985), we assume that within cohesive networks, it is more likely that partners will adhere to the common programme goal and vision (Henrich 2004; Safarzynska et al. 2012). Moreover, SNA studies have shown that social actors build up common understanding within cohesive groups and create strong relationships over time (Reinders 2011; Hermans et al. 2013; Giganti and Falcone 2021).[11]

We use two-mode or bipartite networks to represent the structure of the EIT Climate-KIC programme–based portfolio. On the one hand, EIT Climate KIC projects represent spaces for social interactions, knowledge cocreation, and the incubation of innovations (Fig. 1). These projects are distributed according to the different programmes in thematic areas and are part of the EIT Climate KIC strategy to foster innovation that facilitates transformative change (sustainability transitions to mitigate climate change). This orchestration is implemented by EIT Climate-KIC's directors, managers, and officers overseeing and implementing its programmes. On the other hand, partners are allies to make successful the ambition of facilitating transformations. These actors have their agency and are facilitators of knowledge circulations across projects and programmes of the EIT Climate-KIC. Overall, bipartite networks are helpful to represent the membership of a set of social actors in social spaces such as projects, affiliations, or participation in any social activity (Piepenbrink and Gaur 2013).

The selection of two-mode networks is not a minor one as it implies considering a specific type of network indicators. Traditional indicators for one-mode networks can overweight network metrics in two-mode networks, for example, centralisation or modularity. It has been shown that the asymmetry of the network can affect network metrics (Dormann et al. 2009). As the ratio between partners and projects increases, it is more likely to have higher values of modularity or centralisation.

To deal with such methodological challenges, researchers in ecological and complex networks have developed a corrected version of these indicators to avoid bias (Dormann et al. 2009; Dormann and Strauss 2014). These indicators are usually used to analyse the co-evolution of ecological species interacting, for example pollination, herbivory, or predation (Dormann and Strauss 2014). These networks have high asymmetry. For instance, few pollinators interact with a substantial number of plants. As in our case, ecologists cannot avoid analysing two-mode networks, as these networks better represent the nature of the systems studied, be they project partners or plant pollinators.

A possible solution to avoid biased results is to consider the asymmetry of the network in each TW and identify to what extent it affects the metric evaluated using null models (Dormann et al. 2009). In our case, the asymmetry of the networks slightly varies across the first three TWs evaluated (see Appendix 2.1). In other words, these networks are almost symmetric. Nevertheless, the last time is slightly more asymmetry than the other three (see Appendix 2.1). However, modularity slightly decreases (–0.050), and degree centralisation barely increases (+0.009) compared with TW 3, as we will show in our results in the following section. Therefore, we argue that the asymmetry of the networks is not significantly biasing our analysis of network structure over time.

However, we acknowledge that network asymmetry could be challenging to replicate our method in other portfolios as they may have higher asymmetries. Therefore, we selected indicators that are not profoundly affected by the asymmetry of the network. Specifically, we calculate the following two-mode network metrics to identify the architecture of each network: *degree, betweenness centralisation*, and *connectance*.

We estimate the *degree* and *betweenness centralisation* to identify brokered structures (Guimera et al. 2007; Rafols and Meyer 2010). Centrality measures near 1 indicate a concentration of interaction and flow of information. As a proxy of broad networks, we use a measure for bipartite networks called *connectance* (C) (Dormann et al. 2009; Pinheiro et al. 2019). This measure indicates the number of projects shared across partners and vice versa (the number of partners shared across projects). When *connectance* (C) equals 1, all projects are connected to all partners. To identify modular structures, we use the Girvan–Newman modularity (M) for bipartite networks (two-mode networks) (Newman and Girvan 2004). This metric indicates the perfect modular structures when values equal 1. This measure also lets us identify the number of modules in each network.

We study the diversity of projects and partners' attributes as a complementary strategy. We use as attributes for projects EIT Climate-KIC's programme architecture, including five thematic areas, geographical programmes,[12] and thirteen innovation subprograms, and for the partners, twenty-six countries and five types of organisations.[13] We then calculated Simpson's (1D)[14] diversity to measure the dominance of each of these attributes in the network (Harrison and Klein 2007; Stirling 2007; Somerfield et al. 2008). For instance, we found that Sustainable Land Use was a dominant thematic area over the first TW (2016–7); meanwhile, we did not find disparity in the organisations' countries in the same TW. Therefore, note that Simpson's indicator does not provide information about the variety of attributes; this metric details the distribution and frequency *between* attributes (Harrison and Klein 2007). While used as a complementary strategy, such analysis is also central to explaining how the programme logic and investment architecture underlying the project portfolio relate to the funding agency's transformative goals and niche-building process.

We use all these metrics to characterise the four phases in Section 2. Table 3 details the expected level of the metrics values according to every phase proposed. In theory, we expect brokered or broad networks in the early stages. In other words, we expect high values of degree and betweenness centrality (brokered networks) or, conversely, high values of connectance (C) (broad networks). We also expect high values of Simpson's indicator (1D) during the diversification phase and an increased network diameter[15] during the replication phase. Finally, we expect modular structures with steady values of diversity in the mature stages of the portfolio's network development.

Moreover, we study the possible effect of the investment portfolio strategy on generating connectivity and intermediation in network development. To do so, we calculate Spearman's rank correlation (R_s) between nodal network metrics—degree and betweenness centrality, and projects' and partners' investment (Zar 2005). We also calculate the frequency of the interactions between projects and partners due to the investment of each of these nodes. In other words, we study how the investment of partners and projects influences their interactions. In so doing, we develop a straightforward visual indicator to study the proportion of EIT Climate-KIC's programme-based investment and partners' investment in every interaction in the network (or *dyads*). Values near 1 indicate that the EIT Climate-KIC accounts for 100 per cent of the investment in that project; meanwhile, –1 indicates that a single partner is providing 100 per cent of the funding for that project. This visual indicator can be translated into an index that permits us to estimate the transformation of the investment portfolio strategy and its influence on the network quality in the four TWs.

Finally, to have a proxy of the effect of long-term partner interactions in the niche network development (Safarzynska et al. 2012; Wen et al. 2015), we analyse whether actors who remained in the last TW were more extensively interacting than actors who did not remain in the last TW. To this end, we use the nodal degree centrality (the number of interactions of each actor) as a proxy. We plot networks where the dots are partners and the ties are projects. In other words, two partners are connected due to their shared participation in one of EIT Climate-KIC's projects. We undertake the non-parametric Mann–Whitney *U* test to analyse whether the remaining actors in the last TW had a statistically significant higher nodal degree than in the previous TWs than nodes that disappeared.

Appendix 2 Metrics description and detailed results

Appendix 2.1 Network metrics of every four TWs studied

We report all statistics, metrics, and indices in the main text (Table 4). We present a list of indicators from the literature on complex networks and specifically from the literature associated with bipartite networks. This section shows the essential metrics used in our study.

Definition of the networks

L = number of realised links

Indices based on unweighted links (qualitative networks)

Connectance (C)—*the realised proportion of possible links* is given as follows:

$$C = L/ij$$

Network asymmetry (w)—the ratio between the number of projects and partners is given as follows:

$$w = \frac{i-j}{i+j}$$

The positive values indicate more partners, and the negative values indicate more projects. Rescaled to [−1,1]

Diameter (S)—it is given as follows:

$$S = \max\{s(i,j)\}$$

where) $s(i,j$ is the number of edges in the shortest path from vertex i to vertex j.

Modularity (Q)—two-mode or bipartite networks are characterised by not having vertices of the same type connected. Therefore, the connectance of intracommunity (modules) edges has to be redefined for bipartite networks. To specify Point 4 mentioned earlier, Barber (2007) has defined modularity for bipartite networks as follows:

$$Q = \frac{1}{2m}\sum_{ij}(A_{ij} - P_{ij})\,S(c_i, c_j)$$

where m represents half the total number of observed links in the network, and A_{ij} is the network matrix. The expected value for each link is given in the matrix P_{ij} based on an appropriate null model. For more detail, see Dormann and Strauss (2014).

Degree centrality—the degree and betweenness centrality for a bipartite network is calculated following the standard equation for a one-mode network. Nonetheless, the normalisation for a bipartite network is slightly different. A one-mode network uses the maximum degree possible. In other words, it

Attributes	Simpson (1D)	TW 1	TW 2	TW 3	TW 4
Project thematic	Network	0.5122	0.6808	0.6872	0.7011
	Modules (mean)	0.228016667	0.570283333	0.607433333	0.54607
	Modules (SD)	0.712497137	0.113427364	0.098406054	0.215639669
Project programme	Network	0.6301	0.826	0.8384	0.8388
	Modules (mean)	0.5257125	0.715616667	0.716972727	0.690511111
	Modules (SD)	0.124546026	0.077598311	0.080661429	0.116085749
Partner country	Network	0.8758	0.8914	0.8867	0.8814
	Modules (mean)	0.60521	0.668758333	0.67715	0.71135
	Modules (SD)	0.12808606	0.128406396	0.112099497	0.114296858
Partner type	Network	0.7725	0.7724	0.7851	0.7891
	Modules (mean)	0.454308333	0.599658333	0.686341667	0.66978
	Modules (SD)	0.23888471	0.212439421	0.075602188	0.093342378

TW investment niche architecture network	R_s project Climate-KIC invest vs. normalised degree	P-value	R_s partner co-fund vs. normalised degree	P-value
TW1	0.52685***	0.00016893	0.3324	0.012316
TW2	0.50527***	1.30E-07	0.47518***	9.98E-07
TW3	0.61151***	1.01E-12	0.55886***	7.05E-11
TW4	0.74166***	1.81E-14	0.64611***	2.25E-13

Note: We indicate the significance with ** when $P \leq 0.001$, and when ***$P \leq 0.001$.

TW investment niche architecture network	R_s project Climate-KIC invest vs. normalised betweenness	P-value	R_s partner co-fund vs. normalised betweenness	P-value
TW1	0.19122	0.060948	0.29001	0.030147
TW2	0.2909**	0.0038444	0.40665***	3.93E-05
TW3	0.40006***	1.36E-05	0.31377***	0.000604
TW4	0.47855***	1.23E-05	0.34225***	0.00043

Note: We indicate the significance with ** when $P \leq 0.001$, and when ***$P \leq 0.001$.

is the maximum number of nodes minus 1 ($n - 1$). A bipartite network's maximum degree depends on the maximum number of nodes on each side of the bipartite network (Borgatti and Halgin 2011).

Betweenness centrality—the betweenness centrality is the sum of the fraction of all-pairs shortest paths that pass through a node. The maximum possible value normalises the betweenness values, and in the case of bipartite networks, it is limited by the relative size of the two-node sets (Borgatti and Halgin 2011).

Appendix 2.2 Simpson dominance (disparity) indicator

Simpson's dominance was measured using Simpson's index (1D) in the four TWs with four attributes of the nodes: thematic areas, EIT Climate-KIC's programmes, partner country, and the type of organisation. This indicator was calculated for the whole network and each module. We report the mean of Simpson's index as a proxy of attribute dominance in the modules.

Appendix 2.3 Spearman's rank correlation (R_s)

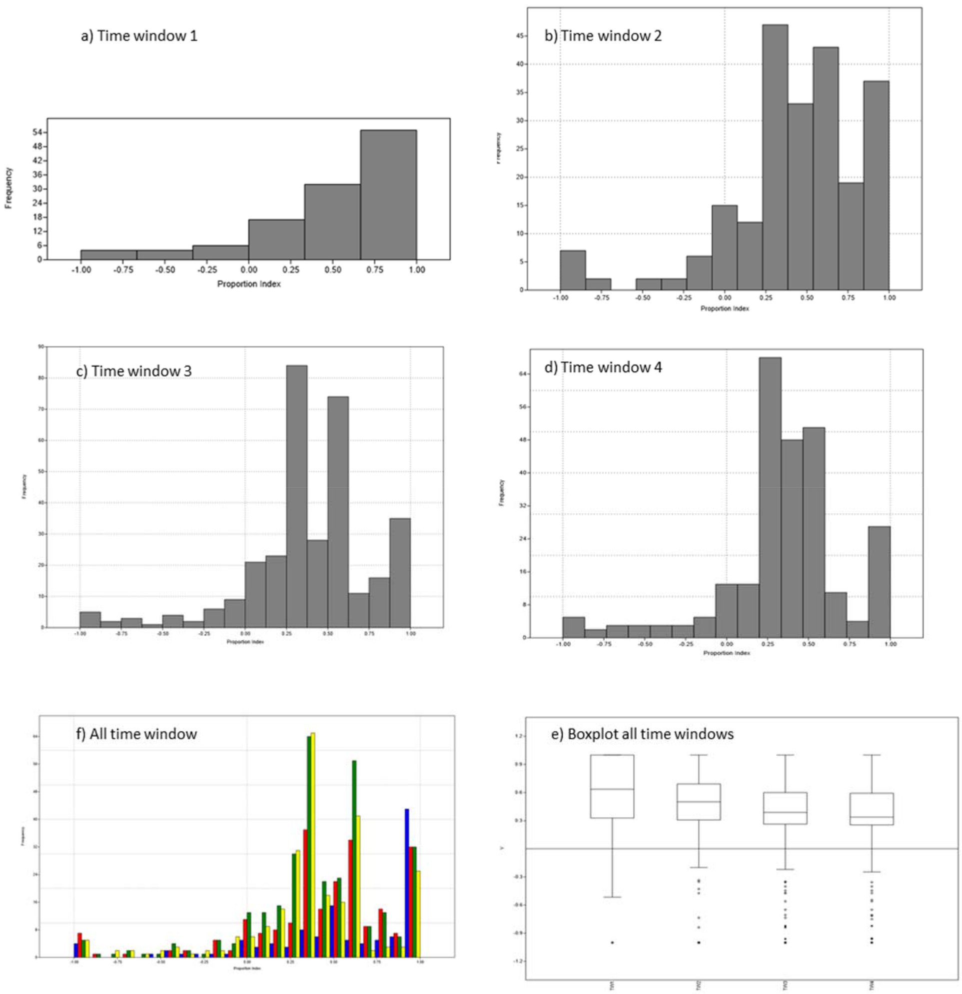
(1) EIT Climate-KIC's investment and network connectivity (degree/betweenness). (2) Partners investment and their connectivity (degree/betweenness). We consider a significant positive correlation with $^{**}P = 0.025$ or $^{***}P = 0.001$. The R_s values from 0.00 to 0.19 indicate a very weak correlation, while those from 0.7 to 1.00 indicate a strong correlation.

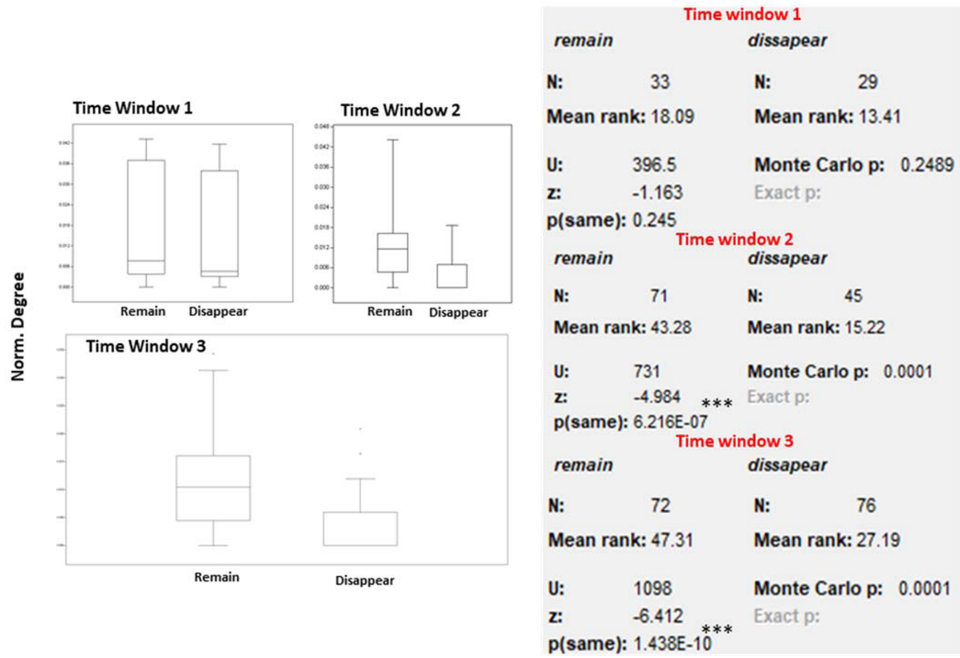
Appendix 2.4 Frequency of more common interactions (dyads) between EIT Climate-KIC projects and partners due to their investment on projects

The x-axes show the proportion index.

$$P_i = \frac{EITClimate\,KIC investment - partner\,investment}{EITClimate\,KIC investment + partner\,investment}$$

P_i indicates the proportion of investment between a partner and a project. To characterise this interaction, we use the investment done by the EIT Climate-KIC in that project and the co-funding of the partner. Subsequently, we calculate the frequency of each P_i value. We independently show the distribution of the P_i values in each TW (a–d). We also show the distribution of P_i, including all TWs (f). The blue colour bars correspond to the first TW. The red bars indicate the second TW, the green bars represent the third TW, and the yellow bars show the fourth TW. Finally, we show the boxplot of each TW to illustrate changes in the evolution of the network.





Appendix 2.5 Mann–Whitney *U* test analysis

We compare the nodal degree of actors that remain in the last TWs and those that disappear using a Mann–Whitney *U* test analysis. This non-parametric analysis compares the nodal degree distribution for partners that disappear and remain in the network. We consider a significant difference between the nodal degree of the remainder and non-remainder actors with $^{**}P = 0.025$ or $^{***}P = 0.001$.