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When does discursive change happen? Detecting phase transitions in discourse networks of sustainability transitions

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ABSTRACT

Sustainability Transitions Research (STR) confronts complex societal challenges by examining societal shifts and their trajectories. An emerging perspective in STR is discursive approaches, which analyse the role of discourses and discourse coalitions in shaping sustainability transitions. However, discursive approaches face challenges regarding the analysis of sustainability transition processes as complex, temporal processes of stability and change. We discuss the nature of these challenges and extend the method of discourse network analysis (DNA) by measuring distinct temporal states (phases of stability) in discourse networks and detecting phase transitions (significant changes) between these discursive states. Whereas most approaches analyse discursive changes in a top-down way, we introduce a method for the bottom-up detection of discursive stability and change. This facilitates a more accurate tracing of how sustainability transitions unfold over time. An empirical application of this extension to the discursive networks around the introduction of a Low Emission Zone demonstrates how and when discourses and actors display significant structural shifts. This methodological innovation addresses the need for measuring stability and change in the complex, discursive, temporal dynamics of sustainability transitions.

1. Introduction

Societal challenges posed by socio-environmental changes have prompted an increasing number of scholars to study sustainability transitions (STs) [1]. To advance the analysis of systemic change and its trajectories, scholars have recommended theoretical and analytical innovations as well as refinements and reflections on methodological approaches [2–4]. This paper responds to these calls in two ways: firstly, by identifying key challenges in the current practice of discourse analysis related to sustainability transitions; and secondly, by formulating a novel method combining discourse network analysis (DNA) with sequence detection in temporal networks, aiming to identify stability and change in sustainability transition processes.

Discursive approaches are an emerging analytical framework in Sustainability Transitions Research (STR), enabling researchers to investigate the role of discourses and discourse coalitions in shaping sustainability transitions [5–7]. These approaches, however, encounter difficulties in analysing sustainability transitions as complex, temporally evolving processes [1,8–10]. As Rosenbloom et al. [11] explain, one of “the opportunities for greater discourse–transition integration […] is to explore the temporal aspects of these dynamics” (p. 1286). We discuss three difficulties in the application of discursive approaches to STR, namely, to treat discourses, coalitions, and transitions as (1) relational, (2) temporal, and (3) dynamic phenomena in Sections 2.1 and 2.2.

To address these challenges, we build on the discourse network analysis approach. DNA connects actors and the discursive elements they sponsor in a network that can change over time. Analysing change in the structure of the resulting graphs can be a useful way to understand the temporal dynamics of transition discourses. In Sections 2.3 and 2.4, we review recent work in STR to demonstrate how recent applications of DNA have addressed the challenges faced by discursive approaches.

However, DNA requires an exploratory research process during which the researcher tries to pinpoint qualitative changes in the discourse network over time. While discursive approaches (including DNA) are successful at documenting the *content* of discursive change, they struggle to identify *when* discursive change happens. While

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Simoens et al. [7] recognise that "discursive studies can enhance the understanding of why a system is configured as it is as well as how and why a system has or has not changed over time" (p. 1849), for example by asking "how can discursive fields that are developed, tested, and modified in the context of a niche be extended over a wider societal context?" [12], the temporality implied in these questions tends to be neglected. Thus, the approach needs to be extended in significant ways to identify the specific timing of discursive stability and change. We propose a novel method that builds on DNA and detects phase transitions between distinct discursive states in sustainability transition processes. In contrast to traditional discursive approaches, this new method detects periods of relative discursive stability ("states") and moments of discursive change ("phase transitions") empirically and from the bottom up. Instead of having researchers impose these moments onto the data to structure and analyse them, our bottom-up method accurately identifies such moments from the data. With this methodological innovation, we aim to improve discursive approaches so they can identify when exactly discursive change takes place and advance the study of the temporal dimensions of STs [6,9,13,14]. The new method is described in Section 3.1, and the code for employing the method is given in the appendix.

We empirically demonstrate the detection of states and phase transitions by applying it to three examples in a case study on the Low Emission Zone in the city of Ghent in Section 4.

While advancing STR from a methodological perspective, this paper also provides theoretical insights, which we discuss in Section 5. In particular, it challenges the attribution of discursive change to exogenous events and instead facilitates a research agenda that explores the role of endogenous discursive dynamics for change [12,15,16]. While events such as the Fukushima disaster have been documented as drivers of discursive change, endogenous dynamics such as discursive learning are typically more difficult to document, yet improve our understanding of the role of agency in sustainability transitions [12,17]. As the new method can be adapted to different notions of discourse, levels of analysis, types of regimes, and theoretical frameworks, this paper will speak to scholars working on STs and scholars with an interest in the analysis and governance of innovations.

2. Theory

2.1. Discursive approaches to sustainability transitions

Sustainability transitions research emerged as a response to persistent societal challenges brought about by deepening environmental changes [1,18]. A distinguishing feature of this field is the examination of such challenges at the level of "systems", focusing on domains such as food and mobility systems, which are defined by prevailing configurations known as "regimes" [1]. Regimes embody the established order or status quo; they shape society and govern its functioning [19]. Consequently, sustainability transitions are conceptualised as radical shifts from one dominant regime to another [1,20]. Over time, the understanding of regimes within STR has expanded, transitioning from a narrow focus on "technological regimes" to encompass practices and institutions within "socio-technical regimes", and ultimately progressing towards more intricate and comprehensive "societal regimes" [20]. Presently, sustainability transitions are conceptualised as co-evolutionary and mutually reinforcing changes occurring across various domains, including technological, economic, institutional, and socio-cultural spheres, aiming at creating more sustainable societies [20–22].

Discursive approaches address the socio-cultural, discursive dimension of systems, analysing regimes by examining the particular discourses and discourse coalitions that define them. Given that sustainability transitions involve radical shifts from one dominant regime to another, discursive approaches focus on shifting discourses and their coalitions [7,17,23,24]. Shifting discourses might act as entry points for governing transitions, innovations and other types of regime-level changes, such as policy changes [25,26], and are a driving force behind dynamics of regime destabilisation and change [7,16,17]. Discursive shifts might encompass changes in the composition of discourses (storylines), of discourse coalitions (actors), or changes in the relative position of discourses (dominance) [25,27].

Firstly, discursive shifts occur when actors adopt different storylines, which are concise statements that summarise and simplify complex narratives serving discourses [23]. Discourses refer to "shared way[s] of apprehending the world" [28] through which "meaning is given to physical and social realities" [29] at various levels, e.g., the environment [28] or food systems [30]. Discourses are not purely descriptive or neutral; they create meaning, define common sense and demarcate what can be thought or not.

Secondly, discursive shifts occur when changes take place in the loosely organised groups of actors who share a similar interpretation of reality, referred to as discourse coalitions [23].

Thirdly, discursive shifts occur when there are changes in the relative position of discourses or discourse coalitions. Each regime is characterised by a limited number of discourses and coalitions, with one discourse or coalition often dominating the others. This dominant discourse or coalition holds significant power, shaping problem definitions, proposing specific solutions, and materialising into a regime's institutions. Discursive dominance or hegemony, however, is not permanent. Discourses require continuous discursive reproduction to maintain their meaning structures [23]. To ensure their dominance and consolidate their views of reality, discourses and their actors engage in ongoing, complex and strenuous struggles against alternative discourses or coalitions that seek to introduce new cognitions and perspectives [23].

STR traditionally conceptualises change as the result from a combination of external shocks (landscape-level), internal tensions (regime-level), and radical bottom-up alternatives (niche-level) [31]. With regard to the discursive dimension, accordingly, change results from a combination of exogenous pressures such as nuclear disasters (landscape-level) and new discourses (niche-level) and endogenous pressures, such as tensions within the dominant discourse(s) (regime-level). Simoens et al. [7] conceptualise discursive shifts that are triggered by exogenous events as "disruptive discursive change" and those triggered by endogenous dynamics as "dynamic discursive change". While change in other dimensions of regimes, such as institutional logics [32], have been scrutinised for both their endogenous and exogenous triggers, discursive shifts tend to be mainly explained by exogenous triggers [5]. For instance, Wiertz et al. [33] linked discursive change in the German energy transition to the war in Ukraine.

Discursive approaches to sustainability transitions focus on discursive shifts as destabilising forces for unsustainable regimes and stabilising forces for more sustainable regimes [6,25]. Discursive shifts are a prerequisite for any transition to unfold; however, they do not necessarily guarantee a transition [6,7,17,23,24]. Therefore, the analysis of these shifts can uncover the dynamics underlying sustainability transition processes rather than predict them. Most discursive studies on sustainability transitions analyse either regime stability maintained by an incumbent discourse coalition (as opposed to change), or assess discursive shifts in momentary (as opposed to longitudinal) and independent (as opposed to relational) ways. A full integration of the relational, temporal and dynamic dimension of sustainability transitions into discursive analyses constitutes a major challenge, and is discussed in the following section.

2.2. Challenges faced by discursive approaches to sustainability transitions

Discursive approaches have the potential to contribute significantly to the field of STR, yet face some challenges in comprehensively analysing sustainability transitions as complex, temporal processes of change. We identify the nature of these challenges as relating to three essential aspects of sustainability transition processes: their relational, temporal, and dynamic dimension [1].

A first challenge for discursive approaches is treating discourses, coalitions and transitions as relational phenomena. In reality, discourses and coalitions continuously challenge, reinforce and influence each other [23,28], and the interaction, interdependence, and co-occurrence of elements is what defines sustainability transitions as co-evolutionary, complex processes [1,24]. However, discursive approaches tend to neglect the dynamics of interaction and co-evolution between and within discourses and coalitions. In other words, they tend to concentrate on either discourses or discourse coalitions, focus on single discourses and coalitions without exploring their relationship to other discourses or coalitions, as well as overlook how they are shaped by the interplay of storylines and actors (e.g., [34]).

A second challenge for discursive approaches is engaging with discourses, coalitions and transitions as temporal phenomena. Discourses are historically contingent [23,28], and sustainability transitions are processes where timing and temporal dynamics play a critical role [1,9,31]. Since most discursive approaches rely on qualitative techniques, they are inclined to describe dominant discourses and emerging coalitions within a limited and specific time frame (e.g., [35]). In other words, they are tempted to provide snapshots rather than longitudinal analyses of discourses and coalitions, or, in turn, compromise on precision and accuracy.

A third challenge for discursive approaches is engaging with discourses, coalitions and transitions as dynamic phenomena. The role of discursive shifts in unfolding transitions as well as the influence of discursive lock-ins on impeding transitions is well documented [7]. Sustainability transitions researchers aim to comprehend the dialectic relationship between stability and change [1]. Nevertheless, while discursive studies describe the persistence of discourses and coalitions, they tend to neglect the identification of discontinuities in discourses and coalitions, particularly in empirical and longitudinal studies (e.g., [34,36]). In other words, discursive approaches seem to well document the stabilisation of unsustainable regimes but to less often document occasions of discursive regime destabilisation.

Discursive approaches face these three challenges in analysing sustainability transitions as complex, temporal processes of change. In the next section, we discuss how the method of discourse network analysis has been used to overcome these challenges in recent research.

2.3. *Discourse network analysis of sustainability transitions*

Discourse network analysis (DNA) is a mixed-methods approach that combines qualitative content analysis of discourse with quantitative social network analysis [37]. This method enables the visual and statistical analysis of discourses and their coalitions while preserving the interpretive value of discourse analysis. The method has been applied within various theoretical frameworks, including argumentative discourse analysis (e.g., [38]) and the Advocacy Coalitions Framework (e.g., [39]).[1] The process of discourse network analysis begins with the collection of textual data, which may consist of newspapers, parliamentary testimonies, or other materials representing sites of discursive (re)production depending on the discursive arena of interest. These data are then coded using the open-source software Discourse Network Analyzer (https://github.com/leifeld/dna, accessed 30 December 2024). The basic unit of analysis is an actor's contribution to the discursive space, known as "statement". Each statement is coded on four variables: the actor's name, the concept representing the argument, a binary or integer qualifier indicating support or rejection of the concept, and a timestamp. While this paper relies on this four-tiered coding scheme, DNA is flexible in terms of coding frameworks, e.g., a statement may be coded on more than four variables. For example, it is possible to code for different characters like heroes, villains, or victims as in the Narrative Policy Framework and treat them as nodes [40] or add qualifier variables like location or industry sector instead of agreement to further restrict how actor nodes are connected through shared concepts. Once the data have been fully coded, they are exported as networks using the same software. The exported networks are then analysed using computational and network visualisation programs such as R or visone [41].

Discourse network analysis proves valuable to the field of sustainability transitions research as it enhances discursive approaches by addressing the relational, temporal, and dynamic dimensions of sustainability transitions. Because change is understood as involving power struggles between different discourses and actors [23], it fosters our understanding of power and agency in sustainability transitions [5]. Typically, sustainability transitions are said to develop when a powerful incumbent discourse and coalition is destabilised [7,23]. DNA's explicit measurement approach to discourses, discourse coalitions, and their temporal changes allows for more effective operationalisation of discursive shifts and regime changes [38]. For example, the stronger the centrality of actors in a discursive network, the more powerful they are. When niche actors become central, change becomes more likely. When regime actors remain central, change continues to be unlikely. The more polarised a discursive network is through the presence of multiple discourses/coalitions, the more the discursive power of incumbent actors and discourses is challenged and the greater is the potential for change [7]. We demonstrate each of these advantages through existing applications of discourse network analysis to the field of STR.

Firstly, discourse network analysis incorporates a *relational* dimension by explicitly conceptualising discourses and discourse coalitions as networks [37,39]. Building on the universe of coded statements that constitute the discursive space, *discourses* are then operationalised as the *networks of concepts* (i.e., arguments or storylines) which are linked to each other whenever they are used by the same actor. For example, in the concept network of Fig. 1, Concepts 10 and 11 are linked because they are co-used by Actors 3 and 4. *Discourse coalitions*, in turn, are measured as *networks of actors* who are linked to each other whenever they co-support or co-reject the same argument. For example, in the actor network of Fig. 1, Actors 3 and 4 are linked because they both use Concepts 10 and 11. Conversely, Actors 4 and 5 are not connected in the actor network because their evaluation of Concept 17 in the affiliation network differs on the agreement qualifier variable.

Discourses and coalitions can be analysed separately or in a combined way as illustrated in Fig. 1. For instance, studies on the pharmaceutical system in Germany [42] and the energy system in the Czech Republic [43] demonstrate how a single, powerful discourse (coalition), characterised by high levels of similarity in the storylines adopted by various actors, hinder a transition away from unsustainable regimes. Rennkamp et al. [44] shed light on the unfolding of renewable energy transitions in Mexico, South Africa and Thailand by revealing the set of actors and storylines that constitute the dominant discursive coalitions.

Discourse network analysis allows for the analysis of the relations through which discourses and discourse coalitions, respectively, are internally constituted, but also the analysis of the relations through which discursive networks are formed by connecting different coalitions or discourses. In other words, it integrates a relational dimension on two levels: the node level (relations between concepts or between actors), and the subgroup level (relations between discourses or discourse coalitions). Rather than analysing the storylines that compose a specific discourse, the discourses that form a specific discursive network are examined.

[1] It is important to note that different theoretical frameworks conceptualise discourse coalitions differently. Here, we adopt Hajer's [23] understanding of a coalition as a group of actors who share and construct similar storylines but who haven't necessarily met nor coordinated. This understanding is different, for example, from the one advanced by the Advocacy Coalition Framework, which emphasises coordination and the immutability of actors' deep core beliefs.

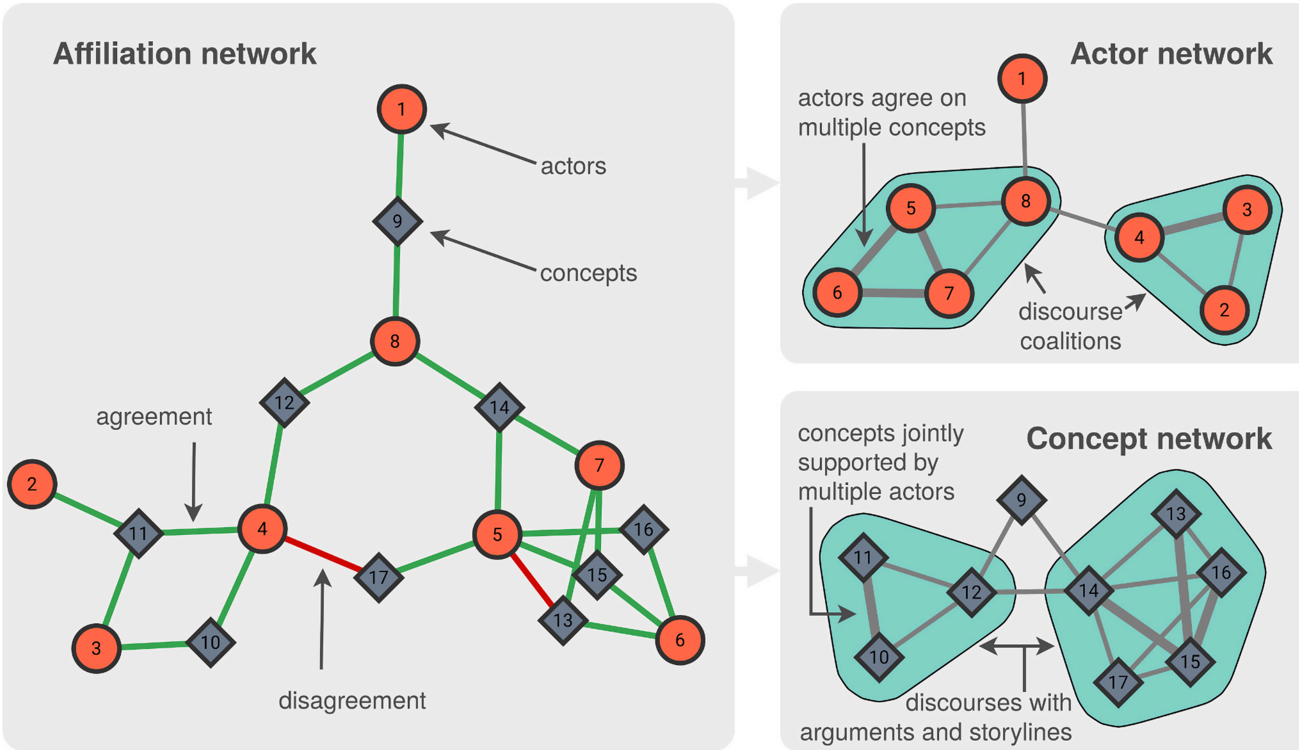

Fig. 1. Discourses and coalitions in discourse network analysis.

A discursive network, whether at the actor or concept level, is characterised by a particular structure, which is shaped by the relations between discourses or discourse coalitions. It may exhibit no clear coalition structure (a "core–periphery structure", (e.g., [42])) or be polarised into distinct coalitions ("modular"), such as observed by Duygan et al. [45] in the Swiss waste management regime. When a system is dominated by a single coalition or core–periphery structure, contestation is weak. This is because dissenting voices are absent, as manifested in the absence of other coalitions, or because dissenting voices do not have sufficient power, as manifested in their peripheral position. Contestation is unlikely to emerge from powerful, incumbent regime actors. Hence, transitions are unlikely in such a constellation. Several features of discursive networks and coalitions can be assessed, such as the polarisation or competition between discursive coalitions by computing between-bloc weighted densities and conflict networks [38].

The importance of integrating a relational dimension into the analysis of discourse, discourse coalitions, and discourse networks is evident in several studies on energy transitions. By analysing the incumbent and emerging discourse coalitions as well as the relations between them, scholars gained insights into energy transition pathways and processes in Germany, Europe, France, and India, respectively [46–50]. Through the comparison of discursive networks, researchers have explored the role of discursive variables in the differentiated unfolding of sustainability transitions. For instance, Brugger and Henry [51] demonstrated how differences in discursive networks between rural and urban areas coincided with varying levels of "success" in local energy transitions. Rinscheid [52] highlighted the differential impacts of the Fukushima incident on discursive networks and transition pathways in Germany and Japan. Nagel and Bravo-Laguna [53], through the comparison of discursive networks on air pollution, emphasised the importance of aligning discourses across governance levels for successful transitions. Lastly, Schneider and Rinscheid [54] compared discursive networks to explain the difference in wind energy deployment between Austria and Switzerland through the lens of (de)legitimation processes.

Secondly, discourse network analysis incorporates a *temporal* dimension by examining the evolution of discourses and coalitions over multiple time intervals within the time frame of the data. By comparing these different discursive networks, it becomes possible to identify periods of discursive stability as well as moments of discursive change. One can choose to compute distinct discursive networks either manually by selecting specific time periods or by utilising the software to compute networks for a set interval, such as every *x* number of days, months, years, or statement events. For instance, Markard et al. [55] investigated the German energy transition, and Schaub [56] analysed the German agricultural transition, by computing discursive networks for different temporal phases in the political debate. Markard et al. [55] demonstrated how a pro-coal coalition shifted its stance over time. Initially, it opposed action outright. Later, it demanded more time and money for a careful phase-out, justifying slow and inadequate progress. Schaub [56] showed how two adversarial coalitions emerged and polarised the agricultural transition. Similarly, Starke et al. [57] demonstrated how the transition towards a European bioeconomy coincided, over time, with an increasingly simplified but polarised discourse network fueled by the publication of the EU Bioeconomy Strategy and European Green Deal.

Thirdly, discourse network analysis incorporates a *dynamic* dimension by enabling the observation of discursive change. By plotting discursive networks for different time intervals, it becomes possible to observe and measure changes in the composition of these networks, thereby capturing transition dynamics [27,58]. The way discursive networks change can either stabilise or destabilise regimes. Dominant discursive networks that exhibit declining ideational congruence, indicated by a decrease in the number of shared concepts or actors measured as within-bloc weighted densities, or conversely, alternative discursive networks that deepen ideational congruence, present opportunities for regime destabilisation [38]. For instance, Brugger and Henry [51] observe a connection between changes in ideational congruence and the success or failure of energy transitions. Markard et al. [55] also find a link between the success of an ideationally congruent anti-coal discourse coalition and the failure of a more dispersed pro-coal coalition. They further attribute the anti-coal coalition's success to the gradual inclusion of powerful actors. In an analysis of discourse networks in Mexico's electricity generation sector over 24 years, Gutiérrez-Meave [59] (p. 516) argues that an erosion of internal consensus in the coalition trying to preserve the status quo along with a strengthened belief alignment in a competing reform coalition changed the power balance and paved the way for reform.

Furthermore, sustainability transitions research is interested in identifying the specific moments of discursive change and the precise time phases of discursive stability to comprehend the dynamics and processes of stability and change [10,17]. In the remainder of this paper, we build on discourse network analysis to develop a new method and illustrate how it enables to do precisely this.

2.4. Transitions between states and phases

Sustainability transitions and the discursive networks embedded within them often occur in a sequence of distinct, measurable phases [9]. However, existing research often neglects to precisely identify the specific timing of when a sustainability transition process transitions from one phase to another [60]. Authors typically opt for one of three empirical strategies to document structural change over time: *Hypothesis-testing* research designs select time intervals before and after an event to assess the structural changes in the discourse network caused by the event (e.g., [52,56,57,61]). *Exploratory* research designs choose equally sized time intervals, for example years, to study the structural development of the discourse network over time and identify turning points or cut points in the annual data (e.g., [39,54]). *Confirmatory* research designs select time intervals based on different "stages" or "phases" of the discourse network as suggested by prior knowledge of the case or a qualitative examination of the underlying textual data. The "right" temporal cut points between the phases are often identified through an exploratory approach so that they best align with the expected phases and in such ways that structural differences between phases can be illustrated (e.g., [55]).

All three research designs involve dividing the timeline into discrete periods, or time windows, which reflect different phases in the discourse network. However, none of the three designs permits a principled and accurate identification of stages or turning points from the data. Empirically and accurately identifying the cut points, or structural breaks, between different phases would speak to STR in theoretically significant ways. Finding phases of relative stability and, conversely, finding the time points at which radical changes take place addresses questions of when and how transitions occur and would allow STR researchers to improve and build new theories on the dynamics and processes of stability and change in sustainability transitions [7,17].

In our conceptualisation, a temporally observed discourse network can be partitioned into different "states". Each state represents a distinct configuration of the regime. For example, in one state, a single dominant discourse coalition could prevail in a core-periphery structure. In another state, two or three coalitions could be in intensive conflict, displaying a polarised network structure. In yet another state, a different coalition could prevail in another core-periphery structure, this time with different actors and concepts. A state could also be characterised not by different actor coalitions but by different discourses that are sponsored by the respective coalitions. States can be distinguished from one another by their relational structure and/or their actor and concept composition. A state can exhibit minor structural or compositional change. It is major change that distinguishes one state from another. A state is often, but not always, characterised by a steady-state equilibrium: actors continuously contribute to the discursive space, and as a consequence this space changes, but it changes around a stable baseline. For example, a state that is characterised by two stable coalitions can sometimes be slightly more polarised and sometimes slightly less polarised, and the relative size and composition of each coalition can change back and forth, but these changes do not show a clear trend.

These different states a discourse network can be in correspond to "phases" or, synonymously, "stages". The difference between a state and a phase is that phases are strictly temporally ordered. Each phase corresponds to one state of the network. But there can be more phases than states because a new phase can bring the network back into a previous state. For example, the first phase of a transition process may see two polarised coalitions (State A), the second phase may see only one coalition left (State B), and the third phase may see a revival of State A such that the second coalition becomes active again and the discursive space is polarised again. In this case, there are two states and three phases. When one phase and state ends, a new phase begins and shifts the transition process into a different state. Discursive shifts are a prerequisite for any sustainability transition to unfold. However, they do not necessarily imply a sustainability transition [6,7,17,23,24]. Phases can be long or short. The transition between two phases can be abrupt or drawn out, but either way, all time points, even around the transition points, can be partitioned into states, albeit with high uncertainty.

Phases are separated by cut points, which indicate moments of radical change, capturing "discursive turning points" [17] and characterising destabilisation processes within sustainability transitions. We refer to these points as "phase transitions" to emphasise that they mark changes from one phase to another at the aggregate level through a complex rewiring of discourse elements. In the physical sciences, such as thermodynamics, statistical physics, cosmology, and chemistry, phase transitions usually denote changes from one system state to another through microscopic changes in the system's particles, for instance when environmental variables change or critical thresholds in particle dynamics are reached [62]. In discursive approaches to sustainability transitions, phase transitions tend to be explained by exogenous events like nuclear disasters and wars (e.g., [33]). For example, Nam et al. [63] explain polarisation and phase transitions in South Korea's nuclear energy ST discourse partly by external events like earthquakes. Nevertheless, internal dynamics within discursive networks, marked by structural and compositional changes, such as discursive learning, also influence phase transitions. While the existence of endogenous dynamics within discursive networks is documented, these dynamics are seldom linked to specific change points. Our method thus facilitates a research agenda that explores processes of discursive change emerging from various spaces [12,15,16].

Because phase transitions in discourses are consequential for sustainability transitions [7,17,23,24], they should be detected empirically from the data using principled and accurate methods. In the following section, we introduce a method for the bottom-up detection of states, phases, and phase transitions in discourse networks. This method is adapted from network science to the problem of changes in discourse networks and sustainability regimes [64–66] and combined with the construction of maximally overlapping time windows for networks. These methods will permit STR scholars to move from assuming the presence of turning points to the empirical identification of such turning points from discourse network data. They will allow STR scholars to detect and quantify when and how strongly discursive structures change, and to trace more accurately how discursive networks develop over time – hence to analyse how sustainability transitions unfold.

3. Material and methods

3.1. Detecting phase transitions in discourse networks

We detect states, phases, and phase transitions in six steps. The first step is to subdivide the temporally ordered list of all statements into maximally overlapping time windows of a fixed size and create one discourse network per time window. Fig. 2 illustrates this process.

The researcher sets a parameter, which we call the window length w. This parameter depends on the case. For example, w could be a time window duration of 100 or 300 days (assuming that statements can be measured daily; with coarser measurement, one could use several weeks or months). At the start of the timeline b, a time window of w days (denoted by $t = 1$) is created, and a discourse network is created over

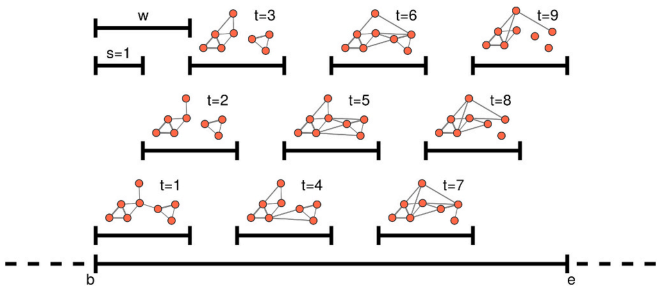

Fig. 2. Temporal smoothing is achieved by creating discourse networks in maximally overlapping time windows along the time axis [67].

the collection of all statements falling into this time period. Then, the time window is moved forward by a minimal time unit, for example $s = 1$ day, which means both the start of the window and the end point of the window are brought forward by $s = 1$ day. In this second time window ($t = 2$), another discourse network is created and saved. This process continues until the end of the timeline is reached ($t = 9$ in the illustration). This results in a collection of $n = \frac{e-b-w+s}{s}$ maximally overlapping and minimally moving time window networks. The large overlap between the consecutive network snapshots smooths the changes from one network to the next network and permits detection of gradual changes.

All of these networks are actor subtract networks, concept networks, or affiliation networks. The literature on discourse networks provides definitions of these different kinds of networks [37,39,67]. It is sufficient here to mention that these networks can be composed of actors (and hence display coalitions of actors as clusters of densely connected actor subgroups), concepts (hence displaying discourses, where arguments, storylines etc. are connected by actor co-usage), or both simultaneously (see Fig. 1). Below, we will illustrate the method empirically using actor networks with the subtract method and concept congruence networks. The network matrices at all time points must contain all nodes, even those with zero ties to any other nodes during times when the nodes are inactive in the ST process.

The second step is to compute a pair-wise distance matrix for all pairs of networks created in the first step. The $n \times n$ distance matrix contains the distance between the first and second network, between the second and third network, the first and third network etc, for all combinations of two networks. To compute distances between all pairs of networks, we applied the sum of absolute differences across all matrix cells of the two network matrices (a variant of the graph edit distance; see [65]). Distances between networks can also be calculated using other distance methods. These include the Euclidean spectral distance between two network matrices, commonly referred to as the Laplacian distance [64,65], and the difference in modularity (i.e., the propensity to form clusters or communities) between the two networks [68].

The resulting distance matrix represents how dissimilar the network structure between any two time points is, smoothed over adjacent time points via the maximally overlapping time window approach.

The third step is to choose a clustering method and apply it to the distance matrix. The result of the cluster analysis is a cluster solution that groups different time points into k clusters. These clusters are the empirically identified states of the discourse network.

Any clustering method that either accepts the desired number of clusters, k, as user input or returns a full hierarchy of nested clusters, which allows the user to extract a cluster solution with the desired number of k clusters, is suitable. The following techniques are suitable and have been added to the software described below: Hierarchical cluster analysis (with single, average, or complete linkage or Ward's method), k-means, partitioning around medoids (PAM), spectral clustering, convergence of iterated correlations (CONCOR), and community detection using the fast & greedy, Walktrap, leading eigenvector, and Girvan-Newman edge betweenness algorithms. Masuda and Holme [65], who first suggested clustering the distance matrix of time points to subdivide temporal networks into states, recommended hierarchical cluster analysis, which we also employed in the case study presented below. Hierarchical cluster analysis alternates between two steps: It merges the most similar time points (i.e., the rows and columns corresponding to the lowest distance in the distance matrix) into a cluster and then recalculates the distance between this cluster and all remaining (clusters of) time points. These two steps are repeated until k (clusters of) time points (where the number k is pre-defined) remain in the matrix. Fast & greedy community detection, in contrast, merges any two time points or clusters in the distance matrix that maximally increase the modularity of the cluster solution given the distance matrix at any iteration step, where modularity is defined as the fraction of edges (or similarity scores) within communities minus the expected fraction if edges (or similarity scores) were distributed randomly. Different graph clustering techniques have specific advantages and disadvantages [69,70].

The researcher needs to decide on a suitable number of states before interpreting the results. Three tools are available to choose the best-fitting number of states: the elbow criterion, silhouette plots, and a comparison of modularity scores. The elbow criterion identifies the point on a two-dimensional line chart of explained variance or within-cluster sum of squares (WSS) versus the number of clusters k where the rate of improvement sharply decreases with increments of k, forming an "elbow" (but see [70] for a discussion of modern replacements). Silhouette plots [71] reveal cluster overlap or blurriness by showing how tightly points are grouped within their own cluster versus how close they are to other clusters. Narrow or negative silhouette bars indicate overlap or poorly defined clusters, while wide, consistently positive bars suggest clear separation between clusters. Modularity [68] evaluates clustering solutions by quantifying the density of similarities within clusters compared to the density expected in a random distribution, with higher modularity values indicating clusters that maximise intra-cluster similarities and minimise inter-cluster similarities. The analysis below presents an application of one these diagnostic tools, silhouette plot, to settle on a suitable number of states.

In the software described below, the user can also specify any combination of clustering methods and a minimum and a maximum k, and the best-fitting result according to the criterion of network modularity is selected automatically to fortify against arbitrary choices of k and the clustering algorithm. It is possible to select the same minimum and maximum k and only a single clustering method at a time for full control over the clustering approach and the number of clusters. In this case, one can use the elbow criterion or silhouette plots to decide which method and which k are most appropriate.

The fourth step is to draw a heat map with two-way dendrograms for the cluster solution to visualise the relationship between the states and assess how clearly the states are separated.

The fifth step is to draw a state dynamics diagram, a chart with a horizontal line that displays shifts between the different identified states (on the y axis) along the timeline (x axis). The state dynamics diagram shows how long the different phases are, whether (and when) the discourse network snaps back into a previous state, how homogenous each phase is, and when phase transitions occur.

The sixth step consists of applying non-metric multidimensional scaling (MDS) [72] to the distance matrix, plotting the resulting coordinates of time point nodes in two dimensions, connecting all temporally adjacent time points with lines with arrow heads, and colouring the time points by their discrete cluster membership from the third step. The MDS plot traces the states spatially. By inspecting the MDS results, one can see how similar the different states are to each other and what trajectory the sustainability transition process takes over time relative to what happened before. In a different application of network state dynamics, this step was proposed by Thongprayoon et al. [66], who call the resulting low-dimensional representation of the temporal trajectory a "temporal network embedding".

Together, these methods provide a comprehensive data-driven assessment of the existence of states, phases, phase transitions, and trajectories. The researcher needs to decide only on the time window duration parameter w (depending on context and how crowded the discourse network is), the clustering method (can be decided using fit criteria like modularity), and the number of states (can be decided using the three diagnostics). The code for detecting phase transitions is given in the appendix. In the next sections, we provide empirical applications.

3.2. Empirical case: background and data collection

We illustrate the detection of phase transitions by examining the policy debate surrounding the implementation of a Low Emission Zone (LEZ) in the city of Ghent, Belgium. LEZs are designated areas where specific polluting vehicles are prohibited from circulating. These zones aim to reduce local air pollution, encourage a shift towards more sustainable modes of transportation, and facilitate the deliberate, gradual phase-out of combustion engine vehicles. Consequently, LEZs can be viewed as technology-centred exnovations that seek to destabilise existing socio-technological mobility regimes and whose discursive dynamics can be seen as entry points for governing transitions, innovations and other types of regime changes [73]. In Ghent, the LEZ is an integral part of the city's comprehensive and systemic "Mobility Plan" and aligns with Flanders's goal of prohibiting all combustion vehicles from entering LEZs by 2035 [74]. Therefore, it serves as a relevant case study for examining discursive phase transitions within the context of sustainability transitions.

The implementation of Low Emission Zones, including decisions on coverage areas and vehicle exclusions, often sparks controversial and highly politicised public debate. In Ghent, plans for the implementation of a LEZ go back to 2015. A LEZ covering the city centre was implemented in 2020 and, according to initial plans, had to be expanded. In the end, it was not expanded beyond the borders of the inner city.

Our database comprises 38 reports from town council meetings and 76 articles from local newspapers, all of which contain explicit references to "*emissie* [emission] zone" and were issued between 1 January 2015 and 31 December 2022. The town council documents offer comprehensive and in-depth insights into the policy debate while the newspaper articles ensure the inclusion of perspectives from non-political actors. We obtained the documents by contacting the city administration and accessing the Gopress database (www.gopress.be, accessed July 2021, now Belgapress), respectively. The coding process using Discourse Network Analyzer 3.0.11 encompassed several variables as specified in Section 4. In total, 2961 statements were coded (town council reports: 2385; newspaper articles: 576) for 105 persons, 29 organisations, and 370 concepts. In the following section, we elaborate on how we identified phase transitions using this coded dataset.

4. Results: identification of phase transitions in the empirical case

We illustrate the method by applying it to three empirical case examples. The three examples demonstrate the process of identifying changes in states and phase transitions, but for different types of discourse networks and time periods. The first example captures phases and transitions in actor networks (discourse coalitions) spanning the entire data period, from February 2015 to December 2021. The second example focuses on phases and transitions in actor networks (discourse coalitions) during the period when actors were most active, from January 2020 to December 2021. The third example outlines phases and transitions in concept networks (discourses) for the entire period of data. In each example, we chose time windows of $w = 20$ weeks moved forward each time by $s = 1$ week as a compromise between level of detail and speed of computation. Statements that were duplicates of previous statements in the same document were ignored. The first and third example comprised 336 networks, whereas the second example contained 85 networks.

The results, shown in Figs. 3, 4 and 5, reveal that the discourse networks for the examined periods were sparse and exhibited minimal modularity. Such characteristics suggest an absence of robust coalitions throughout the process.

In the first example (Fig. 3), the temporal embedding plot displays four clusters. Each cluster indicates the state to which individual networks belong. Every state is represented by a unique symbol and a corresponding colour. Arrows between the nodes indicate the temporal sequence, illustrating the shift of individual networks between these states.

To determine when transitions between states occurred, we inspected the state dynamics plot. This plot integrates the temporal dimension, signifying when a transition to a different state happened. The state dynamics plot shows six phases between the four states, with phase transitions on 8 December 2019, 22 March 2020, 3 May 2020, 9 August 2020, and 13 December 2020. The plot indicates that the networks were relatively similar for the three phases shown in red as State 1.

The heatmap of the similarity matrix further confirms the division into four distinct states, with darker shades denoting increased dissimilarities between networks. The accompanying dendrograms display the specific clusters.

Lastly, the silhouette plot displays an average width value of 0.817, suggesting accurate allocation of networks to their respective clusters. For details on the interpretation of silhouette plots, see [71].

For the second example (Fig. 4), the temporal embedding plot similarly identifies four states. However, the state dynamics plot highlights recurring States 2 and 3, presents 6 phases, and reveals phase transitions on the following dates: 28 April 2020, 21 July 2020, 11 August 2020, 8 December 2020, and 29 December 2020. The plot also suggests that the LEZ debate underwent significant changes, being especially active in the latter half of 2020. The heatmap supports the partitioning into four distinct states, and the silhouette plot, with a value of 0.746, confirms the accurate grouping of networks into clusters.

In the third example (Fig. 5), the temporal embedding identifies five discursive states. This plot presents seven phases and pinpoints phase transitions on the following dates: 11 March 2019, 29 July 2019, 02 December 2019, 2 March 2020, 27 April 2020, and 28 December 2020. The year 2020 surfaces again as a particularly dynamic period in the debate. The heatmap emphasises the division into five distinct states, and the silhouette plot, with a value of 0.753, verifies the accurate assignment of all networks to clusters.

To facilitate the interpretation of the detected states and phase dynamics, separate networks for each of the identified phases were plotted in Figs. 6 and 7 (only for Examples 1 and 2 for space and readibility reasons), using one-mode actor subtract networks with negative edges removed [37]. These networks represent the discourse coalitions involved in the LEZ debate in different phases. Phase transitions are characterised by structural (network structure, ties between actors) and/or compositional change (actors involved). Nodes represent actors, either political parties (Sp.a, Groen, OpenVld, CD&V, N-VA, PVDA, Vlaams Belang) or other organisations. The following interpretation of the phases in Figs. 6 and 7 was supported by a thorough qualitative reading of the data.

Phase 1, Example 1 (23 February 2015 to 8 December 2019) reveals a consensus among political parties to implement a LEZ rooted in environmental concerns. Notably, governing parties (Sp.a, Groen, and OpenVld) exhibited stronger agreement, though two distinct coalitions emerged. Despite a stable actor configuration, the concepts they used shifted, especially around 11 March 2019 and 29 July 2019. In the concept network, we can observe dynamics of discursive learning within and between the distinct coalitions. Discursive learning happens when actors adopt arguments from other actors, either actors of their own discourse coalition or another coalition. Over time, actors increasingly adopted social viewpoints like "LEZ is elitist", departing from their original environmental arguments.

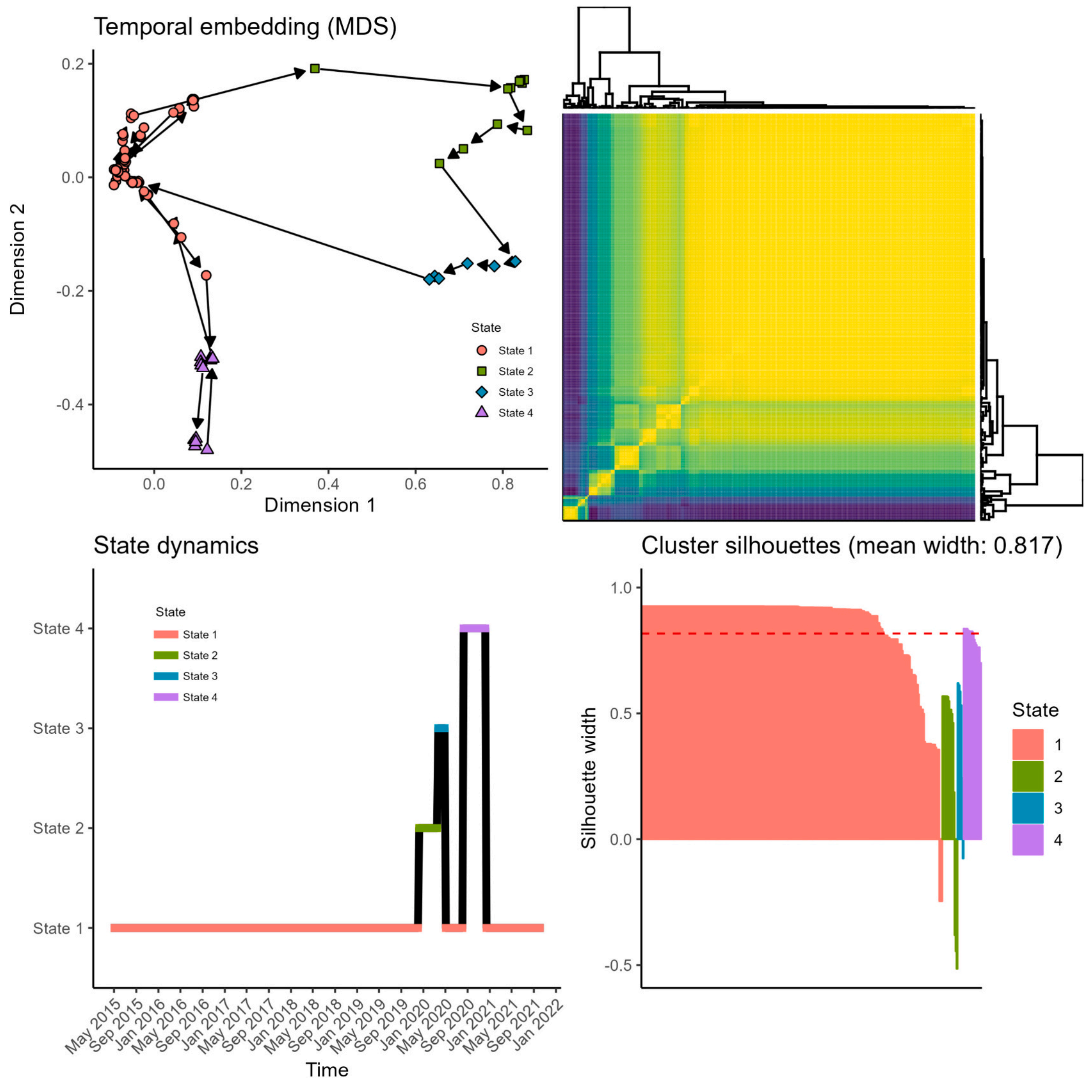

Fig. 3. Example 1, states and phases in actor networks, February 2015 to December 2021.

Phase 2, Example 1 (which corresponds to Phase 4, Example 3, from 9 December 2019 to 22 March 2020) illustrates a reconfiguration of the discursive networks. This is evident in the compositional change, which is characterised by the mobilisation of more organisations into coalitions within the debate. This phase marks the point when the debate expanded beyond the mere inclusion of parties and state actors. There is also evidence of a structural shift with the emergence of an “anti-LEZ” coalition, comprising PVDA, N-VA, and Vlaams Belang (opposition parties), and a “pro-LEZ” coalition, which is depicted on the right side of Fig. 6. This suggests a significant pivot within the transition trajectory.

Phase 3, Example 1 (corresponding to Phase 1, Example 2 and Phase 5, Example 3, 23 March 2020 to 3 May 2020) marks a significant departure from prior phases with noticeable compositional and structural shifts. Discourse coalitions vanished, yet Groen and Vlaams Belang, previously in separate coalitions, reached a consensus. The prevalent theme was COVID-19, especially the suspension of LEZ fines, which both parties supported. This shift was prompted by an exogenous event, the pandemic. The full actor network's phase begins and ends sooner in the restricted actor network (Example 2) and the concept network (Example 3). As per Fig. 7, the restricted network distinctly shows pro- and anti-LEZ coalitions.

Phase 4, Example 1 (corresponding to Phases 2 and 3, Example 2 and Phase 6, Example 3, 4 May 2020 to 9 August 2020) highlights a clearer divide between anti-LEZ and pro-LEZ coalitions, mainly comprised of parties and state actors, maintaining cross-coalition ties similar to Phase 1. A transition on 21 July 2020 is noted in the temporally confined actor network due to political actors' summer absence, yet the concept network sees no distinction between Phases 4 and 5, indicating stable discourses despite changing coalitions.

Phase 5, Example 1 (corresponding to Phase 4, Example 2 and Phase 6, Example 3, from 10 August 2020 to 13 December 2020) displays a strong anti-LEZ and a weak pro-LEZ coalition. Two political actors from the pro-LEZ coalition (Sp.a and CD&V) exited the debate. The concept network reveals that it was the question around the expansion of the LEZ that weakened the pro-LEZ coalition, with two actors being undecided about their position.

Phase 6, Example 1 (corresponding to Phases 5 and 6, Example 2 and Phase 7, Example 3, from 14 December 2020 to 17 December 2021) shows a dominant anti-LEZ coalition (Vlaams Belang, N-VA, PVDA) and a non-existent pro-LEZ coalition. Groen and Sp.a, initially pro-LEZ, aligned with the anti-expansion stance. This shift in alignment reflects in the concepts used. The anti-LEZ coalition was in opposition to the LEZ expansion and its original implementation. A phase transition was observed on 29 December 2020, with an increased number of actors opposing the LEZ expansion and the emergence of varied pro-LEZ views.

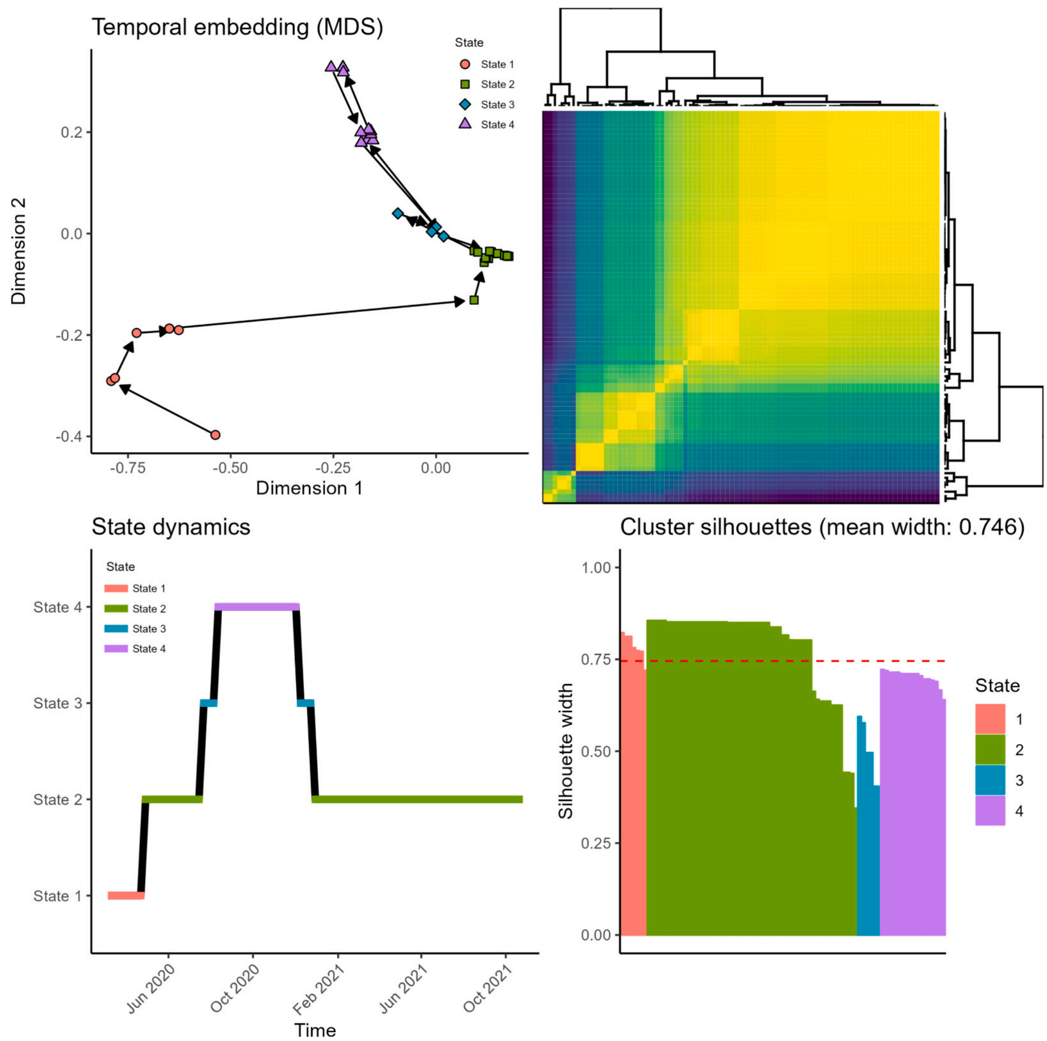

Fig. 4. Example 2, states and phases in actor networks, January 2020 to December 2021.

5. Discussion

We extended DNA significantly by measuring distinct temporal states (phases of stability) in discourse networks and detecting phase transitions (significant changes) between these discursive states. Analysing the empirical case gave us insights into the method, its potential applications, and its relevance for sustainability transitions research. The LEZ case underscores transitions' complex and non-linear nature. The observation of multiple phase transitions indicates a continuous contestation of discursive networks, e.g., around the expansion of the LEZ, and a reshuffling of discursive dynamics, e.g., following the potential expansion of the LEZ. This suggests that sustainability transitions and their governance happen in discontinuous rather than coherent and transparent ways with unforeseen outcomes. It provides insights into the temporal dynamics of discourses and contributes to an understanding of the interplay between stability and change, the promotion and obstruction of transitions, and the shaping of the direction of transitions. The potential expansion of the LEZ, for example, appeared as a pivotal moment while specific actors, like Groen, appeared to play a key role.

Our analysis points towards more detailed dynamics of change and stability than conceptualised by, e.g., the multi-phase framework. The multi-phase framework distinguishes four phases for STs, each differing in speed, size, and timing [75]. In the pre-development phase, the status quo does not visibly change. In the take-off and acceleration phase, structural changes become visible. In the stabilisation phase, a new status quo, which does not visibly change, has emerged. As our method identifies phase transitions from the data, it contributes to a refinement of this framework and proposes a less linear and teleological understanding of STs [1].

An important theoretical implication of our empirical analysis is that it supports a research agenda on the role of endogenous dynamics for change, in particular discursive learning. We can measure how sustainability transitions differ between contexts even when they are exposed to the same exogenous events. This points to the importance of endogenous dynamics of discursive learning, though separating these endogenous dynamics from exogenous sources of variation in ST dynamics can be a challenge in any particular application. For example, in Phase 1, Example 1, the political actor PVDA switched from one discourse coalition to another, away from supporting to resisting a LEZ, after having learnt the argument “a LEZ is asocial” from other actors. Bridge actors play a key role in facilitating discursive learning [39,50]. In this example, PVDA (far-left) learnt the argument from Vlaams Belang (far-right). By contrast, the singular discourse coalition in Phase 3, Example 1 appeared as a very temporary coalition and dissolved as soon as the pandemic faded into the background.

The empirical phase transitions also revealed other endogenous dynamics, including the role of internal coherence and alignment of discourse coalitions in phase transitions, as illustrated by a relatively stable, strongly aligned anti-LEZ coalition compared to an unstable, poorly aligned pro-LEZ coalition. In sustainability transitions, other

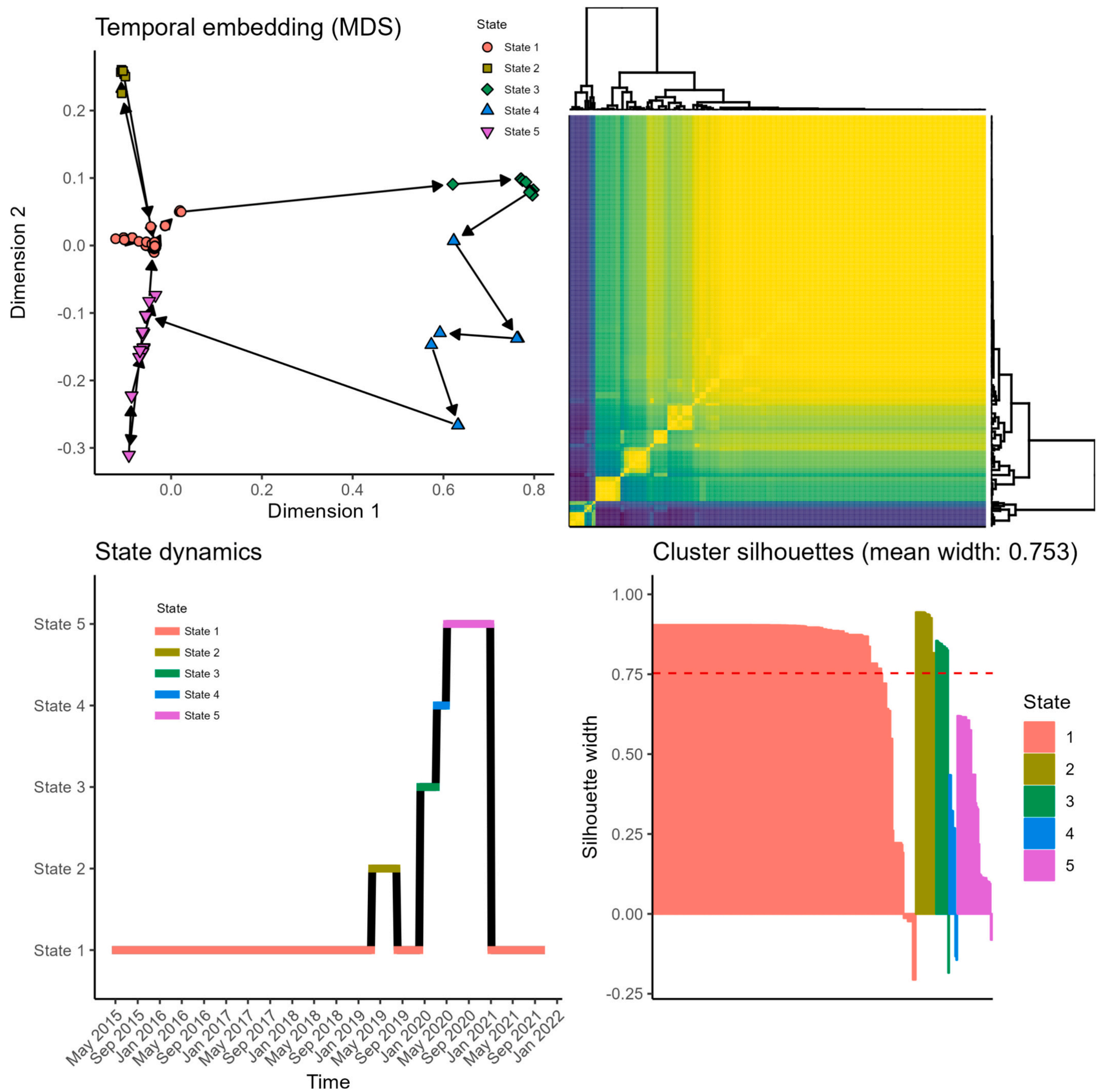

Fig. 5. Example 3, states and phases in concept networks, February 2015 to December 2021.

factors have been proposed as explanations of endogenous discursive shifts, including observed tensions within hegemonic discourses (e.g., [25]) and actors' or coalitions' discursive agency (e.g., [7,16]) such as through performative action by actors and coalitions (e.g., [17]). However, the attribution of discursive shifts to endogenous versus exogenous factors is complex and seldom conclusive. In the proposed method, too, this remains a limitation. While we suggest endogenous factors in our empirical example, we cannot establish them as inherent or exclusive drivers of change. However, to strengthen the explanatory dimension of endogenous dynamics for change, our phase transitions method could be combined with other methods, including in-depth analyses (e.g., using interviews among key actors) of the specific phase transitions identified through DNA, to improve our understanding of power and agency in sustainability transitions.

The three examples showed similar phase patterns with slight timing differences. These similarities give insights into structural changes (e.g., Phase 5, Example 1 and Phase 4, Example 2), while differences reveal how actor coalitions remain stable despite evolving discourses (e.g., Phase 1, Example 1 and Phases 1, 2, and 3, Example 3). Using the method on temporally restricted networks, like Example 2, benefits rapidly changing contexts, but interpretations should be approached with caution because extending the time range may make some phases disappear. For instance, the restricted network showed two phases, but the full network for the same time only showed one, limiting insights into the debate's evolution. However, Phase 6 in the full network reveals pro-LEZ actors' discursive learning. Example 1 highlights consensus between pro and anti-LEZ actors, and Example 2 delves deeper, showing pro-LEZ actors adopting, albeit later, the anti-LEZ arguments which had

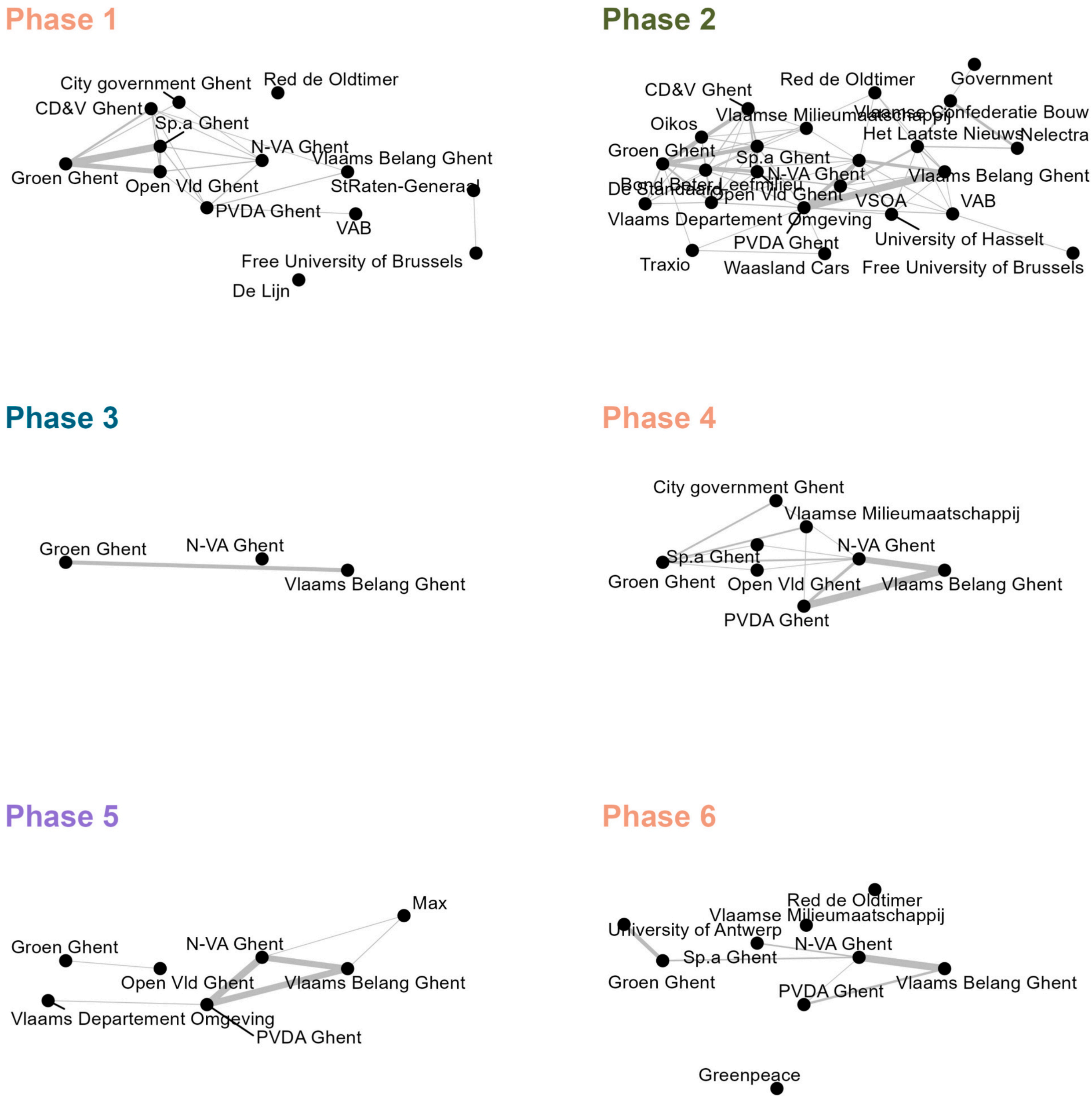

Fig. 6. Actor networks per phase, February 2015 to December 2021.

become common knowledge. These results showcase DNA as a mixed-methods approach, where quantitative findings require qualitative interpretation [4].

Future research should analyse how the discursive phase transitions of the LEZ connect to, and co-evolve with, innovations and other types of regime changes. It should also apply the detection of phase transitions to a variety of cases but also consider different kinds of networks (actor or concept networks, affiliation networks), time window sizes, time resolutions, and numbers of states. This might lead to a more thorough engagement with the empirical material and case, exploit the method more fully, and advance theory about processes of stability and change and their temporal dynamics.

In general, future research should seek to integrate our phase transitions method with other, non-discursive dimensions of systems and regimes, such as technologies and institutions, or subsystems in order to detect phase transitions in larger systems, e.g., the energy transition [60]. In parallel, as transitions are neither purely driven by exogenous events ("disruptive discursive pathway") nor endogenous ones ("dynamic discursive pathway", [7]), the method could be integrated with approaches capturing phase transitions as the result of the dynamic interaction of landscape-level, niche-level and regime-level dynamics [11]. To combine phase transitions, which capture the temporal dimension of multi-phase transitions, with multi-dimensional, multi-sectoral and multi-level dynamics of change, socio-technical configuration analysis (STCA) may be a promising framework [61]. Because STCA relies directly on DNA, an integration of both methods is feasible and promising.

6. Conclusion

The methodology presented here improves the measurement of stability and change processes in discursive approaches to STR and the analysis of temporal dynamics in transitions. To discourse scholars, it offers a reduction of resource costs and increase in reliability in the analysis of complex discursive processes that often span across decades and are recorded in thousands of documents. An empirical application of

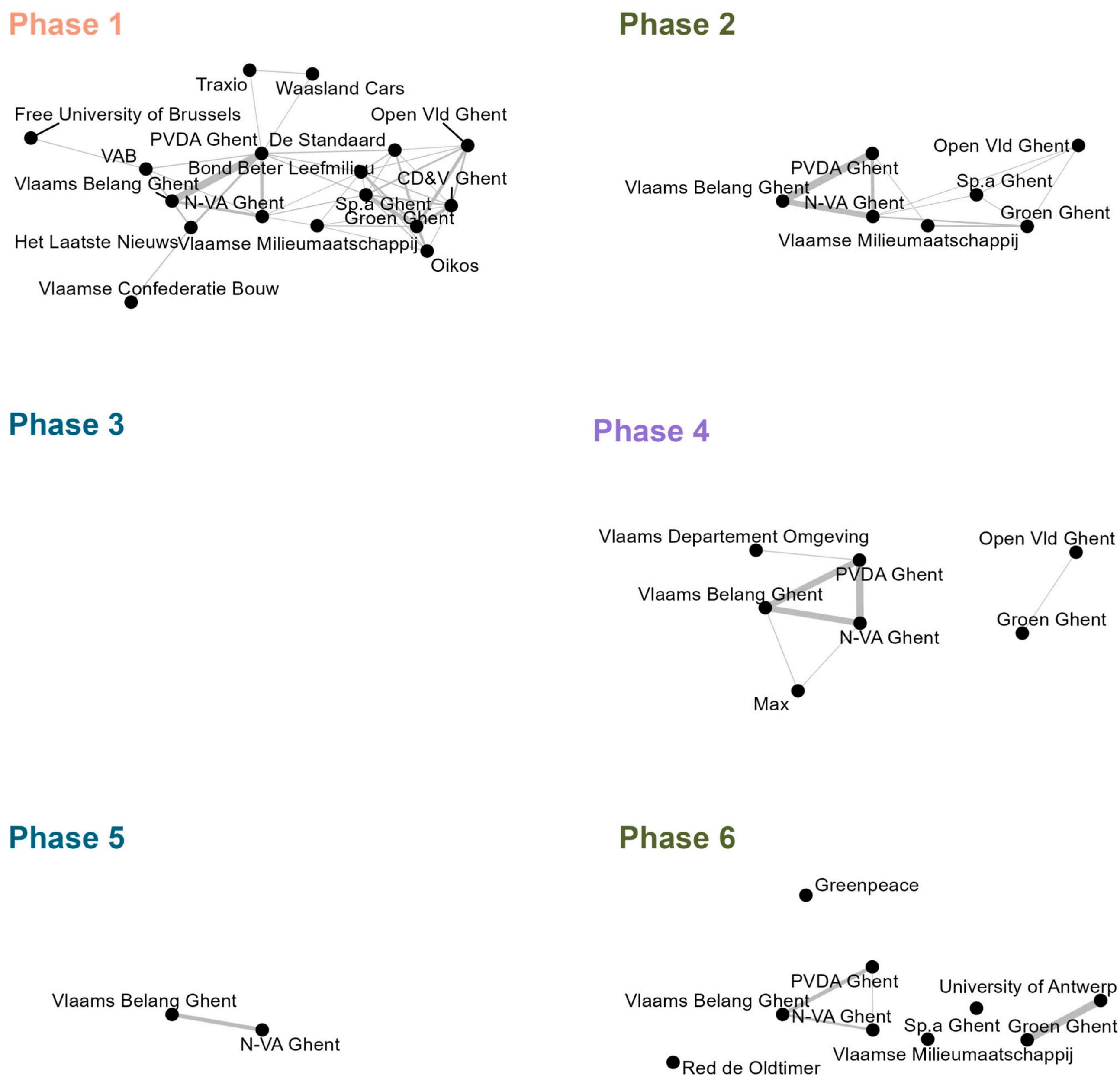

Fig. 7. Actor networks per phase, January 2020 to December 2021.

the method to the Low Emission Zone in the city of Ghent illustrated the data-based detection of phases (discursive stability) and phase transitions (significant structural discursive changes) in the debate. In contrast to traditional discursive approaches, this new method detects periods of relative discursive stability and moments of discursive change in an empirical, bottom-up way. While traditional approaches delineate periods of stability and change in theoretical and exploratory ways, this methodological development measures states and detects phase transitions in discourse networks from the data.

We highlighted points of caution and explored the further potential of the method. Additionally, we addressed theoretical implications for STR. Notably, the method supports a research focus on the role of endogenous dynamics, like discursive learning, in driving change processes.

We view the application of the network state dynamics by Masuda and Holme [65] to discourse networks of sustainability transitions as an initial step towards enhancing the analysis of temporal dynamics in processes of stability and change. We see potential for further experimentation with this new method and encourage subsequent research to explore other graph distance measures or clustering techniques. Stressing the value of diverse applications, we advocate for the method's use across a spectrum of cases and variations within those cases. This approach will allow for a richer engagement with empirical data and fully harness the capabilities of discourse network analysis in STR. Lastly, we urge researchers to contrast findings derived from this method with outcomes from traditional discursive approaches, aiming to deepen theoretical insights into processes of stability, change, and their associated temporal patterns [11].

The methodological development paves the way for research not only in sustainability transitions but also in related disciplines, such as political and policy sciences. The detection of phase transitions in discourse networks is a versatile approach and could be applied to diverse discursive networks across various settings. Therefore, we anticipate that this research will resonate with a wide spectrum of scholars, both within the STR realm and beyond.

CRediT authorship contribution statement

Kimberley Vandenhole: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kristijan Garic:** Writing – review & editing, Writing – original draft, Visualization, Software, Project administration, Investigation, Formal analysis, Conceptualization. **Philip Leifeld:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the final preparation of this work the authors used ChatGPT 4 by OpenAI.com in order to rephrase sentences, and only for that purpose. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Declaration of competing interest

The authors have no competing interests to declare.

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Appendix A. R code for detecting phase transitions

This code example uses GitHub commit b85515d62660353794e6e68b5b811662d3397771 (22 September 2023) of the Discourse Network Analyzer and rDNA software to reproduce Figs. 3, 5, and the first panel of Fig. 6.

```r
# ---- Set up the environment ----

# Load required libraries
library("ggplot2") # For creating plots
library("patchwork") # For combining multiple plots
library("rDNA") # For Discourse Network Analyzer functions
                # (version 3.0.11, 22 September 2023)

# Initialise DNA with a specified memory allocation
dna_init(memory = 4096)

# Load the database with specified coder credentials
dna_openDatabase("database.dna", coderId = 1, coderPassword = "test")

# ---- Construct Phase Transitions Diagrams ----

# Phase transitions diagrams for actor networks
actor_networks <- dna_phaseTransitions(
  cores = 1, # Number of CPU cores to use
  k.min = 2, # Minimum number of clusters
  k.max = 5, # Maximum number of clusters
  clusterMethods = "complete", # Clustering method
  networkType = "onemode", # Type of network (one-mode)
  variable1 = "organization", # First variable for network creation
  variable2 = "argument", # Second variable for network creation
  qualifierAggregation = "subtract", # Qualifier aggregation method
  start.date = "23.02.2015", # Start date for analysis
  stop.date = "17.12.2021", # Stop date for analysis
  timeWindow = "weeks", # Time window for analysis
  windowSize = 20, # Size of the time window
)

# Plot the constructed phase diagrams
plots <- autoplot(actor_networks) # Generate plots for each phase
top_row <- plots[[3]] + plots[[1]] + # Combine the first two plots
    plot_layout(ncol = 2, widths = c(1, 1))
bottom_row <- plots[[4]] + plots[[2]] + # Combine the last two plots
    plot_layout(ncol = 2, widths = c(1, 1))
combined_plot <- top_row / bottom_row + # Combine top and bottom rows
    plot_layout(nrow = 2, heights = c(1, 1), widths = c(1, 1))
print(combined_plot) # Display the combined plot

# Phase transitions diagrams for concept networks
concept_networks <- dna_phaseTransitions(
  cores = 1, # Number of CPU cores to use
  distanceMethod = "absdiff", # Distance method for clustering
  clusterMethod = "complete", # Clustering method
  k.min = 2, # Minimum number of clusters
  k.max = 5, # Maximum number of clusters
  networkType = "onemode", # Type of network (one-mode)
```

```
  variable1 = "argument", # First variable for network creation
  variable2 = "organization", # Second variable for network creation
  qualifierAggregation = "split", # Qualifier aggregation method
  start.date = "23.02.2015", # Start date for analysis
  stop.date = "17.12.2021", # Stop date for analysis
  timeWindow = "weeks", # Time window for analysis
  windowSize = 20 # Size of the time window
)

# Plot the constructed phase diagrams
plots <- autoplot(concept_networks) # Generate plots for each phase
top_row <- plots[[3]] + plots[[1]] + # Combine the first two plots
    plot_layout(ncol = 2, widths = c(1, 1))
bottom_row <- plots[[4]] + plots[[2]] +  # Combine the last two plots
    plot_layout(ncol = 2, widths = c(1, 1))
combined_plot <- top_row / bottom_row + # Combine top and bottom rows
    plot_layout(nrow = 2, heights = c(1, 1), widths = c(1, 1))
print(combined_plot) # Display the combined plot

# ---- Plot Phase 1 Network (as an Example) ----

actor_networks$states # shows all time points from the MDS with
                      # their state number, date, and coordinates

# Generate a specific network using defined date range for Phase 1
phase1 <- dna_network(
  networkType = "onemode", # Type of network (one-mode)
  normalization = "no", # Normalization method
  variable1 = "organization", # First variable for network creation
  variable2 = "argument", # Second variable for network creation
  qualifierAggregation = "subtract", # Qualifier aggregation method
  start.date = "23.02.2015", # Start date for this phase
  stop.date = "08.12.2019", # Stop date for this phase
  isolates = TRUE, # Include isolated nodes
  duplicates = "document" # Handle duplicates by document
)

# Visualise the Phase 1 network
# Nodes represent organizations, and edges represent arguments.
autoplot(phase1, node_label = TRUE, edge_color = "gray") +
  ggtitle("Phase 1") + # Add a title to the plot
  theme(plot.title = element_text(color = "blue")) # Customise title
```

. (*continued*).

Data availability

The coded data used for the empirical example will be made available upon request.

The source code for the analysis has been implemented as part of the rDNA package for the statistical computing environment R. rDNA and its companion Java application Discourse Network Analyzer are available at https://www.github.com/leifeld/dna. For the analyses in this paper, commit b85515d62660353794e6e68b5b811662d3397771 (22 September 2023) from GitHub was used.

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