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Abstract

This article introduces and demonstrates a data-driven systems mapping approach designed to contextualise, communicate, and embed the insights of complexity economics in real world policy questions. This approach allows us to: build networks representing empirical regularities between a broad range of factors, analyse these networks in policy-relevant ways, and embed complexity economics insight in them. In using this approach to connect complexity economics with policy questions and a more rounded view of policy landscapes, we hope to help address a range of calls in recent literature for more usable, interpretable, and inclusive complexity economics outputs. We demonstrate the approach with the policy topic of the energy transition and its relationship with the Sustainable Development Goals (SDGs). We consider how the approach can be tuned to different purposes and contexts and explore two applied questions emerging from existing modelling results and policy topics: (i) the impact of the energy transition on SDGs and the role of biofuels, and (ii) the nature of climate impacts on the economy.

1 Introduction

Complexity economics and related fields have made great progress in recent years (Arthur, 2021; Grubb et al., 2021), offering novel and policy-relevant insights on a range of issues including climate and energy policy (e.g. Way et al., 2022; Lamperti et al., 2020), financial stability (e.g. Kaszowska-Mojsa and Pipien, 2020), and market ecology (Scholl et al., 2021). Acceptance of complexity economics in policy processes faces several challenges, not least the dominance of neo-classical approaches, but progress has been made in some domains where the use of highly-technical modelling is established, for example within central banks (e.g. Carro et al., 2022). However, we assert that the broader policy impact and wider academic relevance of the field is hampered by a tendency for research to involve:

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1. Highly-technical 'black box' modelling where limited effort is made to make models transparent, interpretable, and explorable by non-experts (cf. Geels et al., 2016);

2. Models with a narrow focus on one set of outcomes or objectives (cf. Leijonhufvud, 1997);

3. Findings which are not connected more deeply to the current policy discourses and policy stakeholders (cf. Barbrook-Johnson et al., 2021).

These issues are not intended to be fundamental critiques of complexity economics, but rather serve to highlight the need for the field to address them as it matures.

There are several potential ways of addressing some of these issues. There are several potential ways of addressing some of these issues. Complexity economics could make a concerted effort to connect more to (other) social sciences, to use more theory and findings from sociology and political science. Or it could attempt to connect more strongly to science-policy dialogues beyond those where modelling is commonplace and/or adopt a more participatory or co-produced approach to working with policy makers. These types of efforts are beginning in places (e.g. Grubb et al., 2021; Anzola et al., 2017) but are not widely adopted, or even accepted as valid in large parts of the field.

There is also an underdeveloped connection between complexity economics and the field of systems thinking (Scrieciu et al., 2021). Systems thinking, similar to complexity economics, does not have a singular or settled definition. We use the term here to refer to the set of ideas, conceptual frameworks, and methods often used in conjunction with the term 'systems thinking' to understand systems in holistic ways, focussing on their interconnection and feedbacks, rather than focusing on individual variables or individual components (see Scrieciu et al., 2021 for a fuller discussion of the definition in relation to complexity economics). These two research areas have numerous overlaps, and some common roots, which have tended to be ignored. Systems thinking also has a strong tradition of working with policy processes and stakeholders to embed insights in wider efforts to address real world challenges.

Systems mapping offers one way forward which brings together many of these threads. Here, we are referring to systems mapping as a suite of related methods intended to build understanding and describe holistic views of systems, often using networks to describe causal and influence relationships between relatively high-level factors in a system (Barbrook-Johnson and Penn, 2022). Specific methods include Causal Loop Diagrams and Systems Dynamics (Sterman and Sweeney, 2000), Participatory System Maps (Penn and Barbrook-Johnson, 2022) , Bayesian Belief Networks (Pourret et al., 2008), and Rich Pictures (Bell et al., 2016).

All of these methods, to varying degrees, implement holistic views of systems, which can be constructed from a range of data, evidence, and stakeholder views. They allow the connection and representation of a range of other methods (i.e. simple models of other methods can be included in a map (Barbrook-Johnson and Carrick, 2021)) and can be used in relatively intuitive and interpretable ways. In short, they can offer a unique connection point between complexity economic outputs, policy questions, and social science more broadly. With roots in systems thinking they also have much in common with the complexity economics view of the world. Systems mapping is also undergoing a spike in popularity and a range of methodological innovations are underway (Barbrook-Johnson et al., 2021; Barbrook-Johnson and Penn, 2022).

We demonstrate the use of systems mapping to play this role of contextualising, communicating, and embedding the insights of complexity economics, using a data-driven systems mapping approach applied to the topic of the energy transition and its impacts on the Sustainable Development Goals (SDGs). As the energy transition begins to accelerate, its impact on the SDGs is increasingly important but is underexplored with traditional or complexity economics models, despite a wealth of models with a narrower focus on energy system and economic relations. We use the example of Brazil to focus geographically.

The rest of this chapter is structured as follows. First, we outline some of the relevant developments in the literature on complexity economics, discussions on bridging analytical divides, and developments in systems mapping. Next, we outline our approach to data-driven systems mapping, explaining the process of mapping with quantitative data and how to interpret and analyse maps. We then outline our case study, the SDGs and energy transition in Brazil. Our findings are presented, dovetailed with a reflective discussion on how we use the method and how we believe the approach generates value. Finally, we conclude by reflecting on what this data-driven systems mapping approach brings to complexity economics and policy analysis and identifying avenues for future work.

2 Developments in the literature

Here, we introduce the strands of literature that underpin our diagnosis of the issue and motivate our approach to help address it. First, we introduce the contributions complexity economics has been making to climate economics and integrated assessment modelling. Next, we outline the literature calling for more interpretable models and greater connection between complexity economics and systems thinking. Finally, we describe some of the recent developments in systems mapping.

2.1 Complexity economics and climate economics

Complexity economics has been making significant contributions and impact in climate and energy economics. The origins of this can be traced to a range of critiques of influential integrated assessment models (IAMs) underpinned by the complexity science approach to modelling. These critiques follow naturally from the assertions of complexity economics on the importance of heterogeneity, disequilibrium, and a range of other issues.

Critiques of existing IAMs include: (i) dealing poorly with uncertainty (Farmer et al., 2015); (ii) lack of representation of actor heterogeneity (Farmer et al., 2015; Mercure et al., 2016; Keppo et al., 2021); (iii) lack of representation of technological change, adoption, and dynamics (Farmer et al., 2015; Keppo et al., 2021); (iv) unrealistic or nonexistent feedbacks between the energy system and economy (Keppo et al., 2021), or climate and economy (Farmer et al., 2015), or from the interactions of actors (Mercure et al., 2016); reliance on optimisation as an inappropriate modelling paradigm for the issue (Mercure et al., 2016); fully rational actors (Mercure et al., 2016); inability to explore multiple solutions and path dependency (Mercure et al., 2016) or appropriately nuanced policy scenarios (Keppo et al., 2021); poor representation of capital markets (Keppo et al., 2021); and poor interpretation and use of results (Keppo et al., 2021).

While these critiques are generally forcefully and appropriately made, it is much harder to develop and apply the alternative models that address them. However, complexity economics, and models with complexity economics elements, have begun to appear and be used. One example is the 'E3ME' model and its extensions (e.g. Mercure et al., 2018, 2021). This is a disaggregated and demand-led macroeconomic model with post-Keynesian and complex economics underpinnings. It uses a disequilibrium approach, represents capital markets more fully, and describes technology progress and dynamics. Key recent findings include a detailed exploration of winners and losers as fossil assets become stranded (Mercure et al., 2018), and the economic benefits of climate policy, and how they fall different between different countries, depending on whether they are energy importers or exporters, and how price-competitive they are as exporters (Mercure et al., 2021).

Technology dynamics, and specifically costs, is the focus of another example; the probabilistic energy technology costs and resulting energy system cost modelling presented in Way et al. (2022). They use an empirically tested and probabilistic technology cost forecast methodology to explore the overall cost of three global decarbonisation scenarios. They find that cheap and abundant renewable energy is likely and moreover suggest the greatest economic benefits will be found in decarbonising more quickly rather than slowly.

Neither of the models above take an explicitly agent-based approach, perhaps one of the main characteristics associated with complexity approaches; however, the 'Dystopian Schumpeter meeting Keynes' (DSK) model presented in Lamperti et al. (2018) and Lamperti et al. (2020) does. The DSK model implements a fully agent-based macroeconomic model and couples it to a climate model. Findings include exploration of the chances of a successful energy transition and the impacts of climate shocks on the transition. Whether the impact of shocks is on labour productivity and/or energy efficiency was shown to be key in determining impact on the energy transition and economy. An energy efficiency shock has low economic impact compared to labour productivity shocks, but has a much greater impact on the transition, by entrenching path dependency favouring fossil fuels.

2.2 Bridging analytical approaches: complexity economics, systems thinking, and policy appraisal

The inroads of complexity economics into energy and climate economics are promising. However, the models remain (understandably) large data-hungry black boxes. This means, in common with traditional IAMs, they do little to address wider calls for more interpretability and connection between modelling and other analytical approaches (Barbrook-Johnson and Carrick, 2021). Geels et al. (2016) considers bringing together IAMs with socio-technical transition analysis and practice-based action research. While they suggest tight integration of these three approaches is not possible, they do suggest an iterative articulation of results and closer conceptual linking can provide greater value in policy support in a range of contexts. Turnheim et al. (2015) go into further detail on the specific topic of sustainability transitions, suggesting integration between approaches should revolve around aligning and iterating on a shared problem formulation, and orienting analysis towards specific governance problems. Gilbert et al. (2018) broadly concur, emphasising several issues for modellers to consider when aiming to provide policy relevant advice. These include: (i) the value in the iterative process of modelling with stakeholder, not just the outputs; (ii) model development should be agile and collaborative; and (iii) communication of model design and results require careful attention.

At the same time as these calls for more connection between models and other approaches are being made, there are specific calls for complexity economics to be more closely connected to systems thinking (Scrieciu et al., 2021). This connection, if more fully made, would naturally bring a greater focus on participation and connection to policy processes. For example, a richer and more practical embedding of complexity economics outputs is well-made in calls for a broader, more complexity-appropriate approach to policy appraisal (Grubb et al., 2021; Mercure et al., 2021). In this vision of policy appraisal, ex ante analysis of interventions broadens, from a simple weighing of the most easily measured costs and benefits and an assumption that the policy will only have a marginal impact, to a consideration of a wider set of risks and opportunities and the possibility the policy may transform the systems it affects.

2.3 Advances in systems mapping

Systems mapping (defined here as a suite of related methods intended to understand and describe holistic views of systems, often using networks to describe causal and influence relationships) has been undergoing somewhat of a renaissance, or at least rising interest, in the last fifteen years (Barbrook-Johnson et al., 2021; Barbrook-Johnson and Penn, 2022). This has created innovation in both methods, as well as the process of building and using maps. For example, methodological innovations have occurred around system map analysis (Barbrook-Johnson et al., 2021), bringing agency and actors into maps (McGlashan, 2019), visualisation and interaction with maps (UNDP, 2021), connection with behaviour change approaches (Hale et al., 2022), and contextualising theories of change (Wilkinson et al., 2021). More clarity around process and guidance has also emerged, for example in Barbrook-Johnson and Penn (2022).

At the same time as these advances, and in part driven by it, there has been a raised recognition of the value of systems mapping in policy making circles. Systems and complexity toolkits, including approaches to systems mapping, are being developed by several parts of the UK government, for example the Government Office for Science, the Systems Research Programme in the Department for Environment, Food and Rural Affairs, and the 'Handling Complexity in policy evaluation' guidance published by the UK Treasury. More broadly, institutions as varied as OECD (Hynes et al., 2020), Rocky Mountain Institute (Gray et al., n.d.), the UK Ministry for Justice (Madden and Ohlson, 2020), and UNDP (UNDP, 2021) have advocated for systems mapping.

These innovations in method and in practice, and raised interest in policy circles, raise the question of how systems mapping should be built into research processes and how we can generate most value from it. Mercure et al. (2021) provides one vision, placing systems mapping clearly at the start of a research and policy cycle which then leads on to more quantitative tools as part of ex ante policy appraisal. Similarly, Barbrook-Johnson et al. (2021) places systems mapping at the start of ex post policy evaluation efforts. The approach presented here fits with this, but also extends systems mapping's potential role, such that it might be used to connect model findings to policy processes and broader social science knowledge.

3 Complexity economics and data-driven systems mapping

3.1 The mapping process

In a typical systems mapping exercise, given a system or a policy of interest, the main goal is to determine, often in a participatory fashion, the system's key factors and the links between them. The core outputs are a process and network which represent a comprehensive and shared vision of the forces at work, which in turn can be used in policy design and appraisal. We attempt to demonstrate that: (i) systems mapping is a suitable approach to contextualise, embed, and communicate insights of complexity economics models in real world policy forums, and that (ii) network estimation methods provide a good basis for data-driven systems mapping exercises when the system of interest is large and/or intricate.

In practice, a systems mapping process is often iterative and involves desk-based literature and context reviews, data collection and analysis, and multiple rounds of interviews and discussions with experts and policy stakeholders. Figure 1 summarises an iterative process in which data-driven mapping complements stakeholder engagement: first, the system of interest is defined, that is, priors on the factors that compose the system are established. Findings from complexity economic models may inform such priors. Second, data-driven methods are deployed to estimate the links between the factors in the system. Here, we demonstrate the use of two data-driven network modelling techniques - correlation networks and the PC algorithm. Third, the map is analysed and, depending on the findings, the system of interest might be redefined and the estimation adjusted. Next, the results can be discussed with stakeholders and, if needed, the system definition and estimation may be further refined. At this stage, findings from complexity economics models can be contextualised within a larger system, as well as embedded in real world policy debates, where the map acts as the key communication tool.

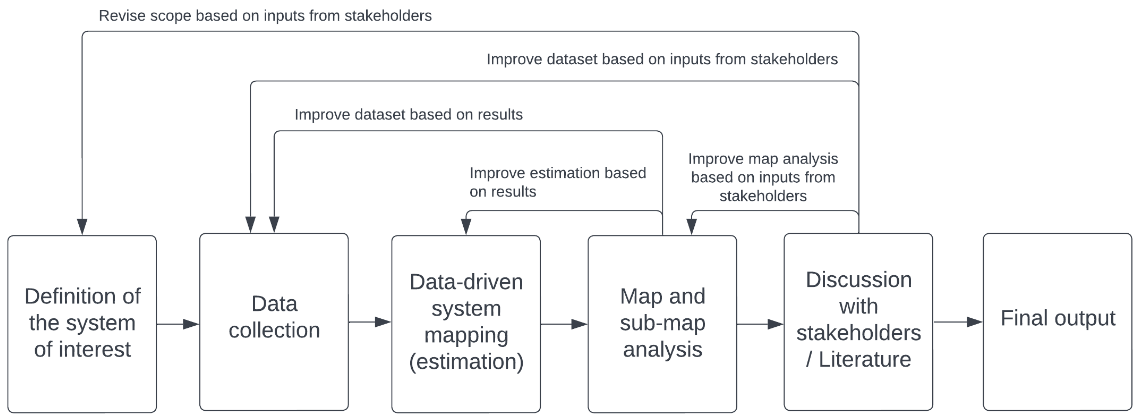


Figure 1: Overview of a systems thinking workflow with a data-driven systems mapping component.

Our application illustrates the use of data-driven systems mapping at the earlier stage of the research process, up until the map analysis stage, prior to engagement with other stakeholders. In the following subsections we briefly present the network estimation methods and our approach to the map analysis.

3.2 Data-driven system mapping: network estimation

To estimate our maps, we use correlation thresholding and the PC algorithm, two common network estimation techniques suitable for the estimation of SDGs networks (Ospina-Forero et al., 2020) and relatively easy to implement and communicate to policymakers and other stakeholders. In a network model, the factors in the system of interest are referred to as nodes and the links between them are called edges (directed or undirected, i.e. with a direction indicated by an arrowhead, or not), so we follow this convention in the following sections. The meaning of edges in these networks depends on the methods used to create them. Neither of the methods we used attempt causal inference, so we refer to them as empirical regularities or relationships and avoid using causal language. Care must be taken to avoid causal interpretation of edges with stakeholders.

A key point to emphasise here is how we envisage these and related methods being used in a data-driven systems mapping approach with or without a participatory element. Quantitative methods come with a set of norms and practices on how they should be applied. When we are using them in a systems mapping mode, i.e. building them into a systems and participatory approach, we will need to be clear, but more flexible about the limits of some of these norms and practices since our purpose and aims are quite different from a traditional statistical analysis. This means we may be more flexible about data quantity requirements while tolerating potentially higher p-values to generate richer, denser maps, for example. We believe this is acceptable if we are explicit about it, and it is justified if the purpose of the exercise is to use data-based insights as a basis for further discussions.

3.2.1 Correlation thresholding

Correlation thresholding is one of the most common network estimation techniques, largely because it is easy to implement, to interpret, and does not impose restrictive assumptions on the relationships between the variables (Ospina-Forero et al., 2020). The method consists of two main steps: first, given a set of nodes $X = \{X_1, ..., X_n\}$ we estimate a full correlation matrix. Then, starting with an empty network, for each pair of nodes (X_i, X_j) in X we populate our network with an edge between X_i and X_j if the estimated correlation between them and/or its corresponding p-value passes the chosen threshold(s).

The method allows for a few variations worth discussing. Different measures of correlation may be used depending on the type of data and on the nature of the interdependency between the variables. In our case study we do not use the Pearson correlation coefficient because we do not expect nor are we strictly interested in linear relationships between the nodes. Instead, we use the Spearman's correlation coefficient, which evaluates monotonic associations, therefore being able to pick up on nonlinear (and linear) relationships.

It is also possible to estimate undirected or directed correlation networks (by using contemporary correlations or by lagging the explanatory variables, respectively). Moreover, different criteria may be used to determine the existence of an edge between two nodes, and these can be tailored to the goals of the research. As discussed above, false positives (higher p-values) or weaker interdependencies (lower correlation coefficients) may be better tolerated or even desired at the initial, exploratory stages of an iterative process that subjects the data-driven findings to expert scrutiny and further refinements.

3.2.2 Independence-based PC Algorithm

Correlation thresholding is a good baseline, but as it focuses on pairwise relationships only it cannot address issues caused by confounders or, more generally, map relationships between nodes of the system while accounting for the other nodes of the system (conditional dependence). One alternative is to think of the system as a network of conditional dependencies that can be modelled as a graph and use conditional independence tests to learn the structure of the graph. In other words, when assessing whether there is an edge between two nodes X_i and X_j, all variables in the system are taken into account.

To implement such an approach, here we use the PC algorithm (Spirtes et al., 1993, 2001), named after the authors Peter Spirtes and Clark Glymour, one of the main algorithms for causal structure learning. The PC algorithm works in three steps: 1) it determines the skeleton of the network, that is, it estimates all network edges, without considering the direction of relationships; 2) it determines the edge orientation for v-structures $x \rightarrow z \leftarrow y$, that is, a structure where two variables x and y have a common effect z; 3); based on the results from steps 1 and 2, determines further edge orientations (Heinze-Deml et al., 2018).

Step 1 starts with a complete undirected graph, that is, with all possible undirected edges between nodes. Then, for each pair of nodes in the network, if X_i and X_j are independent given any subset of nodes in the network, then the edge between X_i and X_j is deleted, otherwise the edge between X_i and X_j is kept (Kalisch et al., 2022).

In Step 2, the algorithm orients edges by identifying all v-structures, that is, by identifying all triples $x - z - y$ that can be oriented as $x \rightarrow z \leftarrow y$. In such cases, we say that z is an unshielded collider: unshielded because x and y are not connected, and a collider because both x and y have a direct influence on z. This is done using information from step 1. Specifically, given a triple $x - z - y$, if z is not in the separating set for x and y from step 1, then z must be a collider and the triple is oriented as $x \rightarrow z \leftarrow y$.

In step 3, the algorithm further orients edges by considering that (i) cycles are not allowed and (ii) that for partially oriented triples such as $x \rightarrow z - y$, it must be the case that $x \rightarrow z \rightarrow y$, otherwise z would be an unshielded collider and would have already been identified as such in step 2 (Kalisch et al., 2022).

At this point, it is worth noting two of the PC algorithm's key assumptions: acyclicity (Heinze-Deml et al., 2018) and causal sufficiency. The first, which is used in the step 3 as discussed above, implies that the system cannot have feedback loops. The second means that the algorithm assumes the absence of hidden variables. In many settings these are relevant limitations and other methods should be considered.

3.3 Map analysis: analysing and interpreting the networks

Once the network has been estimated, different approaches can be used to analyse the system and interpret the results. In our case study, we follow Barbrook-Johnson and Penn (2021, 2022) and proceed in three steps: (i) observing the structure of the full maps, (ii) network analysis, and (iii) submap analysis. The first two steps build an overview of the system map as a whole, while the third focuses on specific sub-sections. In step 1 we begin with a visualisation of the map and consider its basic shape and features, such as the number of edges, islands, and isolated nodes. A force-directed layout algorithm (Jacomy et al., 2014) can be used to aid the visualisation. At this stage it is possible to compare the structure of the maps obtained with different methods and criteria, to identify large and/or relevant islands, and to reflect on the incidence of isolated nodes. In step 2 we turn to a more formal approach to exploring the structure of the full maps, using three traditional network analysis measures: (i) betweenness, which measures the number of paths between other nodes that a node is on, it gives a sense of nodes that play bridging or bottleneck-type roles in the map; (ii) closeness, a measure of the distance between a node and all other nodes, it captures how central a node is to the map; and (iii) degree, which simply measures how many connections a node has. The idea is to identify which nodes are more relevant in each of the measures, as well as key nodes that score high in all metrics or have unexpected values (i.e. high scores when we did not expect them to be important, or high scores in one metric, but low in the others).

Finally, in step 3 we analyse sub-sections of the networks, or submaps. For a node or group of nodes of interest, the idea is to analyse a bespoke version of its ego network or nodes connected to or from it. In our application, we build and analyse submaps based on the findings from steps 1 and 2, motivated by specific policy questions, and guided by findings from a complexity economics model. Here, we present two-step ego networks, but Barbrook-Johnson and Penn (2021) discuss a variety of different ways to construct submaps. If the network is directed, the submap analysis can be thought of in terms of the nodes 'upstream' and 'downstream' from a node of interest (that is, flowing into the node of interest, or away from it), as we demonstrate in our case study.

At this stage it is also important to inspect and consider the plausibility of the edges, directed and undirected. The absence of expected links may also be considered. A good framework for such discussions is to think in terms of potential biases. Table 1 below presents a summary of three typical types of bias to consider:

While any data-driven estimation method will have its limitations and is subject to bias (for example, from misspecification of the system), within the context of a systems thinking exercise such issues could be the basis for further discussions with stakeholders. Additional data collection may be possible or, alternatively, limitations in data availability or other resources may be acknowledged. In either case, the discussion would add transparency to the process and contribute to a shared vision not only on the findings and its policy implications, but also on its limitations and uncertainties.

Confounder bias	Mediator bias	Collider bias
Relationship: Counter-intuitive A-B link?	Relationship: Counter-intuitive A-B link?	Relationship: Missing an expected association between A and B?
Is there an unobserved variable (i.e. that we have not included in our analysis) that is a common cause of A and B? What data could we add to the analysis to address this?	Is there an unobserved mediator that could make the causal chain more intuitive? What data could we add to the analysis to address this?	Is there an unobserved variable that is caused by both A and B? What data could we add to the analysis to address this?

Table 1: Confounder, mediator, and collider bias.

4 Case study: SDGs and the energy transition in Brazil

To focus geographically, we consider the energy transition in Brazil. Our system of interest is a network of SDG indicators augmented with nodes for the energy transition and other energy sector and macroeconomic factors as additional controls.

4.1 The Sustainable Development Goals

In 2015, the 2030 Agenda for Sustainable Development, with 17 Sustainable Development Goals, was adopted by the United Nations General Assembly. The goals are: 1) No poverty, 2) Zero hunger, 3) Good health and well-being, 4) Quality education, 5) Gender equality, 6) Clean water and sanitation, 7) Affordable and clean energy, 8) Decent work and economic growth, 9) Industry, innovation, and infrastructure, 10) Reduced inequalities, 11) Sustainable cities and communities, 12) Responsible consumption and production, 13) Climate action, 14) Life below water, 15) Life on land, 16) Peace, justice, and strong institutions, and 17) Partnerships for the goals. For each goal there are between 5 and 19 targets, and between 6 and 28 indicators (U.N. General Assembly, 2015). It is the indicators we use as a key inputs in our analysis, as variables in network estimation.

The 2030 Agenda envisions the integration of economic, social, and environmental development, so in the original formulation of the SDGs they were always intended to be treated as an integrated whole, rather than individual targets. The academic literature has reflected this, and there is a fast-emerging literature on SDGs interactions (Breuer et al., 2019; Bennich et al., 2020). Bennich et al. (2020) provide an excellent review of the studies in this space, highlighting the variety in what interactions are considered; from interactions only between SDGs goals, targets, and/or indicators, through including policy interventions or 'external' influences, through to looking at interactions at national scale rather than globally. There is also variety in how these interactions are explored, with a wide range of data and evidence and analytical approaches used. Many approaches conceptualise the interactions as networks of SDG indicators, as we do here.

The most recent IPCC Working Group III report (Shukla et al., 2022) summarises an assessment of the literature on the interaction between the SDGs and climate change mitigation options, including the energy transition. The analysis shows potential synergies and trade-offs between pairs of mitigation options and SDGs discussed in the literature, like electrification contributing to increased employment. It does not consider how mitigation options may affect one another, nor interactions between the SDGs themselves, however it is the only example we are aware of of the interaction between the SDGs and the energy transition being considered in a systematic fashion.

Our core contribution to the SDGs interaction literature is three-fold. First, we include in SDGs interactions the energy transition and macroeconomy, both between these groupings and within, using quantitative data. Second, we include in the analysis outputs of complexity economics models in the form of model findings. Third, we contribute methodologically, building on the analytical approaches described in Ospina-Forero et al. (2020), by using the systems mapping analysis approach focussed on developing policy-relevant submaps and narratives from systems maps, described in Barbrook-Johnson and Penn (2021).

4.2 Energy transition and the SDGs: recent developments in Brazil

In Brazil, the share of renewables in the energy matrix has been historically high (between 39% and 58% since 1970) and significantly higher than the world average (46% versus 14% in 2019), mainly due to the role of hydropower and bioenergy from sugarcane (Empresa de Pesquisa Energética, 2022*a*,*b*). Nonetheless, given the environmental costs and climate exposure associated with further expanding hydro from its current levels, wind and solar energy have gained relevance in the last ten years as a means to diversify the production of renewable energy.

Within this context, affordable and clean energy (SDG 7) is the only goal achieved and maintaining in Brazil, as measured by (i) the population with access to electricity, (ii) access to clean fuels and technology for cooking, (iii) CO2 emissions from fuel combustion, and (iv) the share of renewable energy in total primary energy supply. Other SDGs on track for achievement, but with challenges remaining, are Climate Action, Clean Water and Sanitation, and Quality Education (Sachs et al., 2022).

In all other dimensions, the current performance is less promising: in two areas, challenges remain and the current pace of improvement is too slow for goal achievement. In ten other areas, significant or major challenges remain, with scores stagnant or only moderately improving. Finally, Reduced Inequalities is the SDG with worse performance: major challenges for achievement remain and the score is decreasing (Sachs et al., 2022). Therefore, how the country's advantage in clean energy and the recent diversification of renewables in the energy matrix interact with other dimensions of sustainable development is a relevant policy question. Specifically, we are interested in how variations in the share of biofuels, wind, and solar interact with other SDG indicators.

4.3 Data, model specification, and workflow

Data on the SDG indicators were obtained from the United Nations SDGs database, which we complemented with data from the World Bank, Climate Watch Data, the Economic Commission for Latin America and the Caribbean, the World Inequality Database, and the Brazilian Integrated System of Disaster Information (S2ID). To characterise the energy transition, we augment the SDGs system with the supply and production of fossil, renewable, and nuclear energy. We also control for key macroeconomic factors. Data on the energy sector, including energy transition indicators, and on macroeconomic factors are from the Brazilian Ministry of Mines and Energy, the Brazilian Institute for Applied Economic Research, the World Bank, the Brazilian Institute of Geography and Statistics, and the Brazilian Sugarcane Observatory.

As previously discussed, we proceeded through a series of steps, which we summarise in Table 2 below.

Below we present and discuss some key findings from three different model specifications: we begin with a larger system of SDG indicators, energy sector nodes, and a broad set of macroeconomic controls; in the second specification we consider a system of SDGs goals with (non-hydro) green energy nodes, including all biofuels aggregated in a single indicator, and only key macroeconomic factors; in turn, the third map disaggregates biofuels with a focus on sugarcane.

5 Findings

We now turn to an exploration of the system maps developed for Brazil. This section aims to demonstrate how we can use our data-driven systems mapping approach to explore empirical regularities in data, look for interesting or unexpected associations, understand what gaps or erroneous relationships might be present, and unearth new questions about the system and topics within it. Though we call it a 'findings' section, the section is not intended to present conclusive findings, but rather demonstrate the proposed approach and provide provocations for future work.

5.1 Observations on the structure of the full maps

We begin with a large system of 109 nodes including SDG indicators, factors descriptive of the energy transition, and a set of macroeconomic and energy sector indicators. Table 3 presents an overview of the full map structures estimated using correlation thresholding and the PC algorithm.

Row 1 presents a dense network of pairwise correlations and, as such, is a step that allows the researcher to visualise all possible links suggested by the data and reflect on the strength of the links. Nonetheless, this method cannot be used to address confounders nor to identify mediators or colliders. Rows 2 to 4, on the other hand, present networks of conditional dependencies estimated with the PC algorithm and, after controlling for other nodes of the system, the networks are sparser.

As this exercise is meant as a base for further discussions with stakeholders, we have higher tolerance to false positives and we aim for denser, more comprehensive maps. Here, we illustrate

Step	Description	Objectives
1	Data gathering and cleaning: initial processing the SDG indicators data and brainstorming energy and macroeconomic data to bring in. Conceptual mock ups of system maps.	Understanding data gaps and thinking through the energy transition within the Brazilian context.
2	Prototyping the map - with a preliminary dataset, created versions of the map with different methods and threshold criteria (for correlation coefficient and p-values).	Understanding which relationships are more robust and which methods deliver the most usable maps.
3	First iteration of analysis - first proper analysis sweep, exploring full map carefully, and running submap analysis.	Understanding the overall map structure, submaps, and areas to be improved (e.g., which open questions we could address with more data).
4	Second iteration of analysis - refined scope and datasets, re-run main map and submap analysis.	Richer understanding. Can be repeated as needed before moving to the next stage.
	Further stages we would envisage in a full data-driven systems mapping process. Not presented in this chapter.	
5	Stakeholder input begins - use maps as discussion tools with stakeholders.	Develop understanding of stakeholder needs and views.
6	Refine based on stakeholder input - collect more data, develop new analysis, refine existing analysis to meet stakeholder needs and suggestions.	Understand relationships and analysis suggested by stakeholders.
Ongoing iteration as desired	Repeat iteration between data, maps, stakeholders as desired.	Ongoing learning and application to new questions. Map becomes living document refined and updated when needed.

Table 2: Brazil case study workflow.

how such tolerance can be implemented as we adjust the conditional independence tests p-values: row 2 presents the network obtained with p-value=0.05 as the threshold. This version is much sparser and characterised by several small islands. In row 3, we set p-value=0.15 and, as a result, the map has more edges and two larger islands. In row 4, the p-value is increased to 0.20. The number of edges increases only slightly but in this version we see the relevance of one large island, hinting at a more interpretable representation of the system.

Next, we consider a system of SDGs with only (non-hydro) green energy nodes, including all biofuels aggregated in a single indicator, and key macroeconomic factors (Table 4).

The maps have 63 nodes (55 from SDG indicator data, 5 from energy system data, and 3 from macroeconomic data). The correlation network has 280 edges, and the PC algorithm network

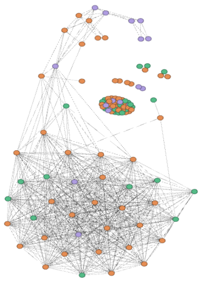
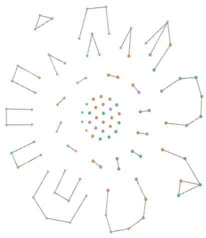
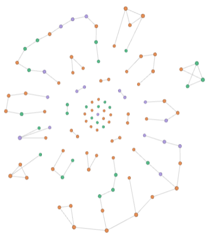
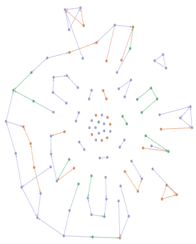
No.	Full map structure	Notes on data and method	Process and learning
1		• 109 factors and 606 edges • Correlation only • p-value=0.10 and correlations above 0.9 • Undirected edges	First correlation network. The network is dense but has a large number of isolated nodes.
2		• 109 factors and 60 edges • PC algorithm only • p-value =0.05 • Undirected edges	First exploration and sense checking. Lots of isolated nodes and small islands of nodes.
3		• 109 factors and 76 edges • PC algorithm only • p-value =0.15 • Undirected edges	Some 'usable' structure, sense checking relationships. As a basis for further discussions with stakeholders, p-value=0.15 worked better than p-value=0.05, without major differences in network density.
4		• 109 factors and 80 edges • PC algorithm only • p-value =0.20 • Directed edges	Adding directed edges where possible. Checking the impact of using p-value=0.20.

Table 3: Overview of first iteration maps produced.

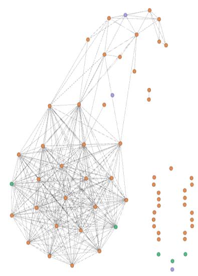
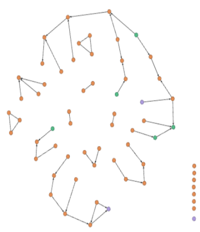
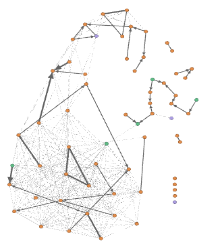
No.	Full map structure	Notes on data and method	Process and learning
1		• 63 factors and 280 edges • Correlation only • p-value=0.10 and correlations above 0.9 • Undirected edges	Removal of potentially redundant macroeconomic factors and SDG indicators reduces the density of the network.
2		• 63 factors and 47 edges • PC algorithm only • p-value =0.15 • Directed edges	The network has similar density, but a lower number of small islands and isolated nodes than in the first specification.
3		• 63 factors and 311 edges • Combined including nodes and edges in either correlation or PC algorithm (i.e. the union of the two networks)	The 2-cluster structure of the correlation network dominates.

Table 4: Overview of second iteration of maps produced.

has 47. The combined map (bringing together the PC algorithm and correlation networks) has 311 edges (20 directed, 291 undirected). 47 of these edges are present in both the PC algorithm and correlation networks.

In Figure 2 we visualise all three networks (i.e. correlation, PC algorithm, and combined) with a force-directed layout algorithm (Jacomy et al. 2014). The correlation network has a clear two-part structure. There is a large cluster of densely interconnected nodes to the bottom, and a smaller cluster jutting out to the top. The smaller cluster is dominated by various factors for consumption of specific materials and some economic-related factors (e.g. GDP and vulnerable employment) whereas the bigger cluster contains a mix of different factors with no obvious theme or pattern. This version is less dense than the previous, but still suggests a high-level of potentially erroneous associations between factors that could be driven by common causes. Perhaps more interesting is the position of total greenhouse gas emissions in the correlation network. It is one of the connection points between the two clusters, forming part of both. Overall, the patterns in the correlation network are not always obvious or intuitive and the lack of directionality does not help with this. Correlation networks are the bluntest tool in our toolbox, but are potentially a useful foundation to build on.

The PC algorithm network in panel B is much sparser, but has fewer disconnected nodes. There is a clear structure of several 'islands' of connected nodes, including: (i) a relatively large island bringing together factors related to water and sanitation, connected via women in parliament, to energy and economic factors (this island is shown in Figure 3); (ii) two economic-related islands; (iii) a triad of factors related to children's health; and (iv) several smaller islands dominated by material consumption factors.

The larger island, shown in Figure 3, has some potentially interesting properties. First, there is a clear horizontal structure, i.e. the map does not contain long chains of connections following the same direction, but rather 'zigzags' up and down with common factors connecting small chains flowing up from them. Women in parliament is one such example, connecting energy-related factors with a set of water and sanitation-related factors. This is a much more intuitive structure than some of those in the correlation network.

The combined network is shown in panel C in Figure 2. Here, the edges that appear in both networks are emboldened. The structure of the correlation network dominates, with the same two large and small clusters, however a third cluster emerges to the right with factors related to energy and the economy. Potentially interestingly, women in parliament, safe water services, and energy from biofuels and wind are the connection points between the two parts of the network. Macroeconomic and energy related factors are clearly well represented in this new cluster.

5.2 Network analysis

Now we turn to a more formal approach to exploring the structure of the full maps, using traditional network analysis measures. It is important to note, we are running this analysis on the combined network, which represents a combination of two different data-driven networks, but is itself not technically data-driven since the combination is informed by our judgement. However, analysing the combined network using network analysis is still appropriate given our purpose in this exercise (i.e. to help 'digest' the map while considering all possible associations

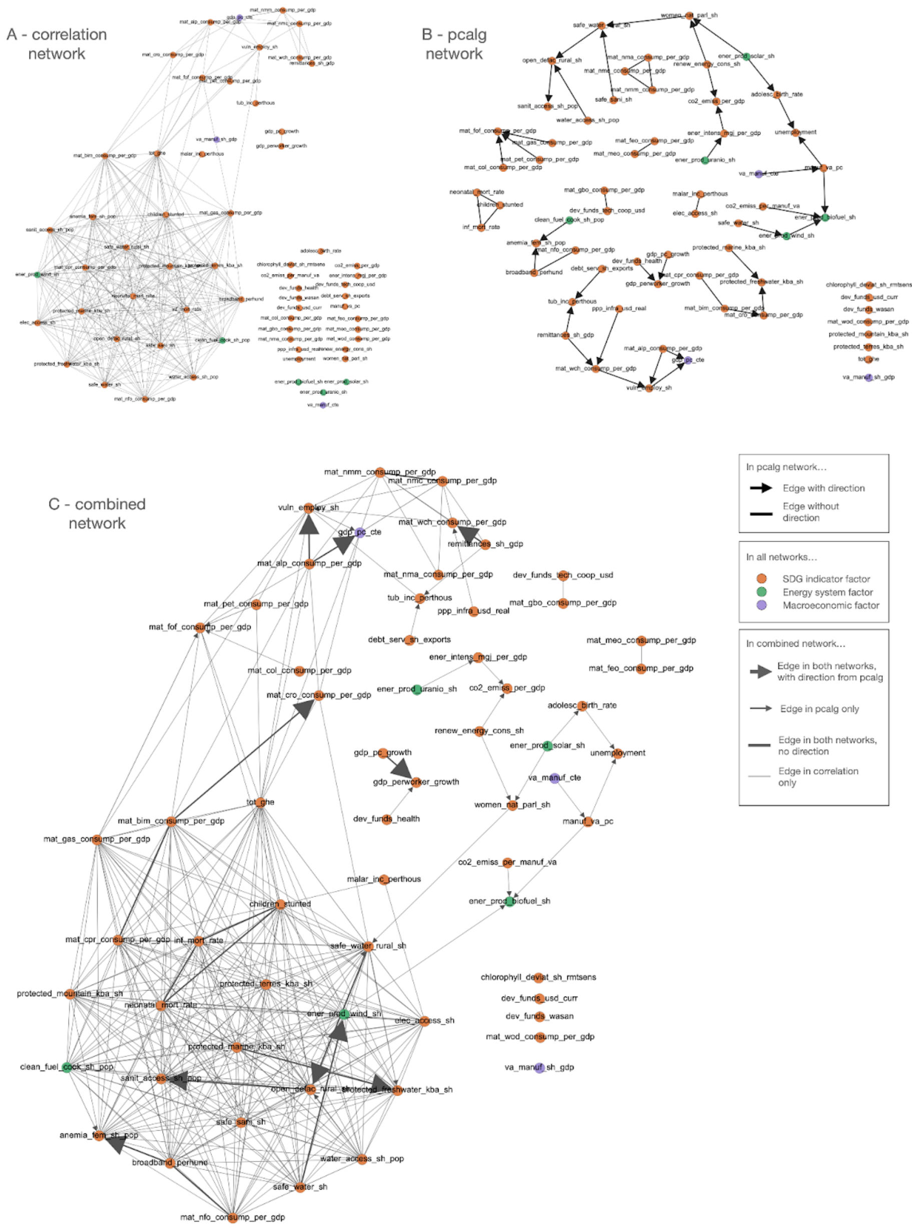


Figure 2: *Full view of the three system maps.* (A) Visualisation of correlation network. (B) Visualisation of PC algorithm network. (C) System map based on both networks combined with edges that appear in both maps emboldened. All maps are laid out using a force-directed layout algorithm with some manual alterations.

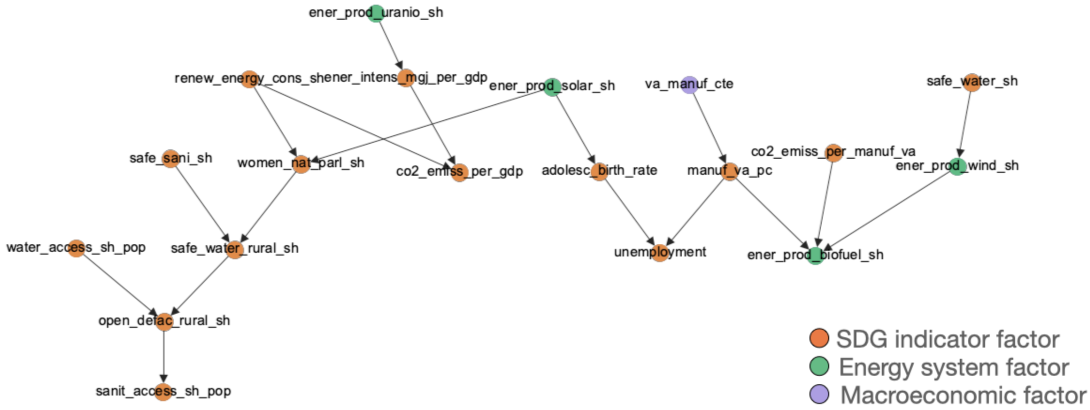


Figure 3: *Largest 'island' in the PC algorithm network.* This submap shows a self-contained set of connected nodes in the PC algorithm network.

and use it as an exploratory tool), but we should keep in mind that it is likely dominated by the correlation network because of its much higher number of edges. We could run the network analysis using weights to emphasise one or other of the networks, or indeed edges that appear in both. Here, we use a simple network analysis with no weights, even if an edge appears in both. Table 5 shows the top five nodes for three network measures described above: betweenness (which capture if the node is a 'bridge' or 'bottleneck'), closeness (which captures if a node is 'in the thick of it'), and degree (number of connections).

	Betweeness (bridge or bottleneck)	**Closeness** ('in the thick of it')	**Degree** (number of connections)
1	• Proportion of population using safely managed drinking water services - rural • Total greenhouse gas emissions	• Annual growth rate of real GDP per employed person • Total official development assistance • Material consumption*	• Total greenhouse gas emissions
2	• Proportion of seats held by women in national parliaments	• Total official development assistance to medical research and basic health sectors • Annual growth rate of real GDP per capita	• Children moderately or severely stunted • Proportion of population using safely managed drinking water services - rural

3	• Vulnerable employment	• Total greenhouse gas emissions	• Proportion of women aged 15-49 years with anaemia • Access to clean fuels and technologies for cooking • Energy production - wind • Proportion of population practising open defecation • Proportion of population using safely managed sanitation services
4	• Energy production - wind	• Proportion of population using safely managed drinking water services - rural • Material consumption*	• Fixed Internet broadband subscriptions • Electricity Access • Infant mortality rate • Material consumption* • Neonatal mortality rate • Protected marine area • Protected mountain area • Protected terrestrial area • Proportion of population using basic sanitation services • Proportion of population using basic drinking water services
5	• Energy production - biofuels	• Energy production - wind • Material consumption*	• Material consumption* • Protected freshwater access

Table 5: Network analysis: top five nodes for scores on betweenness, closeness, and degree. Note, for all measures there are examples of factors having equal scores. *Various raw materials, as reported in the Global SDG Indicators Database.

These network measures reveal three potentially interesting patterns. First, energy production from wind appears in all three top fives, reflecting its position in the large cluster from the correlation network and as a connection point into the third cluster that appeared when we combined the correlation and PC algorithm networks. Second, total greenhouse gas emissions again appears structurally important, with high scores on all three measures. Third, access to safely managed drinking water services, which is an essential dimension of sustainable development, also appears in all three lists.

In the following section, we focus further on wind and on biofuels energy (which is linked to wind), two of the nodes with interesting patterns in the network analysis that are directly related to the energy transition. This is one example of further analysis being informed by the wider network analysis, but all of the patterns above are potentially worth exploring further through focussed analysis or stakeholder engagement.

5.3 Submap analysis

Now we have a feel for the overall network structure within the data, it is time to conduct some more focussed analysis based on pulling out sub-sections of the map (or 'submaps') for closer inspection. This is where we more meaningfully operationalise the idea of contextualising, communicating, and embedding complexity economics in policy using this systems mapping approach. The submaps we extract are identified and constructed in different ways (following Barbrook-Johnson and Penn, 2021) to allow us to focus on these topics and make more sense of the map, both from a data-driven and stakeholder engagement perspective.

As submaps allow us to interrogate the map more closely and often raise new questions, it is common to expand and re-run analysis on specific submaps in an exploratory manner. These are part of the iterations of analysis we described above, and are often best done with stakeholders involved. Here, we demonstrate this with three pieces of submap analysis: (i) exploring the policy-relevant question of how the energy transition might impact SDGs; (ii) zooming into wind energy and then considering the Brazil-specific question of biofuels and their role; and (iii) contextualising a complexity economics modelling finding, building on findings of the DSK model (Lamperti et al., 2018, 2020) on climate shocks and the energy transition.

5.3.1 Bringing in policy questions - the energy transition and the Sustainable Development Goals

Figure 4 shows a submap of the combined map, constructed from the five nodes which represent the energy transition in some sense (i.e. energy produced from wind, solar, biofuels, nuclear, and renewable energy consumption) and only showing nodes within two steps downstream (i.e. following arrows away from or without direction). There is a mix of intuitive and more puzzling connections.

We can see nuclear energy affecting energy intensity which in turn is associated with CO2 emissions per unit of GDP. Likewise, renewable energy consumption affects carbon emissions per unit of output, which is an indicator for the SDG 9 ("Industry, Innovation and Infrastructure"). Overall, the links between energy intensity, renewable energy consumption, and carbon emissions per GDP are expected, given that the latter depends on the type and values of energy consumption in the economy, which is reassuring.

There are also other intuitive, if somewhat seemingly unrelated, relationships between renewable energy and SDG 5 (Achieve gender equality and empower all women and girls) and 6 (Clean Water and Sanitation). We see consumption of renewable energy and the share of solar in energy production linked to access to safe water in rural areas and to safe sanitation (SDG 6) via the share of women in parliament (SDG 5). We also see a link between the share of wind in energy production and access to safe water (SDG 6).

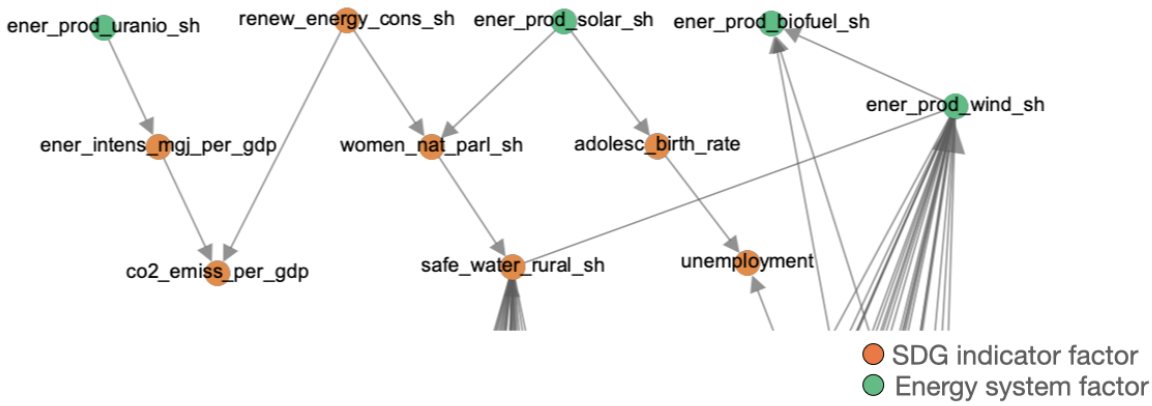


Figure 4: *Downstream of energy transition-related factors.* Green factors are energy system factors, orange factors are SDGs factors. This map shows nodes downstream from five factors closely associated with the energy transition (i.e. renewable energy consumption, and production of wind, solar, biofuel, and nuclear energy). The map shows nodes within two steps of these factors using the directed edges from the pcalg network, correlation edges are preserved but the nodes they connect to are not. The submap thus shows the SDGs factors closely connected to the energy transition factors.

These dependencies remain even conditioned on income levels and growth, which are included in the system. Nonetheless, these associations might be reflecting confounders or meditators that are still omitted. For example, the link between representation of women in parliament and consumption of renewable energy could result from a common cause, such as progressive preferences/government. Alternatively, a mediator could explain the link: more decentralised power generation could empower communities and, as a result, boost the participation of women in politics. Further discussing these omissions with stakeholders and considering how to address them would be important from a gender equality (SDG 5) perspective, because the policy implications are different under each of these two hypotheses. The same idea applies to the link between solar energy and women in parliament.

Similarly, the connection between renewable energy and water and sanitation infrastructure could reflect preferences for investing in both sectors or that expanding solar and wind power generation enables investments in other essential infrastructure, for example via an increase in tax revenues. These possible mechanisms could be further investigated with stakeholders from the energy, water, and sanitation sectors.

A less intuitive relationship appears between solar energy production and adolescent birth rates (SDG 3 – Ensure healthy lives and promote well-being for all at all ages). Rather than dismiss these surprising results, we should dig deeper. Education could be a factor influencing both, investments in solar energy and adolescent birth rates (with a negative association). Alternatively, if more solar energy is linked to unemployment in communities reliant on fossil energy sectors, then unemployment could be a mediator. Interestingly, adolescent birth rate is linked to unemployment in the map, an association that has been well-documented and widely investigated in many contexts. Further investigating the position of unemployment in this submap and the impacts of solar energy on the labour markets and on adolescent birth rates would therefore be of interest to stakeholders in the labour and health sectors.

5.3.2 Zooming-in on wind energy and biofuels

The difference between energy production from wind and solar in the network is stark. As indicated in the network analysis above, wind is connected to many more factors in the map than solar energy, mainly because the latter is an isolated node in the correlation network. This result is not surprising given that the advent of solar energy in Brazil is a more recent event and that the share of solar energy production is still the lowest in the country's energy matrix (Empresa de Pesquisa Energética, 2022*a*). Besides being connected to several nodes in the correlation network, the wind energy share is associated with the share of biofuels, a major source of energy in Brazil.

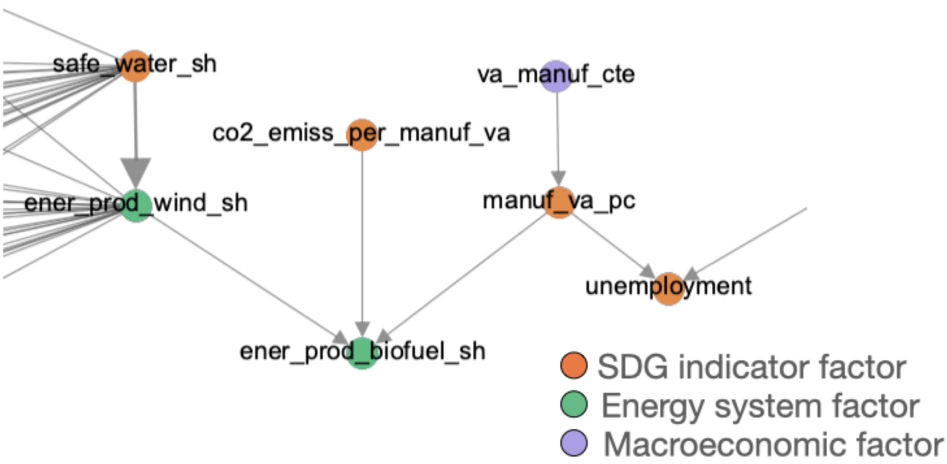


Figure 5: *Ego network of biofuels.* This network shows the two step ego network of biofuel production, but cuts out many of the nodes connected via wind energy production.

In the combined map, looking upstream from biofuels (Figure 5) we can see that manufacturing value added and CO2 emissions per unit of value added in manufacturing have a strong relationship with biofuels, as does wind energy. Since biofuels include sugarcane products, firewood, vegetable oils, and waste energy sources, which in turn can be transformed into thermal, mechanical, and light energy, the plausibility of these associations and any mechanisms behind them would be interesting topics for further research, as would discussions with specialists in the energy and manufacturing sectors, especially considering that industrialization is an important dimension of the SDGs. Again, these could be explored further using the confounder-mediator-collider prompts.

Looking downstream from biofuels there is little to say about the potential knock-on effects, as it has only incoming arrows. To demonstrate how submaps exploration can inspire further literature reviews, data collection and mapping, we iterated again, still within the context of the energy transition and the SDGs, but this time with an extra focus on the role of biofuels and land use as the starting point. The idea is to explore the interdependencies between biofuels, land use, and food prices in Brazil, in light of a strand of literature that considers co-movements in oil and agricultural output prices as the latter is increasingly used as input for energy production (Hassler and Sinn, 2016; Peersman et al., 2021).

We collected additional data to disaggregate biofuels with a focus on sugarcane. Specifically, we included sugarcane and ethanol production, as well as data on the supply of electricity from sugarcane. Other sources of renewable energy included are woodfire, solar, wind, and hydro. We also include data on the sugarcane and forest shares of the Brazil's land area, and a food price index. This third iteration map contains 53 factors, including nodes that capture renewable sources of energy, the SDGs, and key macroeconomic variables. As before, the correlation network is much denser with 294 edges, the PC algorithm map has 34, and the combined network 309. The resulting submaps that 'mimics' Figure 5 by again focussing on biofuels are shown in Figure 6. This further iteration shows the biofuel factors much more tightly connected into the map, with all of them holding a central position in the main cluster of the map.

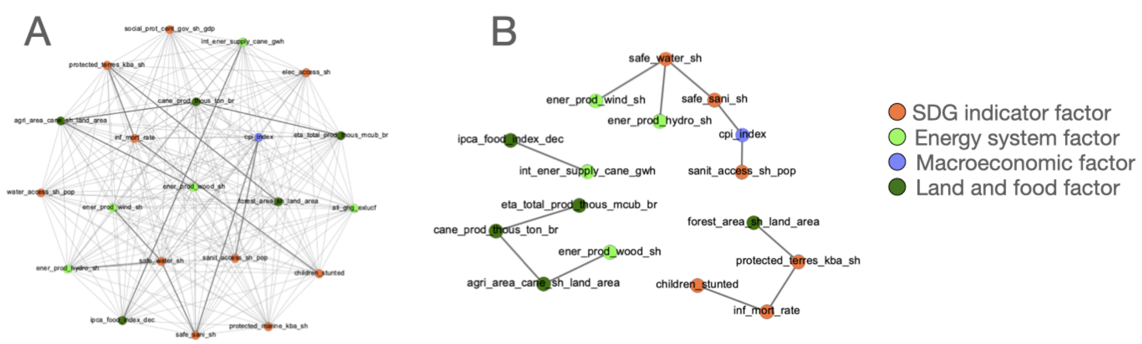


Figure 6: *Ego networks of biofuels 2.* (A) The two step ego network of the biofuel related factors. (B) The same network, but with only the edges appearing in both correlation and PC algorithm networks shown.

When we thin the map by only including connections which appear in both PC algorithm and correlation networks, we see a different picture. Firstly, we see a chain from land area producing sugarcane to sugarcane production, to ethanol production. While the PC algorithm was not able to direct these edges, for policy purposes expert knowledge and/or further data collection could be used to complete this section of the map. We also see a relationship between electricity supply from sugarcane and food prices, but electricity supply from sugarcane is not linked to the rest of the chain, an issue that could be discussed with sector specialists.

Similarly, the link between land area producing sugarcane and the share of energy production from wood could be further investigated, as well as the lack of a link between forest area, wood, and sugarcane production. Still regarding land use, we see forest area associated to protected land, which in turn is linked to child health outcomes. Again, a reflection on confounders and mediators would be worthwhile, since knowing either their common cause or key mediators could be key in designing policy for both the health and environmental dimensions of the SDGs.

5.4 Contextualising a complexity economics model finding

Now, we demonstrate how submap analysis can be used to contextualise findings from complexity economics modelling. Generally, a data-driven map (of a broad system) can be used in one of two ways here:

1. **As an extension to another model:** in this role, the map is a device to communicate and discuss the findings of a more narrowly focused model with stakeholders so that the model assumptions, policy implications, and limitations can be considered in the policy debate within a broader context.

2. **As the centre or substrate for a range of analysis:** in this role, the map itself is the basis for policy analysis, in which case the insights from a more focused model may suggest ways to improve or further extend the map of the system.

If the objective is the former, contextualising the model will involve discussing where the system map corroborates or contradicts the model design and findings and what elements are missing from the model that the map indicates might be important. If the objective is the latter, the discussions would focus on what further mapping work (i.e. extensions, data improvements, methods, analysis) the model suggests. In practice, which of these approaches is more relevant will depend on the stakeholders' objectives; here we illustrate both types of reasoning.

5.4.1 The DSK model and the SDG-energy system

The DSK (Dystopian Schumpeter meeting Keynes) agent-based model in Lamperti et al. (2018) simulates the impacts of climate change on the economy. Specifically, the model assesses the impact of climate damages on the trajectory of GDP growth, unemployment, and on the likelihood of economic crisis (large output losses). The key idea is that climate damages affect firms heterogeneously, through various channels, and become more likely as the mean surface temperature increases due to emissions from the energy and manufacturing sectors. Output and unemployment will therefore be affected as the climate shocks hit the productive sectors.

The main components of the DSK model relate to the SDG-energy system by overlapping with the SDGs 7 (Affordable and clean energy), 8 (Decent work and economic growth), 9 (Industry, innovation, and infrastructure), 11 (Sustainable cities), 13 (Climate action), and 17 (Partnerships for the goals). Below, we use the SDG-energy system map to discuss three key components of the model: emissions, labour productivity shocks, and damages to capital stocks.

We use the sugarcane-focused system map because it includes more nodes for climate damages, the key element in DSK that links the effect of emissions on temperature to the economy. We conclude with a discussion on other possible extensions of the DSK model that the evidence in the data-driven SDG-energy map suggest could be relevant for Brazil.

5.4.2 Energy mix, energy efficiency, and emissions

In the DSK model, emissions result from activity in the energy, capital goods (machines and tools), and consumption goods sectors. The energy sector provides electricity using a mix of green and dirty power plants, and while green plants do not produce emissions, dirty plants burn fossil fuels and leave a carbon footprint. In the capital and consumption goods sectors, emissions vary with the environmental friendliness of the technologies in place and with the total amount of energy units used in the production process. Over time, research and development done by energy and capital goods firms may improve the environmental friendliness and the energy efficiency of the technologies deployed. Therefore, in this setting emissions are intuitively related to the share of renewables in energy consumption and to energy efficiency.

Conceptually, these components of the DSK model relate to the SDG 7 (Affordable and clean energy), which includes indicators for the relative contribution of renewable energy and clean fuels, energy efficiency (proxied here by energy intensity), and for clean and renewable energy RD, and to the SDGs tracking emissions (13 - Climate action and 9 - Industry, innovation, and infrastructure). Empirically, the PC algorithm network is in line with the model set up in that it shows CO2 emissions linked to the share renewables in energy consumption and to energy efficiency (Figure 7).

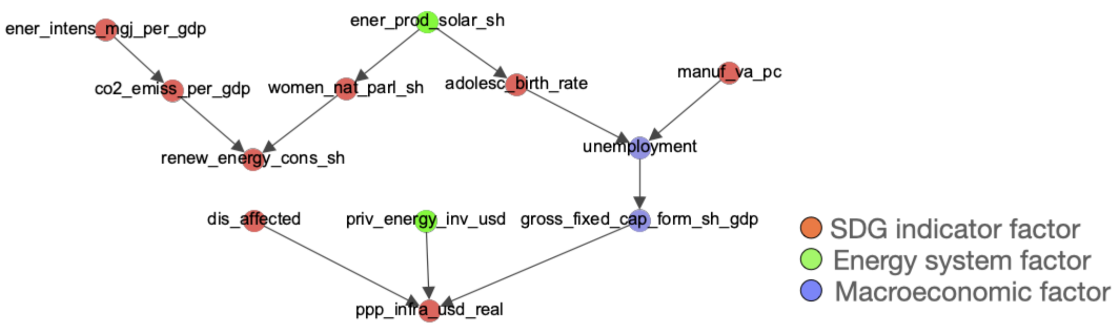


Figure 7: *Largest 'island' in the PC algorithm network for biofuels.* This submap shows energy intensity connected to emissions and to the share of renewables in energy consumption.

These patterns are also consistent with the results in Lamperti et al. (2020). The authors use the DSK model to study the likelihood of climate shocks driving the transition to a sustainable growth equilibrium. They find two equilibria for the model, one carbon-intensive lock-in with the share of low carbon energy production approaching zero, and one equilibrium in which the share of renewable energy converges to high levels. The authors find that negative climate shocks that reduce energy efficiency have relatively little effects on growth and unemployment, but disproportionately lower the chances of an energy transition by inducing technical changes that favour fossil fuels.

Beyond these expected relationships, the SDG system suggests that the share of renewable energy may be affected by the participation of women in the national parliament. This unexpected link could be capturing the effect of omitted mediators correlated with the representation of women in politics such as progressive, pro-green energy policies, so further developing the network around these nodes could bring to light interesting policies or scenarios to be tested with the DSK model.

Moreover, while the DSK model is focused on supply-side drivers of the energy mix, the link between women in parliament and the share of renewables in the network hints on the importance of demand-side factors. Specifically, this link could be driven by a common cause such as progressive voter/consumer preferences, so improving the map to control or proxy for such confounders could be a viable approach to consider the role of demand-side drivers of clean energy within the broader system.

5.4.3 Labour productivity shocks

One of the main findings from the DSK model is that the effect of climate change on the economy depends on how firms are hit by climate events. Specifically, considering four types of shocks (to labour productivity, energy efficiency, capital stocks, and to inventories), simulation results show that shocks to labour productivity harm the economy the most. That is, compared to a baseline scenario without climate damages, when labour productivity decreases due to climate events, over time, the average output growth is much lower than it would have been otherwise, unemployment is much higher, and the likelihood of large downturns increases too. The idea is that when climate shocks decrease labour productivity, firms' production costs increase, leading to a decline in profits and competitiveness, in turn causing output contraction and unemployment. Importantly, such effects are higher when the shocks affect labour productivity than when they affect energy efficiency.

These factors (GDP and labour productivity growth, and unemployment) are accounted for in SDG 8 (Decent work and economic growth) and, in line with the findings in Lamperti et al. (2018) and in Lamperti et al. (2020), in Figure 8 we see that GDP growth is associated to labour productivity, but not to energy intensity.

The SDG network also shows an intuitive link between funding for health and labour productivity, suggesting an alternative channel for impacts and policies related to labour productivity shocks. For example, if climate damages also cause post-disaster recovery to be prioritised over other funding for health, the pressure on labour productivity could be even higher. This kind of effect is not explicitly considered in DSK, but could be an interesting extension or scenario of the model. Similarly, this version of the SDG system does not include nodes to control for health outcomes of workers, so further expanding the health sector in the map could be an important component of the next mapping iteration. While these links are reassuring as they are intu-

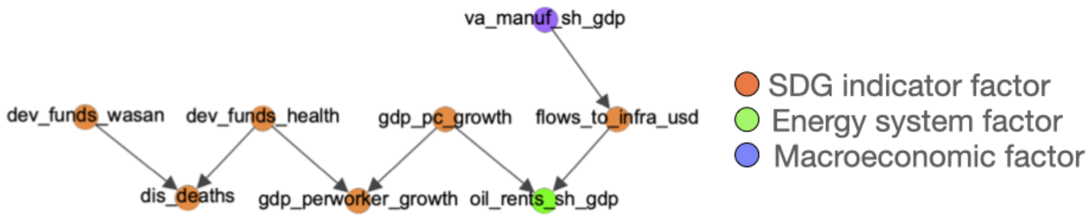


Figure 8: *PC algorithm network for biofuels.* This submap shows labour productivity connected to output growth and to funding for the health sector.

itive and show that key mechanisms of the DSK model are aligned with empirical regularities observed in Brazil, it would also be worth discussing with stakeholders and further studying in the data-driven network why we do not see nodes downstream from labour productivity in the map.

5.4.4 Damages to capital stocks

Shocks to capital stock, on the other hand, have a different dynamic in the DSK model. Unless these shocks are combined with shocks to labour productivity, their impacts on average output growth and unemployment are relatively limited. This is because even though these shocks immediately reduce a firms' production capacity, investments to replace the destroyed assets limit the effects of the shock on average output and unemployment. Nonetheless, these unplanned investments by firms are associated with larger levels of debt, so overall this debt-investment coping mechanism adds instability to the economy.

While the SDG-energy network does not control explicitly for damages to machines and tools, the SDG 11 (Sustainable cities) indicators include types of climate damages that proxy for shocks to capital stock (i.e. affected persons). As shown in Figure 7 above, we see an association between the number of persons affected by natural disasters and public-private investments in infrastructure, in the same island as other measures of investment in physical capital. While these nodes represent only proxies for the quantities analysed in the DSK model, additional data collection could be considered to extend the SDG-energy network and more accurately capture the relationship suggested by DSK.

It is also worth noting that none of the proxies for the physical damages in the SDG-energy network have links with output or unemployment, which is consistent with the DSK model's findings. Finally, the SDG-energy network suggests that funding for health and sanitation are related to the fatalities caused by climate shocks and, as argued before, this could be another factor interacting with the labour productivity shocks to be considered in future modelling.

5.4.5 Other model extensions

The DSK model is focused on how climate damages worsened by emissions could impact firms' decisions and affect the energy mix and emissions, output, and unemployment in the long run. As such, it focuses on the climate effects most directly related to a firm's key decisions (i.e. production, investment, and RD). The authors recognise enriching the model to account for health and deaths as an important topic for future research, and as discussed above the findings from the SDG-energy network support this assessment.

Finally, given the known importance of deforestation for emissions in Brazil and its relationship with agriculture, biofuels, and land use, another 'system-suggested' extension of the DSK, from our map, is the inclusion of an agriculture/land use box to account for emissions beyond the energy and manufacturing sectors: the PC algorithm SDG-energy map shows the level of output per capita in the "sugarcane island" (Figure 9, panel A), associated to the share of land area used for sugarcane production and, indirectly, to the production of ethanol, suggesting that activity in the agriculture sector could play an important role in the climate-economy system of countries with large agricultural and forest land areas.

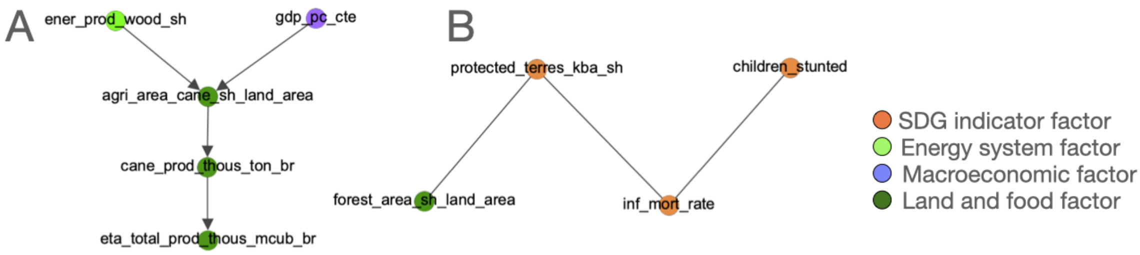


Figure 9: *Land use in the PC algorithm network for biofuels.* (A) "Sugarcane island". (B) Forests and protected areas.

Therefore, further investigating and modelling how the economy relates to the climate in this sector could be a major model development avenue. On the other hand, neither the share of forests in the total land area nor emissions are currently linked to the sugarcane cluster (Figure 9, panels A and B), so further improving the map to investigate the absence of such links could be of relevance for the future modelling exercises and for the policy debate in Brazil.

6 Conclusion

This chapter introduced and demonstrated a data-driven systems mapping approach designed to contextualise, communicate, and embed the insights of complexity economics in real world policy topics and questions. In using this approach to connect complexity economics with policy questions and a more rounded view of policy landscapes, we hoped to help address a range of calls in recent literature for more usable, interpretable, and inclusive complexity economics outputs.

We demonstrated the approach with the topic of the energy transition and its relationship with the SDGs in Brazil. We explored how the approach could be tuned to different purposes and contexts and explore two applied questions emerging from existing modelling results and policy topics: (i) the impact of the transition on SDGs and the role of biofuels, and (ii) the nature of climate impacts on the economy.

We hope we have made clearer our inherently diffuse aims and the different ways in which the approach can have value. Specifically, we have tried to demonstrate how a data-driven system mapping approach can:

- **Contextualise complexity economics insights:** by building a system map with different types of factors (i.e. economic, energy, social, health etc) and considering where complexity economics models and their findings sit in this map, we intend to contextualise these findings, helping place them in the wider set of systems they are embedded in. In doing so, we stay true to a holistic complex systems and system thinking approach but also bring the focussed findings of individual narrowly focussed models with us. We believe this type of exercise is valuable in understanding the broader (policy) implications of model findings.

- **Embed insights in real world policy debates:** the breadth and inclusiveness of the system map also allows us to connect to a range of policy debates. The map acts as the connecting device, or the substrate, between multiple policy topics and questions, a broader understanding of the system(s), and complexity economics model findings.

- **Communicate insights:** by doing all of the above, we hope we provide a useful communication device for a complexity and systems-based understanding of the topics under discussion, and the position of complexity economics within them. Large system maps can become 'horrendograms' (Penn, 2018) but if care is taken in visualising, analysing, and reporting them, and in building engagement and ownership with stakeholders, we believe they are useful tools in communication. They provide an intuitive yet broad and inclusive understanding which allows us to connect other ideas, thoughts, and models. This is an excellent complement to simple models and narratives, which are intuitive but narrow, and more complex or quantitative models which are more realistic and rigorous but less intuitive.

As this chapter has sought to introduce and demonstrate this approach, there are many potential directions for future work. We plan to pursue six specific streams:

1. **Contextualising a wider range of complexity economics findings and models:** we demonstrated this with one model, the DSK model, in a fairly simple way, but there are many more models and key findings we could include. For example, we could embed the strategies and incentives for different countries in the energy transition as outlined in Mercure et al. (2021). This would allow us to contextualise this finding, by asking what further impacts different country-level strategies in the transition may have on the economy, energy system, and the SDGs?

2. **Embed model coverage in the system map:** a second, but different, activity connected to existing models would be to visualise the coverage of different models in the system map (i.e. to show what factors and relationships the models capture, and which they don't). This would be valuable in making model coverage and assumptions clearer and help us understand where their limits and overlaps are more clearly, aiding comparison and appropriate interpretation.

3. **Use additional methods for network estimation:** there are many other potential methods for building the systems map we have described, beyond correlation networks and the PC algorithm; not least, as described in Ospina-Forero et al. (2020). These methods should be used in combination, with the maps they produce compared and combined to enrich the description we have of the system. In particular, methods which allow cyclical structures in directed networks and those which consider interaction (as PC algorithm does) should be used.

4. **Developing 'systems-suggested' analysis:** a core part of the approach to analysing system maps we use, building on Barbrook-Johnson and Penn (2021, 2022), is identifying factors that have unusual or interesting network properties, and then building submaps and the associated analysis from these. We did not do this in this chapter (instead focussing on factors connected to policy topics and existing models), but this would be an obvious next step.

5. **Embedding this data-driven approach in a larger participatory research design:** we have only demonstrated the data-driven element in this chapter. It can, and should, be built into a wider engagement or participatory process if we want to generate richer knowledge from and with the map(s) and build understanding with stakeholders. We outline how this might be done above, but we do plan to actually do this with this map over the coming months in Brazil, and to develop a similar map for China or the UK and engage there too.

6. **Bring in more social science:** Complexity economics could make a concerted effort to connect more to (other) social sciences, as some models do not build fully on the long and relevant literatures in the social sciences, especially sociology and political science (cf. Gilbert and Bullock, 2014). We did not attempt to demonstrate a strong social science element in this chapter, but we consider this an important gap and plan to address it with systems mapping in future work. One of the strengths of this approach is that we can bring in factors/nodes of any type, we are not constrained to only energy or economic factors, and even if we do not have data on a factor we can incorporate it to the system through a participatory process as outlined above.

7 Contributions

FSdM conducted the majority of the analysis and wrote the paper. PBJ designed the original idea, conducted some analysis, and wrote the paper.

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