World Development 138 (2021) 105136

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Modeling interlinkages between sustainable development goals using network analysis ☆

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ARTICLE INFO

Article history:
Accepted 2 August 2020
Available online 25 September 2020

JEL classification:
Q01
O1
O20
Q56
D85

Keywords:
Sustainable Development Goals (SDGs)
System analysis
Network analysis
Sustainable development indicators

ABSTRACT

Universal, ambitious, and arguably ambiguous, the UN's Sustainable Development Goals (SDG) are difficult to measure, monitor, prioritize and achieve. They are a multi-dimensional construct of economic, social and environmental indicators that work through complex interlinkages. We investigate these interlinkages at the SDG target level to identify the trade-offs and synergies between the SDGs. Second, we identify the community of interlinked SDG targets to determine if the SDGs can be benchmarked and prioritized for different regions. Employing network analysis approach the analysis is based on the IAEG-SDG data for the period 2000–2017. We find several positive and negative interlinkages (reinforcing and balancing feedbacks) between the SDG targets. The trade-offs, however, are much weaker than the synergies. Analyzing network structures for different regions, our results suggest that universal benchmarking of SDGs is counterproductive. We argue that it may be useful to identify a specific community of SDG targets, and use them as a guide to prioritize certain goals in different regions.

1. Introduction

The Sustainable Development Goals (SDGs) represent a universal set of goals that are interconnected in a complex network of interactions.[1] Their universality implies that none of the SDGs are prioritized, whereas their integrated multi-dimensional nature results in complex feedbacks between the SDG targets. The urgency in the recent (IPCC, 2018) special report to effectively deal with climate change and the time-bound nature of Agenda 2030 emphasizes efficient implementation and monitoring of the SDGs. This involves effective benchmarking of the goals and the need to identify different dynamics at work within the SDGs targets, for the different regions of the world.

National Central Statistics Organizations (CSOs) and recent research (Kroll, 2015; Nicolai, Hoy, Berliner, & Aedy, 2015; Sachs, Schmidt-Traub, Kroll, Durand-Delacre, & Teksoz, 2016; Green Growth Knowledge Platform, 2016; Schmidt-Traub, Kroll, Teksoz, Durand-Delacre, & Sachs, 2017), typically quantify each SDG in silos, evaluating the performance of an individual country vis-a-vis each SDG. This implies that the complex interlinkages (negative and positive feedbacks) between the economic, social and environmental dimensions of the SDGs remain unaccounted (Spaiser, Ranganathan, Swain, & Sumpter, 2016; Schmidt-Traub et al., 2017; Saito, Managi, Kanie, Kauffman, & Takeuchi, 2017; Allen, Metternicht, & Wiedmann, 2018; Allen, Metternicht, & Wiedmann, 2017; Weitz, Carlsen, Nilsson, & Skånberg, 2018). We investigate these interlinkages at the SDG target level to detect the trade-offs (negative feedback) and synergies (positive feedback) between the SDGs. Second, we identify the community of interlinked SDG targets to determine if the SDGs can be benchmarked and prioritized for different regions. The analysis focuses on OECD countries due to availability of good quality data. The focus on the SDG targets instead of the individual SDGs is inten-

☆ We are grateful to the participants at Development and Sustainability conference, University of Michigan, Ann Arbor; 8th Inter-Agency Expert Group Meeting, Stockholm for the valuable comments and suggestions and the seminar participants at IGA, London School of Economics and Political Science for their comments and thank Ankit Jajodia for research assistance. Research grants from Swedish Research Council for Sustainability and Swedish Energy Agency are gratefully acknowledged. The usual disclaimer applies.

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[1] The SDGs or Agenda 2030 consist of 17 global goals "to achieve a better and more sustainable future for all". They consist of 169 targets. The SDGs, were introduced for the period of 2015–2030, by the United Nations General Assembly, and are part of UN Resolution 70/1. They have been ratified by 193 countries.

https://doi.org/10.1016/j.worlddev.2020.105136
0305-750X/

tional. Each SDG consists of several targets and indicators, which enables us to identify the channels of underlying interlinkages between the various SDGs in greater detail. The analysis is further extended to other regions such as Sub Saharan Africa (SSA), South Asia (SA), East Asia, Latin America and Middle East and North Africa (MENA).

We contribute to the research programme by bridging several gaps and limitations in the existing SDG interlinkages literature. We provide domain researchers a tool to identify key variables in specific regions, across multiple development goals, which can then be analyzed in depth based on field studies and other data. We also identify key thrust areas for policymakers both in terms of benchmarking and resource allocations.

Theoretically, we provide a basis to further explore mechanisms based on quantitative evidence from historical datasets. Most studies discuss the concept or framework of the interlinkages of the SDGs without presenting an underlying theoretical model or analytical evidence. ICSU (2017) provides a few country-level applications, but even these are focused on specific goals (SDGs 2,3,7 and 14). Also, several studies do not make a scientific assessment of these interlinkages and instead rely on an ad hoc qualitative examination (Nilsson, Griggs, & Visbeck, 2016).

This is the first study to model the interlinkages and employ network analysis at global level to identify the interactions among the SDGs. It provides appropriate visualization tools that convey important results to policymakers. In particular, we build a correlational network, using IAEG-SDG data on SDG indicators from the UN Sustainable Development dataset, for the period 2000–2017. The interactions are modeled between the different pairs of SDGs (El-Maghrabi, Elisabeth, Israel, & Verbeek, 2018).[2] The analysis results in – (a) the application of correlational network analysis methods to build a network model of SDG interlinkages, and (b) using network statistics such as eigenvector centrality and betweenness centrality, and automatic community detection algorithms to identify key indicators that work in synergy to contribute towards achievement of SDGs. We find that for the OECD countries, targets for SDGs 5–7, 10, 15 and 17 have high centrality, indicating their high influence to other SDG targets.

Identifying these key interlinkages are critical to inform the policy maker for prioritizing SDG targets and strategies for sustainable development and achieving Agenda 2030. We also conduct the network analysis for other regions of the world. Our results show that though trade-offs exist, they are much weaker than the synergies. Policy-makers are thus better informed to focus on strong positive synergies. Based on our research, we further argue that benchmarking the SDGs makes sense only within the context of the region.The OECD countries, South Asia and Sub-Saharan Africa etc., all have different regional context and setting universal global targets or benchmarks is inappropriate.

In the following section we review the developing body of literature that investigates the interlinkages between the SDGs. This is followed by a discussion on the Methods and Data. Section 5 presents the results followed by a discussion and conclusion in subsequent sections.

2. Research on SDG interlinkages

The theoretical foundation for SDGs has been argued to be weak (ICSU & ISSC, 2015; Szirmai, 2015), and a comprehensive sustainable development theory does not exist. Instead, there are different contested theoretical approaches and definitions (Hopwood & O'Brien, 2005; Holden, Linnerud, & Banister, 2014). The SDGs have also been criticized for being too ambitious, universal, expansive and with potential inconsistencies, particularly between the socio-economic development and the environmental sustainability goals (Spaiser et al., 2016; UN SDSN, 2015; ICSU, 2017; Bali Swain, 2018; Easterly, 2015; Stern, Common, & Barbier, 1996; Redclift, 2005; Zeng et al., 2020). Furthermore, the 17 SDGs (169 targets) are difficult to quantify as opposed to the eight Millennium Development Goals (MDGs) that were precise and measurable (Easterly, 2015).[3]

A growing body of literature assesses, reviews and quantifies robust SDG indicators (Kroll, 2015, 2015, 2016, 2016, 2016, 2017, 2017, 2018, 2017, 2018, 2017, 2016). Three prominent studies in this literature include the GGKP Report on Measuring Inclusive Green Growth at the Country Level (Green Growth Knowledge Platform, 2016); the SDG Index and Dashboards Global Report prepared by the UNSDSN and the Bertelsmann Stiftung (Sachs et al., 2016); and the Overseas Development Institute Report (Nicolai et al., 2015). The GGKP Report on Measuring Inclusive Green Growth[4] (IGG) at the Country Level is not limited to the SDGs, and focuses on the Inclusive Green Growth and their interaction in a dynamic perspective (Fay, 2012). The Overseas Development Institute's report (Nicolai et al., 2015) develops a grading system for each of the SDGs and classifies them into three categories: reform, revolution, and reversal. The SDG Dashboards report (Sachs et al., 2016), employs geometric and arithmetic averages to compute scores for the data across all indicators that apply to each of the SDG. The method enables them to calculate scores for each of the 17 goals that are averaged to find the overall SDG Index for each country. The Scandinavian countries (Sweden, Denmark and Norway) are found to have the highest SDG index, implying that they are the closest to achieving the SDG targets for 2030.

The universality and the potential inconsistencies within the SDGs has been much criticized. The International Council for Science (ICSU) has expressed concerns about the potential incompatibility of the SDGs, specifically the incompatibility of socio-economic development and environmental sustainability. A few researchers investigate it further to quantify the inherent inconsistencies, conflict and interlinkages between the SDGs and targets (Spaiser et al., 2016; Redclift, 2005; ICSU, 2017; Reyers, Stafford-Smith, Erb, Scholes, & Selomane, 2017). For instance, Spaiser et al. (2016) explore the nature of these inconsistencies using dynamical systems models, they find that the focus on economic growth and consumption as a means for development underlies the inconsistency. Such studies reveal that the interdependencies between the various SDG targets need to be taken into account in strategy and policy formulation (Allen et al., 2018; Weitz et al., 2018; LeBlanc, 2015).

Measuring and monitoring SDGs in silos can also overflow into the operationalization of the government's agenda. Nilsson et al. (2016) argue that individual ministries of the governments take responsibilities for different areas. The policymakers lack the knowledge and tools to identify the core synergies and tradeoffs and how they advance or retreat the expansive SDGs agenda. Identifying interlinkages between the various SDG targets can thus be effectively used to build a decision framework for both prioritization of goals and strategic planning (Allen et al., 2018). LeBlanc (2015) investigates the interlinkages and maps each target with its own goal and also with other SDGs to create an interlinkages

[2] We note that Zhou and Moinuddin (2017) also use a similar approach, but that study is limited to nine countries in Asia and remains limited to examining interlinkages.

[3] Even with the MDGs, the lack of reliable data rendered the unreported, invisible to the decision makers. For instance, for the MDG indicators, only three African countries have data on all indicators (United Nations, 2014).

[4] The GGKP report identifies five broad characteristics of IGG: Natural Assets; Resource Efficiency and Decoupling; Resilience and Risks; Economic Opportunities and Efforts; and Inclusiveness.

matrix. For example, his results show that SDG12 (Responsible consumption and production) is the most connected with other goals, whereas SDG 14 (Life below water) is connected with only two other goals.

The nexus literature captures these interlinkages between subsets of the SDGs, for example, the Water-Energy-Food (W-E-F) nexus that describes the interactions among water, energy and food (Lawford et al., 2013). Energy, in the form of hydropower is another critical component within this nexus (Rasul, 2014; Tan, Erfani, & Erfani, 2017). With rapid population growth and socio-economic development and additional pressures from climate change, the energy and W-E-F nexus approach contributes to understanding the interlinkages and achieving the targets of SDGs (Bazilian et al., 2011; Ringler, Bhaduri, & Lawford, 2013).

A new body of research is emerging on how to use systems thinking and analysis to support national target prioritization and assessing SDG interlinkages (Allen et al., 2018; Weitz et al., 2018; Nilsson et al., 2016; Barbier & Burgess, 2017; Campagnolo, Eboli, Farnia, & Carraro, 2018). Neumann, Anderson, and Denich (2018), Mohr (2016), ICSU (2017), Nilsson (2017) present a qualitative visualization of the interlinkages between the SDGs. Others identify synergies and trade-offs between the goals by analyzing the indicators data for each goal using pairwise correlations (Pradhan, Costa, Rybski, Lucht, & Kropp, 2017). Barbier and Burgess (2017) employ a welfare function to provide insight into the correlations between different goals while quantifying and measuring them. Using the true systems approach (Obersteiner et al., 2016) find that policies centered around SDG 12, Sustainable Consumption and Production, are the most effective at reducing trade-offs in terms of environmental initiatives and food prices.

We present our work in relation to this literature as creating a network analysis-based approach to quantifying the importance of different SDGs and their interlinkages to one another. We use network statistics and automatic community detection algorithms, as detailed in the next section to identify, first the "most important" individual SDG targets, and subsequently, the "most important" community of SDG targets.

3. Methods

We model the complex interlinkages between the SDG target variables using a correlational network. Network analysis provides a powerful means of mapping complex interactions. The following subsections describe the basic ideas and measures used for the network analysis modeling. The mathematical basis for our network modeling approach is presented in Appendix A.1.

3.1. Network analysis

A network is defined as a collection of nodes (or vertices) and edges (or links) that connect the nodes. Each edge may also be weighted (indicating the strength of association between two nodes) or unweighted (indicating only whether there is some association or not). Some basic network concepts including the mathematical definition of networks based on graph theory, notions of weighted, directed and dynamic networks are available in Barabási (2003).

Two variables have a "synergy" when there is a positive interlinkage, and they have a "tradeoff" when there is a negative interlinkage. The theoretical justification for this conceptualization needs to be more carefully developed but we provide a limited statistical justification for the idea in this paper. When two variables are synergistic, and if they are measured in the same direction (i.e., increase is good for both variables) – for instance, GDP growth rate and life expectancy at birth – an increase in one variable due to policy changes should result in an increase in the other variable too. This corresponds to a positive correlation coefficient. Similarly, two variables have a tradeoff interlinkage, if they manifest a negative correlation coefficient in the data. In this paper, for visualization, we use the variables as they are available in the UN dataset to illustrate the basic methodological idea of using network analysis.

Note that if variables are specified in "opposite" directions – for instance, GDP growth rate and poverty rate, where increase is the preferred direction for GDP growth rate, and decrease is the preferred direction for the poverty rate – the interlinkage (correlation) needs to be interpreted appropriately.

Once we define synergies and tradeoffs in terms of positive and negative interlinkages, these interlinkages themselves are measured using a correlation measure between the two variables, which in turn is estimated as the sample correlation from the historical timeseries data available for these variables. Since all variables potentially have interlinkages with every other variable, we present the entire set of interlinkages as a network and use thresholds to quantify the numerically significant linkages.This also allows us to handle the problem of spurious correlations statistically. In practice, domain and regional expertise will need to supplement statistical methodology to avoid the reporting of spurious correlations.

In the first step of our analysis, each of the SDG targets is treated as a node in a correlational (or association) network and an edge between different nodes exists depending on the strength of the association between the different targets. This type of analysis is often used in genetics (Friedman & Alm, 2012), finance (Mizuno, Takayasu, & Takayasu, 2006) etc. to identify significant interlinkages. In the present context, if two SDG target variables have a significant interlinkage, an edge exists between these SDGs in the network. Network analysis is used in this paper because: (a) it provides a clean visualization and conceptualization of interlinkages between variables; (b) it allows us to use well-developed notions such as centrality, community analysis etc. that can be transferred easily to the domain of policy-maker.

Apart from presenting the visualization of the interconnections, we use an array of network statistics called "centrality" measures to analyze these networks. These centrality measures allow us to weigh the "importance" of any node in the network. In terms of SDG interlinkages, a target variable that has high centrality indicates that it has many significant interlinkages with other SDG target variables. This allows us to identify the most important variables that should be prioritized for effective policies.

3.2. Network centrality measures and community detection

There are a number of centrality measures developed in the network analysis literature to capture the notion of "highly central" or "most important" node. We use a few common measures, namely, degree centrality, betweenness centrality, eigenvector centrality (or eigencentrality), and closeness centrality etc. All these statistics measure the importance of a node in a network (i.e., its centrality) based on different notions of what makes a central node. Brief definitions are provided here, but more detailed analyses of these different measures and their strengths and weaknesses in specific scenarios can be found in Barabási (2003) among other sources.

There are two neighbor-based measures in our list – degree centrality and eigen centrality, and two path-based measures – betweenness centrality and closeness centrality. The neighbor-based measures take into account only the node and its immediate neighbors directly, whereas the path-based measures are more global in the sense that they measure the importance of a particular node based on its position in the midst of all the different paths in the whole network.

2. **Eigen centrality (or eigenvector centrality)** takes into account how many neighbors a node has and whether it has important, i.e., more central neighbors. This extends the notion of degree centrality by giving more weight to the importance of a node's neighbors rather than just counting the number of neighbors. A node with high eigen centrality has many important neighbors.
3. **Betweenness centrality** measures the extent to which a node lies on the paths between other nodes. From an information flow perspective, high betweenness centrality of a node implies that a node has considerable influence within a network due to its control over the information passing through the network. Betweenness centrality of a particular variable therefore is a measure of the capacity of this variable to bridge target variables that are dissimilar to each other.
4. **Closeness centrality** is a path-based measure of centrality similar to betweenness centrality. A node with high closeness centrality is, on average, closer to all the nodes of the network than a node with low closeness centrality. In this case, the closeness of a node is measured in terms of the sum of the inverse edge weights of this node to all the other nodes in the network.

Intuitively, a target that has high centrality relative to other targets is important to identify for policymakers because focusing on such a target has immediate impact. Addressing this particular target has a cascading effect as it is connected to a number of other important targets, potentially with reinforcing effects, especially when considering a measure like eigenvector centrality. Similarly, focusing on targets with high betweenness centrality has useful policy implications. A target with high betweenness centrality serves a bridging role by connecting a number of other targets. Addressing such a target (or a small set of such targets) would result in an economical and efficient means of addressing multiple targets which are all connected by these high betweenness centrality targets. While we used the undirected, signed network project for the visualizations, we will use the unweighted network to compute the centrality measures, to account for the variation in the correlation weights.

In addition to providing these centrality statistics for our network visualizations, we identify groups of SDG indicators that are "similar" to each other. We use community detection algorithms to show that some variables are more connected to each other, though they belong to different SDGs or even different pillars of the SDGs (e.g., the social, the economic, and the environmental).

In network analysis, community detection refers to the identification of groups of nodes in a network that have higher probability of being connected to each other than to other nodes in the network. There are multiple algorithms corresponding to the different ways this idea is implemented (Barabási, 2003). We use the automatic community detection algorithm based on modularity, to identify the groups of variables which have the most interlinkages with each other in the correlational networks. This provides further insight for policymakers who wish to identify the most significant variables to target efficiently, or researchers who wish to study cascading or inhibiting effects of policies implemented on individual SDGs.

4. Data

We employ the 20 June 2018 version of the IAEG-SDG data compiled through the UN System in preparation for the Secretary-General's annual report on "Progress towards the Sustainable Development Goals", for our network analysis. The data that support the findings of this study are available in the UN-SDG website throughhttps://unstats.un.org/sdgs/indicators/database/. These data were then appropriately processed to address the missing observations, before being used in our analysis. The dataset we use has information for 18 years (2000–2017) though different variables have different availabilities. It contains over 1 million observations for over 200 countries.[5] Many variables have multiple sub-categories, e.g., employment rates for males, employment rate for people in 25–50 age group etc. Also, many of the variables are of different types – continuous, counts, ratios etc – but we treat them similarly for our initial analysis. To facilitate the implementation of the global indicator framework, the majority of indicators used in our analysis are tier 1 category variables as classified by the UN IAEG-SDGs. Tier 1 indicators are conceptually clear, with an internationally established methodology and standards, and for which data is regularly produced by countries for at least 50 per cent of countries and of the population in every region where the indicator is relevant.Though tier 1 indicators are not an exhaustive cover for each SDG, they allow us to cover most of the important variables that are acceptable to the CSOs in most countries. A few additional indicators (tier 2 and tier 3) have also been employed in the analysis.[6] The description of the 105 indicators used in our analysis is presented in Appendix A Table 1.

Though the IAEG-SDG data is the best available global data on SDGs, it has limitations. It has missing data for several indicators, possibly due to poor reporting or difference in definitions (for example in SDG 5, V20 – "Proportion of ever-partnered women and girls subjected to physical and sexual violence by a current or former intimate partner in the previous 12 months (percentage)", different reporting standards for different countries. OECD countries use 15–49 years whereas other developing countries use different standards). This results in a reduction in the effective number of observations for some pairs of variables. Hence the correlation measures could potentially be biased. While studying interlinkages, SDGs are usually classified into various groups. Barbier and Burgess (2017), for instance, divide SDGs into three broad systems or groups. These are Economic (SDG 1–3, 6–9), Social (4, 5,10,16,17) and Environmental (11–15). As there are over 100 variables, a detailed description of the missing observations for each variable and the strength of the correlation coefficient between pairs of variables is difficult to portray in tabular form. Appendix A.2 presents visualization of the data availability (Fig. 4) and the strength of correlation between pairs of variables (Fig. 3). Since, we use the correlation coefficient as the primary tool for this analysis, we provide the bivariate availability (i.e., what proportion of total possible observations are available for any pair

[5] Countries for which data was available and that are included in our analysis are: (a) Sub-Saharan countries – Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Congo, Dem. Rep., Congo, Rep, Côte d'Ivoire, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda, Zambia, Zimbabwe; (b) South Asia – Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka; (c) East Asia – Cambodia, China, Guam, Hong Kong, Indonesia, Korea, Dem. People's Rep, Lao, Macao, Malaysia, Mongolia, Myanmar, Philippines, Singapore, Taiwan, Thailand, Vietnam; (d) OECD countries – Norway, Greece, Poland, Portugal, Austria, Hungary, Romania, Iceland, Russian Federation, Belarus, Ireland Belgium, Italy, Slovak Republic, Slovenia, Spain, Croatia, Sweden, Latvia, Switzerland, Czech Republic, Denmark, Turkey, Estonia, Luxembourg, Ukraine, Finland, United Kingdom, France, Germany, Netherlands, USA, Canada, Australia, New Zealand, Japan, Israel, South Korea.

[6] IAEG-SDGs classify the SDG indicators into three tiers based on their level of methodological development and the availability of data at the global level. In our analysis we employ the indicators classified as of 15 October 2018. Tier 2 indicators are conceptually clear with an internationally established methodology and standard, but data is not regularly produced by countries. Tier 3 have no internationally established methodology or standards, but methodology standards is being (or will be) developed or tested.

of variables to compute the correlation coefficient) instead of the availability in each variable itself.

5. Results

As discussed in the introduction, the intent of this study is threefold. In this section we discuss our results with respect to these three objectives. First, we model the interlinkages between the different SDG target indicators using network analysis. We present the network visualization, various centrality measures and the results of community detection for OECD data, to identify the key SDG targets that work together in synergistic communities to achieve sustainable development. This is important both detecting interlinkages and for prioritization of the SDGs and making strategic decisions to invest limited resources effectively.

Second, we extend the analysis to other regions, to empirically and visually demonstrate that SDG's should be benchmarked at the regionally disaggregated level. The socio-economic development is significantly different in OECD and the Sub-Saharan Africa region, for example. Disaggregating the data takes care of the problem of scale and zoning effects, to a limited extent (Openshaw & Taylor, 1979).[7] Finally, we show that all the SDGs are not synergistic, and there may be tradeoffs between different goals depending on the region under consideration.

5.1. OECD countries network analysis

We begin our analysis with the OECD countries that have better reported data and data quality. OECD results are presented in Fig. 1. As described in the Methods section, we create a correlation network of target indicators. We use three different thresholds (low threshold = 0.2, medium threshold = 0.5, high threshold = 0.8) to identify significant interlinkages among target indicators. Fig. 1 presents the visualization of the undirected networks at these thresholds. At low thresholds the network is dense (more edges) and includes weak interlinkages (Fig. 1(a)). As the threshold level increases, the network becomes sparser (fewer edges) and only relatively strong interlinkages survive (Fig. 1(b) and (c)).

For the OECD networks, when using a low threshold of 0.2, there are $3,514$ edges, and increasing the threshold to 0.5 and then 0.8, changes the number of edges to $1,036$ and 132 respectively. Clearly, a higher threshold for the edge weight implies fewer edges survive in the network (Fig. 1(c)), whereas a lower threshold presents a network where majority of target variables are connecting to each other (Fig. 1(a)), as one would expect. In the social sciences literature (Cohen, 1988), an effect size of 0.5 and above is considered strong, thus we discuss the results with the "medium" threshold (Fig. 1(b)).

The most important target indicators in the network for OECD countries are identified by the centrality measures presented in Appendix A Table 2 (column 1). It shows the five most central SDG target indicators, as ranked by each of these centrality measures. The rankings may vary slightly, depending on the centrality measure used. We limit our discussion to the degree and eigenvector centrality statistics in this paper. For OECD countries Red List Index[8] (SDG 17); labour share of the GDP (comprising wages, social protection transfers, SDG 10); and proportion of women in managerial positions (SDG 5), top the list. Environmental factors such as average proportion of Mountain key biodiversity areas (SDG 15); and other factors like, proportion of population with access to electricity (SDG 7); and proportion of the population using safely managed drinking water services (SDG 6), are also critical target indicators. Other centrality measures also identify target variables for SDGs 2, 9 (economic) and SDG 12 as important.

While identifying indicators with high centrality need to be focussed on, for effectively achieving SDGs, identifying the community of target indicators that work together in synergy (or tradeoffs) has important implications. Using modularity and automatic community detection (see Barabási, 2003 for more details), we identify three main communities of target indicators for OECD countries with medium threshold (Fig. 1(b)). These communities suggest a network of SDG target indicators that work in tandem. They act as a guide to create policies that reinforce each other, magnifying the impact on sustainable development. The bottom right hand side community is dominated by economic SDGs (SDG 1–3, 6–9) with some very special aspects of social SDGs (4, 5 and 10) and environmental SDGs (11, 12 and 15). This community of target indicators suggests that SDG policies should focus on the proportion of poor population, undernourishment, government expenditure on agriculture, local breeds at risk of extinction, maternal mortality ratio, child mortality, sanitation, access to electricity, clean fuel and technology, number of commercial bank branches, unemployment rate and manufacturing value added as a proportion of GDP. Combined with these economic aspects, the community includes social factors such as a certain level of proficiency in functional skills, women empowerment and labour share of GDP, comprising wages and social protection transfers. The environmental aspects of this community include people affected by disaster, material footprint per capita among the bottom 40 percent of the population, biodiversity indicators and mountain green cover. This community suggests a comprehensive policy that targets the well-being of the relatively disadvantaged sections of the population.

The second (middle) community is more focussed towards the institutional aspects of social (SDGs 5, 16 and 17) and environmental factors (SDGs 11, 13, 14, 15), with some very specific aspects of economic factors (SDGs 2, 6, 8 and 9). Social aspects include adopting and implementing constitutional, statutory and/or policy guarantees for public access to information, Human Rights compliance and net official development assistance. Environmental factors, such as, people affected by environmental disasters, protected marine zones, expenditure on ocean science, forest area net change rate, mountain green cover and area, countries that are contracting to the International Treaty on Genetic Resources for Food and Agriculture and Ngoya protocol etc. Along with these institutional factors, economic factors such as population above pensionable age receiving pension, access to clean water, population with account at financial institution, and carbon-dioxide emissions per unit of GDP.

The left hand side community is the smallest and reinforces similar institutional aspects as the middle community with the focus on all aspects of gender equality (SDG 5) and registration of birth and death (SDG 17), people of pensionable age receiving pension (SDG 1) and crude death rate attributed to ambient air pollution (SDG 3). Again compliance with various international environmental conventions (SDG 12) and land area (SDG 15) are amongst important environmental factors.

Detecting communities allows us to specifically identify target variables that work synergistically towards achieving SDGs. They further enable us to strategize and prioritize the goals and or targets that work towards that objective. SDGs are ambitious and universal, but the available resources are limited. Given these constraints, network analysis enables us to identify communities

[7] Scale effect problem implies that the results vary with the level of aggregation, whereas, zoning effect problem shows the consequences of how boundaries are drawn.

[8] The IUCN Red List of Threatened Species is the world's most comprehensive inventory of the global conservation status of biological species. It uses a set of criteria to evaluate the extinction risk of thousands of species and sub-species. These criteria are relevant to all species and all regions of the world. With its strong scientific base, the IUCN Red List is recognized as the most authoritative guide to the status of biological diversity.

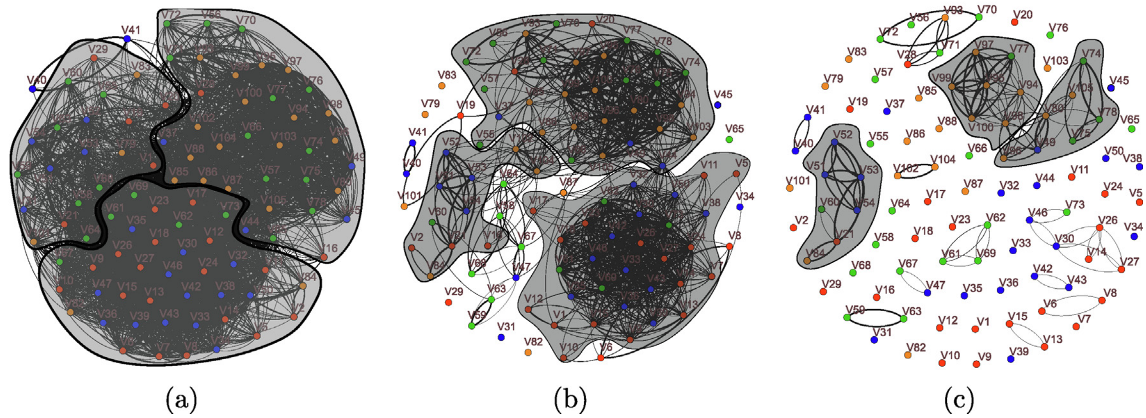

Fig. 1. Correlation networks for SDG target variables for OECD countries with a (a) high threshold, (b) medium threshold, and (c) low threshold. The SDGs have been broadly categorized into 4 groups in this analysis. Red nodes represent indicators V1 to V29 belonging to SDGs 1 to 6, Blue nodes represents SDGs 7–12 and include indicators V30 to V54, SDGs 13–15 are represented by green nodes with indicators V55 to V78 and the orange nodes represent indicators V79 to V105 of SDGs 16 and 17.

of target variables that may more effectively reach SDGs with limited resources.

5.2. Benchmarking and Regional differences

The convention in development research and practice is to benchmark target variables to quantify progress towards goals. Some of the quantitative targets are provided in the 2030 Agenda for Sustainable Development (UN, 2015). When such targets are missing, studies use policy documents like Europe 2020 strategy or the average indicator score of the 5 percent top (or bottom) performers in the data as a benchmark (Campagnolo et al., 2018). However, different countries and diverse economic systems have distinctive infrastructure and hence different trajectories (Spaiser et al., 2016).

In an earlier paper, in the context of Millennium Development Goals (MDGs), Ranganathan, Nicolis, Bali Swain, and Sumpter (2017) argue that universal goals that ignore imbalances and inequalities within countries might be counter-productive to overall human development in the long run. In other words, universal target setting or benchmarking is especially counter-productive for the multi-dimensional SDGs, unless regional context and development is accounted for.

In this paper, we extend the idea and argue that it is more effective to use regional data for specific groups of countries to create sub-networks of interactions. The network models presented for OECD, South Asia, Sub-Saharan Africa etc. (Fig. 2) have little similarity. Using global standards as benchmarks is thus counter-productive. To perform any meaningful analysis for any one country or group of countries, we thus need to benchmark using these sub-networks.

Given our analysis, we make a few points. First, benchmarking makes sense only if the region is relatively homogenous in terms of its level of development etc. Second, the level of analysis is of critical importance. Benchmarking of SDGs at the global or national level will be very different from the operationalization of the SDGs for businesses or any particular sector of the economy or even at the level of the local government. Third, it will require the adaptation of the SDG indicators to the level of analysis as some targets are designed for national data while others are more local in scope.

It is clear from Appendix A Table 2 (column 2) that for South Asia the top ranked centrality measures are, proportion of population below the poverty line – SDG 1; official flows for agriculture – SDG 2; proportion of births attended by skilled health personals – SDG 3; proportion of women married or in union before age 18 – SDG 5; adults with account in financial institution or mobile-money-service provider – SDG 8; manufacturing employment as a proportion of total employment – SDG 9; and above ground bio-mass in forest – SDG 15. These target variables are distinctly different from those for OECD countries.

Note that the South Asia network and communities are distinctly sparser than the OECD network, as OECD countries have better reported data for the SDG indicators that are at once expansive in their scope and demanding in resources and effort required to collect them. For South Asia, the center community identifies socio-economic target variables to achieve the SDGs. Most of the target variables in this community are identified as the proportion of population below the international poverty line – SDG 1; total official flows for agriculture and local breed at unknown risk of extinction – SDG 2; maternal mortality rate, births attended by skilled health personal and international health regulations – SDG 3; proportion of population with clean fuel and technology – SDG 7; passenger volume by road – SDG 9; and the number of victims of international homicide – SDG 16. With the largest number of poor people living in South Asia, it is not surprising that any sustainable development policy cannot ignore to focus on basic economic, social and security conditions and well-being of the citizens.

The emphasis on basic standard of living does not imply that South Asia can ignore the environmental targets. The left hand side and centre top communities for South Asia (Fig. 2(b)) are primarily focused on targets that are related to the environment. These include carbon dioxide emissions per unit of GDP, forest area as a proportion of total area, land area, above ground biomass, party to the International Treaty on Plant Genetic Resources for Food and Agriculture, reported number of Standard Material Transfer Agreements, compliance with convention of hazardous waste and other chemicals, urban population in slums and progress in multi-stakeholder development effectiveness monitoring frameworks.

We have discussed the network communities and statistics for OECD and South Asia here, however, a cursory look at Fig. 2 will confirm that each region has its own specific structural and development contexts and hence universal benchmarking would be ineffective. The SDGs by their very nature are all-encompassing. Thus, our analysis suggests that the SDG benchmarks should to be region-specific.

5.3. Synergies and tradeoffs

Using the pairwise correlation between the target indicators enables us to identify the positive and negative feedbacks. Positive

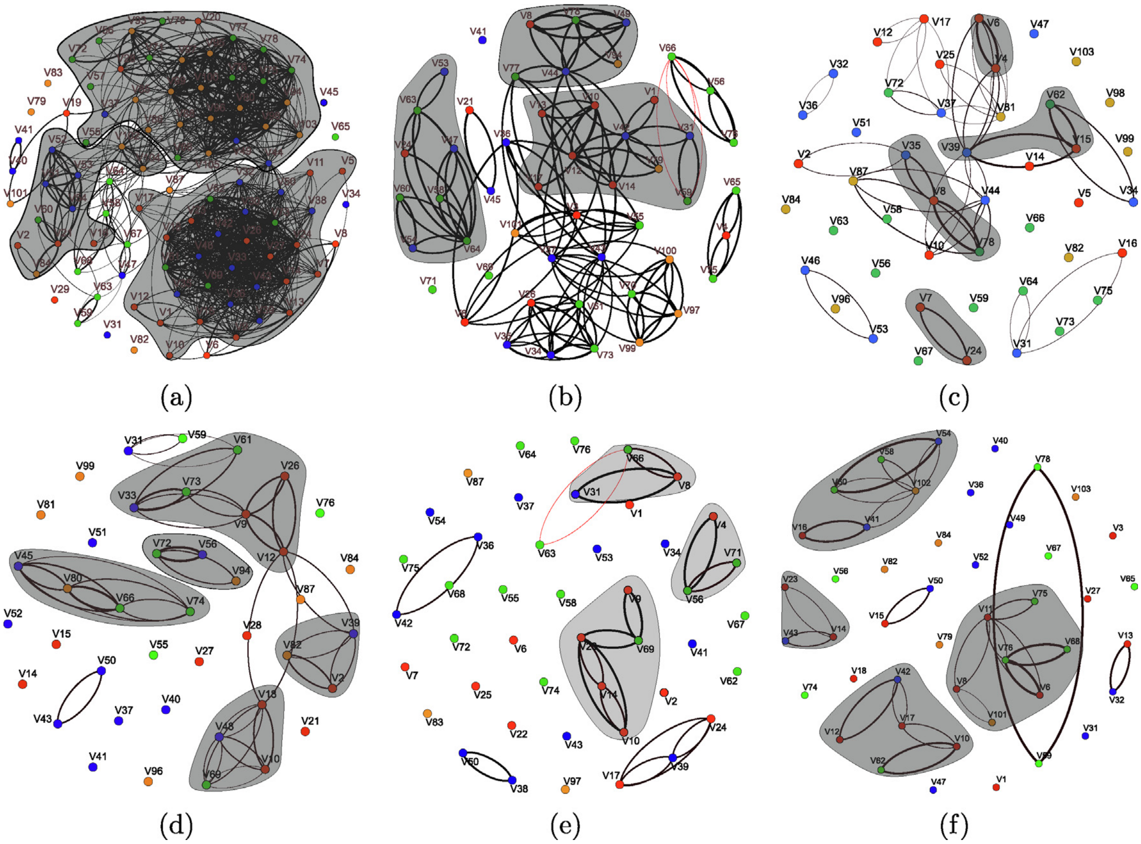

Fig. 2. Trade-off and synergies for medium threshold (0.5) in (a) OECD, (b) South Asia, (c) East Asia, (d) Latin America, (e) Sub-Saharan Africa, and (f) MENA countries. The black edges in both the figures represent the synergies between the targets, whereas the red edges are the trade-offs. Each node in the network reflects the indicators of the SDG sub-targets. The SDGs have been broadly categorized into 4 groups in this analysis. These groups are color-coded. For all sub-figures: the green nodes represent indicators V1 to V29 belonging to SDGs 1 to 6 and the red nodes represent indicators V30 to V54, SDGs 13–15. Blue nodes represents SDGs 7–12 and include indicators V30 to V54, and the orange nodes represent indicators V79 to V105 of SDGs 16 and 17.

correlations indicate positive feedbacks, which implies that investment in one variable will also boost the other variable. Negative correlations indicate negative feedbacks, implying that investment in increase for one variable might result in decrease in the other variable. In Spaiser et al. (2016), we investigate SDGs and find internal inconsistencies within them, due to existence of tradeoffs between the various SDGs. Investigating these interlinkages further at the target variable (sub-SDG level), our analysis finds a major result that very few tradeoffs are strong enough to survive in the correlational network at the medium threshold level.

Appendix A Table 2 and Fig. 2 present the network statistics and communities for the various regions at the medium threshold level. As compared to the OECD countries, the communities of network for other regions of the world are much more disaggregated with communities of SDGs 1–6 and SDGs 13–15. Sub-Saharan Africa shows very few interlinkages. Most of the synergies are dominated by the interlinkages between the target variables for SDGs 1–6 and SDGs 7–12. SDGs 16 and 17 are peripheral and the trade-offs are mostly within SDG 15 (V63 Above-ground biomass in forest, V63 Forest area net change rate).

Very few tradeoffs (red edges) exist at the medium threshold level. Only two tradeoffs can be identified for South Asia (Fig. 2(b)) and a single one for Sub-Saharan Africa (Fig. 2(e)). One of the two trade-offs for South Asia is between SDG 7 and SDG 15. Examined at the target variable level, this trade-off exists between the forest area net change rate and the proportion of population with primary reliance on clean fuels and technology. Thus, though the trade-offs exist, they are much weaker than the synergies for South Asia, Sub-Saharan Africa, OECD and other regions of the world. This indicates that policy-makers are thus better advised to focus on the strong positive synergies as the net impact of the trade-offs appears to be weak, given the evidence from our analysis. However, it is important to note that more trade-offs survive at a different threshold, indicating that the availability of better data is both essential, and might result in a different evaluation. Also, note that there is another interpretative step required to move from correlations to interlinkages, as discussed at the start of Section 3.1. These results need to be carefully examined in context by domain and regional experts.

6. Conclusions

The SDGs are more interconnected than the MDGs (LeBlanc, 2015). SDGs thus require a multi-dimensional, integrated policy approach that takes the synergies and tradeoffs into account. A silo-based approach of data collection and monitoring by CSOs and implementation by the government and its ministries is inappropriate. For instance, breaking up the inherent interconnections between sectors and various actors to maximize the sectoral interests in artificial silos cannot address the relation between economic growth and environmental quality (Zhou & Moinuddin, 2017).

We provide a unified framework to study the interlinkages between SDG targets and perform network analysis for OECD, South Asia and Sub-Saharan Africa based on IAEG-SDG data, which suggests how we can identify critical network “communities” of variables, synergies and tradeoffs. Applying this methodology to specific problems and regions can result in identifying key targets, interlinkages, and network communities for input into prioritization of SDGs. In addition, through network statistics, community identification and visualization, we demonstrate that different benchmarking needs to be region and context specific. We note that though our results show that trade-offs exist in historical data, they are not as strong as the synergies, which needs to be more carefully explored by domain and regional experts.

More specifically, our framework can provide policymakers input on the prioritization of SDG targets, using network centrality measures or community detection algorithms. SDG targets with high eigencentrality in carefully-constructed domain-specific and region-specific networks are key for policymakers who want to exploit cascading mechanisms as these targets are well-connected to other key variables in the network. On the other hand, targets with high betweenness centrality represent bridging variables, and policymakers who want to achieve efficiency by focusing on a few variables to achieve maximum impact on all targets could focus on these, and achieve diffusion of results across multiple dimensions of sustainable development over time.

Information on synergies and trade-offs between the SDG targets has helped identify the inherent inconsistencies within Agenda 2030. ICSU (2017) quantifies SDG synergies and tradeoffs to find 238 positive and 66 negative interactions in a total of 316. The remaining were neutral. We find significantly fewer negative interactions in the data, especially when focusing on OECD countries, providing evidence that policy implementation issues (for instance the fact that policies to correct shortcomings will likely be implemented by good governments and result in a mitigation of negative interactions) could affect theoretical considerations. While this needs to be further explored carefully by domain experts, our results provide clear region-specific evidence that policy-making needs. Identified SDG target communities within our network analysis for the OECD countries, South Asia and Sub-Saharan Africa are different and thus require policy interventions that are geared towards those key targets. By the same logic, our analysis demonstrates that central SDG targets community at the global, regional or national level, may be very different at the sub-regional, sectoral or local level of implementation. Similarly, benchmarking cannot be a blanket recommendation at the SDG level for all countries.

CRediT authorship contribution statement

Ranjula Bali Swain: Conceptualization, Methodology, Validation, Investigation, Data curation, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Shyam Ranganathan:** Methodology, Software, Validation, Investigation, Data curation, Writing - review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Tables

See Tables 1 and 2.

Table 1
Description of variables.

SDG	Variable description	Tier classification
SDG 1	No Poverty	
	[1] Proportion of population below international poverty line (per cent)	tier 1
	[2] Proportion of population above statutory pensionable age receiving a pension, by sex (per cent)	tier 2
	[3] Number of people affected by disaster (number)	tier 2
	[4] Direct economic loss to cultural heritage damaged or destroyed attributed to disasters (millions of current United States dollars)	tier 2
SDG 2	No Hunger	
	[5] Prevalence of undernourishment (per cent)	tier 1
	[6] Local breeds classified as known being at risk (number)	tier 2
	[7] Proportion of local breeds classified as known being not at risk	tier 2
	[8] Local breeds classified as known being not at risk (number)	tier 2
	[9] Proportion of local breeds classified as being at unknown level of risk of extinction (per cent)	tier 2
	[10] Local breeds classified as being at unknown level of risk of extinction (number)	tier 2
	[11] Agriculture orientation index for government expenditures	tier 1
	[12] Total official flows (disbursements) for agriculture, by recipient countries (millions of constant 2016 United States dollars)	tier 1
SDG 3	Good Health and Well-Being	
	[13] Maternal mortality ratio	tier 2
	[14] Proportion of births attended by skilled health personnel (per cent)	tier 1
	[15] Under-five mortality rate (deaths per 1,000 live births)	tier 1
	[16] Crude death rate attributed to ambient air pollution (deaths per 100,000 population)	tier 1
	[17] Average of 13 International Health Regulations (IHR) core capacities	tier 2
SDG 4	Quality Education	
	[18] Participation rate in organized learning (one year before the official primary entry age) (per cent)	tier 1
	[19] Proportion of population achieving at least a fixed level of proficiency in functional skills, both sex, 16–65 years and literate (per cent)	tier 2
SDG 5	Gender Equality	
	[20] Proportion of ever-partnered women and girls subjected to physical and sexual violence by a current or former intimate partner in the previous 12 months (percent) (Note different reporting standards for different countries, for OECD countries it is 15–49 years)	tier 2

Table 1 (*continued*)

SDG	Variable description	Tier classification
	[21] Proportion of women aged 20–24 years who were married or in a union before age 18 (per cent)	tier 1
	[22] Proportion of girls and women aged 15–49 years who have undergone female genital mutilation/cutting (per cent)	tier 1
	[23] Proportion of seats held by women in national parliaments (percent of total number of seats)	tier 1
	[24] Proportion of women in managerial positions (per cent)	tier 1
	[25] Proportion of women who make their own informed decisions regarding sexual relations, contraceptive use and reproductive health care (per cent of women aged 15–49 years)	tier 3
SDG 6	Clean Water and Sanitation	
	[26] Proportion of population using safely managed drinking water services, by urban/rural (percent)	tier 1
	[27] Proportion of population using safely managed sanitation services, by urban/rural (percent)	tier 1
	[28] Proportion of bodies of water with good ambient water quality (percent)	tier 3
	[29] Nationally derived total extent (square kilometers)	tier 1
SDG 7	Affordable and Clean Energy	
	[30] Proportion of population with access to electricity, by urban/rural (per cent)	tier 1
	[31] Proportion of population with primary reliance on clean fuels and technology (per cent)	tier 1
	[32] Renewable energy share in the total final energy consumption (per cent)	tier 1
	[33] Energy intensity level of primary energy (megajoules per constant 2011 purchasing power parity GDP)	tier 1
SDG 8	Decent Work and Economic Growth	
	[34] Annual growth rate of real GDP per capita (per cent)	tier 1
	[35] Number of automated teller machines (ATMs) per 100,000 adults	tier 1
	[36] Number of commercial bank branches per 100,000 adults	tier 1
	[37] Proportion of adults (15 years and older) with an account at a financial institution or mobile-money-service provider (per cent of adults aged 15 years and older)	tier 1
	[38] Material footprint per capita, non-metallic minerals as default (tonnes)	tier 2
	[39] Unemployment rate, by sex and age (per cent)	tier 1
SDG 9	Industry, Innovation and Infrastructure	
	[40] Freight volume, road transport (tonne kilometres),	tier 1
	[41] Passenger volume (passenger kilometres), road transport	tier 1
	[42] Manufacturing value added as a proportion of GDP (percent)	tier 1
	[43] Manufacturing employment as a proportion of total employment (per cent)	tier 1
	[44] Carbon dioxide emissions per unit of GDP (kilogrammes of CO2 per constant 2010 United States dollars)	tier 1
SDG 10	Reduced Inequalities	
	[45] Growth rates of household expenditure or income per capita among the bottom 40 per cent of the population (per cent)	tier 1
	[46] Labour share of GDP, comprising wages and social protection transfers (per cent)	tier 1
SDG 11	Sustainable Cities and Communities	
	[47] Proportion of urban population living in slums (per cent)	tier 1
	[48] Number of people affected by disaster (number)	tier 2
	[49] Direct economic loss to cultural heritage damaged or destroyed attributed to disasters (millions of current United States dollars)	tier 2
SDG 12	Responsible Consumption and Production	
	[50] Material footprint per capita, non metallic materials default category (tonnes)	tier 2
	[51] Compliance with the Basel Convention on hazardous waste and other chemicals	tier 1
	[52] Compliance with the Montreal Protocol on hazardous waste and other chemicals	tier 1
	[53] Compliance with the Rotterdam Convention on hazardous waste and other chemicals	tier 1
	[54] Compliance with the Stockholm Convention on hazardous waste and other chemicals	tier 1
SDG 13	Climate Action	
	[55] Number of people affected by disaster (number)	tier 2
SDG 14	Life Below Water	
	[56] Coverage of protected areas in relation to marine areas (Exclusive Economic Zones) (per cent)	tier 1
	[57] National ocean science expenditure as a share of total research and development funding (per cent)	tier 1
SDG 15	Life on Land	
	[58] Forest area as a proportion of total land area (per cent)	tier 1
	[59] Forest area (thousands of hectares)	tier 1
	[60] Land area (thousands of hectares)	tier 1
	[61] Average proportion of Freshwater Key Biodiversity Areas (KBAs) covered by protected areas (per cent)	tier 1
	[62] Average proportion of Terrestrial Key Biodiversity Areas (KBAs) covered by protected areas (per cent)	tier 1
	[63] Above-ground biomass in forest (tonnes)	tier 1
	[64]Above-ground biomass in forest per hectare (tonnes per hectare)	tier 1
	[65] Forest area certified under an independently verified certification scheme (thousands of hectares)	tier 1
	[66] Forest area net change rate (per cent)	tier 1
	[67] Proportion of forest area with a long-term management plan (per cent)	tier 1
	[68] Proportion of forest area within legally established protected areas (per cent)	tier 1

(*continued on next page*)

Table 1 (*continued*)

SDG	Variable description	Tier classification
	[69] Average proportion of Mountain Key Biodiversity Areas (KBAs) covered by protected areas (per cent)	tier 1
	[70] Mountain green cover area (square kilometres)	tier 2
	[71] Mountain Green Cover Index	tier 2
	[72] Mountain area (square kilometres)	tier 2
	[73] Red List Index	tier 1
	[74] Countries that have legislative, administrative and policy framework or measures reported to the Access and Benefit-Sharing Clearing-House (1 = YES, 0 = NO)	tier 3
	[75] Countries that are parties to the Nagoya Protocol (1 = YES, 0 = NO)	tier 3
	[76] Countries that have legislative, administrative and policy framework or measures reported through the Online Reporting System on Compliance of the International Treaty on Plant Genetic Resources for Food and Agriculture (PGRFA) (1 = YES, 0 = NO)	tier 3
	[77] Countries that are contracting Parties to the International Treaty on Plant Genetic Resources for Food and Agriculture (PGRFA) (1 = YES, 0 = NO)	tier 3
	[78] Total reported number of Standard Material Transfer Agreements (SMTAs) transferring plant genetic resources for food and agriculture to the country (number)	tier 3
SDG 16	Peace Justice and Strong Institutions	
	[79] Number of victims of intentional homicide per 100,000 population (victims per 100,000 population)	tier 1
	[80] Countries that adopt and implement constitutional, statutory and/or policy guarantees for public access to information	tier 1
	[81] Proportion of population aged 18–29 years who experienced sexual violence by age 18, (per cent of population aged 18–29)	tier 2
	[82] Unsentenced detainees as a proportion of overall prison population (per cent)	tier 1
	[83] Bribery incidence (per cent of firms experiencing at least one bribe payment request)	tier 1
	[84] Proportion of children under 5 years of age whose births have been registered with a civil authority (per cent of children under 5 years of age)	tier 1
Institutions in compliance with the Paris Principles (1 = YES, 0 = NO)	tier 1	
	[86] Countries with National Human Rights Institutions not fully compliant with the Paris Principles (1 = YES, 0 = NO)	tier 1
	[87] Countries with National Human Rights Institutions and no application for accreditation with the Paris Principles (1 = YES, 0 = NO)	tier 1
	[88] Countries with National Human Rights Institutions and no status with the Paris Principles (1 = YES, 0 = NO)	tier 1
SDG 17	Partnerships	
	[89] Developing countries and least developed countries share of global merchandise exports (per cent)	tier 1
	[90] Developing countries and least developed countries share of global services exports (per cent)	tier 1
	[91] Developing countries and least developed countries share of global merchandise imports (per cent)	tier 1
	[92] Developing countries and least developed countries share of global services imports (per cent)	tier 1
	[93] Proportion of new development interventions drawn from country-led result frameworks by providers of development cooperation (per cent)	tier 2
	[94] Progress in multi-stakeholder development effectiveness monitoring frameworks that support the achievement of the sustainable development goals (1 = YES, 0 = NO)	tier 2
	[95] Countries with national statistical legislation exists that complies with the Fundamental Principles of Official Statistics (1 = YES, 0 = NO)	tier 3
	[96] Countries with national statistical plans with funding from donors (1 = YES, 0 = NO)	tier 1
	[97] Countries with national statistical plans with funding from Government (1 = YES, 0 = NO)	tier 1
	[98] Countries with national statistical plans with funding from others (1 = YES, 0 = NO)	tier 1
	[99] Countries with national statistical plans that are fully funded (1 = YES, 0 = NO)	tier 1
	[100] Countries with national statistical plans that are under implementation (1 = YES, 0 = NO)	tier 1
	[101] Dollar value of all resources made available to strengthen statistical capacity in developing countries (current United States dollars)	tier 1
	[102] Countries with birth registration data that are at least 90 percent complete (1 = YES, 0 = NO)	tier 1
	[103] Countries that have conducted at least one population and housing census in the last 10 years (1 = YES, 0 = NO)	tier 1
	[104] Countries with death registration data that are at least 75 percent complete (1 = YES, 0 = NO)	tier 1
	[105] Net official development assistance (ODA) to LDCs as a percentage of OECD-DAC donors' GNI (per cent)	tier 1

A.1. Network model of interlinkages

For any two random variables X and Y, we can define the symmetric strength of interlinkage based on their correlation ρ, where we use the standard Pearson product-moment correlation formula

$$\rho_{XY}^{sym} = \rho_{YX}^{sym} = (E[XY] - E[X]E[Y])/\sqrt{\left(E\left[X^2\right] - E[X]^2\right]E\left[Y^2\right] - E[Y]^2)}$$

This symmetric strength of interaction corresponds to the perceived interlinkage between the two variables over the time period they are measured. This strength of interlinkage does not account for any causal relationship that may exist between the two variables. To capture the possible causal relationship, we may use the Granger notion of causality and define an asymmetric strength of interlinkage as

$$\rho_{XY}^{asym} = \left(E\left[X_{lag}Y\right] - E\left[X_{lag}\right]E[Y]\right)/\sqrt{\left(E\left[X_{lag}^2\right] - E\left[X_{lag}\right]^2\right]E\left[Y^2 - E[Y]^2\right)}$$

$$\rho_{YX}^{asym} = \left(E\left[Y_{lag}X\right] - E\left[Y_{lag}\right]E[X]\right)/\sqrt{\left(E\left[Y_{lag}^2\right] - E\left[Y_{lag}\right]^2\right]E\left[X^2 - E[X]^2\right)}$$

Table 2
Network statistics.

OVERVIEWS	OECD (1)	SASIA (2)	EASIA (3)	SSAFRICA (4)	LATIN AMERICA (5)	MENA (6)
NODES	95	51	46	44	41	45
EDGES	1036	150	56	30	58	44
CENTRALITY Measures (variable ID, as in table 1)						
	Red List Index (73)	Biomass in forest (64)	Unemployment rate (39)	Seats held by women in national parliament (23)	Official flows foreign (12)	Birth registration data (102)
	Access to electricity (30)	Adults with account in financial institutions (37)	Population aged 18-29 yrs experienced sexual violence by age 18 (81)	Mountain diversity areas (69)	Participation rate in organized learning (18)	Agriculture Orientation index for govt. expenditure (11)
DEGREE	Labour-share of GDP (46)	Proportion of manufacturing employment (43)	CO2 emission/GDP (44)	Protected areas (56)	Local breeds at unknown risk (9)	Legislative, administrative and policy framework (76)
	Mountain diversity areas (69)	Pop below poverty line (1)	International Health Regulations core capacity (17)	Forest area net change rate (66)	Unemployment rate (39)	Land area (60)
	Safe drinking water (26)	Births by skilled health personals (14)	Adults with account in financial institutions (37)	Unemployment rate (39)	Countries with legislation framework (74)	Manufacturing value added as proportion of GDP (42)
	CO2 emission/GDP (44)	Biomass in forest (64)	Unemployment rate (39)	Seats held by women in national parliament (23)	Official flows foreign (12)	Agriculture Orientation index for govt. expenditure (11)
	ODA to LDC(105)	Adults with account in financial institutions (37)	Population aged 18-29 yrs experienced sexual violence by age 18 (81)	Mountain diversity areas (69)	Local breeds at unknown risk (9)	Birth registration data (102)
BETWEENNESS	Red List Index (73)	Proportion of manufacturing employment (43)	CO2 emission/GDP (44)	Forest area net change rate (66)	Participation rate in organized learning (18)	Legislative, administrative and policy framework (76)
	Birth registration data (102)	Pop below poverty line (1)	Standard Material Transfer Agreements (78)	Local breeds not at risk (8)	Energy intensity of primary energy (33)	Local breeds not at risk (8)
	Death registration data (104)	Protected areas (56)	Adults with account in financial institutions (37)	Protected areas (56)	Unemployment rate (39)	International Health Regulations core capacity (17)
	Red List Index (73)	Pop below poverty line (1)	Unemployment rate (39)	Seats held by women in national parliament (23)	Participation rate in organized learning (18)	Agriculture Orientation index for govt. expenditure (11)
EIGENVECTOR CENTRALITY	Access to electricity (30)	Women married before 18 yrs (21)	Disaster damage (4)	Local breeds at unknown level at risk (10)	Official flows foreign (12)	Legislative, administrative and policy framework (76)
	Labour-share of GDP (46)	Adults with account in financial institutions (37)	Local breeds at risk (6)	Births by skilled health personals (14)	Local breeds at unknown level at risk (10)	Birth registration data (102)
	Safe drinking water (26)	Biomass in forest (64)	CO2 emission/GDP (44)	Mountain diversity areas (69) Unemployment rate (39)	People affected by disaster (48)	Local breeds at risk (6)
	Women in managerial positions (24)	Official disbursement for agriculture (12)	Population aged 18-29 yrs experienced Sexual violence by age 18 (81)		Mountain diversity areas (69)	Land area (60)

Notes: 1. For full variable details refer to description of variables in Table 1 (indicator numbers in parenthesis). Network statistics on 'Closeness centrality' available from the authors on request.

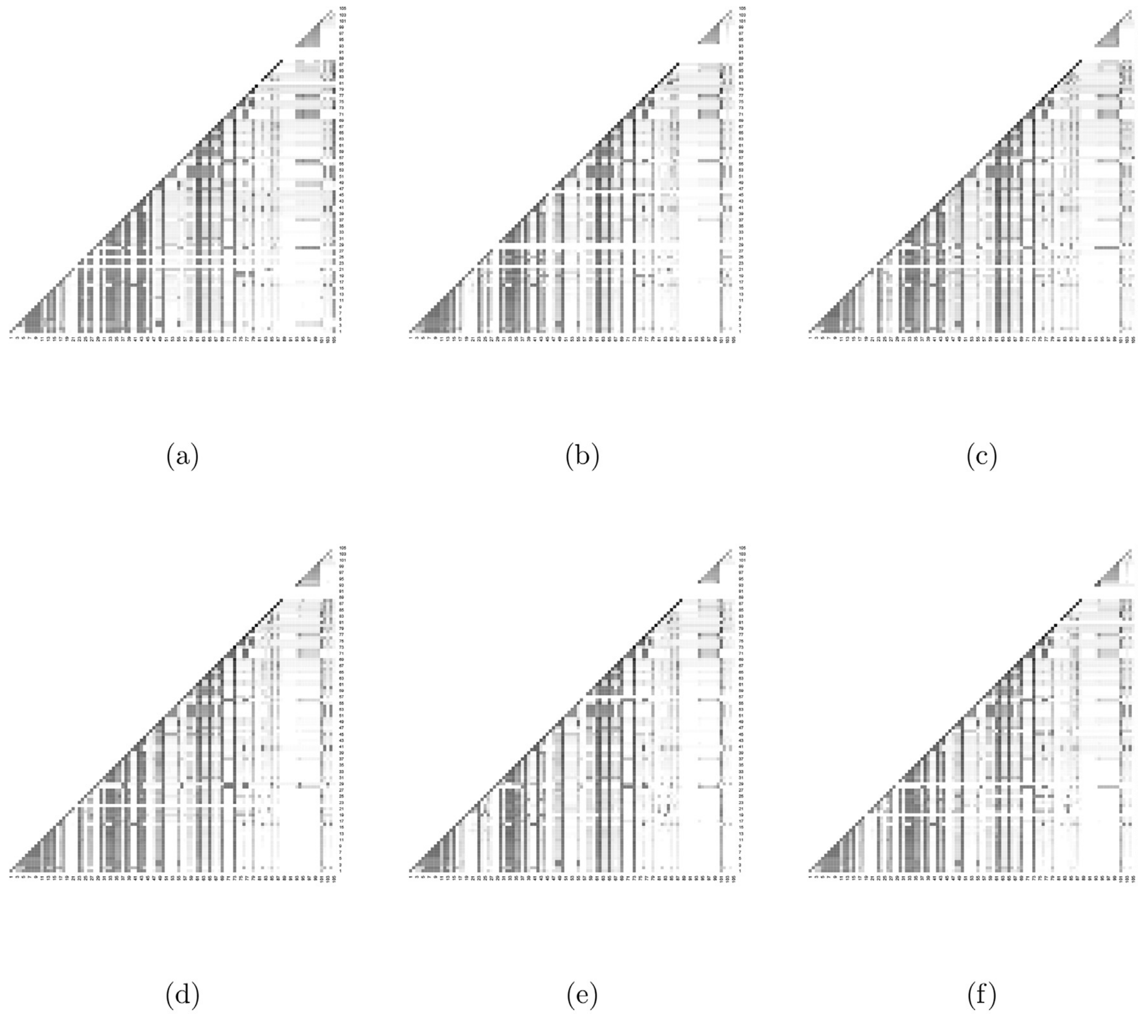

Fig. 3. The relative availability of data in each of the different regions (OECD, South Asia, East Asia, Latin America, Sub-Saharan Africa and MENA countries in that order) for the 105 variables that are included in the network analysis is depicted in these visualizations. The relative availability is defined as the actual number of observations used to compute the correlation coefficient for a particular pair of variables divided by the number of years and the number of countries in the region. Darker shades of grey indicate higher relative availability of data, while lighter shades indicate lower relative availability. When a row or column is blank, it indicates that variable does not contain any data for computing correlation coefficients with any of the other variables.

where X_{lag} and Y_{lag} are time-lagged versions of X and Y, i.e., $X_{lag}(t) = X(t-1)$ when we consider a lag of one time unit. Note that, if we assume stationarity conditions on the variables, $E[X_{lag}] = E[X], E\left[X_{lag}^2\right] = E\left[X^2\right]$ hold.[9]

In our application, X and Y are two target variables for the SDG, e.g., "Proportion of population in a country below the international poverty line", and "Total unemployment rate". Since X and Y are timeseries data, and are also available for different countries, we estimate the ρ using the sample correlation function as:

$$\hat{\rho}_{XY}^{sym} = \frac{1}{sd_X sd_Y}\frac{1}{N}\frac{1}{T-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(X_i(t) - \overline{X_i}\right)\left(Y_i(t) - \overline{Y_i}\right)$$

where we have data for N countries and T years. The $\overline{X_i}$ and $\overline{Y_i}$ represent the time-average of a particular country's X and Y.

[9] For the purposes of this definition we do not make these assumptions, although in practice the stationarity assumption will help in analysis. In fact, many of the timeseries we are interested in, for policy applications, are unlikely to be stationary because of the fundamental inter-connectedness between the variables, and the fact that policy changes result in non-stationary processes affecting these variables.

The estimate of the asymmetric strength of interlinkage that captures a Granger notion of causality would be given by:

$$\hat{\rho}_{XY}^{asym} = \frac{1}{sd_X sd_Y}\frac{1}{N}\frac{1}{T-2}\sum_{i=1}^{N}\sum_{t=2}^{T}\left(X_i(t-1) - \overline{X_i}\right)\left(Y_i(t) - \overline{Y_i}\right)$$

The corresponding effect of Y on X would involve the correlation of the lagged Y with unlagged X and this would potentially be different from $\hat{\rho}_{XY}^{asym}$. Note that the interlinkage definition captures both synergies and tradeoffs between variables as the correlation coefficient can be positive or negative. Using these $\hat{\rho}_{XY}^{asym}$ and $\hat{\rho}_{YX}^{asym}$ as edge weights, we can build a network of interlinkages among all variables. These weighted, directed, signed networks then capture the relationships between the variables. The network model of the SDG interactions can thus be represented as the graph $G_{SDG} = (V, E, W)$, where the vertices V are the SDG variables of interest, the edges are ordered pairs $e_k = (X, Y)$ which are the interlinkages between the variables X and Y, and the edge weights are weights assigned to each edge $W(e_k)$, given by the $\hat{\rho}_{XY}^{asym}$ formula above, where $e_k = (X, Y)$.

While this model allows us to understand the strength of interlinkage as a continuous edge weight (between -1 and 1), in this

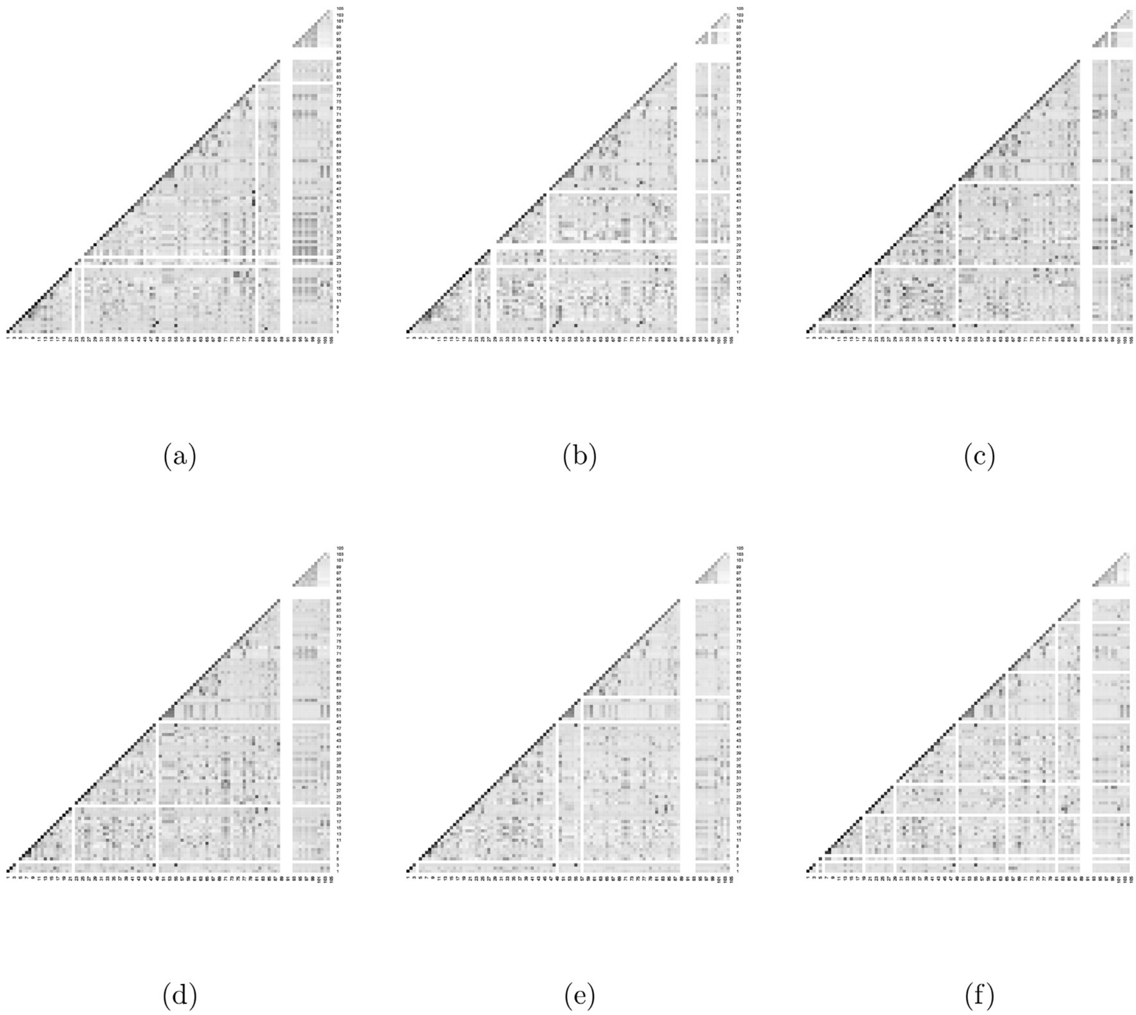

Fig. 4. The absolute correlation coefficients of data in each of the different regions (OECD, South Asia, East Asia, Latin America, Sub-Saharan Africa and MENA countries in that order) for the 105 variables that are included in the network analysis is depicted in these visualizations.

paper we will focus on an unweighted, signed and undirected network projection of G_{SDG}. This is primarily due to data issues. Reliable estimates of the true correlation is difficult to obtain because the data are extremely noisy.[10]

The unweighted network projection $G'_{SDG} = (V', E')$ is obtained from the weighted directed network by taking the set of vertices to be the same, i.e., $V = V'$, and with the set of edges E' obtained from E in the following manner for the k^{th} edge. The edge weight between vertices X and $Y : e'_k = 0$, if $|e_k| < \alpha, e'_k = 1$ if $e_k > \alpha$, and $e'_k = -1$ if $e_k < -\alpha$, where α is an arbitrary threshold. Thus, we classify the continuous variable e_k as 0, positive or negative, depending on a pre-determined threshold value α. This provides a more robust picture of the network of interlinkages between the SDG target variables as it removes some of the noisiness associated with the actual data.

While the unweighted projection of the full network can be made from either the directed or undirected network, in this paper, we will focus only on the undirected network. Thus, we measure the interlinkages as the symmetric sample correlation $\hat{\rho}^{sym}_{XY} = \frac{1}{sd_X sd_Y}\frac{1}{N}\frac{1}{T-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(X_i(t) - \overline{X_i}\right)\left(Y_i(t) - \overline{Y_i}\right)$ and then use the thresholding function described above, to obtain the unweighted projection. Since it is natural to look for causative mechanisms in policy applications, we briefly discuss the weighted network representation in the Discussion section, but leave further analysis of the weighted, directed networks to future work.

A.2. Visualization of data availability and correlation strengths

The availability of data is an important point to consider in analyzing the results we present. In this appendix, we present a visual representation of the available data and the correlation coefficients. The information is provided as a heatmap in greyscale that provides a visual representation of the proportion of data available (relative to the maximum possible number of observations) for calculating the correlation coefficients between pairs of variables. Darker shades indicate high availability of data whereas lighter shades indicate lower availability of data. The heatmaps enable us to visually grasp the information in an easy manner instead of the exact numerical values of these proportions that can result in an information overload. These visualizations have an additional advantage as the aim is to identify the relative strength of the computations. As more data becomes available, it is likely that all the

[10] Note that we can define standard errors for the correlation estimates using either the Fisher transformation or other approximations. In this paper, we will not report the standard errors though they may be estimated directly. This is because the data quality is not uniformly good, and hence the estimates of the interlinkages through correlation coefficients are not reliable. Specifying the correlations as weights without an accompanying measure of the standard error for the correlation coefficient is likely to be misleading. We thus provide only the unweighted, signed network description using a thresholding function on the correlation coefficients.

variables will contain more observations. Since the data availability is region-specific, we indicate data availability also in regional terms in Fig. 3.

In Fig. 4, we also show the relative strengths of the correlation coefficients. Due to the missing data, the highest absolute correlation coefficient is about 0.25. We do not indicate the sign of the correlation coefficient in this visualization as the aim is to compare the relative strengths of the correlation coefficients. The figure shows that there are small clusters of variables that are relatively highly correlated with each other, whereas most variables have relatively low correlation. This is also the justification for why we impose a threshold in creating our correlational networks.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.worlddev.2020.105136.

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