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Income-based variation in Sustainable Development Goal interaction networks

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The 17 United Nations Sustainable Development Goals (SDGs) are set to change the way we live, and aim to create, by 2030, a sustainable future balancing equitable prosperity within planetary boundaries. Human, economic and natural resources must be used in tandem to achieve the SDGs; therefore, acting to resolve one SDG can impair or improve our ability to meet others that may need these resources to be used in different ways. Trade-offs arising from these SDG interactions are a key hurdle for SDG implementation. We estimate the network of SDG interactions—the sustainome—using global time series of SDG indicators for countries with different income levels. We analyse the network architecture to determine the hurdles and opportunities to maximize SDG implementation through their interactions. The relative contributions of SDGs to global sustainable success differ by country income. They also differ depending on whether we consider SDG goals or targets. However, limiting climate change, reducing inequalities and responsible consumption are key hurdles to achieving 2030 goals across countries. Focusing on poverty alleviation and reducing inequalities will have compound positive effects on all SDGs.

Many conflicts result from the way people interact with each other and with our planet[1]. Since 1992, a range of global initiatives have emerged to find a more sustainable and equitable solution to these conflicts. In 2015, the United Nations set a 15-year plan[2,3], composed of 17 Sustainable Development Goals (SDGs) and 169 associated targets, to promote prosperity for all while protecting our planet[3]. These goals touch on all aspects of human life and therefore interact in complex ways. They do not exist in isolation, and synergies and conflicts can emerge from their interactions[2,4–6]. For example, traditional approaches to increasing agricultural productivity (SDG2) will lead to biodiversity and natural habitat loss affecting our ability to meet SDG15 (ref. [7]).

The interdependencies of SDGs were recognized from their inception[4], but the effects of actions to achieve one goal on the ability to achieve others were anticipated only recently. Some work helped to highlight how interactions between SDG pairs can be negative or co-beneficial[6,8,9]. However, in many instances, the statistical approach limited the ability to make inferences relevant for interventions. One particular hurdle to date is the lack of recognition in these analytical approaches that interactions can and will vary depending on the socioeconomic characteristics of countries. Accordingly, there is little knowledge of the context of the network emerging from direct and indirect interactions between SDGs, and there are no robust inferences of associations between goals. This is important because efforts to meet SDGs in isolation can be counterproductive[10] if they affect other SDGs negatively.

Not all interactions may be negative, and investment in some SDGs can have additional benefits on multiple goals. There are also other barriers to SDG implementation, as the status quo on some goals can be advantageous for some groups (vested interests) or indeed desirable (for socioeconomic reasons)[11]. Understanding the SDG network can help to find new indirect ways to progress on specific SDGs while avoiding non-SDG barriers[11]. Likewise, identifying indirect positive effects of SDGs on other goals can help define the best governance structures to capitalize on synergies and accelerate progress towards the 2030 targets[12–14]. Finally, using a robust and unified approach to estimating direct and indirect interactions among goals can help us determine whether those interactions differ among countries, which could also explain diverging views on SDG interlinkages[15].

Applying network science to the SDG

Studying the topology and drivers of networks has given us crucial insights about complex systems such as health[16,17], ecosystems[18], financial systems[19] and our societies[20]. Network theory provides analytical tools to determine how such mathematical representations of systems can evolve through time and how they might respond to perturbations[21]. We apply a network approach to the SDGs to estimate what we call the sustainome—the system of SDG interactions. The sustainome can be represented as a network, where the vertices are the SDGs (goals or targets) and the edges are relationships between them. We estimate the sustainome network of interactions at two scales: among the 169 SDG targets and among the 17 SDGs themselves. The concept of the sustainome is inspired from the conceptual definition of sustainomics[22], defined as the study of how to achieve sustainability by maintaining six capitals (infrastructure, finance, communities, people, ecosystems and biodiversity) while generating the flows we require from those capitals to achieve the SDGs.

Relationships among goals can be defined in a number of ways, from shared concepts in their definitions[4] to dependencies in indicator trajectories[19]. Within a sustainome framework, interactions between the SDGs are represented as the associations between progress towards each SDG (see Methods). For example, if initiatives are implemented to increase gross domestic product, will they be associated with a degradation of biodiversity? Several organizations have monitored macroscale indicators associated with the SDGs in most countries over the past decades, which allows us to determine global interactions among the SDGs.

Estimating the sustainome

The World Bank (see Methods) developed a set of 331 indicators to inform the SDGs (Supplementary Table 1) using data collected

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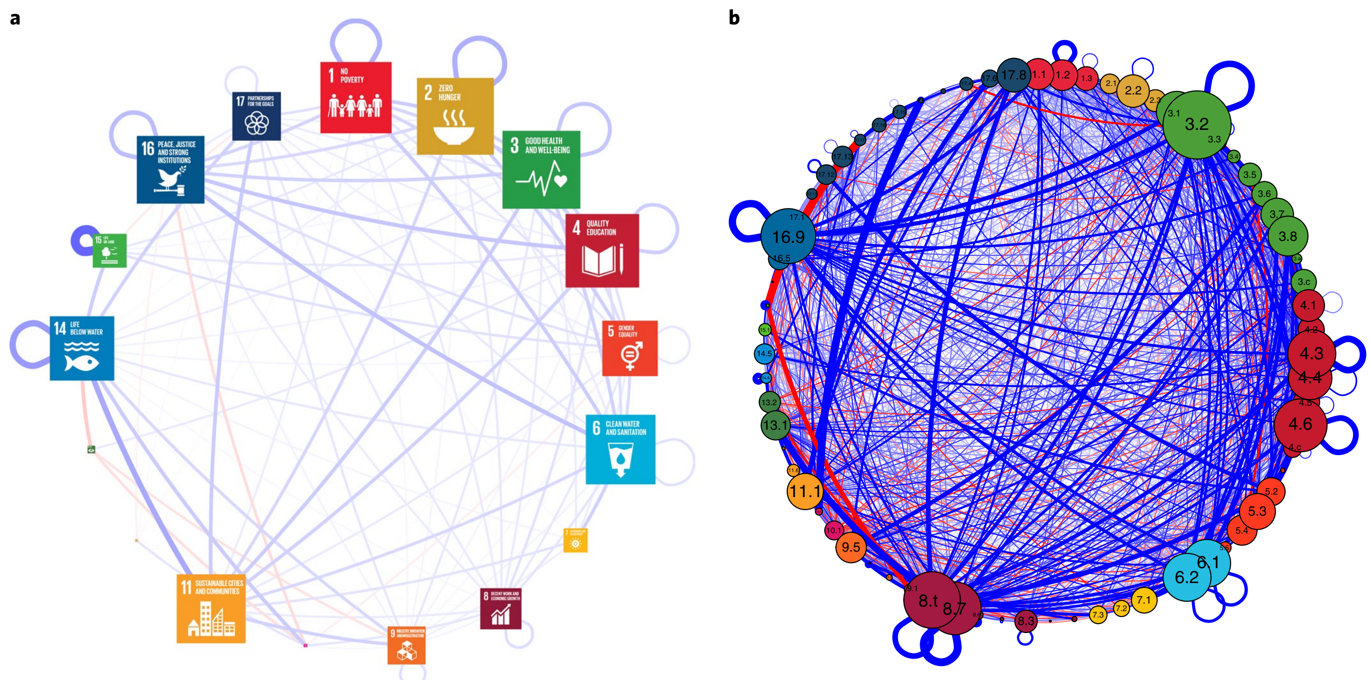

Fig. 1 | SDG and target sustainome including all countries. a,**b**, Sustainomes for SDGs (**a**) and targets (**b**), each of which are represented by nodes. The edges are associations (positive in blue and negative in red) deemed to differ from zero, with the line thickness representing the magnitude ranging from −1 to 1. Node sizes correspond to the target or SDG eigenvector centrality, highlighting the structural importance of each node. Nodes in **a** are presented in a sequential manner and clockwise following the SDG order, starting with SDG1 at the top. In **b**, targets are aggregated by SDGs and presented in sequential order in a clockwise manner following the SDG numbers. Targets are colour coded to match the SDG colours. Credit (icons): United Nations (SDG).

regularly over the past 27 years for 263 countries[23]. The World Bank associated each of these indicators to SDG targets so that the indicators can be used as a measure of progress towards SDGs and their targets. Afterwards, the United Nations developed a set of indicators under the auspice of the Inter-agency and Expert Group on SDG Indicators. This set of indicators largely overlaps with that of the World Bank, which has more country representation and for more years. The World Bank data also allowed us to use indicators that were not given as a disaggregated percentage by age class and gender (which could not be re-aggregated without knowing the age and gender composition of each country and each year), thus minimizing collinearity issues in subsequent analyses. Therefore, we used the World Bank indicators to inform interactions between their respective identified 71 targets and 17 SDGs (98 SDG targets still lack indicators).

Causal relationships are notoriously difficult to infer from longitudinal studies. As a first step, we determined whether associations exist based on multiple measures of interactions (that is, several indicators per target and goal). We estimated pairwise interactions between targets and SDGs using pairwise meta-analyses of the standardized coefficients of association between the relevant indicators (54,615 indicator association mixed effects models; 2,556 and 153 meta-analyses for targets and SDGs respectively; see Methods for details). We obtained two weighted networks that are undirected (as we estimated associations, and directionality can only be estimated if the direction of causality is known) and signed (positive and negative associations)—one with 71 nodes (target sustainome network) and another with 17 nodes (SDG sustainome network) (Fig. 1).

While this network representation describes the state of interactions among goals (and targets), we are interested in understanding how these interactions may affect the evolution of this network towards the overall sustainability vision. So, in addition to describing the state, we also describe the local dynamics of this network. This helps us to understand, given the observed sustainome architecture, the probable fate of goals and targets if interactions are not changed as we try to progress towards them. To estimate this, we used the respective graph Laplacian[24]. Decomposition of the graph Laplacian showed that both sustainome networks are unstable and composed of antagonistic subgroups (targets: eight positive eigenvalues; SDGs: two positive eigenvalues). As we try to progress towards the SDGs, these antagonistic groups behave in different ways from one another; progressing towards sustainability for one group leads to moving away from sustainability for the others. In the case of the SDG sustainome, we have two clusters of SDGs (SDG13 alone and SDG10 plus SDG12) that are antagonistic to the rest. If we progress towards those goals, we will not be able to meet the others. These are also goals that have more negative links than positive ones in the network (Fig. 2, all countries) and are more likely to challenge our ability to meet all SDGs.

The sustainome differs by country income level

Level of income is a major descriptor of the macroeconomic context of countries[25,26], and this context is expected to matter for SDG implementation[2]. Therefore, we replicated this network approach across the four income-based groups of countries defined by the World Bank[27] to determine whether the sustainome architecture varies by income.

The topology of the SDG sustainome changes drastically across income category (Figs. 3a and 4a and Supplementary Figs. 1 and 2). In these networks, some goals emerge as clear structural priorities for the SDG sustainome (SDG1 (no poverty) and SDG10 (reduce inequalities) for the low- and high-income country sustainomes, respectively; Figs. 2, 3a and 4a). These goals have large eigenvector centrality in their respective networks, meaning that their interactions with other goals are dominant features of the network and will affect many other goal interactions indirectly. We do not

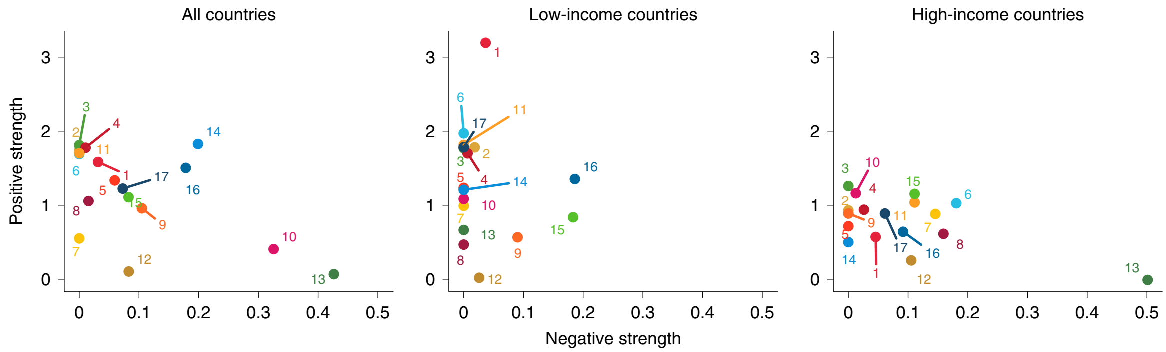

Fig. 2 | Topological centrality of SDGs depending on the sum of their positive (positive strength) and negative (negative strength) associations. Results are shown for all countries (left), low-income countries (middle) and high-income countries (right). Numbers correspond to SDGs. Colours correspond to the SDG colours used in Fig. 1.

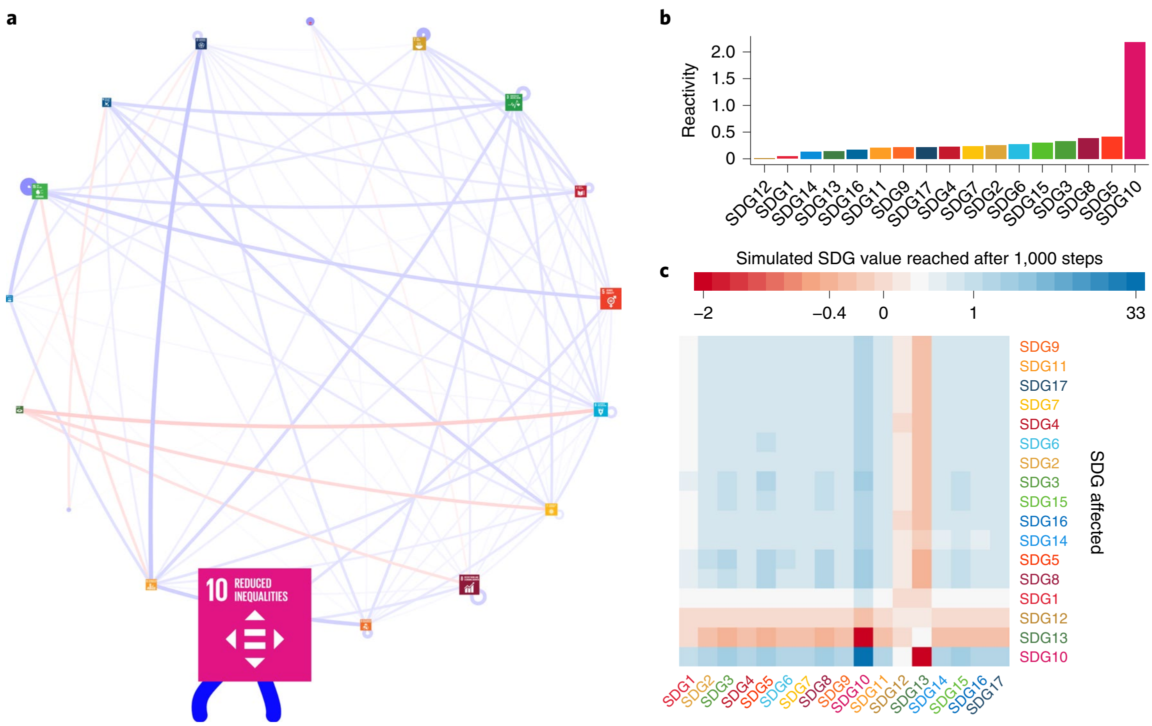

Fig. 3 | Sustainome, SDG contributions to reactivity, and fates of each SDG for high-income countries. a, Sustainome. Node sizes correspond to the SDG eigenvector centrality, highlighting the structural importance of each node; therefore, some nodes are very small. Nodes are presented in a sequential manner and clockwise following the SDG numbers, starting with SDG1 at the top. The connectors between the same SDG show the association within that goal. **b**, Contribution of each SDG to the reactivity of the sustainome in **a**. **c**, Fate of all SDGs at the end of simulations (a_{1000}, see Methods; rows) as we intervene on each given SDG (columns), given the interactions in the sustainome (negative values correspond to a degradation of the SDG). A value of 2 means that the indicator values for this SDG increased 2-fold; a value of −2 means that the indicator values for this SDG deteriorated 2-fold over the 1,000 simulation steps. Credit (icons): United Nations (SDG).

expect such observations to have emerged by chance, as such patterns do not emerge when we simulate random networks with the same characteristics as the sustainomes (Supplementary Fig. 3). The sustainome is also most reactive to small changes in interactions for these two goals (Figs. 3b and 4b). This means that all goals will be disproportionately affected by actions to meet SDG10 in high-income countries (Fig. 3c) and SDG1 in low-income countries.

The SDG sustainome of low-income countries does not contain antagonistic groups (all eigenvalues of the Laplacian are ≤ 0; Fig. 4c). It therefore appears that the SDGs align in those countries and interventions in relation to one goal are unlikely to undermine progress towards achieving other goals (Fig. 4c). The current way of handling SDGs can lead us to an overall sustainable solution where all goals are met in low-income countries.

To further understand the future directions of SDG goals and targets given the sustainomes we estimated, we estimated SDG goal progress (see Methods, Figs. 3c and 4c and Supplementary Figs. 1 and 2) and target progress (Supplementary Fig. 6) as we simulated progress on the other goals and targets, respectively. In contrast with low-income countries, for high-income countries, SDG13 (climate actions) and, to a lesser extent, SDG12 (responsible consumption) are at odds with the other goals (Figs. 2 and 3c). Again, these

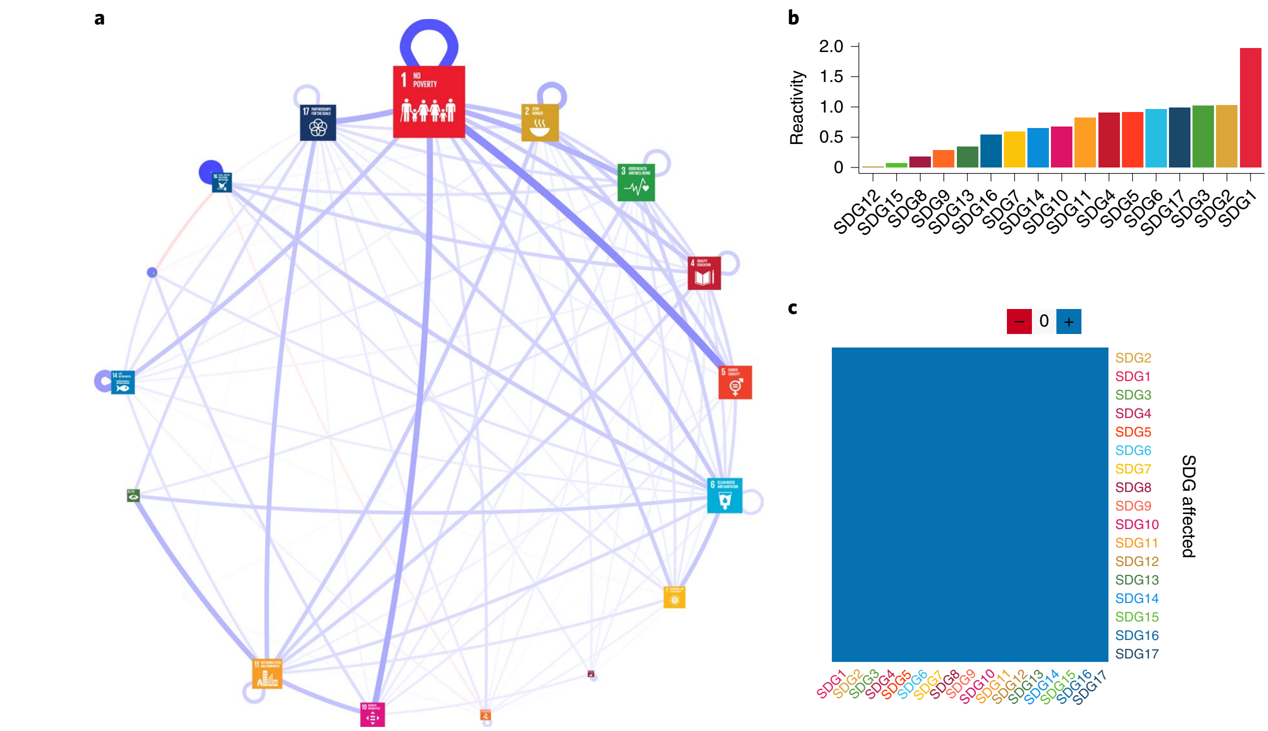

Fig. 4 | Sustainome, SDG contributions to reactivity, and fates of each SDG for low-income countries. a, Sustainome. Node sizes correspond to the SDG eigenvector centrality, highlighting the structural importance of each node; therefore, some nodes are very small. Nodes are presented in a sequential manner and clockwise following the SDG numbers, starting with SDG1 at the top. **b**, Contribution of each SDG to the reactivity of the sustainome in **a**. **c**, Fate of all SDGs (rows) as we intervene on each given SDG (column), given interactions in the sustainome ('+' and '–' represent positive and negative influences, respectively). Credit (icons): United Nations (SDG).

observations are not expected to have occurred by chance when comparing these results with the same analyses on relevant random networks (Supplementary Figs. 4 and 5). We cannot infer directionality, given the analyses, but we observe that a conflict emerges between SDG13 (and SDG12 to a lesser extent) and the other goals. This means that progressing towards these goals impairs our ability to address all of the other goals (and vice versa). Overall, the sustainome will react most (Fig. 3b) to interventions on SDG10 ('reduce inequalities'), which will have the most positive effect on all other goals apart from SDG12 and SDG13 (Fig. 3c).

Goal sustainome does not scale from target sustainome

The picture at the target level is more complex (Supplementary Fig. 7). Target 3.2 (reduce child mortality) remains a structurally important component for SDG implementation because it has the largest eigenvector centrality (Supplementary Fig. 7), as well as disproportionately more positive strength than negative strength (Supplementary Fig. 8). In other words, when summing all of its associations, it has stronger positive associations than negative ones with the other targets. The interaction pattern of target 3.2 with other targets does not change with income (regarding both negative and positive strength; Supplementary Fig. 8), and the target sustainomes for all income groups react most to changes in a reduction in child mortality (Supplementary Fig. 9). Accordingly, focusing on child mortality in all countries will have beneficial effects for many other targets.

This target-level analysis also shows that the goal sustainomes do not scale up from the target sustainomes. The interactions are drastically different in the target sustainome compared with its respective goal sustainome. This reinforces the importance to interpret any analytical results of SDG interactions at the same scale as the data used. The goal sustainome provides insights for broader governance, while the target sustainome can help point out important potential interventions (for example, child mortality reduction). Child mortality, inequalities, responsible consumption and climate change mitigation form a core of interactions the mechanisms of which we need to understand better to progress towards the SDGs.

By looking at interactions that impede SDG implementation (the subset of negative edges in the sustainome and the eigenvector centrality of targets in this subset; Supplementary Fig. 10), we see that these network subsets differ widely across incomes. Health proves an important barrier in lower-income countries as the three largest eigenvector centralities belong to SDG3. A wide diversity of sustainability goals are important barriers (larger eigenvector centrality) for high-income countries—particularly climate challenges, inclusivity and equity in economic growth, infrastructure access and access to education, as well as greening of infrastructure.

Discussion

Our understanding of the sustainome will evolve as more data become available, not only to enrich existing indicators, but also to define clear global indicators for the 98 targets currently unmonitored. It is also crucial to synchronize and integrate the multiple indicator datasets available to ensure working from a common inferential foundation. Additional data will also enable us to move from associative studies to causal inferential frameworks, as the current data sparsity constrained us to the current approach. Causal inference is rapidly developing thanks to recent breakthroughs that open tangible avenues for sustainome inference[28].

Our analysis of the sustainome provides new insights into the best way to achieve as many SDGs as possible by 2030. First and foremost, the way SDGs interact differs by country income level. Much of our international agenda in sustainability over the past three decades has focused on sustainable development, particularly for low-income countries. In these countries, the SDGs are currently not conflicting and we can progress on all 17 goals without outstanding trade-offs. This is not the case for the three other income categories, for which barriers among SDGs emerge. Prioritizing reducing childhood early deaths will have compounded the positive effects on other targets across all goals for all countries.

Second, we should contextualize targets and prioritize goals by country income levels. Prioritizing poverty alleviation in low-income countries and reducing inequalities in high-income countries will have compounded positive effects on all SDGs. For high-income countries, combatting the potential effects of climate change presents the most barriers to achieving other goals. This may be because current approaches have relied on diverting resources from other socioecological activities to combat the effects of climate change instead of attempting to embed climate change mitigation measures in the everyday lives of everyone, but with other SDGs in mind. Innovation programmes should focus on developing new governance, new technologies and new approaches to embed climate change actions in the way we tackle inequalities. Our ability to both increase resilience to climate change and decrease emissions in those countries depends on providing solutions that can be adapted across socioeconomic strata[29]. Indeed, a focus on inclusivity and equity in developing infrastructure and investment strategies (SDG13) will have indirect benefits for most goals.

Given the current approaches to address the 17 goals, we are most likely to achieve all of them in tandem only in low-income countries. In these countries, approaches to meeting the goals do not seem to conflict and our sustainomic approach clearly concludes that poverty alleviation will have simultaneous positive effects on all goals[30]. This shows that efforts to tackle poverty will pay off in the long term. It also means that all other countries will need to adapt sustainability strategies to the social, economic and ecological specificities of at least three groups of countries clustered by income level.

Another important finding is that the SDG sustainome did not scale up from the target sustainome because the structurally important targets in the target sustainome were not necessarily associated with goals that were structurally important in the SDG sustainome. Despite this, the overall conclusions derived from both sustainomes in low- and high-income countries are broadly in accord. The dynamics of the target sustainome were more complex, and the wicked problems[31] emerging from interactions more diverse (Supplementary Fig. 9). Staying flexible on targets but remaining focused on goals appears to offer more opportunities to avoid SDG conflicts and achieve overall sustainability across contexts and countries.

Methods

Estimating target and SDG networks. We used World Bank indicator time series to inform SDG targets. The World Bank has developed a data bank of indicators categorized by the targets for which they are relevant[23]. Several data banks of SDG indicators are now available. We chose the World Bank dataset after comparing it with others as we found it to be more comprehensive within indicators (more countries and more years were available for indicators). It also had transparent metadata, including a description of the statistical concept and methodology for each indicator, and a description of the limitations associated with each indicator. It presented a good inferential foundation for meta-analyses. We used 331 indicators, collected from 1990 to 2017, to inform 71 targets for all 17 SDGs. Original time series of natural disasters summarized for target 13.1 in the World Bank data were retrieved from the EM-DAT[32].

We estimated the association between each indicator pair using linear mixed-effect models (MEMs) with the country of observation origin as a random effect, and an autoregressive correlation structure with a lag of one year within countries (using nlme in R[33]). We validated this treatment of between-country heterogeneity and autocorrelation within time series for each model. We centred indicators on their mean and scaled by their variance to obtain standardized coefficients of association assuming a Gaussian distribution for the residuals, which were validated given observed residual distributions. Before fitting MEMs, scaled indicators were also informed by target directionality. The scaled time series were multiplied by −1 if the indicator definition was opposed to the desired trajectory and 1 if they were concomitant. For example, if our target is a reduction in child mortality and the indicator reports the number of children who died annually in a country, we would like to see a decrease in this indicator. That way, when we estimated the association of indicator pairs, we could use the standardized coefficients of associations (β values) to estimate whether indicator interactions were contrary or not to our targets. $\beta < 0$ indicates that an association is undesirable given our targets, while $\beta > 0$ indicates that an association moves indicators in the desired direction.

To estimate target interactions and SDG interactions, we used these β values with their associated standard errors and meta-analysed these effects for each target and SDG pair given the target and SDG membership of each indicator involved in the MEM, respectively. A pair of indicators was only considered once in these meta-analyses, which were MEMs of the standardized coefficients with a constant fixed effect (the interaction estimate) weighted by the standard error of the β values (using metafor in R[34]). Resulting estimated association coefficients ($\hat{\beta}$) significantly different from zero (with $P < 0.05$) were retained to estimate the signed weighted network **A** so that $a_{ij} = a_{ji} = \hat{\beta}$, which is a 71×71 ($i \times j$) matrix for targets and a 17×17 ($i \times j$) matrix for SDGs.

Network state. Given the way the sustainome is defined we can envisage the edges representing some notion of transfer (information or energy) between the goals/targets. We therefore used the graph Laplacian **L** of the signed network **A**[24] to determine network stability (stable when all eigenvalues of the graph Laplacian are ≤0):

$$L_{ij} = \begin{cases} L_{ij} = A_{ij} i \neq j \\ L_{ij} = -\sum_k A_{ik} i = j \end{cases}$$

If the network was unstable, we determined the number of antagonistic clusters in the networks using simulations. We simulated the vector of target/SDG states through time (1,000 steps), $\mathbf{a}_t$ so that:

$$\mathbf{a}_{t+1} = A \cdot \mathbf{a}_t \wedge \mathbf{a}_0 = [1]^n$$

where n is the respective dimension of **A** (17 for SDG and 71 for targets). We repeated this simulation 17 times for SDG and 71 times for targets, and for each set intervene on a single goal/target, i, at each time step ($\mathbf{a}_{i,t} = \mathbf{a}_{i,t} + 0.1$) before estimating $\mathbf{a}_{t+1}$.

Contributions of targets and SDGs to the sustainome. We then estimated the partial contribution of each target and SDG in its respective signed networks to the reactivity[35] of the network to perturbation. This provides an understanding of the relative contribution of each target and SDG to the sustainome dynamics as we attempt to drive it towards our goals. Finally, we estimated the eigenvector centrality of each node in its respective networks, as well as its positive and negative strengths to understand its relative contribution to the sustainome topology. The eigenvector centrality provides a measure of the relative contribution of a goal/target to the overall topology of the network. A goal with large eigenvector centrality will have large indirect effects on other goals, not only those with which it is associated, but also effects propagating through its neighbours. Hence, it provides an integrated estimate of the overall weight of a goal in shaping the fate of all goals[21]. Strength (s) is a measure of the weight of associations between a goal and the goals with which it is directly associated $\left(s \mid i = \sum_j A_{ij}\right)$; the more a goal has connection, the larger its strength. As we have both positive and negative edges (associations), we estimated the positive strength and negative strength. Goals with large negative strength and small positive strength will tend to be a hindrance for other goals, and vice versa.

Income-group-level estimations. This network analytical process, including network estimation, was replicated for a subset of countries categorized by their income using World Bank categories. Low-income countries are currently defined by a gross national income (GNI) per capita of US$1,025 or less. Lower-middle-income countries currently have a GNI per capita of between US$1,026 and US$4,035. Upper-middle-income countries currently have a GNI per capita of between US$4,036 and US$12,475. High-income countries currently have a GNI per capita of US$12,476 or more. We determined whether sustainome findings were consistent across income groups. There are many ways we can determine whether these centrality measures occurred by chance[36]. Given the uncertainties surrounding the association estimates, and the way we estimated them, we wanted to first assess whether topological constraints (that is, the assortment of those associations) could lead by chance to the observed centrality measures. Therefore, for each sustainome, we randomly shuffled the existing associations (**A**), keeping the symmetry of the matrices constant ($a_{ij} = a_{ji}$), 1,000 times. We then estimated centrality measures for each goal for each of the 1,000 randomized matrices and estimated how likely each was to obtain the observed centrality measures in these 1,000 random estimates.

Code availability
Code is available at http://www.github.com/dlusseau/sdg/.

Data availability
All of the data used for these analyses are freely available from the World Bank SDG indicators via the website (https://datacatalog.worldbank.org/dataset/sustainable-development-goals) or the World Bank API.

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Author contributions
D.L. conceived the study. D.L. and F.M. designed the statistical models. D.L. carried out the analyses. D.L. and F.M. wrote the manuscript.

Competing interests
The authors declare no competing interests.

Additional information
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