

# Income-based variation in Sustainable Development Goal interaction networks

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## Abstract

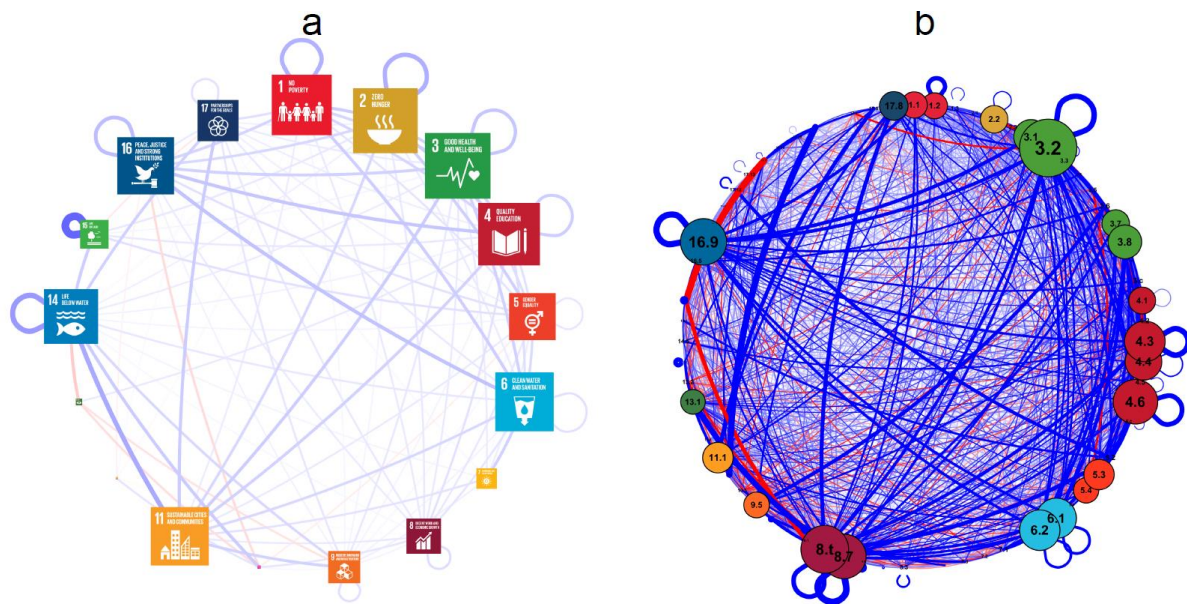
The seventeen United Nations sustainable development goals (SDGs) are set to change the way we live and create by 2030 a sustainable future balancing equitable prosperity within planetary boundaries. Human, economic and natural resources have to be used in tandem to achieve the SDGs and therefore acting to resolve one SDG can impair, or improve, our ability to meet others that may have to use these resources in different ways. Trade-offs arising from these SDG interactions are a key hurdle for SDG implementation. We estimate the network of SDG interactions 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 maximise SDG implementation through their interactions. The relative contribution of SDGs to global sustainable success differ by country income. It also differs 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. Focussing on poverty alleviation and reducing inequalities will have compounded positive effects on all SDGs.

Many conflicts result from the way people interact with each other and with our planet<sup>1</sup>. 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<sup>2,3</sup>, composed of 17 sustainable development goals and 169 associated targets, to promote prosperity for all while protecting our planet<sup>3</sup>. Those goals touch on all aspects of human life and therefore interact in complex ways. These goals do not exist in isolation and synergies and conflicts can emerge from their interactions<sup>2,4-6</sup>. For example traditional approaches to increasing agricultural productivity (SDG1) will lead to biodiversity and natural habitat loss therefore affecting our ability to meet SDG15<sup>7</sup>.

The inter-dependencies of SDGs were recognised from their inception<sup>4</sup>, 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<sup>6,8,9</sup>. 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 socio-economic 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 counter-productive<sup>10</sup> 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)<sup>11</sup>. Understanding the SDG network can help to find new indirect ways to progress on specific SDGs while avoiding non-SDG barriers<sup>11</sup>. Likewise, identifying indirect positive effects of SDGs on other goals can help define the best governance structures to capitalise on synergies and accelerate progress towards the 2030 targets<sup>12,13</sup>. 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<sup>15</sup>.



**Figure 1.** SDG (a) and target (b) sustainome including all countries. Nodes are targets (b) or SDGs (a) and 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 size corresponds to the target or SDG eigenvector centrality highlighting the structural importance of each node. Nodes are presented in a sequential manner and clockwise following the goal order, starting with goal 1 at the top (a). Targets (b) are aggregated by goals and presented in sequential order in a clockwise manner following goal numbers. Targets are colour-coded with the SDG colours (b).

### Applying network science to the SDG

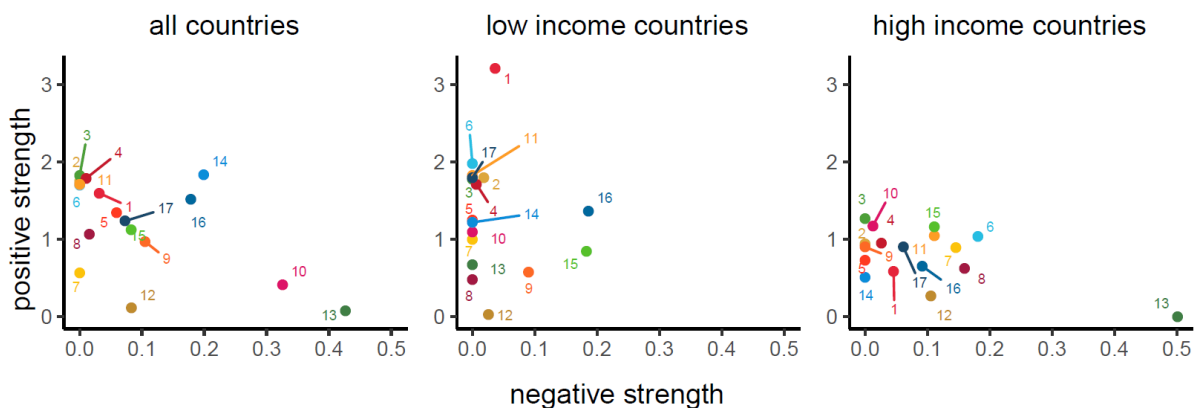
Studying the topology and drivers of networks has given us crucial insights about complex systems such as health<sup>16,17</sup>, ecosystems<sup>18</sup>, financial systems<sup>19</sup> and our societies<sup>20</sup>. Network theory provides analytical tools to determine how such mathematical representations of systems can evolve through time and how they might respond to perturbations<sup>21</sup>. We apply a network approach to the SDGs in order 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 the network of interactions at two scales: among the 169 SDG targets and among the 17 SDG themselves. The concept of the sustainome is inspired from the conceptual definition of sustainomics<sup>22</sup>, 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<sup>4</sup> to dependencies in indicator trajectories<sup>19</sup>. 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 GDP, will they be associated with a degradation of biodiversity? Several organisations 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 (WB; see methods) developed a set of 331 indicators to inform the SDGs (Supplementary Table 1) using data they have collected regularly over the past 27 years for 263 countries<sup>23</sup>. The WB associated each of these indicators to SDG targets and so the indicators can be used as measure of progress of SDGs and their targets. After, the UN developed a set of indicators under the auspice of the Inter-agency and Expert Group on SDG Indicators (IAEG-SDGs). This set of indicators largely overlaps with that of the WB, and the latter has more country representation and for more years. The WB data also allowed us to use indicators that were not given as disaggregated percentage by age class and gender (which could not be re-aggregated without knowing the age-gender composition of each country and each year) hence minimise collinearity issues in subsequent analyses. Therefore, we used the WB 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 existed based on multiple measures of interactions (i.e., several indicators per target and goal). We estimated pairwise interactions between targets and SDG using pairwise meta-analyses of the standardised coefficients of association between the relevant indicators (54615 indicator association mixed effects models, 2556 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) (Figure 1).

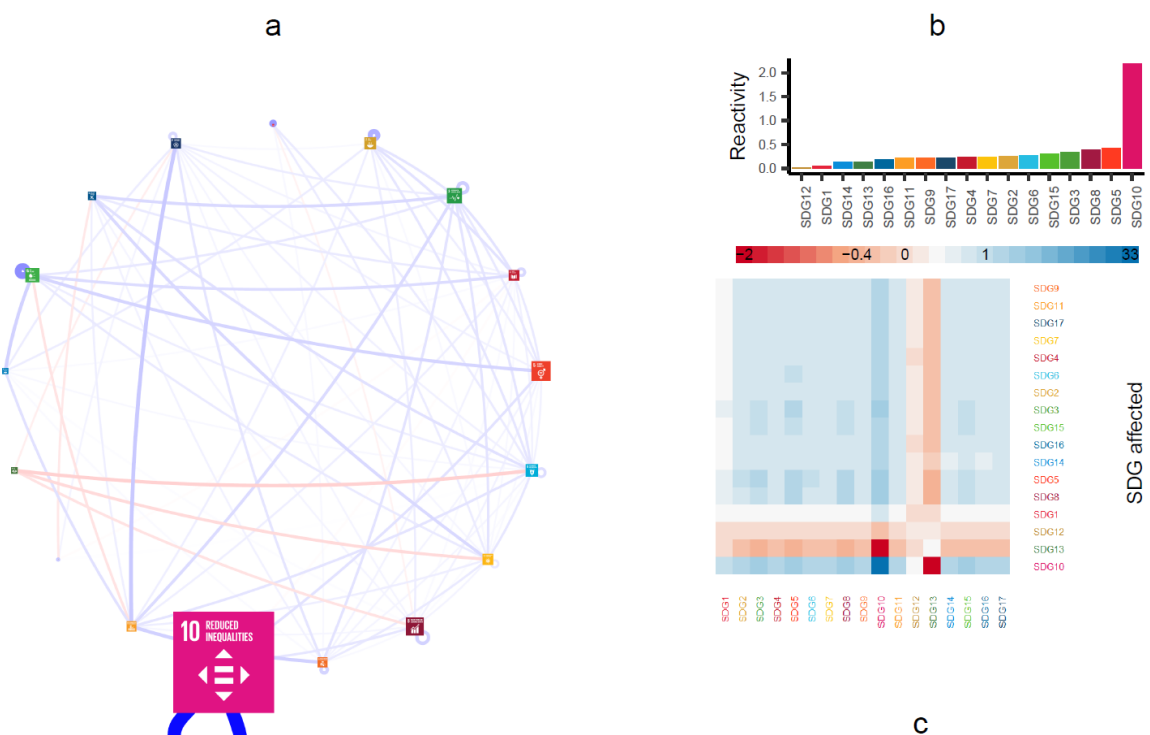


**Figure 2.** Topological centrality of SDG depending on the sum of their positive (positive strength) and negative (negative strength) associations when considering all countries, low income countries and high income countries. Numbers correspond to the SDGs. Colors correspond to the SDG colours.

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. These helps understand given the observed sustainome architecture the likely fate of goals and targets if interactions are not changed as we try progress towards them. To estimate this, we used the respective graph Laplacian<sup>24</sup>. Decomposition of the graph Laplacian showed that both sustainome networks are unstable and composed of antagonistic subgroups (target: 8 positive eigenvalues, SDG: 2 positive eigenvalues). As we try to progress 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 (the first one SDG13 alone and the second composed of SDG10 and SDG12) that are antagonistic to the rest. If we progress 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 (Figure 2 – all countries) and are more likely to challenge our ability to meet all SDGs.

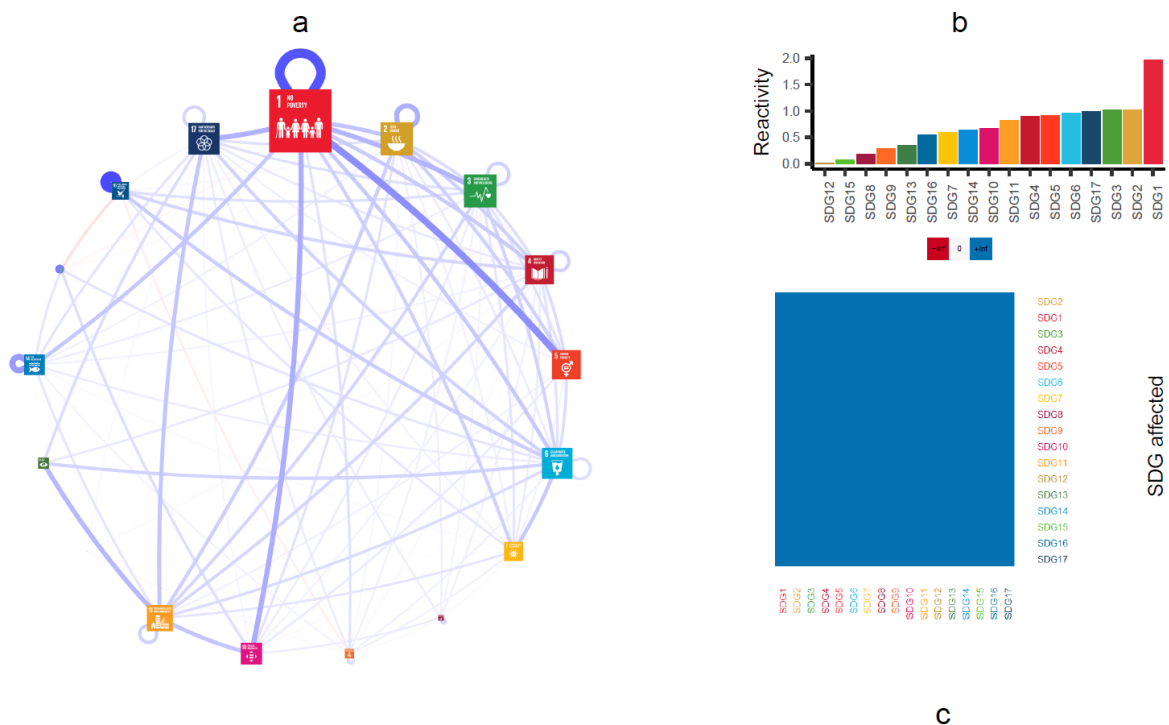
### The sustainome differs by country income level

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



**Figure 3.** The sustainome for high income countries (a), the contribution of each SDG to the reactivity of this sustainome (b) and the fate of all SDGs (a<sub>1000</sub>, rows) as we intervene on each given SDG (column) given interactions in the sustainome (negative values correspond to a degradation of the SDG). Node size (a) corresponds to the SDG eigenvector centrality highlighting the structural importance of each node, therefore some nodes are very small. Nodes in the sustainome (a) are presented in a sequential manner and clockwise following the goal numbers, starting with goal 1 at the top.

The topology of the SDG sustainome changes drastically across income category (Figures 3a & 4a; Supplementary Figures 1 & 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 sustainome respectively; Figures 2, 3a & 4a). These goals had 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 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 Figure 3). The sustainome is also most reactive to small changes in interactions for these two goals (Figure 3b & 4b). This means that all goals will be disproportionately affected by actions to meet SDG10 in high income countries (Figure 3c) and SDG1 in low income countries.



**Figure 4.** The sustainome for low income countries (a), the contribution of each SDG to the reactivity of this sustainome (b) and the fate of all SDGs (rows) as we intervene on each given SDG (column) given interactions in the sustainome (negative values correspond to a degradation of the SDG). Node size (a) corresponds to the SDG eigenvector centrality highlighting the structural importance of each node, therefore some nodes are very small. Nodes in the sustainome (a) are presented in a sequential manner and clockwise following the goal numbers, starting with goal 1 at the top.

The SDG sustainome of low income countries does not contain antagonistic groups (all eigenvalues of the Laplacian  $\leq 0$ , Figure 4c). It appears therefore that the SDGs align in those countries and interventions in one goal are not likely to undermine progress on other goals (Figure 4c). The current way to handle 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, Figures 3c & 4c, Supplementary Figures 1 & 2) and target progress (Supplementary Figure 6) as we simulated progress on the other goals and targets respectively. By contrast to low income countries, for high income countries, SDG13 (‘climate

actions') and, to a lesser extent, SDG12 ('responsible consumption') is at odds with other goals (Figures 2 & 3c). Again, these observations are not expected to have occurred by chance when comparing these results to the same analyses on relevant random networks (Supplementary Figures 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 those goals impairs our ability to address all other goals (and vice-versa). Overall, the sustainome will react most (Figure 3b) to interventions on SDG10 ('reduce inequalities') which will have the most positive effect on all other goals but SDG12 and SDG13 (Figure 3c).

### **The goal sustainome does not scale from the target sustainome**

The picture at the target level is more complex (Supplementary Figure 7). Target 3.2 ('reduce child mortality') remains a structurally-important component for SDG implementation because it has the largest eigenvector centrality (Supplementary Figure 7) as well as disproportionately more positive strength than negative strength (Supplementary Figure 8). In other words when summing all 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 Figure 8), and the target sustainomes for all income groups react most to changes in a reduction in child mortality (Supplementary Figure 9). Accordingly, focussing 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 as compared to 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 (e.g. child mortality reduction). Child mortality, inequalities, responsible consumption and climate change mitigation form a core of interactions which mechanisms we need to understand better to progress toward 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 Figure 10) we see that these network subsets differs widely across income. Health proves an important barrier in lower income countries as the three largest eigenvector centrality belongs 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 becomes 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 synchronise 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 which open tangible avenues for sustainome inference<sup>28</sup>.

Our analysis of the sustainome provides new insights in the best way to achieve as many SDGs as possible by 2030. First and foremost, the way SDGs interact differs by country income levels. Much of our international agenda in sustainability over the past three decades focussed 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, in which barriers among SDGs emerge. Prioritising reducing children early deaths will have compounded positive effects on other targets across all goals for all countries.

Secondly, we should contextualise targets and prioritise goals by country income levels. Prioritising 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 present the most barriers to achieving other goals. This may be because current approaches have relied on diverting resources from other socio-ecological activities to combat the effects of climate change instead of attempting to embed climate change mitigation measures in the everyday lives of everyone and 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<sup>29</sup>. Indeed, a focus on inclusivity and equity in developing infrastructure and investment strategies (SDG13) will have indirect benefits for most goals.

Given 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 meet the goals do not seem to conflict and our sustainomic approach clearly concludes that poverty alleviation will have simultaneous positive effects on all goals<sup>30</sup>. This shows that efforts to tackle poverty will pay off in the long-term. It also means that all other countries we 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 to 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 was more complex and the wicked problems<sup>31</sup> emerging from interactions more diverse (Supplementary Figure 9). Staying flexible on targets but remaining focussed 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 categorised by the targets for which they are relevant<sup>23</sup>. Several data banks of SDG indicators are now available. We chose the World Bank data after comparing it to others and found it to be more comprehensive within indicators (more countries and more years where available for indicators). It also had transparent metadata, including a description of statistical concept and methodology for each indicator and a description of limitations associated with each indicators. 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<sup>32</sup>.

We estimated the association between each indicator pair using linear mixed effect models (MEMs) with 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<sup>33</sup>). We validated this treatment of between-country heterogeneity and autocorrelation within time series for each model. We centered indicators on their



mean and scaled by their variance to obtain standardised coefficient of association assuming a gaussian distribution for the residuals; which was validated given observed residual distributions. Prior to 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 report the number of children that 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 standardised coefficients of associations ( $\beta$ s) to estimate whether indicator interactions are contrary or not to our targets.  $\beta < 0$  will indicate that the association is undesirable given our targets while  $\beta > 0$  will indicate that the association moves indicators in the desired direction.

To estimate target interactions and SDG interactions we used these standardised coefficients ( $\beta$ ), with their associated standard errors (SE) and meta-analysed these effects for each target and SDG pairs given the target and SDG membership of each indicators involved in the MEMs respectively. A pair of indicators was only considered once in these meta-analyses, which were mixed effect models of the standardised coefficients with a constant fixed effect (the interaction estimate) weighted by the SEs of the  $\beta$ s (using metafor in R<sup>34</sup>). 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 was a 71 x 71 matrix for targets and a 17 x 17 matrix for SDGs.

**Network state.** Given the way the sustainome is defined, association in the way indicator values change through time, 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 networks **A**<sup>24</sup> to determine network stability (stable when all eigenvalues of the graph Laplacian  $\leq 0$ ):  $L_{ij} = \begin{cases} L_{ij} = A_{ij} & i \neq j \\ L_{ij} = -\sum_k A_{ik} & i = j \end{cases}$ . 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 (1000 steps), **a**(t) so that:

$a_{t+1} = A \cdot a_t \wedge a_0 = [1]^n$  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 ( $a_{i,t} = a_{i,t} + 0.1$ ) before estimating  $a_{t+1}$ .

**Contributions of targets and SDGs to the sustainome.** We then estimated the partial contribution of each target and SDG in their respective signed networks to the reactivity<sup>35</sup> 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 their respective networks as well as their positive and negative strengths to understand their 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. Goals 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<sup>21</sup>. Strength (s) is a measure of the weight of associations between a goal and those goals with which it is directly associated ( $s|i = \sum_i A_{ij}$ ); the more a goal has connection, the larger its strength. As we have both positive and negative edges (associations), we estimated here positive strength and negative strength. Goals with large negative strength and small positive strengths will tend to be hindrance for other goals and vice-versa.

**Income group level estimations.** This network analytical process, including network estimation, was replicated for subset of countries categorised by their income using World Bank categories. Low income countries are currently defined by a GNI per capita of \$1025 or less. Lower-middle income



countries have currently a GNI per capita between \$1026 and \$4035. Upper-middle income countries have currently a GNI per capita between \$4036 and \$12475. High income countries have currently a GNI per capita of \$12476 or more. We determined whether sustainome findings were consistent across income groups. There are many ways by which we can determine whether these centrality measures occurred by chance or not<sup>36</sup>. Given the uncertainties surrounding the association estimates, and the way we estimated them, we wanted to first assess whether topological constraints, i.e. the assortment of those associations, could lead by chance to the observed centrality measures. We therefore, for each sustainome, shuffled randomly the existing associations (**A**), keeping the symmetry of the matrices constant ( $a_{ij} = a_{ji}$ ), 1000 times. We then estimated centrality measures for each goal for each of the 1000 randomised matrices and estimated how likely it was to obtain the observed centrality measures in these 1000 random estimates.

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

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

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**Author Contributions.** DL conceived the study. DL and FM designed the statistical models, DL carried out the analyses and DL and FM wrote the manuscript.

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**Author Information.** DL and FM have no competing interests associated with this work.