Fundamental Research 5 (2025) 360–369

Contents lists available at ScienceDirect

Fundamental Research

journal homepage: http://www.keaipublishing.com/en/journals/fundamental-research/

Article

# SDG space: Revealing the structure and complementarities among sustainable development goals in China

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A R T I C L E I N F O

*Article history:*
Received 17 April 2023
Received in revised form 16 January 2024
Accepted 17 January 2024
Available online 28 February 2024

*Keywords:*
Sustainable development goals
Network analysis
SDG space
Product space
China

A B S T R A C T

To achieve the United Nations Sustainable Development Goals (SDGs) by 2030, it is essential to understand the interlinkages between the goals. Previous research has investigated these interactions by focusing on their correlations. However, few studies have systematically prioritized them from a structural perspective through the complementarity measurements and empirically validated their policy effectiveness, such as which goals and indicators impact other SDGs most, especially in China. This study introduces a new concept known as the ‘SDG space’ by employing the “Product Space” approach in network science and economics. It measures the complementarities between SDGs and indicators through their network structures in investigating effective policy design. Using the most recent available but unpublished data for 31 Chinese provinces, the SDG space was constructed at the 17 SDG and 118 indicator levels by analyzing the probability of comparative advantage between each SDG or indicator pair co-occurring in the same place. Historical data confirm that in the ‘SDG Space’ network, a goal connected to other well-developed goals would enjoy better future growth and vice versa. The structure reveals that SDG 4 (Quality Education), 15 (Life on Land), and 1 (No Poverty) are critical goals with transformative synergies to other SDGs. Furthermore, we identified strong complementarities between land-based ecosystems and clean water and climate actions using the finer-grained indicator-level space. These findings help pave the way for China toward a sustainable future by providing science-based policy recommendations for decision-makers. They can be generally applied to other countries and regions to assist in navigating toward sustainable development.

## 1. Introduction

In pursuing sustainable development, the United Nations proposed the Sustainable Development Goals (SDGs) framework, providing a roadmap for countries to achieve 17 goals by 2030. Balancing development and the environment is a complex and challenging task. Many tools have emerged to evaluate sustainability progress, such as the SDG Index and Dashboards report by Sustainable Development Solutions Network [1] and the Road Map on Statistics for Sustainable Development Goals by the United Nations Economic Commission for Europe [2]. However, monitoring progress in silos without fully considering interdependencies among the goals may hinder sustainable development [3]. Interlinkages between SDGs, including synergies and trade-offs, are critical to understanding, evaluating, and monitoring sustainable development progress and making influential and coherent policy decisions. Scholars have applied diverse approaches to untangle the complex SDG system and identify influential interactions [4], such as a 7-point scale qualitative analysis by the International Council for Science [5] and studies pointing to the importance of specific SDGs, including Quality Education and Gender Equality [6]. In addition, a growing strand of research has emerged from analyzing potential interactions between SDGs, such as the water-energy-food nexus [7]. Understanding the interlinkages and prioritizing the influential SDGs is essential for achieving a sustainable future [8,9].

However, the quantitative way to unravel the interlinkages among 17 SDGs is relatively limited with a narrow perspective, and few tools can inform policymakers on prioritizing the development of goals [10]. Existing literature quantifies the trade-offs and synergies of SDGs using the pair-wise statistical correlations [4,6,11–13], such as Pearson coefficient, Spearman coefficient, autoregressive coefficient and spatial

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https://doi.org/10.1016/j.fmre.2024.01.005

**Table 1**
**Concepts clarification between 'product space' and 'SDG space'.**

| | Product Space | SDG Space |
|---|---|---|
| Network | the relatedness or proximity between products traded in the regional market | the complementarities or proximity between SDGs at a given regional level |
| Nodes | Products | SDGs |
| Edges | the similarity of productive ability required to produce two products within a given region | the complementarities between two SDGs, reflecting the similarity of external resources necessary to achieve them |

autocorrelation coefficient, which are part of, related to, or derived from regressions. The intensity and direction of these interconnections are subject to fluctuations because they only consider the relationship between goal/indicator pairs, which are highly dependent on data collection, selection, and quality temporally and spatially, leading to an unstable structure among goals [4]. Given this complexity, a stable SDG interaction network is needed to predict future sustainable development progress and inform policy-making decisions.

Here, we extend the concept of 'product space' in network science and economics to the 'SDG space' to measure the interactions between SDGs. The 'product space', derived by the countries' revealed comparative advantages (RCA) of the products, can measure the pattern of economic specialization and its impact on a country's future economic performance. The definition of 'proximity' in product space quantifies the similarity of productive ability (labor intensity, capital, land and resource endowment, technological sophistication, etc.) required to produce two products within a given region [14]. These productive factors can affect the structure of the product space [15], with some areas being more densely populated with comparative advantages for specific products. Products close in this structure, or 'related', tend to require similar capabilities for production and are, therefore, more likely to be produced efficiently simultaneously [16].

The concept of 'proximity' in the 'product space' can be extended to the 'SDG space', which measures the structure and closeness of interactions between Sustainable Development Goals (SDGs). It measures the direct complementarities between each pair of SDGs and also considers the overall performance of the network structure. The concepts between 'product space' and 'SDG space' are clarified in Table 1. The SDG space assumes that goals within a certain distance (i.e., with a sufficiently strong network link) are more likely to exhibit synergies, where the improvement of one goal can enhance the development of another, compared to goals that are farther apart in the space. The proximity between two SDGs is shaped by the similarity in the requirements for realizing them, such as biophysical conditions and institutions across environmental, social, and economic dimensions. The high complementarities between SDGs, named as their synergies, imply the similar requirements of biophysical conditions and socio-economic status for achievements [10].

Moreover, the structure of SDG space has significant policy implications: a goal, target, or indicator that is densely connected is at a central place and can contribute to the development of many other goals, while one that is less connected may experience stagnant progress due to a lack of synergies. By constructing the SDG space based on the product space methodology, this paper investigates the synergies and complementarities between different SDGs and the implications for sustainable development.

China is rapidly urbanizing and is committed to achieving sustainable development goals by 2030. Due to our expertise, data availability, and contextual familiarity, this paper uses China as a pilot site. We focus on SDG synergies represented by the links in the SDG space. Emerging studies suggest that a sustainable future can be efficiently achieved by reinforcing mutually beneficial interactions (synergies) rather than mitigating negative interactions (trade-offs) [17]. By investigating the relationship between 17 SDGs and 118 indicators in 2015 at a provincial level, we hope to answer the following research questions: 1) What is the structure of China's SDG space at the provincial level in 2015? 2) Is the method robust and stable compared to traditional methods and predictive of future sustainable development? 3) What specific policy implications can be drawn from the SDG space to guide China's sustainable future?

We propose an integrated network modeling approach that captures the complex complementarities between societal, environmental, and economic progress to answer the above questions [18]. Using this approach, we construct the 'SDG space' based on the 17 SDGs and 118 indicators. We then verify its robustness by comparing it with the correlation coefficient networks and test its predictive power using historical data and statistical learning methods. Moreover, we use network science methods to identify the core and periphery, communities, and betweenness centrality of the SDG space for policy implications. We prioritize the prominent synergies using the SDG space in 2015 to promote sustainable development progress in China. The proposed methodology can also be applied elsewhere to examine the structure of sustainable development and establish priorities.

## 2. Materials and methods

### 2.1. SDG space construction

The revealed comparative advantage (RCA) of region $j$ in achieving goal/indicator $s$ is defined as:

$$RCA(j,s) = \frac{g(j,s)/\sum_{s'} g(j,s')}{\sum_{j'} g(j',s)/\sum_{j',s'} g(j',s')} \tag{1}$$

where g(j,s) is the level of goal/indicator $s$ in region $j$. Thus, RCA(j,s) measures how good region $j$ is at achieving $s$ compared to achieving all other goals/indicators relative to the average level of all regions. RCA(j,s)>1 implies that region $j$ is relatively good at $s$ compared to its other capabilities; that is, $j$ has a revealed comparative advantage in $s$.

The network link between $s$ and $s'$, which measures the complementarities between the capacities to achieve the two goals/indicators, is then.

$$\begin{aligned}\theta(s,s') &\equiv \min\left\{P(RCA(j,s)>1|RCA(j,s')\right.\\ &\qquad \left.>1, P(RCA(j,s')>1|RCA(j,s)>1)\right\}\\ &= \frac{\sum_j I(RCA(j,s)>1|RCA(j,s')>1)}{\max\{\sum_j I(RCA(j,s)>1), \sum_j I(RCA(j,s')>1)\}}\end{aligned} \tag{2}$$

where I (·) is the indicator function, which returns to 1 if the input statement is true and 0 otherwise.

In the above equation, *θ(s,s')* is the (minimum) conditional probability that a region is relatively good at achieving one of the two goals/indicators, given it is relatively good at achieving another. It measures the co-occurrence of comparative advantages in *s* and *s'*. Therefore, a larger *θ(s,s')* implies a greater complementarity between the skills to achieve the two goals. For example, job positions simultaneously emphasize social and linguistic skills, and students are good at math and physics, indicating complementarities between the skill pairs.

In this methodology, we can identify the pair-wise SDGs that can synergize. The synergies between pairs of goals capture how a pair supports each other, either by enhancing the productivity of a province that can achieve two goals easily or by the ease of simultaneously achieving two goals together. We call the resulting network to measure the SDG complementarity as 'SDG space'. In the 17-17 matrix, each off-diagonal element represents the proximity between a pair of SDGs. For more intuitive interpretation, all SDG space visualizations are graphed through Gephi.

### 2.2. Network analysis

Since SDG space maps SDG complementarity (synergies) as a network, we can use techniques from network science to identify the structure of the SDG space, such as their communities and the core/periphery, as well as to detect influential sustainable development goals or indicators.

#### 2.2.1. Clustering

Community detection can be used to understand the dynamics of certain groups that are susceptible or resilient to the structure of sustainable development goals (SDG space). Moreover, it can reflect the community evolution prediction, that the involvement can predict the upcoming changes in a network structure. We use the Clauset-Newman-Moore greedy modularity maximization method to find the community partition with the largest modularity for both goal-level and indicator-level community partition. This unsupervised method begins with each node in its community and repeatedly joins and pairs the communities that lead to the largest modularity until no further increase in modularity is a maximum. This method is achieved through the Python networkx package's community detection algorithm. Since the clusters are created from an unsupervised methodology, the demonstration of communities from the resulting SDG network can be related to real-world SDG dynamics, so decision-makers can leverage their complementarity between existing goals by exploring them in clusters.

#### 2.2.2. Centrality and betweenness

We discuss the core and periphery of goals in the clusters by measuring goals' centrality-betweenness. We compute the shortest path between the centrality of nodes, which measures the sum of the fraction of all pairs' shortest paths that go through a random node. The detailed algorithm is from Ulrik Brandes [27]. We apply the method through the Python network x package, the betweenness_centrality function.

#### 2.2.3. Network stability

Previous studies mostly used correlation coefficients to construct the network between different SDGs [4,11–13,28]. This way, synergies are detected as positive correlation coefficient values ranging from 0 to 1. However, correlation coefficient networks are criticized for their instability. In comparison, this study employs the co-existence of RCAs to construct the proximity values between SDGs and defines synergies as SDGs with proximity values greater than a designated cut-off value. The stability of the network structure for SDG interactions is critical to serve as an effective guide for policy-making toward sustainable development.

Since all networks in our study are 17-17 symmetric matrices, we can use mathematics functions for matrices to compare the stability of these networks. A matrix norm, representing the matrix spaces and their linear operators, is a way to measure a matrix's size, distance, and length. In a word, the value of matrix norms can be used to compare the differences between matrices. Moreover, to compare the values between matrices, the difference in norm values needs to be measured under a standard basis by scaling the size.

In our case, to measure the norm difference between correlation coefficient networks in 2010 and 2015, we first calculate the distance (norm value) between these two metrics. We then normalize the difference by the norm size of the 2015 network. The equation follows:

$$\Delta Norm = Norm(A_{15} - A_{10}) \times 100 / Norm(A_{15}) \tag{3}$$

where $A$ represents the correlation coefficient networks. Similarly, all networks can be applied to the above method for comparison. The smaller the value is, the smaller the differences between two networks and vice versa. We conducted these analyses through the 'norm' function in Matlab.

### 2.3. Test of the SDG space theory

We test the effectiveness of the SDG space in policy recommendations using historical data. The aim is to determine whether measurements of the 2005 SDG space structure could predict sustainable development over the 2006–2015 period.

**Hypothesis:** Goals with higher levels of synergies, or complementarities, tend to exhibit greater progress in the following period, while those with lower synergies tend to have less progress.

**Step 1: Measurement of the growth potential through 2005 SDG space and real-world growth**

We measure each goal's growth potential (*GP*) in 2005 of every province by computing the weighted average of scores of proximate goals with network links in the SDG space serving as weights. Therefore, the goals with high growth potentials enjoy strong synergies, and the goals with low growth potentials lack complementary capabilities in future development. The growth potential of goal $s$ in 2005 is (here, we omit the province subscript):

$$GP_{s,05} = \sum\nolimits_{s' \neq s} Y_{(s',05)} W_{(s's)} \tag{4}$$

where $Y$ is the SDG level of a different goal in 2005, and $W$ represents the strength of the network link between two goals.

Furthermore, real-world growth is measured as the subtraction of SDG scores between 2015 and 2005. The values can be positive and negative.

**Step 2: Statistical regressions and machine learning**

We aim to determine if the 2005 growth potential of a goal can be used to predict its growth between 2005 and 2015 in reality. To do this, we employed both traditional statistical regression methods and machine-learning techniques to analyze the relationship.

For ease of analysis, the goals of each province were treated as individual samples in the linear regression. The regression was run twice for samples with relatively high and low growth potentials (cut-off values of 5% and −5%).

The equation is as follows:

$$\Delta Y_{05-15} = \beta_0 + \beta_1 Y_{05} + \beta_2 GP_{05} \tag{5}$$

where $\Delta Y_{05-15}$ represents real-world growth potential and $Y_{05}$ is the SDG score in 2005.

Moreover, to understand the complex and nonlinear relationship, we use 'fitrensemble' package in Matlab to create a gradient-boosting machine learning model, automatically optimizing hyperparameters with cross-validation. This ensemble regression model was then visualized and interpreted through the partial dependence plot (PDP).

**Step 3: Visualization and interpretation**

To further understand the relationship, three visualizations were created. The first visualization involved plotting graphs of the top 20 province goals with either the highest or lowest growth potentials and comparing their growth from 2005 to 2015. Additionally, scatterplots were created to show the relationship between SDG growth potential and actual SDG growth for both high and low-growth-potential samples, with regression lines added to provide a clearer picture.

Last, the PDP helps us understand the nonlinear relationship between the initial SDG level, the SDG growth potential in 2005, and the subsequent SDG growth between 2005 and 2015. This plot gives us an insight into how these two predictors impact the outcome and allows us to identify any potential non-linearities in the relationship. By visualizing the relationship in this way, we can better understand the factors that contribute to SDG growth and the impact that the growth potential in 2005 has on the subsequent growth of the goals.

**Data Sources:** The provincial-level SDG Index scores draw from a comprehensive study by Xu et al. (2020) [29], which meticulously compiled

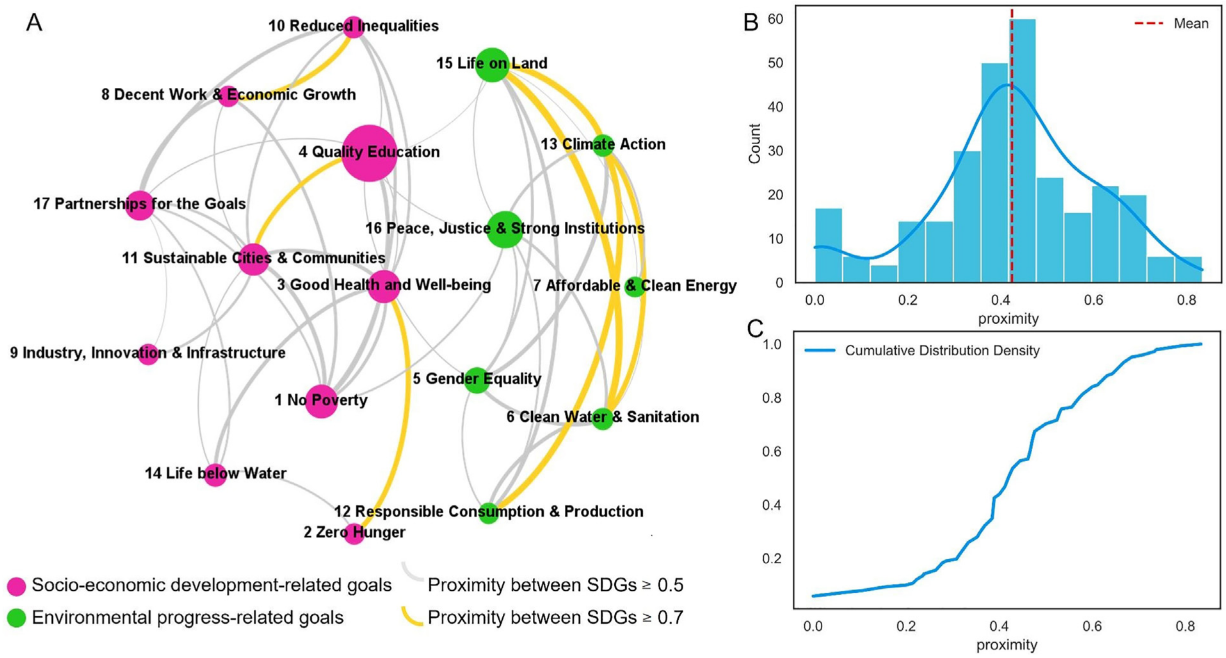


**Fig. 1.** (A) The 'SDG space' with proximity larger than 0.5 in 2015. Community detection reveals two communities of complementary SDGs: 1). Primarily human development and socioeconomic progress-related SDGs (Cluster 1: red dots) and 2) Primarily environmental progress-related SDGs (Cluster 2: green dots). The size of the node denotes their betweenness centrality. The thickness of the edges indicates the value of proximity, representing the strength of the complementarity between two goals, which measures the ability to achieve one SDG with its ability to achieve the other SDG. The blue-colored edges are proximity ≥ 0.7. The network is graphed in Gephi. (B) The proximity distribution. (C) The cumulative distribution of proximity.

various SDG indicators of China's 17 SDGs. This extensive dataset encompasses a total of 119 indicators spanning 31 Chinese provinces from 2000 to 2015. Rigorous normalization procedures were employed to facilitate meaningful comparisons across the various SDGs. This normalization process effectively transformed the data into a uniform scale, ranging from 0 to 100. Notably, indicators falling within the predefined upper and lower bounds were systematically distributed along this spectrum, with 0 signifying the lowest performance and 100 representing the pinnacle of achievement. It is worth highlighting that Indicator 1–5, which pertains to the coverage rate of measures aimed at disaster prevention, exhibited a consistent value of 100 across all regions. Consequently, this indicator was intentionally omitted when calculating the 'SDG space'. As such, the final analysis considered 118 out of the 119 SDG indicators, encompassing the 17 SDGs and spanning all 31 provinces of China.

## 3. Results

### *3.1. SDG space: a stable structure in empirically mapping goal-to-goal synergies in China*

Proximity, measured by the co-occurrence of their comparative advantages, is quantitatively understood as the complementarity between two goals. Fig. S1 provides a hierarchically clustered matrix showing this revealed comparative advantage (RCA) proximity between each pair-wise SDG. An SDG space with a smooth and homogeneous color implies constant proximity values, while a ladder-like color suggests a matrix with heterogeneous values. From Fig. S1, their clustered matrix is modular because some goals are clustered with their matrix values close to 1, while others have values close to 0.

As shown in Fig. 1B, the distribution of the whole SDG space's proximity values mostly fits into a normal distribution, that 75% of the values lie in proximity between 0.2–0.6 based on their cumulative distribution (Fig. 1C). Their mean is 0.42, and the standard deviation is 0.18. Thus, we set the initial cutting point to define SDG synergies as links with proximity larger than their distribution mean (0.4). Moreover, to validate our SDG synergy definition and robustness of network clusters, we compare SDG space structures with different proximity cut-off points (Fig. S2): A) 0.4, B) 0.5, and C) 0.6. We found 83 edges (interactions) and 17 nodes (goals) for SDG space with proximity ≥ 0.4. In comparison, 47 edges and 17 nodes, and 27 edges and 16 nodes are included in the SDG spaces with proximity larger than 0.5 and 0.6. In particular, seven edges with proximity ≥ 0.7 are highlighted in the graphs. This set of links and nodes can be used to visualize the SDG space representing SDG synergies and their closeness structure.

Fig. S2 shows the SDG space with different cutting-off points, and most nodes in these graphs form two clusters based on an unsupervised clustering method, the Clauset-Newman-Moore greedy modularity maximization from the networkx package [19]. Nodes in the same cluster mean these goals require similar settings of external resources such as human, social, and physical capital investment, institutional governance, and research support for sustainability improvement, and higher potential for synergies thus may happen among them. The two clusters in Fig. 1A can be summarized as 1) primarily human development and socioeconomic progress-related SDGs (Cluster 1: red dots) and 2) primarily environmental progress-related SDGs (Cluster 2: green dots). Both clusters are stable among the three graphs in Fig. S2, yet Cluster 1 has a slight split in Figure S2-C. The left side of Cluster 1 is split into two sub-clusters. Sub-cluster 1-1 is in a transition position to environmental-related SDGs, such as SDG 2 (Zero Hunger), 3 (Good Health and Well-being), and 14 (Life below Water). In comparison, Sub-cluster 1-2 consists of SDG 1 (No Poverty), 4 (Quality Education), 8 (Decent Work and Economic Growth), 9 (Industry, Innovation, and Infrastructure), 10 (Reduced Inequalities), 11(Sustainable Cities) and 17 (Partnerships for the Goals), which lies more in human development-related SDGs.

### *3.2. Robustness of the SDG space: more stable and consistent than correlation networks*

Aside from the consistency of the classification, the three network representations in Fig. S2 also have a stable core-periphery structure, especially in Fig. S2A and Fig. S2B. The core is formed by goals related

**Table 2**
**Network similarity comparison between 2005 vs.2010 and 2005 vs. 2015.**

| Norm difference | 2010 vs. 2015 | 2005 vs. 2015 |
|---|---|---|
| Correlation network (in percentage) | 31.25 | 71.14 |
| SDG space network (in percentage) | 17.18 | 18.01 |

[a] the smaller the difference percentage is, the more similar (stable) the two networks are.

**Table 3**
**Regression estimates of SDGs growth during 2005–2015.**

| Estimated coefficients | SDGs with network growth potentials lower than −5 | SDGs with network growth potentials higher than 5 |
|---|---|---|
| (Intercept) | 28.284 | 7.8629 |
| $GP_{05}$ | 0.31482 ** | 0.44835** |
| $Y_{05}$ | −0.26813 *** | −0.066571 |

[a] $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

to environmental and human development progress separately, whereas the periphery is formed by goals in the intersection of these two clusters. In particular, SDG 16 (Peace, Justice, and Strong Institutions) and SDG 4 (Quality Education) are robust in the graphs at the intersection between the two cores, serving as a bridge to connect two clusters, especially in Fig. S1-B. In this way, it is expected that setting up effective, resilient, and accountable institutions, assuring equal access to essential social services, and providing equitable quality education opportunities can help build synergies of both clusters and foster sustainability progress on a broader scale and even all other SDGs. Moreover, the highlighted edges with proximity ≥ 0.7 happen in the core areas of both clusters, indicating their solid synergies. For instance, deep interlinkages are found between SDG 6 (Clean Water and Sanitation) and 13 (Climate Action); SDG 6 and 15 (Life on Land); SDG 12 (Responsible Consumption and Production) and 13; and SDG 13 and 15 in the right-side cluster. For the left side cluster, strong connections are between SDG 2 (Zero Hunger) and 3 (Good Health and Well-being), 4 (Quality Education) and 11 (Sustainable Cities), 10 (Reduced Inequalities), and 8 (Decent Work and Economic Growth).

The clustering results from an unsupervised clustering method and their consistent core-periphery structures validate the robustness of the SDG space we constructed. Moreover, the unsupervised results remain consistent with the construction of the SDG framework from the United Nations, which decomposes sustainability from three dimensions: society, environment, and economy [20]. Given the stability of the structure with slight variation when a different proximity threshold is chosen, we chose threshold proximity ≥ 0.5 in the following analysis of its clear visualization in clusters and core-periphery structure. Fig. 1A provided the SDG space in 2015.

Moreover, we construct the correlation structure and the SDG space using data from 2005, 2010, and 2015 to compare their network stability. Their structure visualizations are shown in Figure S3. Moreover, we calculate the stability measurement of the networks in matrix norm and compare the norm differences with their structures in 2015. As shown in Table 2, SDG space stayed relatively stable; the 2005 network and 2010 network are 17.18% and 18.01% different from the 2015 network, while the correlation structure confronted significant changes in years; the 2005 network is 71.14% different from the 2015 network. The smaller the difference percentage is, the more similar the two networks are. Therefore, the SDG space we construct is much more stable than the correlation coefficient structure. Empirically, the stable structure of SDG networks across the years can help answer real-world policy questions, such as which goals should be developed in the first phase. In contrast, others can be performed later to facilitate sustainable development. In contrast, an unstable structure generated from the correlation coefficient network can only be silent on these decision-making processes.

Moreover, we use a simple example in the supplementary spreadsheet to differentiate the real-world policy implication between product space and correlation coefficient networks and clarify the innovation of our SDG space in measuring the complementaries between SDGs. This example uses three students' physics, math, and English academic scores for calculation. The results on the correlation coefficient show high similarities in their three subjects' performance because a good student has overall good academic performance, compared to a badly-academic-performed student. In comparison, the proximity results from product space indicate a high complementarity between math and physics (proximity = 1) and no complementarities between math/physics and English (proximity = 0), indicating a student who has skills to learn math (i.e., logic, calculation, etc.), can use these skills to enhance his physics learning. However, English learning requires very different skills than math/physics, such as memory capability, vocabulary, etc. These skills have no complementarities with skills to learn math or physics.

### 3.3. Testing the SDG complementarity network theory

To further validate the effectiveness of SDG space in its policy recommendations, we use historical data from 2005 to test if the 2005 SDG space holds any predictive power over the SDG development trajectories from 2005 to 2015. More specifically, we calculate the SDG growth potentials of different goals in different regions in 2005 as the weighted averages of proximate goals and then compare these network-derived growth potentials in 2005 with the later changes in the goals.

Fig. 2A shows the 20 SDGs with the highest growth potential and 20 SDGs with the lowest network growth potential in 2005 among 30 regions (blue bins) and their actual SDG growth from 2005 to 2015 (black lines). It is found that the top 20 SDGs with positive changes in SDG scores also have relatively higher SDG growth potentials from 2005 to 2015. This observation also fits SDG scores with negative changes. The consistency of our predictions generated by the SDG space (lines) with the actual SDG values (bins) indicates that the SDG complementarity network theory effectively predicts the sustainability development progress over time intuitively.

Moreover, statistical regression results from Fig. 2B and Table 3 both indicate a significant positive relationship between the growth potential in 2005 ($GP_{05}$) and SDG growth from 2005 to 2015 ($\Delta Y_{05-15}$), in controlling the SDG level in 2005. The positive regression lines and scatter points in Fig. 2B show an increasing relationship trend in both high and low growth potential points, with growth potential specifically lower than −5 (left side) and higher than 5 (right side). The positive coefficients in the regression table confirmed the conclusion.

Specifically, the estimated coefficients of SDGs with negative and positive network growth potentials in 2005 are 0.31 and 0.44, respectively, which can be interpreted that for a specific SDG in a province, when its nearby connected SDGs in the SDG space increase by a unit, then the SDG would increase by 0.31/0.44 units in the coming ten years. The larger t-stat and small p-value indicate that the regression model is statistically significant. We can confidently interpret that if a specific SDG were synergistic with other SDGs of high growth potentials in 2005, it would likely achieve better SDG performance in the future.

We start by choosing the cutting points for statistical regressions above as −5 and 5 to identify SDGs with the lowest and the highest growth potential in 2005. We have also tried multiple cutting-off points, such as −5/5, −10/10, and −15/15, and they share similar conclusions. To further depict a comprehensive picture of the relationship, we introduce a machine learning technique to evaluate and visualize the non-linear relationship between SDG growth from 2005 to 2015 and the interactions of the SDG growth potential in 2005 in controlling the SDG level in 2005.

We can see from Fig. 2C, the two-way partial dependence plot (PDP) that SDG growth from 2005 to 2015 positively changes with the SDG growth potential in 2005, keeping the SDG level in 2005 constant. The conclusion further validates the above discussions that an SDG with a

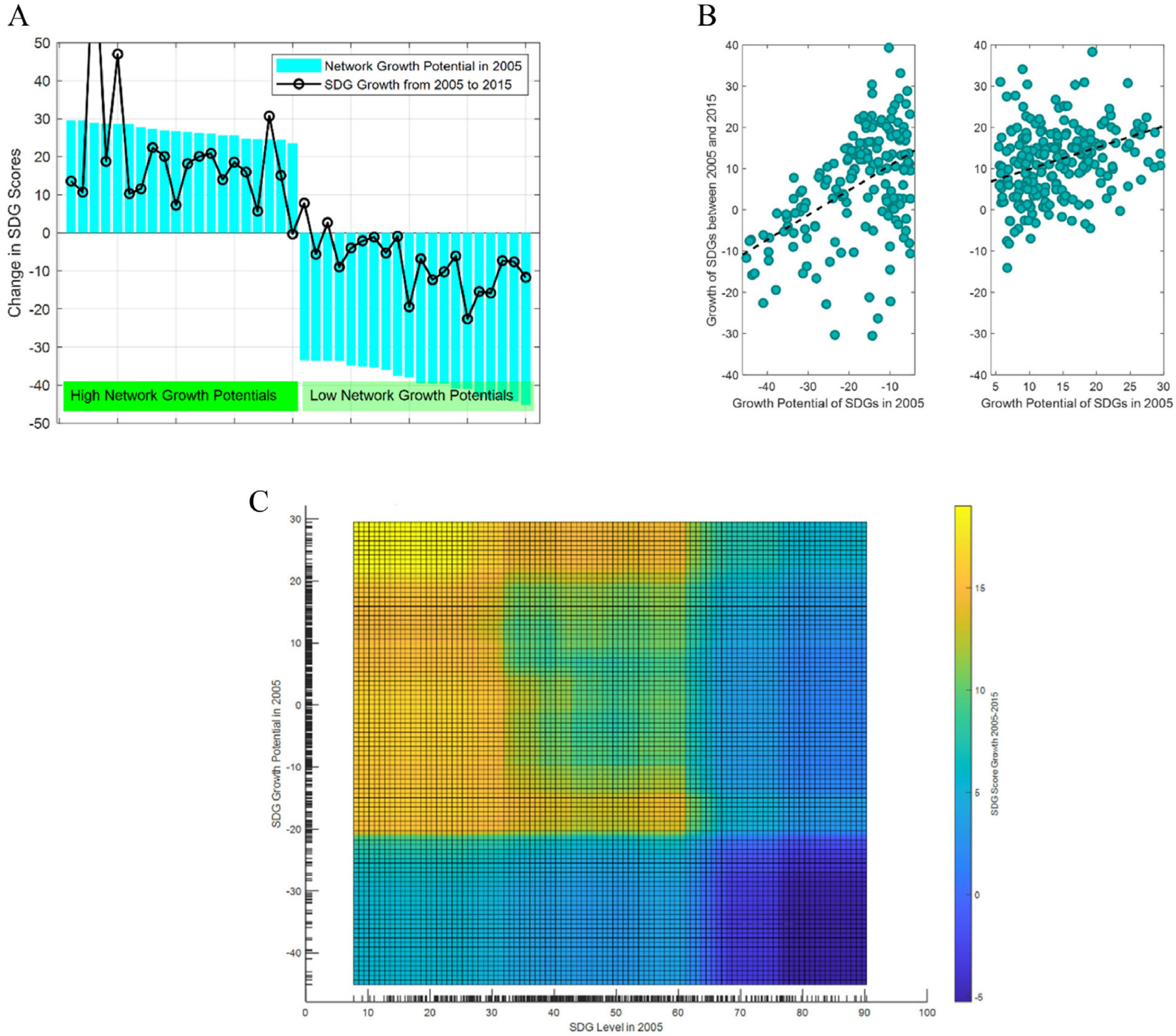


**Fig. 2. Test of the theory from different perspectives**. (A) Top and bottom 20 SDGs of network growth potential in 2005 and their real-world SDG growth from 2005 to 2015. (B) Scatter plots and their regression results between the growth potential of SDGs in 2005 and the growth of SDGs from 2005 to 2015 for high and low growth potentials. (C) Two-dimensional Partial Dependence Plot. The dependent variable is the change in the SDG score in 2005–2015; the independent variables are the SDG level and SDG growth potential in 2005. The model to predict SDG changes is a gradient-boosting machine learning model, trained with data on all SDGs of all provinces. The hyperparameters are optimized using the 'fitrensemble' function in Matlab.

higher SDG growth potential in 2005 would be more likely to have a higher SDG growth from 2005 onwards to 2015.

### *3.4. Indicator-level space: similar to goal-level space but with more complexities*

We apply the same method to construct the indicator-to-indicator SDG space (Fig. 3A) and use proximity larger than 0.5 as its cutting point to keep consistent with goal-to-goal SDG space. The clustering method automatically identifies three clusters, as shown in Fig. 3A. Cluster 1, the largest community, is colored in orange, including 46 nodes. This community has all indicators of SDG 14 (Life Below Water). Moreover, SDG 3 (Good Health and Well-being), SDG 17 (Partnerships for the Goals), SDG 6 (Clean Water and Sanitation), SDG 4 (Quality Education), and SDG 15 (Life on Land) have the dominant share that over 40% of indicators are distributed in Cluster 1. These goals belong to the top 6 goals with the highest weighted degrees and betweenness centrality in Fig. 3B. Cluster 2, the second largest cluster, has 43 nodes colored in red. SDG 9 (Industry, Innovation, and Infrastructure) has the most targets (10), meaning 71.43% of its indicators. SDG 1 (No Poverty) has this community's highest indicator percentage (80%). Moreover, Goals 2 (No Hunger), SDG 8 (Decent Work and Economic Growth), and SDG 11 (Sustainable Cities) are noticeable, with a dominant percentage account (larger than 50%) in this cluster. These goals belong to the socioeconomic development-related cluster at goal-level SDG space (red dots in Fig. 1A). Cluster 3, the smallest cluster, has 28 nodes colored in green. SDG 5 (Gender Equality) has four targets in this cluster. Besides, Goals 7, 10, 12, 13, 15, and 16 have over 40% of indicators in the cluster. Except for Goal 10 (Reduce Inequalities), these goals belong to the environment-related cluster at goal-level SDG space (green dots in Fig. 1A). Based on the clustering results, these indicator-level communities are consistent with goal-level communities, mainly separated into environmental-related and socio-economic-related clusters. The top goals in these two clusters, shown in Figs. 3C, D, are in the same cluster in goal-level space except for SDG 10 (Reduced Inequality). Moreover, indicator-level space identifies a third cluster, which hosts the indicators related to goals with a high weighted degree or betweenness centrality (Fig. 3B). Therefore, the indicator-level clusters validate the effectiveness of clustering in goal-level SDG space.

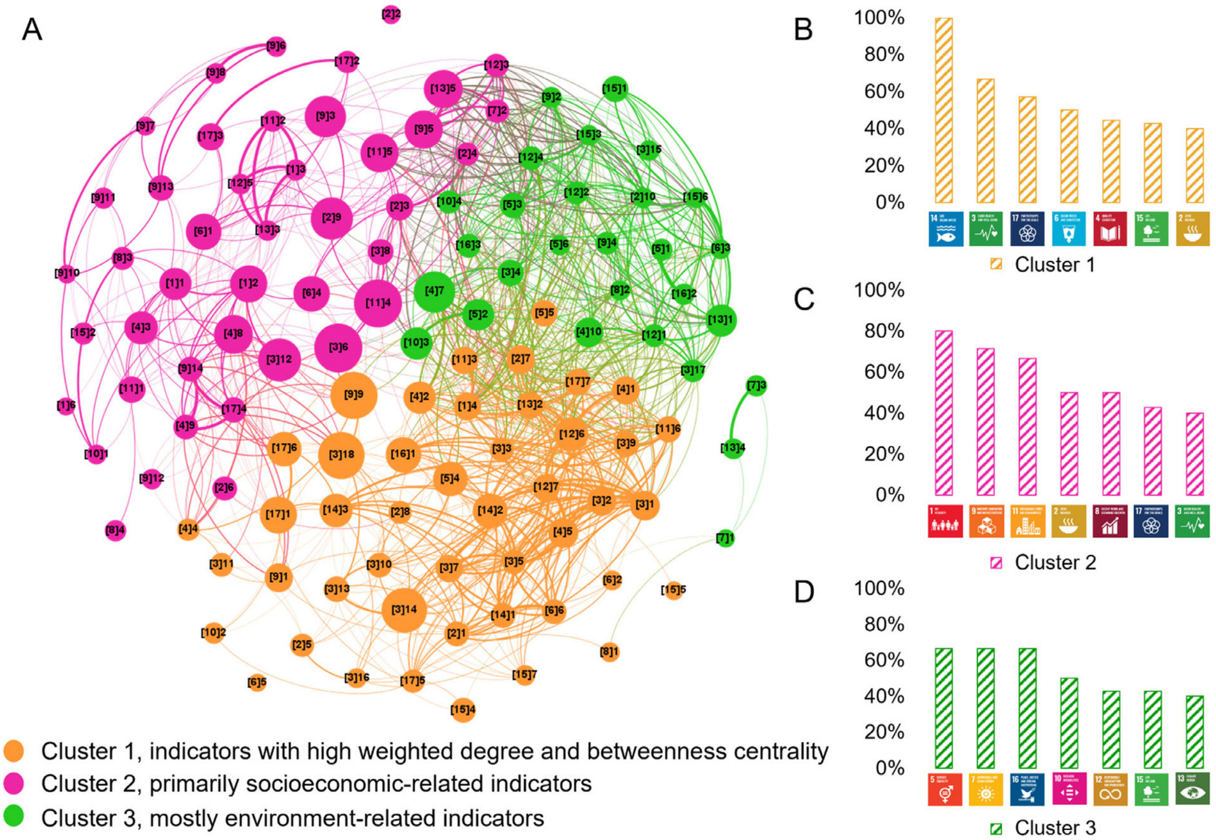


**Fig. 3.** (A) Indicator-level SDG space (The cutoff point for constructing the SDG space: proximity ≥ 0.5, Visualisation filter proximity ≥ 0.6). Each node is an SDG indicator, and the number in the square bracket denotes the goal to which it belongs. Their betweenness centrality values size the node. (B) Distribution of SDG indicators in different clusters.

However, indicator-level space provides more sophisticated details. For example, the goal-level space categorizes SDG 14 (life below water) into the socio-economic cluster, which is confusing because life below water is generally included as an environmental goal. However, when we dig into how indicators in SDG 14 are distributed in the indicator-level space's clusters, these indicators belong to cluster 1: the cluster with high weighted degrees and betweenness and centrality values, which is more reasonable than the goal-level space. Moreover, we find that indicators of different goals have strong proximities with each other. For example, indicators [9]14 (Proportion of the population using the internet (%) and [4]9 (Proportion of youth and adults with internet (%)); [11]3 (Direct economic loss concerning global GDP, damage to critical infrastructure and number of disruptions to basic services, attributed to disasters (% GDP)) and [1]4 (Direct economic loss attributed to disasters with the global gross domestic product (GDP); [7]3 (Rate of primary energy intensity change) (%) and [13]4 (Rate of primary energy intensity change); etc. These indicators belong to different goals but are clustered in indicator-level space because they measure similar objects from different perspectives. Their high proximities in our SDG space also validate the effectiveness of our proposed SDG complementarity network theory.

## 4. Discussion

### *4.1. The goal-to-goal SDG space and its policy implications*

When we investigate the SDG space with a distance threshold set as 0.5 (Fig. 1A), we found SDG 11 (Sustainable Cities and Communities), SDG 4 (Quality Education), SDG 15 (Life on Land), and SDG 1 (No Poverty) are the most connected. On the contrary, SDGs 7 (Affordable and Clean Energy), 2 (Zero Hunger), and 9 (Industry, Innovation, and Infrastructure) are the least connected. Regarding their betweenness, SDGs 4, 16, 17, 3, 15, and 1 are nodes with noticeable values. Combining the results of betweenness centrality and the weighted degree (Fig. 4), SDGs 4 (Quality Education), 15 (Life on Land), and 1 (No Poverty) are pivotal in achieving sustainable development in the future of China.

SDG 4, quality education, is connected to five nodes in its cluster and is also connected with three nodes in the other cluster. In this way, SDG 4 is emphasized as a significant node that education performs as a catalyst in achieving many other SDGs in China. The most emphasized connections are between education and cities (SDG 11) and with no poverty (SDG 1). China has a long tradition of prioritizing education development, such as increasing education investment and expanding educational opportunities for girls. It can hopefully reduce poverty by improving livelihood income, reducing inter-generational transmission of poverty, eliminating gender inequality, etc. [21]. Investment in education can also increase people's knowledge of environmental protection, which helps the formation of sustainable societies. In one way, urbanization positively influences education coverage, literacy, etc. [22]. Alternatively, urbanization may bring unexpected environmental problems, such as natural disaster risk [23]. It is pointed out that individuals' awareness and knowledge of disaster risk reduction may help to build sustainable cities [24]. Moreover, decision-makers' knowledge of disaster-related infrastructure construction and management is conducive to increasing the resilience of urban regions. In such a way, these practices related to quality education, sustainable cities, and poverty alleviation generate synergies with other goals and assist in achieving China's sustainable development agenda.

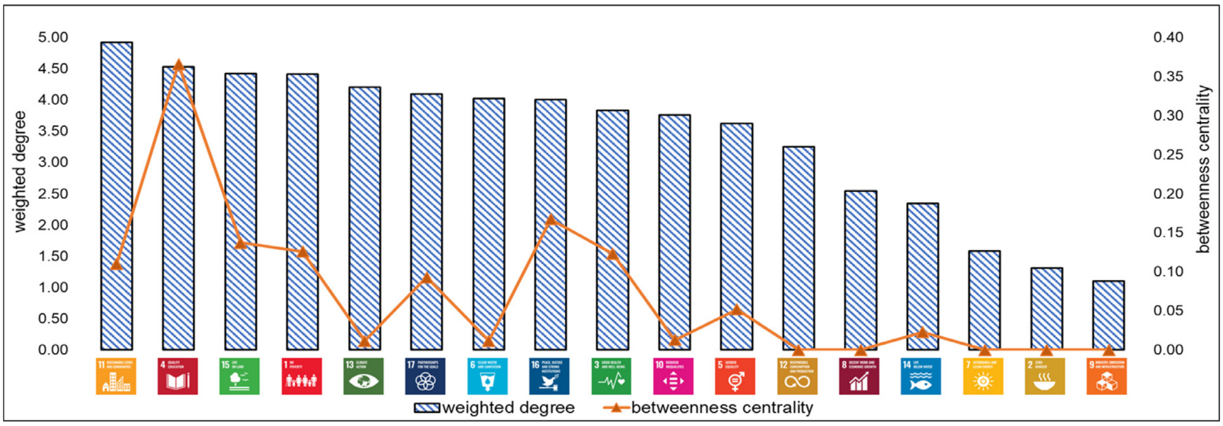


**Fig. 4. The node statistics of the 'SDG space' with proximity larger than 0.5 in 2015**. Two node attributes are displayed. Weight degrees are blue columns in descending order, while betweenness centrality values are orange for visualization.

**Table 4**
**Influential SDG indicators**.

| Label | Definition | Weighted degree | Betweenness centrality |
|---|---|---|---|
| [3]6 | Tuberculosis incidence per 100,000 population | 35.04 | 0.02 |
| [11]4 | Ratio of industrial solid waste generated to the waste regularly collected and utilized | 39.55 | 0.02 |
| [9]9 | Proportion of population covered by a mobile network | 38.87 | 0.02 |
| [3]18 | Health care rate for children under 7 years old | 34.15 | 0.02 |
| [3]14 | Post-natal care coverage (visit rate) | 26.79 | 0.02 |

SDG 15, life on land, is another critical feature detected in the SDG space. Lives and their healthy terrestrial ecosystems (i.e., forest, land) provide and ensure raw materials and ecosystem services to people and society. SDG 15 is connected to six nodes in its cluster and one node in the other cluster. The two most vital connections are SDG 15–6 (0.83) and SDG 15–13 (0.79) (Fig 1C). The strong synergies between land-based ecosystems with clean water and climate action are notable. In one way, the irrational usage of land resources may destroy the functions of terrestrial ecosystems, such as impairing their potential to digest and clean wastewater. It disturbs the run-offs and evapotranspiration balances and may further impact the quality and availability of water resources through the hydrological cycle changes [25].

On the other hand, maintaining a healthy ecosystem, such as forests and wetlands, can reserve carbon sink potential under the ground without escape and support climate change mitigation and adaptation efforts. Thus, focusing on forest protection, soil conservation, and biodiversity conservation can facilitate China's pathway toward a sustainable future. Our results share similarities with existing quantitative analysis using correlation coefficients in constructing networks. For example, SDG 16 (Peace, Justice, and Strong Institutions) and 17 (Partnerships for the Goals) are crucial to turning the potential from synergies into sustainable development reality [5], which have high betweenness centrality values. Effective institutions, governance systems, partnerships, and related resources can favor a practical, integrated, coherent approach to implementing a sustainable society. In this way, we call for attention to transform or establish effective institutions, which is critical to sustainable development, along with an advocate for people's awareness of sustainable development and collaboration. In addition, no poverty (SDG 1) and quality education (SDG 4) show high synergistic relationships with many other goals. Thus, poverty elimination and education opportunities should be emphasized during China's urbanization course to achieve a sustainable future and be prioritized worldwide.

We also observe some unique observations in China that have yet to be widely discussed in previous research concerning global SDG interactions. For example, the SDG space highlights sustainable cities (SDG 11) and life on land (SDG 15), with weighted solid degrees and high betweenness centrality values. The difference can be due to the specific context of China, given its large population and cities with an unprecedented population scale and its diverse geographic conditions with high biodiversity on land. We further break down the network structure into indicator levels to know more details and decipher the potential casualties.

### 4.2. The indicator-to-indicator SDG space and the policy implications

Indicator-to-indicator space provides more details on policy implications than goal-to-goal level analysis. For example, more specific information can be told concerning the strong connection between SDG 15 and 6, the most vital synergistic relationship identified in the SDG goal space. Indicator [15]6 (Proportion of total water resources used) shares high RCA proximity with [6]3 (Level of water stress: freshwater withdrawal as a proportion of available freshwater resources). Close connections can also be recognized between other pairs of indicators, such as [15]1 (Forest area as a proportion of total land area) and [15]3 (Proportion of land that is degraded over the total land area) with [6]3. Similarly, strong synergies between SDGs 15 and 13 can be explained by several pairs of indicator-level solid synergies, such as measures taken to prevent land degradation ([15]3 proportion of land that is degraded over the total land area) can help lower greenhouse gas emissions ([13]5 $CO_2$ emissions intensity per GDP).

Moreover, these synergies identified in our indicator-level SDG space can help us understand the mechanisms between goals. For example, strong synergies are identified between water resource conservation ([15]6, the proportion of total water resources used) and greenhouse gas emission reduction ([13]5). The potential mediating mechanism lies in the various ecosystem services that forests can provide. Healthy forest ecosystems can bring about multiple functions in regulating water and nutrient supply, storing carbon offsets, mitigating climate change, and providing clean and affordable timber for energy resources as compensation for fossil fuel. Therefore, the sustainable management of forests and conservation of their related terrestrial ecosystems are imperative in connecting biodiversity, water consumption, and climate change mitigation.

In addition, we also identified some influential indicator level nodes by calculating the weighted degree and betweenness centrality, which is ignored in goal-level space (Table 4). For example, [3]6 (Tuberculosis incidence per 100,000 population), [3]18 (Health care rate for children under seven years old), and [3]14 (Post-natal care coverage (visit rate)) are critical nodes. Tuberculosis remains a major global health problem and a leading death cause [26]. It has long been a disease in the low-income population, usually in crowded places without adequate health facilities. The widespread of this disease also impacts the household and national economies since young labor forces can be hugely hampered. Thus, policy prioritization on Tuberculosis care can have strong social, environmental, and economic synergies, significantly affecting our pathways toward sustainable development. Similarly, neonatal and child health could also have a lifelong impact on human development. As these health-related indicator nodes hold critical positions in the SDG space, deeper investigation into their potential influences on other indicators, policy implementations on health risk reductions, and possible financing issues can be treated as invaluable efforts in achieving universal health coverage and fostering a sustainable future.

## 5. Conclusion

This paper introduces a new concept, the 'SDG space', to measure and assess the complementarities between the Sustainable Development Goals (SDGs) to inform future sustainability progress. The focus is on the structure of the SDG network and its ability to predict future developments for different goals in different regions. This information will aid decision-makers in prioritizing goals according to the specific circumstances of their regions and achieving sustainable development more systematically.

In practice, we constructed the SDG space targeting the 31 Chinese provincial-level administrations at 17 SDGs and 118 indicators levels. Strong connections are found between SDG 11 (Sustainable Cities and Communities), SDG 4 (Quality Education), SDG 15 (Life on Land), and SDG 1 (No Poverty). Moreover, SDGs 4, 15, and 1 are critical nodes in the network. Thus, it is suggested that quality education provision, terrestrial ecosystem conservation, and poverty eradication should be prioritized in achieving sustainable development in China. Besides, SDG 16 (Peace, Justice, and Strong Institutions) and 17 (Partnerships for the Goals) are vital in turning the potential from synergies into sustainable development reality. The indicator-level SDG Space unravels more details concerning the interactions. For example, critical indicators such as tuberculosis incidence, children's health care rate, and post-natal care coverage are expected improvements for a country with a vast population like China, whose labor forces in quantity and quality matter significantly for long-term sustainability. Thus, health risk reductions and related financing issues are called for attention. The modeling and visualization of the synergistic relationships between the SDGs/indicators highlight the importance of these areas for China's sustainable development journey, which could also drive global sustainability progress. These findings emphasize the need for tailored policy designs and implementation tools, including sophisticated city-level data, to inform more detailed plans.

While we have presented a comprehensive framework for the development, validation, and practical applications of the 'SDG space', it is essential to underscore that this promising method is still in its nascent stages. Consequently, further validation efforts are imperative, mainly through the applications of additional datasets. Extending the method to encompass a broader array of SDG-related data sources will significantly contribute to its efficacy and robustness as a tool for policy analysis.

One of the primary limitations of this study is that it mainly facilitates the synergies between SDGs within the realm of the 'SDG space', which is a relatively narrow focus. This method does not account for the inherent trade-offs between SDGs, which often arise as a problem when policymakers seek to address specific goals. For instance, consider policymakers endeavoring to enhance water quality. While direct policy interventions may involve investments in water treatment facilities and establishing stringent water quality standards, these actions may inevitably introduce trade-offs, which could encompass land-use conflicts for new water treatment facilities or economic losses associated with elevated treatment standards. However, this research predominantly delves into the intricacies of direct and indirect synergies between SDGs, leaving the trade-offs beyond the scope of this paper.

Another noteworthy limitation pertains to the practical applications of the prioritized goals and indicators, named as 'bridge' goals generated through this method. While our approach can identify priorities of SDGs, such as the percentage of the population residing in city slums or the nitrogen management index, it does not inherently provide precise policy directives for pathways toward achieving these SDGs. Policymakers and stakeholders will still necessitate their expertise and nuanced decision-making acumen to devise practical strategies aimed at reducing slum populations and improving nitrogen management. Nonetheless, as we pivot toward leveraging finer-scale datasets with improved spatial resolutions in future applications of the method, it is anticipated that it will yield more granular insights and guidance for policymakers in their pursuit of practical policy implementations.

## Author contributions

Conceptualization S.Q.; Methodology S.Q., M.G., K.Y.; Writing – Original Draft M.G., C.Z.; Revised Draft M.G., K.Y.; Writing – Review & Editing S.Q., M.X; Data Curation Z.X. Data Visualization: M.G., K.Y., C.Z., Z.L. All authors provided critical feedback and contributed to the final version of the manuscript.

## Article impact statement

A more stable and comprehensive method to benchmark the Sustainable Development Goals' interactions and structure in understanding their complementarities in Chinese provinces for effective policies with validations.

## Declaration of competing interest

The authors declare that they have no conflicts of interest in this work.

## Acknowledgments

Shen Qu thanks the support from the Excellent Young Scientists Fund from the National Natural Science Foundation of China (72022004). Mimi Gong thanks the support from Joseph Laurence Maison Fellowship and MSU Cloud Computing Fellowship.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.fmre.2024.01.005.

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