Three main dimensions reflected by national SDG performance

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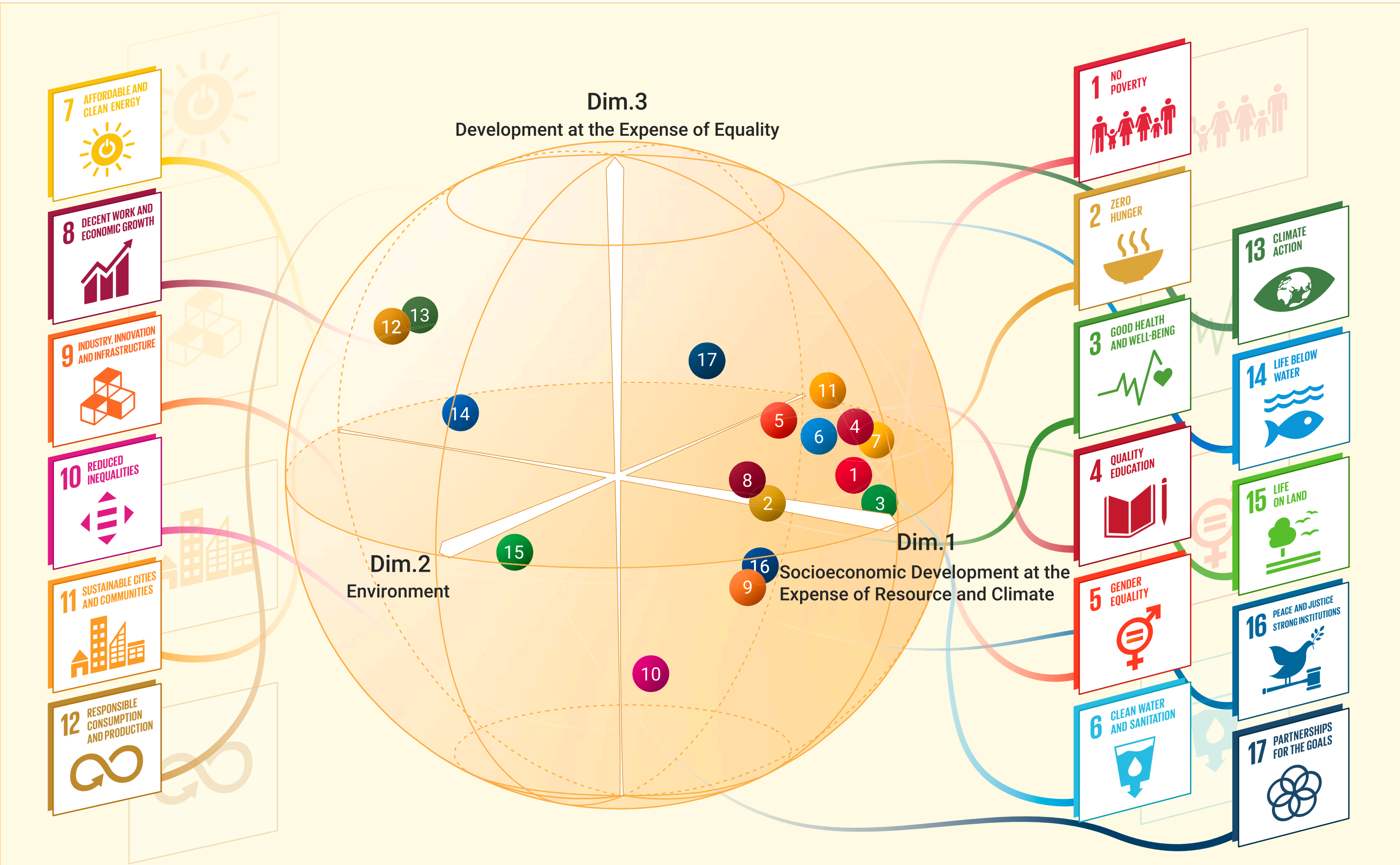
Received: April 13, 2023; Accepted: August 31, 2023; Published Online: September 9, 2023; https://doi.org/10.1016/j.xinn.2023.100507

GRAPHICAL ABSTRACT



PUBLIC SUMMARY

- Three dimensions capture ~70% of the variability of national SDG performance.
- Economy is the main driver of the spatial variations of these dimensions.
- Systematic conflicts exist between economic growth and resource and climate goals.
- Sustainable transformation of the current development paradigm is urgently needed.

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Received: April 13, 2023; Accepted: August 31, 2023; Published Online: September 9, 2023; https://doi.org/10.1016/j.xinn.2023.100507

Citation: Wu X., Fu B., Wang S., et al., (2023). Three main dimensions reflected by national SDG performance. The Innovation **4(6)**, 100507.

Unraveling the complexity of the 17 interacting sustainable development goals (SDGs) is crucial for their achievement. Empirically revealing the dimensions of the SDGs helps generalize the dominant features of SDGs and better understand their drivers. Here, using a database of 166 countries' progress toward achieving each individual SDG, we found that about 70% of the variability of national SDG performance can be captured by three dimensions: socioeconomic development at the expense of resource and climate, the environment, and development at the expense of equality. Moreover, these dimensions are mainly affected by the economy; as gross domestic product (GDP) per capita increases, the first dimension increases monotonically, the environment dimension decreases and then increases, and the inequality dimension increases and then decreases. Our findings indicate a dim prospect of eventually achieving all SDGs because of the conflicts between economic growth and resource and climate goals under the current development paradigm, highlighting the importance of sustainable transformation.

INTRODUCTION

As human activities have become the leading force within the Earth system, we have entered the Anthropocene,[1–3] a new geological epoch accompanied by ecological and environmental problems that threaten human survival and sustainable development. To tackle the most pressing problems humanity faces, such as climate change, biodiversity loss, land degradation, poverty, and inequality, the United Nations (UN) adopted the 2030 Agenda for Sustainable Development in 2015, offering a shared blueprint for joint sustainable actions for all countries.[4] At the heart of the agenda are the 17 ambitious sustainable development goals (SDGs), which cover 169 targets and 231 unique indicators and point out critically important areas for peace and prosperity for people and the planet now and into the future.[4] Regrettably, the world is currently off course for achieving the 17 SDGs by 2030, and urgent action is required to address the cascading and interlinked crises dominated by pandemic, climate change, and conflicts.[5,6] Because the 17 SDGs are integrated, indivisible, and interact in complex ways,[7] it is crucial to approach the design and implementation of relevant policies and measures from a holistic and systematic perspective.[8]

The complexity in achieving the 17 SDGs has been unraveled to some degree by classification of SDGs based on their interlinkages.[9] The UN addresses the three pillars of sustainable development: economic, social, and environmental. Such thought is also reflected in the SDG "wedding cake" conceptualization presented by the Stockholm Resilience Center,[10,11] which shows that economies (SDGs 8–10 and 12) are embedded in societies (SDGs 1–5, 7, 11, and 16), societies are embedded in the biosphere (SDGs 6 and 13–15), and achievement of sustainability requires partnerships (SDG 17). From the perspective of achieving maximum benefit with minimum input through appropriate governance measures, the 17 SDGs can be clustered into three categories: essential needs (SDGs 2, 6, 7, 14, and 15), objectives (SDGs 1, 3–5, 8, 10, and 16), and governance (SDGs 9, 11–13, and 17).[9] Although these classifications have been widely used in SDG studies,[12–15] the combinations of different SDGs are relatively conceptual and based on expert knowledge and have therefore only been treated as predefined categories without quantitative information.

The empirical and quantitative understanding of the interlinkages and integrated nature of the SDGs is a key focus in SDG research.[16] Dimensionality reduction methods, such as principal-component analysis (PCA) and multiple-factor analysis (MFA), provide effective tools for extracting the dominant features from high-dimensional data while retaining trends and patterns, making the data more easily accessible for analysis.[17] Previous studies have utilized these methods to measure the performance of individual goals and overall sustainability using SDG indicator data.[18–20] They have also been employed to identify the principal indicators and simplify the SDG indicator system.[21,22] Furthermore, these methods have been used to analyze the correlations between SDG indicators, identify the primary components represented by the indicators,[16] quantify the synergies and trade-offs between different predefined SDG categories,[15] and analyze the axes of global progress within these categories.[23] However, these studies primarily focused on measuring SDG performance and SDG interactions and were typically conducted at the indicator level, leaving the main dimensions reflected by goal-level performance largely unexplored. Empirically revealing the dimensions of the SDGs can provide a more comprehensive and broader understanding of their interlinkages,[7] enable quantitative generalization of the dominant characteristics of the SDGs, and facilitate a clearer analysis of their drivers.

To fill this knowledge gap, this study addresses three major questions. First, what are the main dimensions reflected by the 17 SDGs? Second, how do these dimensions vary among different countries? Third, what factors influence these variations? To answer these questions, we used PCA to analyze 166 countries' SDG data (Figure S1) from the Sustainable Development Report 2020,[24] a widely recognized and utilized global dataset that provides scores for each of the 17 goals,[25,26] to reveal the main dimensions reflected by national SDG performance. We further analyzed the spatial variation of these dimensions and employed random forest analysis to explore the main drivers behind their variations. Our findings will simplify the inherent complexity of the 17 interacting SDGs and provide insights for broader governance of sustainable development.

RESULTS

Three main dimensions reflected by the 17 SDGs

The key dimensions reflected by the 17 country-level SDG scores were identified by PCA (see material and methods for more details). The first three principal components of variation explain 69.1% of the spatial variation of national SDG performance (Figures 1A and S2). Dimension 1 (Dim1) explains 52.5% of the variance and reflects socioeconomic development at the expense of resource and climate. SDGs 1 (no poverty), 2 (zero hunger), 3 (good health and well-being), 4 (quality education), 5 (gender equality), 6 (clean water and sanitation), 7 (affordable and clean energy), 8 (decent work and economic growth), 9 (industry, innovation, and infrastructure), 11 (sustainable cities and communities), and 16 (peace, justice, and strong institutions) positively contribute to the first dimension (Figure 1), indicating the synergies among these SDGs. However, SDGs 12 (responsible consumption and production) and 13 (climate action) contribute with negative loadings, reflecting the systematic conflicts between these two SDGs and the SDGs mentioned above. Dim2 explains 9.4% of the variance and is dominated by the environment because SDGs 14 (life below water) and 15 (life on land) positively contribute to it. Dim3 explains 7.2% of the variance and refers to development at the expense of equality. SDG 10 (reduced inequalities) contributes most to Dim3 with negative loadings.

Spatial variation of the three identified dimensions

The three identified dimensions show significant spatial differences across geographic regions (Figure 2). The dimension of socioeconomic development at the expense of resource and climate shows the highest values in European and North American countries as well as in Australia and New Zealand and the lowest values in countries in sub-Saharan Africa. East and Southeast Asian countries rank the second highest in this dimension, while the values of other regions are similar. In the environment dimension, European and North American countries have the highest values; sub-Saharan African countries also show

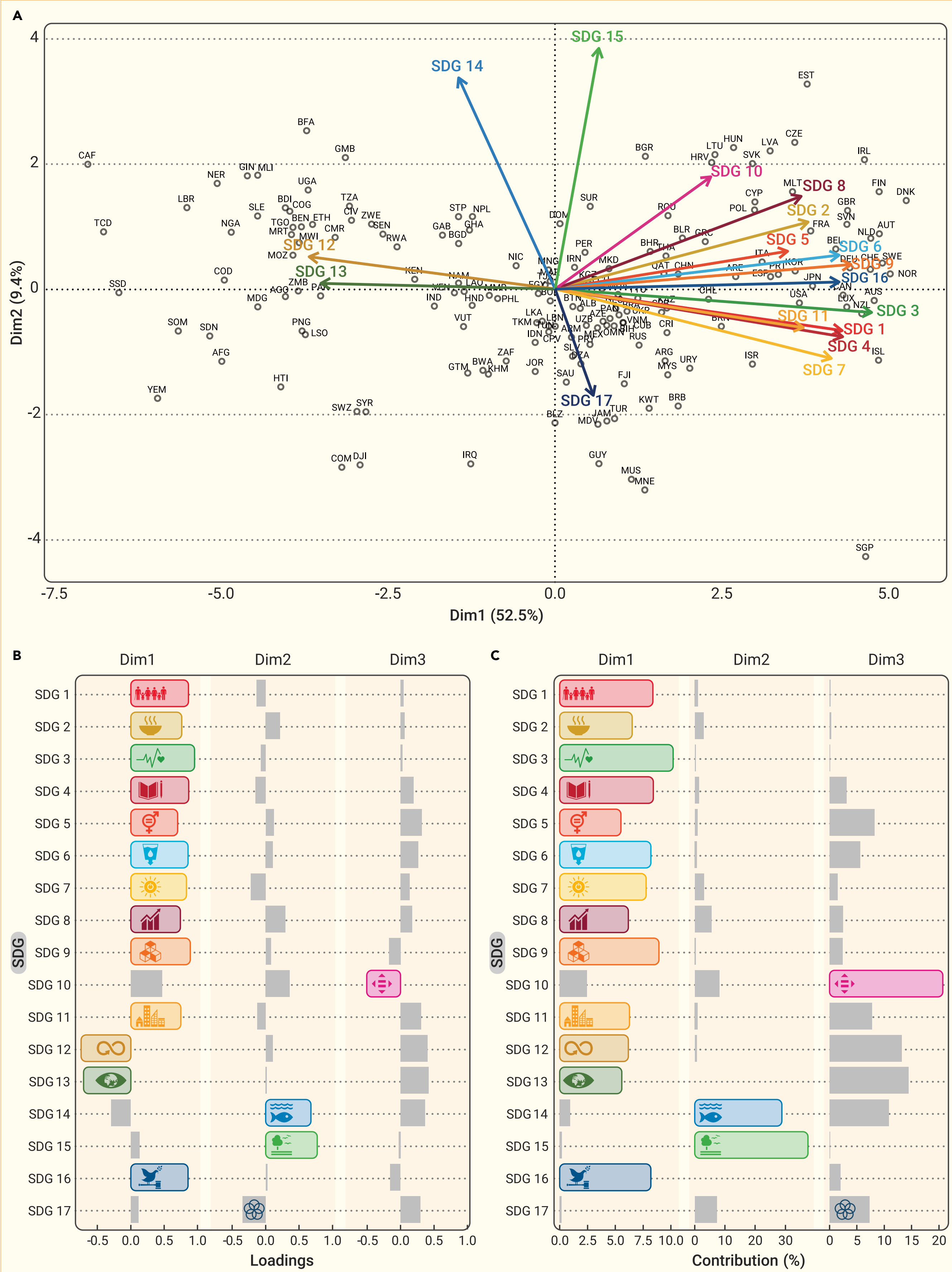


Figure 1. Main dimensions reflected by country-level performance on the 17 SDGs (A) Biplot of the principal-component analysis (PCA) results. The full names and PC values of the countries are shown in Table S1. (B) Loading of each SDG to each dimension. (C) Contribution of each SDG to each dimension. Non-gray bars indicate SDGs with significant loadings (i.e., with an absolute value greater than 0.5).

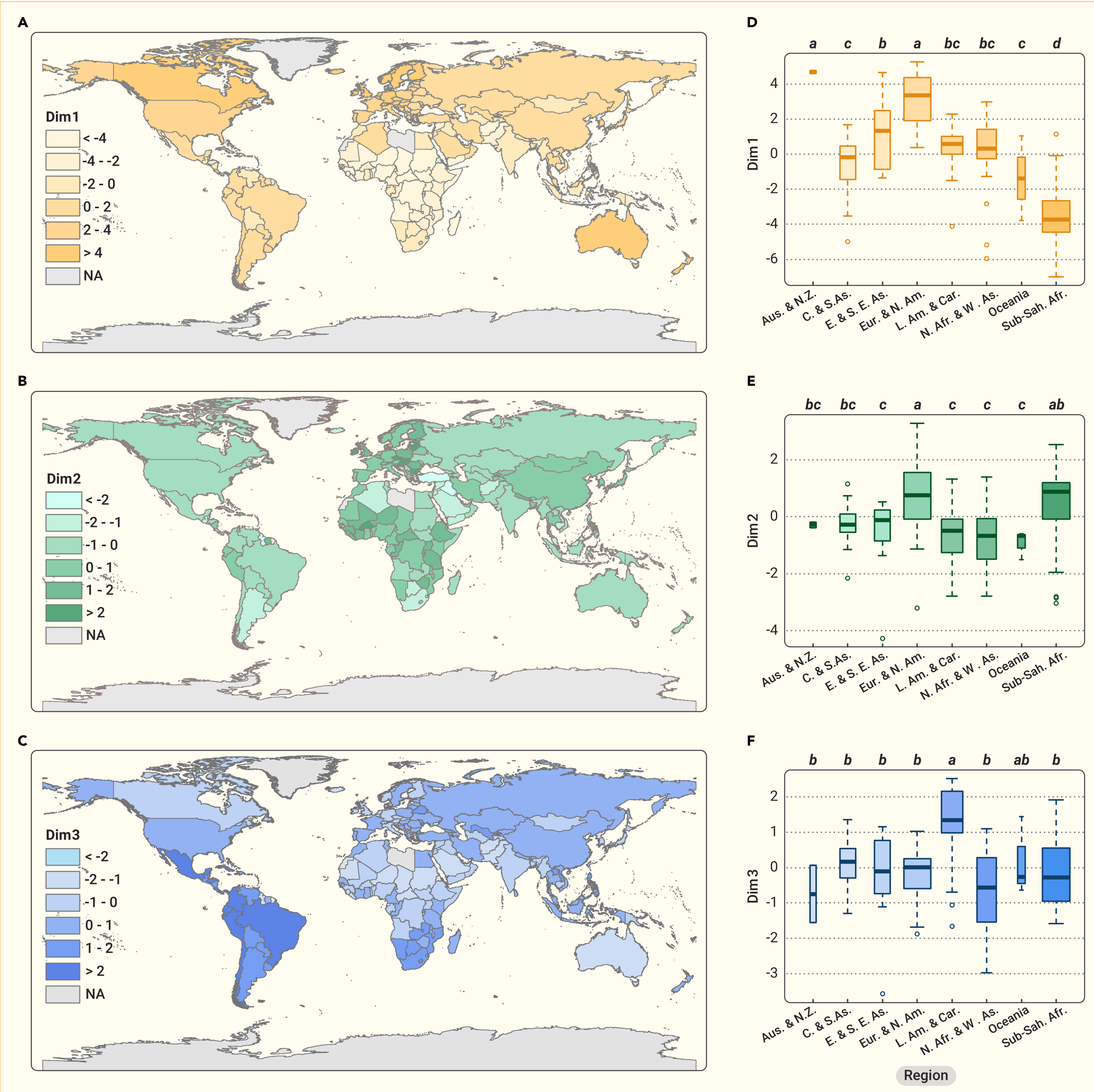


Figure 2. Spatial variation of the dimensions (A–C) The spatial variation of Dim1, Dim2, and Dim3. (D–F) Comparison of different regions for Dim1, Dim2, and Dim3. Regions with different letters at the top of boxplots differ significantly ($p < 0.001$). Countries included in each region are shown in Table S1.

values that are significantly higher than countries in East and Southeast Asia, Latin America and the Caribbean, North Africa and West Asia, and Oceania. Latin American and the Caribbean countries have the highest values in the dimension of development at the expense of equality, while there are non-significant differences among the other regions.

Potential influencing factors of the three identified dimensions

The influence and relative importance of multiple socioeconomic and environmental factors on the spatial variability of the three dimensions were explored by random forest analysis (Figures 3 and S3–S5; see material and methods for more details). The selected variables explain 86.2%, 24.9%, and 46.6% of the variability of Dim1, Dim2, and Dim3, respectively (Figure 3). All of the dimensions are mainly explained by gross domestic product (GDP) per capita, but its influence varies for the different dimensions. As GDP per capita increases, the socioeconomic development dimension (Dim1) increases monotonically, the environment dimension (Dim2) shows an overall trend of decreasing and then increasing, and the inequality dimension (Dim3) shows the opposite trend of increasing and then decreasing. Some environmental factors, such as temperature and precipitation, are also among the top three predictors, but there is little difference between their importance and that of the other factors.

DISCUSSION

This study identified the three main dimensions reflected by the performance of 166 countries in the 17 SDGs: socioeconomic development at the expense of

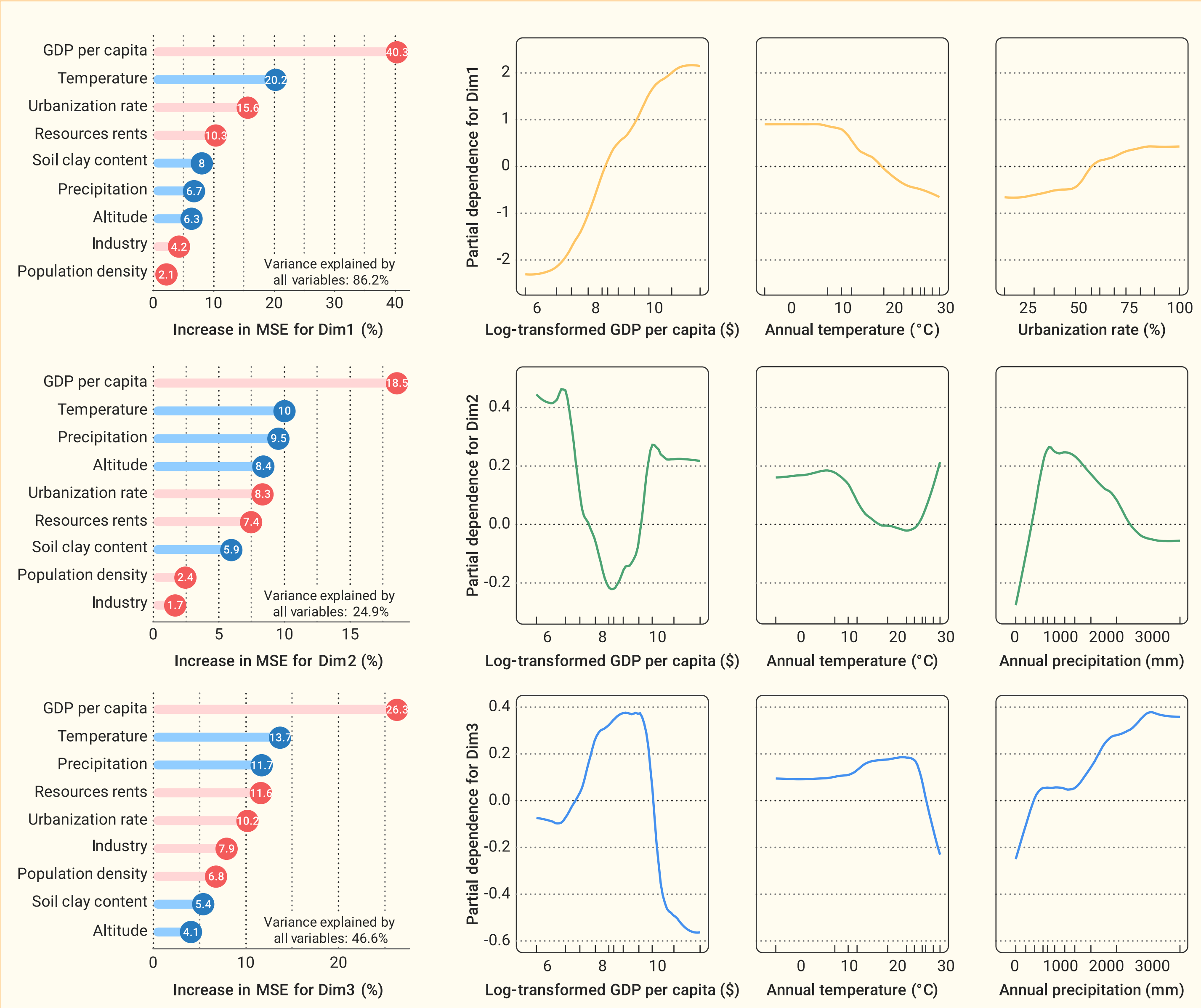
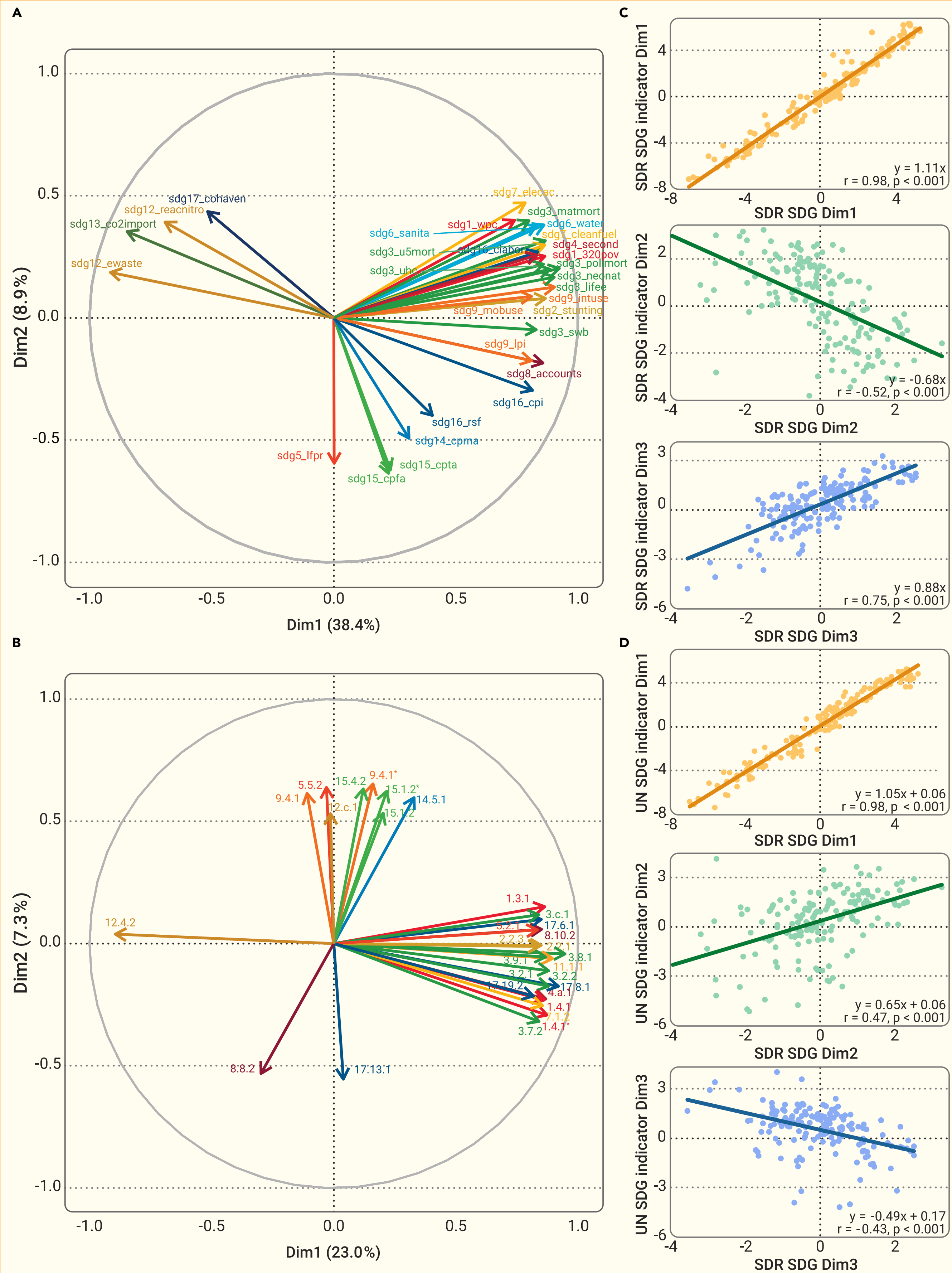


Figure 3. Importance of socioeconomic and environmental variables and partial dependence plots of the three most important variables for each dimension The increase proportions of mean squared error (MSE) are shown as numbers in circles. Red circles represent socioeconomic variables, and blue ones represent environmental variables. Tick marks on the x axis represent the distribution of each variable.

resource and climate, the environment, and development at the expense of equality. Variations of these dimensions are mainly explained by the economy, as represented by GDP per capita. By unraveling the complexity of the 17 interacting SDGs, this study provides a clear and simple way to characterize sustainable development performance and explore the underlying mechanisms. It also lays the foundation for sustainable governance and transformation based on this new understanding.

The three dimensions were identified using SDG data from the Sustainable Development Report 2020;[24] however, the selection of indicators and measuring methods may lead to different evaluations of SDG performance and then different findings.[27] To validate the reliability of our findings, we conducted MFA at the indicator level using two datasets: the SDG indicator dataset from the Sustainable Development Report 2020 (Tables S2) and an additional dataset from the UN SDG Global Database (Tables S3). Unlike PCA, MFA takes into account the varying number of indicators associated with each SDG. The first three dimensions explain 53.1% (Dim1_SDR, 38.4%; Dim2_SDR, 8.9%; Dim3_SDR, 5.7%) and 35.0% (Dim1_UN, 23.0%; Dim2_UN, 7.3%; Dim3_UN, 4.7%) of the variance, respectively (Figures 4A and 4B). Consistent with the dimensions identified at the goal level, the socioeconomic SDGs and SDGs 14 and 15 contribute the most to Dim1 and Dim2 in both datasets, respectively (Figures S6 and S7). Although the contribution of SDG 10 to Dim3 at the indicator level is not as prominent as at the goal level, its indicators still rank among the top 10 contributors for Dim3 in both datasets (Figures S8 and S9). For Dim1, indicators related to the socioeconomic SDGs show a strong positive contribution, while indicators sdg12_ewaste and sdg13_co2import negatively contribute to Dim1_SDR, and indicator 12.4.2 (hazardous waste generated per capita) for responsible consumption and production negatively contributes to Dim1_UN (Figures 4A, 4B, S8, and S9). Dim2 at the indicator level still primarily reflects the environment dimension because several environmental indicators strongly contribute to Dim2_SDR and Dim2_UN. Despite differences in indicators and rescaling methods used, all three dimensions at the indicator level are significantly ($p < 0.001$) correlated with their corresponding dimensions at the goal level (Figures 4C and 4D). These analyses demonstrate the robustness of our findings and support the interpretations of the identified dimensions.

Identification of the dimensions and analysis of their influencing factors based on comparisons among global countries cover the entire development spectrum because one country generally follows the development path of others.[28] By linking the spatial variations of the identified dimensions to the per-capita GDP of different countries, our findings can reveal the influence of the current economic development paradigm on sustainable development. The monotonic increase of



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Dim1 with per-capita GDP indicates that most socioeconomic SDGs and economic growth can be pursued in parallel.[29] Nevertheless, SDGs 12 and 13 exhibit negative contributions to Dim1, indicating that the observed monotonic increase also signifies adverse associations between the current economic development paradigm and responsible consumption and production as well as climate action. Previous studies have shown that economic growth on the current path will generate more human welfare (e.g., better health and nutritional status, higher quality education, and cleaner water provision) but will also cause larger material and environmental footprints and higher greenhouse gas emissions,[30–32] which is consistent with the relationships between economic growth and the first dimension. The trends of the environment (decreasing and then increasing) and inequality (increasing and then decreasing) dimensions, along with per-capita GDP, are consistent with the environmental Kuznets curve[33] and the Kuznets curve[34,35] theories, respectively. According to these theories, during early development of an economy, the focus is on economic growth, not environmental protection, and the benefits of growth tend to accrue primarily for the wealthy, leading to increasing environmental degradation and income inequality. As development continues, people begin to value the environment more, and investment in environmental protection measures and technologies increases, the middle class grows, and social welfare programs expand, leading to a reduction in environmental degradation and income inequality.[33–35] It is crucial to acknowledge that our analyses are derived from cross-sectional data. Further research and analysis of temporal data will provide a more comprehensive understanding of the aforementioned relationships and their dynamics over time.

Our findings show that the current economic development paradigm is expected to eventually achieve most socioeconomic SDGs (SDGs 1–9, 11, and 16) and ensure the ultimate realization of environmental and social equality goals despite the initial deterioration. Unfortunately, the irreconcilable conflicts between economic growth and resource and climate goals (SDGs 12 and 13) make the prospect of achieving all 17 SDGs dim. Sustainable transformation of the existing development paradigm is urgently needed to resolve these systematic conflicts as well as avoid environmental degradation and social inequalities throughout the development process.[36–38] Such transformation calls for intensified and effective collaborations between governments, public organizations, the private sector, and civil society, highlighting the importance of SDG17 (partnerships for the goals).[37,39–41] The concepts of circularity and decoupling without lowering human well-being, which can change patterns of consumption and production, are at the core of such transformation.[39] Circularity promotes reuse and recycling of materials[40] and can be applied in the design and management of resource flows in cities,[42] management of livestock and food loss or waste in agriculture and food systems,[43] and reuse and extension of service life through repair, remanufacture, upgrades, and retrofits in industrial ecosystems.[40] Decoupling requires decarbonization that sustainably reduces and compensates for greenhouse gas emissions,[39] dissociation of net release of pollutants from human well-being,[44] and decoupling of land, freshwater, and non-renewable resource use from socioeconomic progress.[45] Achievement of circularity and decoupling relies on the advancement of new technologies, forms of governance, and business models.[39,40] The fourth industrial revolution and the underlying digital transformation, known as Industry 4.0, holds the potential to enhance corporate profitability, optimize resource utilization, reduce emissions, facilitate the transition to zero-carbon energy systems, monitor and protect ecosystems, promote circular economy and decoupling, and play other crucial roles in supporting the SDGs.[39,46–48] Adoption of innovative business models that connect an organization's purpose and strategy, while aligning with the SDGs and encompassing digital transformation, can simultaneously deliver performance and ensure transformation, creating enduring value for key stakeholders and achieving remarkable results.[49]

It should be noted that the present study has some limitations. Although the comparisons of PCA results based on Sustainable Development Report SDG data and MFA results based on two SDG indicator datasets demonstrated the reliability of the identified dimensions, these analyses used a limited number of indicators (<130) because of data availability. For SDG 14, the Sustainable Development Report 2020 provides scores for only 126 non-landlocked countries. We chose to retain this SDG and impute the scores for the remaining countries (see material and methods for more details) because our primary objective is to comprehend the complex interconnections among all SDGs. However, this process might influence the precise assessment of SDG 14's contributions to various dimensions on a global scale, emphasizing the importance of identifying more metrics in the future to evaluate the impact of landlocked countries on oceans.[24] Our understanding of the dimensions of SDGs may evolve as more SDG indicators and temporal data become available. For clarity, only three PCs that minimize redundancy and loss of information were used, leading to SDG 17 (partnerships for the goals) being excluded in the identified dimensions, but SDG 17 contributed more than half to the fourth PC (data not shown). The relative independence of SDG 17 has also been found in other studies.[10,25] This study only considered domestic factors as influencing factors of the dimensions, although cross-border telecoupling factors such as trade and tourism also affect SDGs.[50–52] Future research should examine impacts of telecoupling factors, such as technology transfer, investment, water transfer, waste transfer, knowledge transfer, human migration, disease spread, and information dissemination.[53]

In conclusion, this study provides an empirical understanding of the complexity of the 17 interacting SDGs by identifying the three main dimensions reflected by national SDG performance. Economic growth is the main driver of variation, and although the current economic development paradigm is expected to eventually achieve most SDGs, it cannot achieve all of them because of the conflicts between economic growth and resource and climate goals, highlighting the importance of sustainable transformation.

MATERIAL AND METHODS

National SDG data

The performance of 166 countries on the 17 SDGs was obtained from the Sustainable Development Report 2020,[24] published by the Sustainable Development Solutions Network and the Bertelsmann Stiftung. It is a well-recognized and widely used global dataset at the whole-goal level.[25,26] In the report, each country's progress toward achieving each individual SDG is described with a score, which represents a percentage of optimal performance. Although a report was published annually from 2017 to 2022, SDG scores cannot be compared among the different years because of changes in the indicators and refinements of the methodology.[24] Given that the Sustainable Development Report 2020 has the greatest number of countries, we chose it for use in this study. A total of 115 indicators (85 global indicators and 30 indicators added specially for Organization for Economic Co-operation and Development [OECD] countries) were used to generate comparable scores in this report. Extreme values were censored from the distribution of each indicator, and the data were then rescaled from 0–100 to ensure comparability across all indicators. The scores for each goal were calculated as the arithmetic mean of the corresponding indicators. The raw indicator data underwent extensive and rigorous data validation processes, mainly from the World Bank, Food and Agriculture Organization, World Health Organization, UN Children's Fund, OECD, and other international organizations.

To ensure the robustness of the identified dimensions based on the 17 SDG scores, we conducted validation at the indicator level using the SDG indicator dataset from the Sustainable Development Report 2020 and an additional dataset from the UN SDG Global Database. This validation aimed to assess the impact of different measurement methods and indicator selections on our main findings. The UN SDG Global Database provides data on more than 210 SDG indicators for a total of 261 countries and areas between 1960 and 2022 (accessed in October 2022). The database is generated based on the official global indicator framework for SDGs from the Inter-Agency and Expert Group on SDG Indicators, which includes 231 unique indicators. For some indicators, the dataset provides sub-indicators disaggregated by sex, age, rural/urban area, etc. However, we only used aggregated (i.e., both sexes, all ages, and all areas) values for these indicators to ensure that all SDG indicators in the analysis had the same weight. Because of data limitations, complete indicator time series are unavailable for all time steps and countries. To ensure consistency in terms of the research period and to include as many indicators as possible, we selected available data for the period 2015–2020 and used the value from the nearest year to 2020 for each indicator to conduct a cross-sectional analysis. Only indicators that cover more than 70% of the UN member states and member states that have data for more than 70% of the indicators remained, resulting in a total of 125 indicators and 181 countries included in this study.

Figure 4. Comparisons between the dimensions identified by the Sustainable Development Report (SDR) SDG data and the dimensions identified by SDR SDG indicator data and UN official SDG indicator data (A) Biplot of the multiple-factor analysis (MFA) results using SDR SDG indicator data. (B) Biplot of the MFA results using UN official SDG indicator data. Only the top 20 and 10 contributing indicators for Dim 1 and Dim 2 are shown, respectively. (C) Relationships between the identified dimensions using SDR SDG and indicator data. (D) Relationships between the identified dimensions using SDR SDG and official indicator data. Details of each indicator are shown in Tables S2 and S3.

Identification of main dimensions of national SDG data

PCA has been used to identify the fundamental axes of plant form and function,[54] the dimensions of the terrestrial biosphere state,[55] and the key axes of terrestrial ecosystem function[56] and to better understand the driving mechanisms of their variabilities.[56] We performed PCA on the goal-level SDG data using the PCA function in the FactoMineR package[57] in R to identify the main dimensions. Each variable was centered on its mean and scaled by its variance. The ade4 package[58] in R was used to determine the number of significant components retained. This package allows us to test the significance of PCA dimensionality and has been used in other studies about plant traits[54] and ecosystem functions.[56] The method is based on computation of the RV coefficient. The number of retained components to minimize redundancy and loss of information was three. We extracted the explained variance of each PC and the SDG loadings (which indicate the contribution of each SDG to each PC) from the PCA results. The significance of the PCA loadings was tested by the threshold method. If the absolute value of the loading was larger than 0.5,[59] then it was considered significant.

Because of data limitations, there are missing scores for SDGs 1, 4, 10, and 14 for 12, 2, 17, and 40 countries, respectively (Figure S1). They were imputed with the imputePCA function in the missMDA package[60] in R, which imputes the missing entries of mixed data using the regularized iterative PCA algorithm. The algorithm first imputes the missing values with initial values (the means of each variable), then performs PCA on the completed dataset, imputes the missing values with the reconstruction formulae, and iterates until convergence.[60] To assess the reliability of our findings based on the imputed SDG scores, we conducted a separate PCA using only 108 countries that have complete data without any missing SDG scores. The three dimensions identified using the non-imputed national SDG performance exhibit similar characteristics to those identified using the imputed scores (Figure S10), and the corresponding dimensions show a high level of consistency (with correlation coefficients exceeding 0.9 for all three pairs, Figure S11).

At the indicator level, the main dimensions of SDG data were identified using MFA, an extension of PCA that is well suited for analyzing tables with observations or individuals across different groups of quantitative variables.[61] The MFA analyses were performed using the MFA function in the FactoMineR package[57] in R. Missing values were imputed using the imputeMFA function in the missMDA package[60] in R, which employs an approach similar to the imputePCA function, with the exception of utilizing the regularized iterative MFA algorithm. In the MFA analysis, the values of SDG indicators were multiplied by 1 when an increase was desirable and −1 when a decrease was needed to achieve the SDG.

Influencing factors analyses

Several socioeconomic and environmental variables were selected to analyze the potential influencing factors of the identified PCs of national SDG data. The socioeconomic data for each country were obtained from the world development indicators of the World Bank, which contain GDP per capita and gross national income, the ratios of value added of different industries (i.e., agriculture, forestry, and fishing; industry; and services) to GDP, the ratio of total natural resources rents to GDP, population density, and urbanization rate in 2020. The environmental variables include average precipitation, temperature, altitude, and soil clay content for each country, calculated based on the Climatic Research Unit gridded Time Series (CRU TS 4.04), the Global 30 Arc-Second Elevation Dataset (GTOPO30), and the Regridded Harmonized World Soil Database v.1.2, respectively. We calculated the variance inflation factor (VIF) of each variable and excluded variables with a VIF greater than 5 to avoid multicollinearity. Only GDP per capita, the ratio of value added of industry to GDP, the ratio of total natural resource rents to GDP, urbanization rate, population density, precipitation, temperature, altitude, and soil clay content remained after this exclusion process.

To identify the variables contributing most to the PCs' variabilities, we conducted a random forest analysis. The importance of the variables was measured by the increased proportion of mean squared error; a higher value means a more important variable. The partial dependencies of variables were used to assess the relationships between the socioeconomic and environmental variables and the PCs and computed by the pdp package[62] in R. The results can reflect the effects of individual variables on the PCs without the other variables' influence. To reduce the risk of interpreting the partial dependence plot outside the data's range (extrapolation risk), the partial dependencies were calculated restricted to the values within the convex hull of their training values.[56]

DATA AND CODE AVAILABILITY

All of the data used in this paper can be obtained from the Sustainable Development Report (https://www.sustainabledevelopment.report/), the SDG Global Database of the UN (https://unstats.un.org/sdgs/dataportal), the World Bank World Development Indicators (https://databank.worldbank.org/reports.aspx?source=world-development-indicators), the Climatic Research Unit gridded Time Series (https://crudata.uea.ac.uk/cru/data/hrg/), the Global 30 Arc-Second Elevation Dataset (https://webmap.ornl.gov/ogc/dataset.jsp?ds_id=10003), and the Regridded Harmonized World Soil Database v.1.2 (https://daac.ornl.gov/SOILS/guides/HWSD.html). All computer code used in conducting the analyses summarized in this paper is available from the corresponding author upon reasonable request.

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ACKNOWLEDGMENTS

This research was financially supported by the National Natural Science Foundation of China (42041007 and 42201306), the China National Postdoctoral Program for Innovative Talents (BX2021042), and the China Postdoctoral Science Foundation (2021M700458).

AUTHOR CONTRIBUTIONS

B.F. and X.W. designed the research. X.W. and Y.Y. performed the data analysis. All authors contributed to interpretation and writing.

DECLARATION OF INTERESTS

The authors declare no competing interests.

SUPPLEMENTAL INFORMATION

It can be found online at https://doi.org/10.1016/j.xinn.2023.100507.

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