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Spatio-temporal changes in the causal interactions among Sustainable Development Goals in China

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Extensive efforts have been dedicated to deciphering the interactions associated with Sustainable Development Goals (SDGs). However, these developments are hampered by a lack of efficient strategies to avoid beneficial synergies being offset by harmful trade-offs. To fill these gaps, we used causal diagnosis and network analysis methods to construct 1302 directed networks of SDGs for 31 provinces in China from 2000 to 2020. We observed a dramatic offsetting effect of SDG synergies and trade-offs in China from 2000 to 2020, with approximately 27% of trade-off indicator pairs turning into synergies and about 25% of the synergy indicator pairs turning into trade-offs. However, our findings suggested that prioritising the progress of high-frequency indicators in virtuous cycles could multiply the positive systemic effects of the SDGs. Moreover, controlling the transition from passive to active in the trade-off network of SDGs remains a challenge in advancing the SDGs holistically.

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Introduction

The Sustainable Development Goals (SDGs) set by the United Nations are integrated and indivisible. The SDG framework aims to balance the economic, social, and environmental aspects of sustainable development (United Nations, 2015; Voulvoulis et al., 2022; Cheng et al., 2022). Action toward one goal (i.e., SDG, target, or indicator) may enhance or detract from the performance of others, respectively, defined as synergy or trade-off among the SDGs (Nilsson et al., 2016; Scharlemann et al., 2020; Sebestyén et al., 2019; Weitz et al., 2018; Wu et al., 2022). According to the consensus from previous studies, addressing trade-offs and fostering synergies remain critical to rescuing the SDGs from failing (Pradhan, 2023). However, effective strategies to achieve this objective are yet to be quantitatively investigated (Nilsson et al., 2018; Ospina-Forero et al., 2022).

Existing studies could primarily be categorised into qualitative evaluation by experts' knowledge or official documents (Breu et al., 2021; Nilsson et al., 2016; Pham-Truffert et al., 2020; Sebestyén et al., 2019; Weitz et al., 2018) and quantitative correlation analysis, including pearson's correlation coefficient (Bali Swain and Ranganathan, 2021), spearman's correlation analysis (Anderson et al., 2022; Kroll et al., 2019; Pradhan et al., 2017; Warchold et al., 2021), multiple factor analysis (Zhang et al., 2022a, 2022b) and autoregressive correlation (Lusseau and Mancini, 2019). These studies highlight that SDG interactions varied according to the country's income (Lusseau and Mancini, 2019; Warchold et al., 2021), level of sustainable development (Wu et al., 2022), population groups (Warchold et al., 2021), and regions (Bali Swain and Ranganathan, 2021; Warchold et al., 2021). Accordingly, the most dominant SDGs (Pham-Truffert et al., 2020), the most frequent SDG interactions (Pradhan et al., 2017), and the influence of levers and obstacles for achieving the SDGs (Anderson et al., 2022) have been discussed. Meanwhile, some studies have explicitly investigated the causation of SDG interaction networks based on methods like expert opinion (Dawes et al., 2022; Van Soest et al., 2019), granger causal analysis (Dörgo et al., 2018), systems model (Anderson et al., 2022; Pedercini et al., 2019), statistical structure learning (Ospina-Forero et al., 2022), and physics-inspired approaches (Ospina-Forero et al., 2022). To compare the impact of databases on the assessment outcomes, researchers have created a unified SDG database to understand the SDG interactions (Warchold et al., 2022).

Nonetheless, the synergies and trade-offs among the SDGs could change in a complex manner over time. Counting only the number of SDG synergies and trade-offs over time may mask the offsetting effects of shifts between synergies and trade-offs. In other words, the benefits of synergising one goal with the others may be offset by the negative impacts of emerging trade-offs associated with another one. While some studies have discussed the offsetting effects of changes in performance across the SDGs (Gusmão Caiado et al., 2018; Salvia et al., 2019; Warchold et al., 2021), very few studies have reported offsetting effects in SDG interactions over time. Additionally, an effective approach to overcoming the offsets is yet another critical gap that requires filling. Addressing these limitations facilitates a deeper comprehension of the dynamic changes in SDG interactions.

Some studies have appraised policymakers about the closed loops and active and passive relations arising from the SDG causal interactions (Breu et al., 2021; Messerll, 2000; Pham-Truffert et al., 2020). Theoretically, closed loops are cycles of interactions and can serve as a self-reinforcing sub-network (Breu et al., 2021; Pham-Truffert et al., 2020), which may be virtuous or vicious. In such a sub-network, promoting an SDG indicator can automatically enhance or inhibit the other SDG indicators. Theoretically, a passive relation in the SDG network signifies that

the influence undergone by the SDG is greater than it exerted on the others. Passive SDGs are susceptible to positive or negative influences from other SDGs. Conversely, an active relation signifies that the SDG's influence on others is greater than that the influence it undergoes (Breu et al., 2021; Pham-Truffert et al., 2020). Active SDGs' progress can stimulate or inhibit other SDGs. The shifts between the active and passive SDGs reflect state changes for SDGs in synergy and trade-off networks. However, previous studies mainly relied on expert experience to identify causality among the SDGs while disregarding their spatial and temporal variation (Breu et al., 2021; Pham-Truffert et al., 2020). Hence, quantifying the dynamics of closed-loop and active-passive relationships in SDG causal interaction networks at fine scales is crucial for exploring ways to promote synergies and mitigate trade-offs among the SDGs.

To address the existing knowledge gaps, in this study, we analysed changes in SDG synergies and trade-offs at the indicator level in China. China was selected due to its robust data availability and research experience on SDG interactions at a subnational scale. Furthermore, China has implemented multiple policies to accelerate the SDGs (Wang et al., 2020). However, the current rate fails to guarantee to achieve all goals (Lu et al., 2019), which remains a common challenge faced by multiple countries worldwide. We aim to explore China's SDGs solutions as a valuable platform for global or other national analyses. Therefore, this study addresses the following questions: (i) What are the offsetting effects and spatial variations of the shift between synergies and trade-offs among SDGs in China over the past 20 years? (ii) What are the spatio-temporal characteristics of the closed loops in China's SDG networks? (iii) What are the spatial and temporal dynamics of active-passive relations among SDGs in China?

We determined the causal direction and intensity among SDG indicators to answer these questions by the spatio-temporal geographically weighted regression method (GTWR). Based on the causal direction and strength among SDG indicators, we constructed 1302 interaction networks among SDG indicators (Fig. S1 and Table S1) at the provincial scale in China (including 31 provinces, excluding Hong Kong, Macau, and Taiwan) yearly from 2000 to 2020. Within the networks, each node acted as a specific SDG indicator. A directional link connected every pair of nodes, the weight of which denoted their interaction intensity, represented as a regression coefficient. The coefficients varied across time and space and were obtained yearly for each province. We constructed networks for synergy and trade-off because one SDG, as an independent variable, can have a positive or negative impact on another SDG, as a dependent variable. For each province, we explored the offsetting effects of changes in SDG synergies and trade-offs over time, identified closed loops in SDG networks, and analysed the dynamics of active-passive relations in the networks.

Methods

Data sources. To thoroughly evaluate the progress of SDGs at the provincial scale in China, we collected provincial statistical data from 2000 to 2020 from the National Bureau of Statistics and Statistical Yearbook. To ensure the representativeness of the SDG indicators, we constructed a provincial SDG indicator system for China by referring to the official UN SDG indicator framework, the Sustainable Development Report 2021, and relevant literature (United Nations Statistics Division, 2017; Jeffrey et al., 2021; Zhang et al., 2022a). The SDG indicator data are available for all provinces in China and sufficiently complete for the research period. We obtained 86 indicators that corresponding to 80

targets and 16 goals, i.e., at least two targets per goal except SDG 14 (Table S1). Since SDG14 is primarily concerned with marine ecosystems, most provinces in China lack relevant indicator data (Zhang et al., 2022a). Therefore, we did not take into account the interactions between SDG14 and other SDGs.

Depending on the nature of the indicators, we classified them as positive, negative, and moderate indicators (Jeffrey et al., 2021; Warchold et al., 2021; Zhang et al., 2022a). Among these, higher levels of sustainability required larger values for positive indicators (e.g., SDG 1.3.1 Unemployment insurance coverage rate), smaller values for negative indicators (e.g., SDG 1.5.1 Number of people affected by natural disasters), and closer to the middle threshold for moderate indicators (e.g., SDG 5.1 Proportion of female employees in employment). To ensure data comparability across the indicators, SDG indicators were rescaled from 0 to 100, where 0 represented the worst possible performance, and 100 described the optimum performance (Zhang et al., 2022a). The rescaling formulas as follows:

$$\text{Positive}: x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times 100 \quad (1)$$

$$\text{Negative}: x' = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \times 100 \quad (2)$$

$$\text{Moderate}: x' = \begin{cases} 100 - \frac{x_{\text{int}} - x}{\max\left(x_{\text{int}} - \min(x), \max(x) - x_{\text{int}}\right)}, x < x_{\text{int}} \\ 100 - \frac{x - x_{\text{int}}}{\max\left(x_{\text{int}} - \min(x), \max(x) - x_{\text{int}}\right)}, x > x_{\text{int}} \\ 100, x = x_{\text{int}} \end{cases} \quad (3)$$

where x' is the normalised value after rescaling, x is the raw data value, $x_{\max}$, $x_{\min}$ donate the upper and lower bounds, respectively, which are defined at the 2.5th percentile of the distribution. Each indicator distribution was censored so that all values exceeding the upper bound scored 100, and values below the lower bound scored 0 (SDR2021). x_{int} donates the optimal value, which is obtained by referring to relevant literature (Wu et al., 2022), while $\max(x)$ and $\min(x)$ are the maximum and minimum values of the original data for the moderate indicator. After data normalisation, the variance inflation factor was used to exclude multicollinearity indicators. Considering the initial datasets' degree of missing and reliability, a total of 65 SDG indicators were used for the study.

Directional interactions among SDGs. Considering the spatio-temporal non-stationarity of the SDG indicators, we used a spatio-temporal geographically weighted regression (GTWR) to analyse the influence of one SDG indicator on the other based on the normalised data. Most SDG networks constructed in the current study are undirected weighted networks (Lusseau and Mancini, 2019) or directed unweighted networks (Dörgo et al., 2018). GTWR method can obtain the direction and strength of interaction between SDG indicators between SDG indicators. The GTWR method can obtain the causal direction and intensity among SDG indicators, where the causal intensity among SDG indicators is determined by the regression coefficient of GTWR. The regression coefficients of this model were descriptors of the spatio-temporal relationship between SDG indicators and varied with the spatio-temporal location (Fotheringham et al., 2015; Huang et al., 2010). Positive regression coefficient values indicated a positive influence of independent variable indicators on dependent variable indicators, overall implying a synergistic effect. In contrast, negative values signified that one indicator hindered the other, implying a trade-off effect. The greater the coefficient's absolute value, the stronger the synergy or trade-off

between the indicators. The GTWR model can be expressed as:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_{k=1}^{d} \beta_k(u_i, v_i, t_i)X_{ik} + \varepsilon_i \quad i = 1, 2 \cdots n \quad (4)$$

where Y_i is the dependent variable for the observation i; X_{ik} is the kth explanatory variable for the observation i. (u_i, v_i, t_i) represents the space-time coordinates of observation i; u_i and v_i are the projected spatial coordinates, whereas t_i is the projected temporal coordinate. ε_i is the error term; $\beta_0(u_i, v_i, t_i)$ is the intercept value; $\beta_k(u_i, v_i, t_i)$ is the regression coefficient, which is a parameter measuring the influence of the explanatory variable X_{ik} on dependent variable Y_i.

Through an augmented Dickey-Fuller test and a spatial autocorrelation for a significant spatio-temporal non-stationarity test, we conducted a spatio-temporal geographically weighted regression of SDG indicators for each province in China from 2000 to 2020. Regression was run 65 times. Each regression analysis used a specific SDG indicator as the dependent variable. The remaining indicators served as independent variables. A total of 651 observation items in 21 years of data from 31 provinces were used for each regression. We calculated the coefficient matrices for the indicator-level interactions for each province year by year. We utilised the adjusted R^2 to assess the fit and effect of the regression model. In general, the closer the adjusted R^2 is to 1, the better the fit. Adjusted R^2 greater than 0.8 were considered credible. To avoid over-interpretation, a coefficient threshold was determined by several experiments to best fit the resulting network structure with the desired property. Coefficient values greater than 0.1, less than -0.1, and between -0.1 and 0.1 indicated synergy, trade-off, and non-significance of the interactions between the two indicators, respectively.

Network analyses. We constructed 1302 complex networks of SDG synergy and trade-offs for each province in China, year by year (Fig. S1) based on the coefficient matrices of the indicator-level interactions using the Networkx package in Python. The established complex networks were directionally weighted due to the directionality of the spatio-temporal geographically weighted regression coefficients. In the network, the nodes denoted SDG indicators, the directional link from node X to node Y represented the impact of node X on node Y, and the weight of the link was determined by the regression coefficient. The absolute value of the coefficient size represented the interaction intensity between nodes. The betweenness centrality of a link was calculated as the sum of the fraction of all pairs of shortest paths that pass through (Ulrik, 2008). The greater the betweenness centrality of a link, the more important it becomes in the network (Qi et al., 2017).

We selected the important links with the top 300 betweenness centrality as sub-networks. We identified the closed loops in the sub-networks using the simple cycle algorithm.To perform an in-depth discussion of the inner mechanism, we considered simple loops with 3 to 5 nodes in the search for loops. Furthermore, due to the long search time of complex networks, we set a 3-hour time limit for each province's annual network detection loop. We counted the frequency of indicator-level nodes in the critical loops that appeared more than thrice.

After constructing SDG synergistic and trade-off networks, we calculated the out-degree and in-degree of each SDG indicator in the networks at the provincial level in China. We identified the active and passive relations among SDGs using the network node's out-degree and in-degree (Breu et al., 2021; Messerll, 2000; Pham-Truffert et al., 2020). The node's out-degree and in-degree reflect its degree of influence on other nodes and the influence other nodes have on it, respectively (Dawes, 2022). There is no a priori justification for favouring one measure with greater weight than another (Xu et al., 2020). Therefore,we calculated the

out-degree and in-degree among goals by arithmetic averaging the corresponding indicators. When the active ratio was greater than 1, the SDG was defined as having an active relation, pushing more effects on other SDGs. If an SDG is more active in the network, it means it has a greater chance of having a stronger positive or negative impact on other SDGs in the network. Conversely, when the active ratio is less than 1, the SDG is defined as having a passive relation (Fig. 1) (Breu et al., 2021; Messerll, 2000; Pham-Truffert et al., 2020). Suppose an SDG is

more passive in the network. In that case, it is more unstable and dependent on other SDGs, as well as more susceptible to positive or negative influences from other SDGs.

We calculated the overall change of the SDG with active and passive relations according to Eq. (5). The SDG with the largest overall change was defined as the typical goal for active and passive changes for each province in synergy networks (Table S2) and trade-off networks (Table S3).

$$C_{t_1 \to t_2} = \sqrt{\left(x(t_2) - x(t_1)\right)^2 + \left(y(t_2) - y(t_1)\right)^2} \qquad (5)$$

where $C_{t_1 \to t_2}$ is the overall change of the SDG from year t_1 to year t_2; x represents the active ratio of SDG in year t; y represents the interaction degree of SDG in year t. If an SDG has become active and has changed the most overall over the last 20 years, strengthening or controlling the development of it is more conducive to promoting the active development of other SDGs; if an SDG has become passive and has changed the most overall over the last 20 years, it is crucial to promote the development of this SDG by identifying what goals are specifically influenced by it.
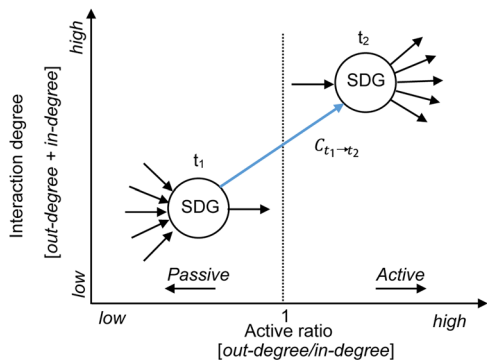

Fig. 1 Diagram of changes in active and passive relations among SDGs (Breu et al., 2021; Messerll, 2000; Pham-Truffert et al., 2020). The active ratio calculated by dividing out-degree by in-degree represented the degree of activity of each SDG. The interaction degree from the sum of out-degree and in-degree represented the degree of influence of an SDG's interaction with other SDGs.

Results

Offsetting effects of changes in synergies and trade-offs. Our results confirmed the existence of an offsetting effect of changes in SDG synergies and trade-offs in China over the last two decades. At the country scale, the number of indicator pairs for synergies and trade-offs remained largely stable from 2000 to 2020. However, the synergies indicators' and trade-offs were dynamic, with complex interchanges occurring over time (Fig. 2a and Fig. S2). Over the past 20 years, approximately 27% of trade-off indicator pairs changed to
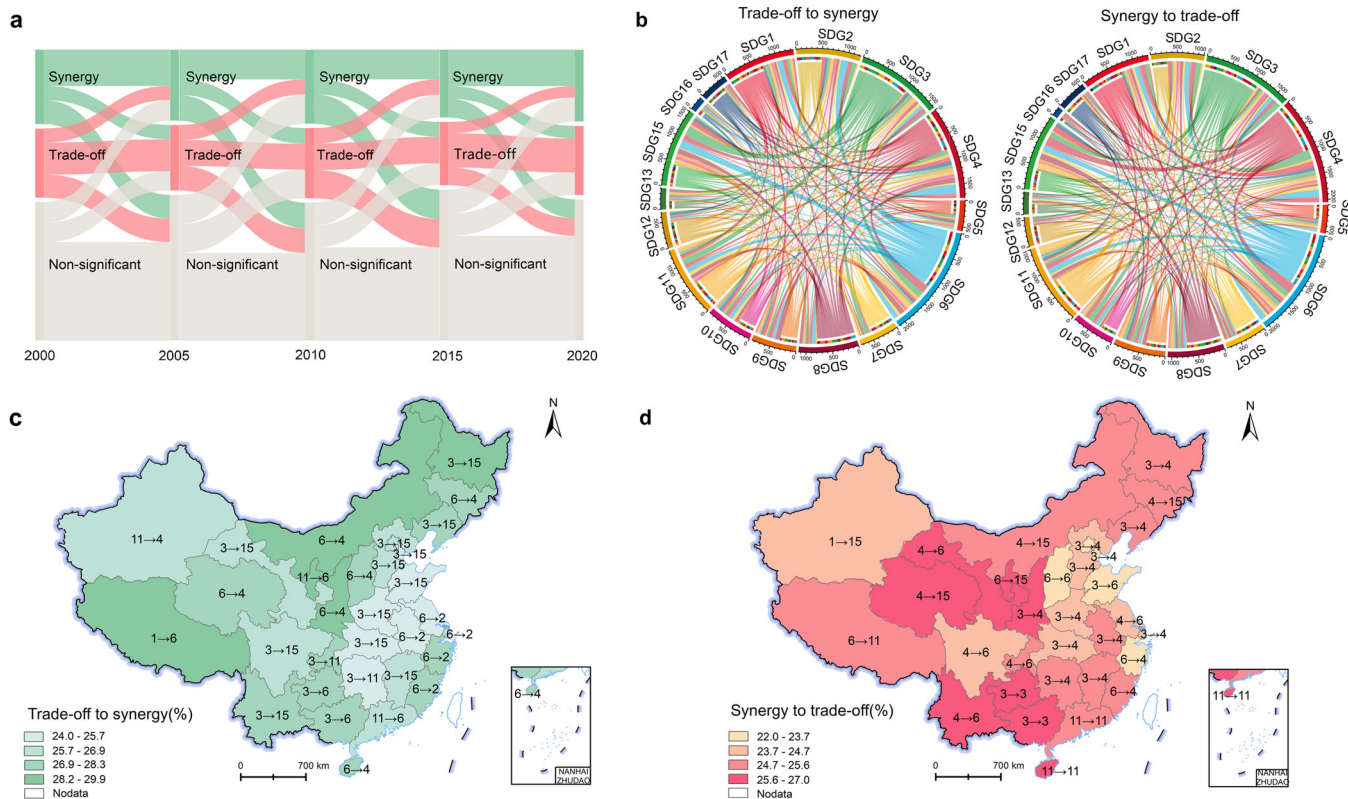

Fig. 2 The dynamics of SDG synergies and trade-offs in China from 2000 to 2020. a Transitions among synergies, trade-offs and non-significant at the country scale. **b** Chord diagram of transitions between trade-offs and synergies at the country scale. **c** Shifts from SDG trade-offs to synergies at the provincial scale. **d** Shifts from SDG synergies to trade-offs at the provincial scale. In **c** and **d**, the colour represents the proportion of SDG indicator pairs that changed between synergy and trade-off relations at the provincial scale. The labels indicate the typical SDG pairs with the largest number of changes in each province from 2000 to 2020.
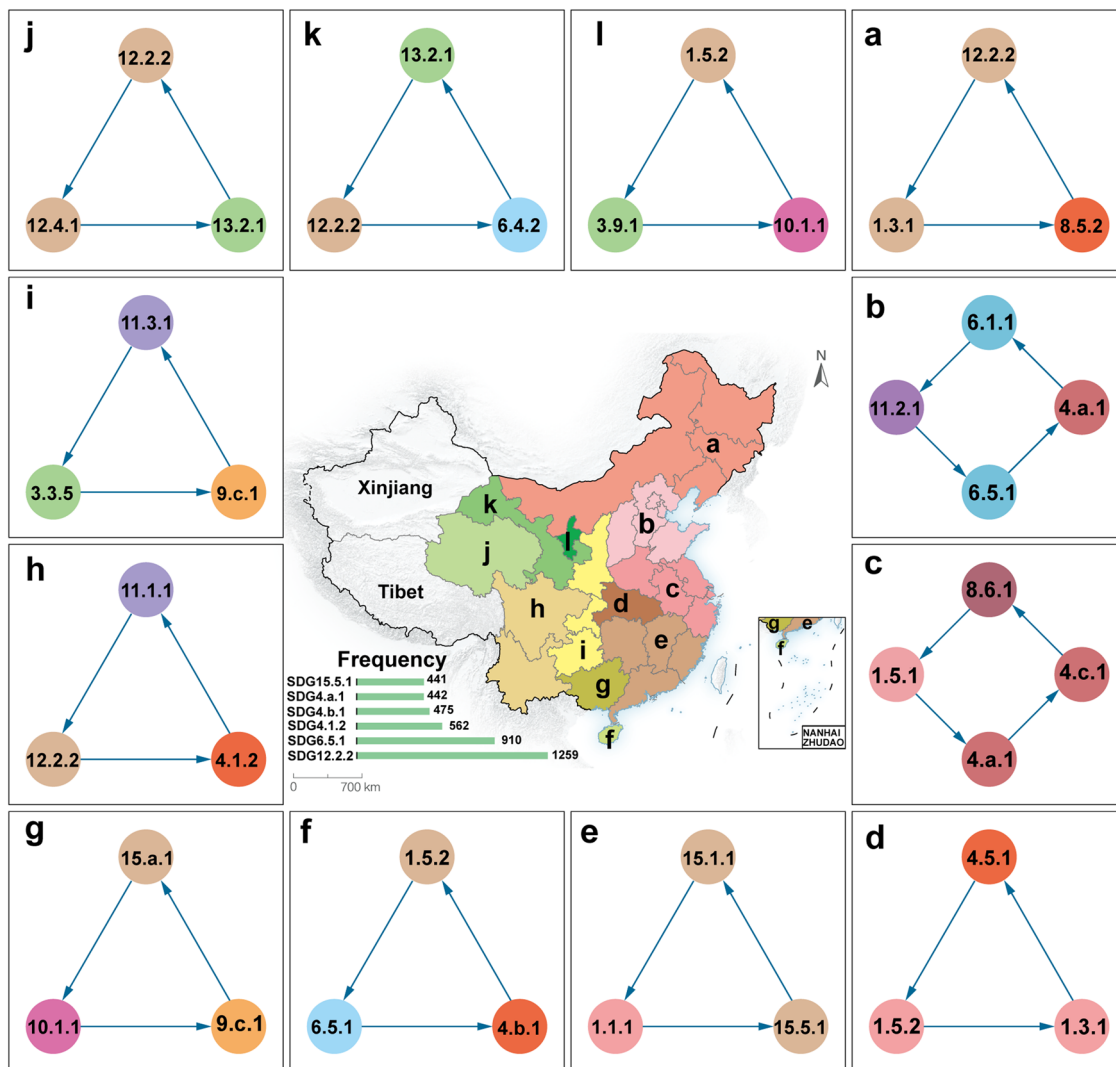
Fig. 3 Spatial patterns of typical virtuous cycles in China. The "**a–i**" symbols indicate the typical virtuous cycle corresponding to the region. The green bar chart represents the frequency of the top six indicators in critical loops.

synergies, and about 25% of synergistic pairs changed to trade-offs (Fig. 2a). Among them, the effect of SDG3 on SDG15 changed from trade-offs to synergies, accounting for a higher proportion. In contrast, its effect on SDG4 changed from synergies to trade-offs, with a higher proportion (Fig. 2b). These changes might be responsible for the offsets in newly generated synergies by the newly emerged trade-offs. That is, the newly generated synergy of SDG3 on SDG15 is offset by the newly generated trade-off of SDG3 on SDG4. Furthermore, we find that approximately 50% of the interactions between SDG indicator pairs have been non-significant in China over the past 20 years (Fig. 2a), indicating that the synergy and trade-off relationship in China is not an either-or relationship.

Additionally, our results demonstrated that the changes between SDG synergies and trade-offs had significant variations across provinces (Fig. 2c, d). The offsetting effect of the synergies of SDG3 on SDG15 by its trade-offs on SDG4 was more pronounced in the Northeastern and Central provinces of China. These observations signified that the beneficial effects of developing the terrestrial ecosystem through health promotion might be offset by its trade-off effects on education in these regions. Similarly, in the Eastern coastal region of China, the effect of SDG6 on SDG2 shifted from trade-offs to synergies while shifting from synergies to trade-offs on SDG4. This implied that the negative effect of clean water on education

might have masked some of its beneficial effects on food security. Meanwhile, we found that SDG3 and SDG11, while promoting SDG6, were inhibited by their internal indicators in Southern China. These observations emphasised the importance of resolving conflicts among indicators within the SDGs as well as promoting synergies among the SDGs.

Closed loops in SDG networks. Our results demonstrated closed loops in China's synergy networks (excluding Xinjiang and Tibet) but not in China's trade-off networks (Fig. 3). These loops provided an opportunity to mitigate the offsetting effects of trade-offs on synergies among SDGs over time. In Southeast China, a virtuous cycle consisting of SDG1.1.1 (eradicate extreme poverty), SDG15.5.1 (red list index), and SDG15.1.1 (forest cover rate) occurred several times (Fig. 3e). It illustrated that poverty alleviation policy had a positive synergistic effect on local terrestrial ecosystems. In return, the improvement of terrestrial ecosystems further promoted the eradication of extreme poverty. Common virtuous cycles were more likely to occur in neighbouring provinces and in consecutive years (Fig. 3 and Table S4). Therefore, integrated policies based on common self-reinforcing cycles can effectively contribute to developing a sustainable regional development.
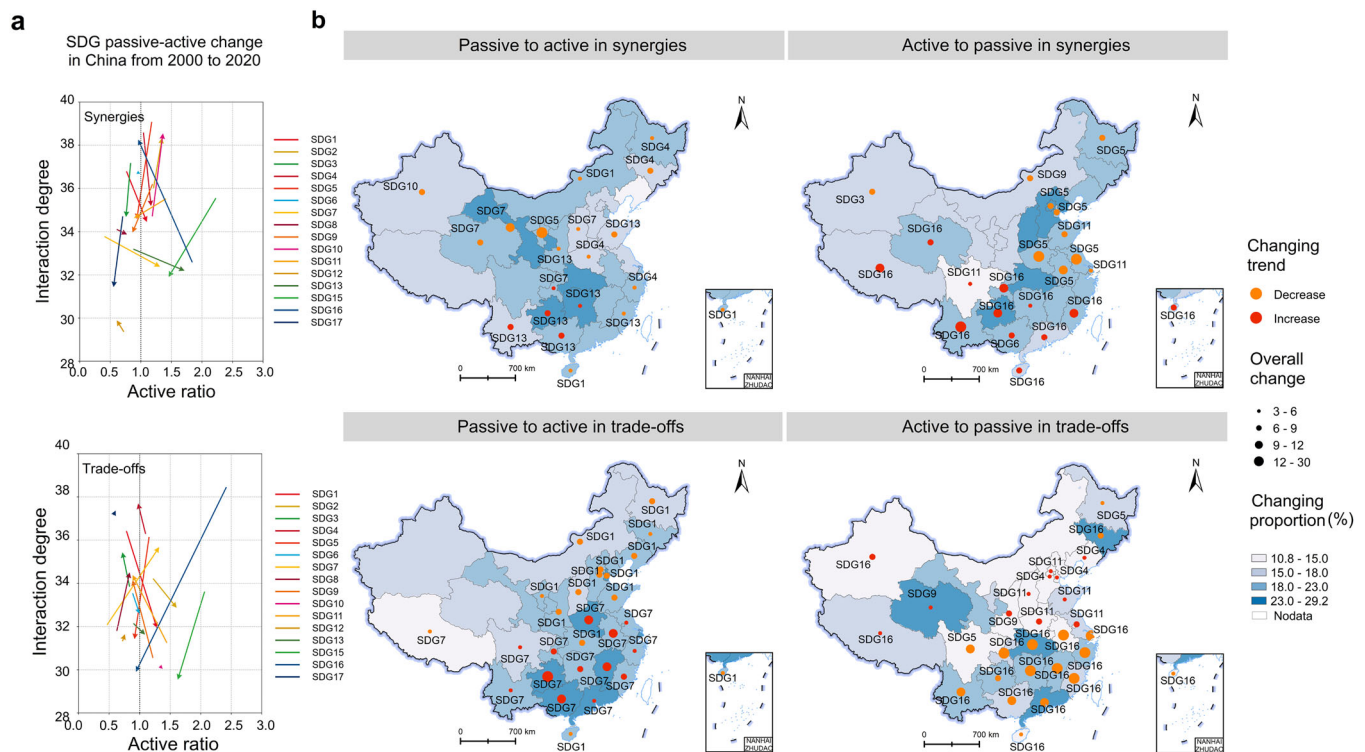
Fig. 4 Changes in active and passive relations among SDGs in China from 2000 to 2020. a At the country scale. **b** At the provincial scale. In **a**, the increase in the active ratio indicated that the SDG was more active on other SDGs. The increase in the interaction degree indicated the rise in the interactions of with other SDGs. In **b**, the background colour represents the proportion of indicators that changed between active and passive relations. The text labels represent typical goals of active-passive changes for the provinces. The colour of the dots reflects the trend of overall change of the typical goals. The size of the dots indicates the magnitude of the overall change of the typical goals.

Progress in one indicator in a virtuous cycle could automatically reinforce other indicators. Conversely, failure to progress in an indicator may trigger a vicious cycle where failures are multiplied across indicators. We identified the high-frequency indicators for virtuous cycles in China (Table S5), including SDG12.2.2 (domestic material consumption), SDG6.5.1 (water resource management), SDG4.1.2 (education completion rate), 4.b.1 (educational investment), 4.a.1 (educational facilities), and SDG15.5.1 (red list index). Prioritising the progress of high-frequency indicators in virtuous cycles, such as improving resource utilisation and water management, and increasing investment in education and ecological funding and its related facilities can multiply the positive systemic effects of the SDG system overall.

Changes in active and passive relations among SDGs. Although closed loops were not observed in China's trade-offs, the active-passive relations changed dramatically in the SDG synergistic and trade-off networks. At the country scale, we found that in China's synergy networks, approximately 19.1% of the indicators had converted from passive to active relations between 2000 and 2020. About 19.3% of the indicators changed from active to passive relations (Table S6). For China's trade-off networks, approximately 20.1% of the indicators were changed from passive to active relations between 2000 and 2020. Approximately 16.5% of the indicators changed from active to passive (Table S6). At the country scale, SDG1 and SDG7 changed from passive to active relations in both synergy and trade-off networks, implying that processes of these SDGs significantly influenced the other SDGs. In contrast, SDG5 and SDG16 changed from active to passive relations in both networks, demonstrating the vulnerability of these SDGs (Fig. 4a).

Our study also highlighted that the changes in the active and passive relations of the various SDGs from 2000 to 2020 were spatially variable at the provincial scale (Fig. 4b). In the synergistic network, we found that from passive to active relations, SDG13 (climate action) and SDG4 (quality education) were the typical goals in Southern China and Northeast China, respectively, implying that progress in these goals could lead to improvement in more SDGs. Meanwhile, some synergy relations changed from active to passive, mainly SDG16 (peace, justice, and strong institutions), SDG5 (gender equality), and SDG11 (sustainable cities and communities) in most provinces. It signifies that the progress toward these goals was more dependent on the progress toward the other SDGs.

Additionally, in the trade-off network, SDG1 (no poverty) was the typical goal that changed from passive to active in the Northern provinces but with decreasing trade-off intensity. In contrast, in the South, SDG7 (affordable and clean energy) was the predominant goal that shifted from passive to active with increasing trade-off intensity. These results suggested that addressing the trade-offs for SDG1 and SDG7 with other goals remains an important task for the future. However, for the change from active to passive trade-offs, we found that SDG11 and SDG16 were the typical goals in most provinces and were similar to those in the synergistic network. This result reflected that while SDG11 and SDG16 were important nodes in the network that were dependent on the progress of other SDGs, they could delay the transmission of trade-off relations in the networks.

Discussion
By combining causal diagnosis and network analysis methods, our study quantified the SDG interactions for 31 Chinese

provinces at the indicator level from 2000 to 2020. Our results revealed the offsetting effects of SDG synergies and trade-offs interconversion . We provided novel insights and innovations for addressing trade-offs and promoting synergies.

First, we defined synergy and trade-off relationships based on the causal relationships between SDGs. Most articles explore the synergies and trade-offs between SDGs by correlation analysis that could not identify the directionality of the interactions (Bali Swain and Ranganathan, 2021; Anderson et al., 2022; Kroll et al., 2019; Pradhan et al., 2017; Warchold et al., 2021). We advanced the current status by identifying the causal direction and strength between SDGs using the GTWR method. Based on the SDG causal network, the spatial and temporal changes in the causal interactions of SDGs are explored in the paper.

Second, we found that while the number of synergies and trade-offs among SDG indicators in China remained largely stable over the years 2000 to 2020, SDG interactions underwent complex changes with spatial and temporal variations. Among them, the effect of SDG3 on SDG15 in Northeastern and Central China changed from trade-off to synergy from 2000 to 2020. This change might be attributed to the growing popularity of green and low-carbon lifestyles, which contributed to better air quality and improved terrestrial ecosystems (Shi et al., 2022; Zhang et al., 2021a, 2021b). Similarly, in the Eastern coastal zone, the relationship between SDG6 and SDG2 shifted from trade-offs to synergies, possibly attributed to the role of control and management of coastal water pollution on the improvement of water quality and food safety (Wang et al., 2022). Nonetheless, these benefits might be offset by the emerging trade-offs between SDG3 and SDG4. This was possibly due to the potential conflict between investments in education and health care (Li and Huang, 2009; UN Department of Economic and Social Affairs, 2012), and the effect of the new crown epidemic on the education system and international visits (Mok et al., 2021). These results illustrated the complexities of SDG interactions. They emphasised that the offsetting effects of changes in SDG synergies and trade-offs might impede achieving SDGs in any country or region. Therefore, to address this offsetting effect, we leverage virtuous cycles, promote active synergy and inhibit active trade-offs in the SDG network from mitigating beneficial synergies from being offset by harmful trade-offs among SDGs.

Third, we identified closed loops in the SDG synergy and trade-off network in China and its 31 provinces to explore effective ways to address trade-offs and promote synergies. An important and interesting finding of our study was that China's provinces had closed loops in the synergistic network, but not in the trade-off network. The discovery of virtuous cycles offers the possibility of finding specific paths for advancing SDGs in China. High-frequency indicators in virtuous cycles are potential entry points for policy development that can efficiently facilitate the multiplication of positive effects in virtuous cycles. Likewise, we found that several spatially adjacent provinces shared common virtuous cycles in consecutive years. This finding was consistent with existing research that demonstrates that China's urban spatial form tends to develop into urban agglomerations (Han et al., 2021).

Our study further identified high-frequency indicators, including SDG12.2.2, SDG6.5.1, SDG4.1.2, 4.a.1, 4.b.1 and SDG15.5.1 in China. Prioritising SDG12 (responsible consumption and production) could reduce the consumption of natural resources like wood, promote water security, and have long-term benefits for food security (Zhang et al., 2022a). Enhancing water resources management (SDG6.5.1) has the potential to improve water resource efficiency, protect the ecology, and promote economic development (Wang et al., 2018). Promoting quality education (SDG4) could improve the health of the population (Huang, 2022) and increase the drive for technological innovation

(Zhou and Luo, 2018). In addition, achieving SDG15 (life on land) through strengthening nature reserve management and policy guidance (Cui et al., 2021), protecting native forests, and improving the structural complexity of terrestrial ecosystems (Hua et al., 2016; Zhang et al., 2021a, 2021b) could promote biodiversity recovery for better environmental improvement and green economic development.

Fourth, while there were no closed loops in the SDG trade-off networks, we highlighted the dynamics of the active-passive relations among SDGs to deepen our understanding of SDG interactions. Previous studies have established a typology of SDGs that act as buffers and multipliers by defining the activity ratio of SDGs to reflect the active and passive relations among SDGs (Breu et al., 2021; Pham-Truffert et al., 2020). However, these studies constructed the SDG networks based on expert experience gleaned from a systematic literature review (Breu et al., 2021; Pham-Truffert et al., 2020). To address this limitation, we used reliable statistical data and causal diagnostics to reduce the uncertainty of such analyses while also providing simultaneously offer the possibility of uncovering the spatio-temporal variability of the active-passive relations.

Our study revealed that SDG13 (climate action) in Southwest China and SDG4 (quality education) in Northeast China had typically changed from passive to active relations in the synergy network. This finding confirmed that climate actions could reduce the economic losses of disasters and contribute to achieving other SDGs (Guo et al., 2019). In addition, accelerating education development can help to stimulate employment, raise incomes, and advance the progress of other SDGs (Vladimirova and Le Blanc, 2016). These changes can be viewed positive signs towards achieving China's SDGs. However, SDG1 (no poverty) in Northern China and SDG7 (affordable and clean energy) in Southern China changed from passive to active relations in China's trade-off networks. This meant that solely pursuing these goals in isolation without considering their trade-off impacts on the other goals might jeopardise their ability to progress smoothly in China. Therefore, maintaining stable implementation and optimisation of poverty alleviation policy is critical in promoting sustainable development in China (Liu et al., 2021). Similarly, formulating plans to promote clean energy development must consider its negative impact to minimise trade-offs with other SDGs (D'Odorico et al., 2018; World Wide Fund for Nature, 2018; Zahoor et al., 2022; Zhang et al., 2022c).

In addition, SDG11 and SDG16 were susceptible to synergies and trade-offs with other SDGs in China. Existing studies show that SDG11 and SDG16 are prone to changes in the local economy level, infrastructure development, and industrialisation (Liu et al., 2021). The development of these SDGs requires rational planning of the local economy by policymakers to achieve orderly construction, moderate development, and efficient city operation. In addition, the trade-off effects generated by other SDGs must be integrated when formulating policies to efficiently promote SDG11 and SDG16 in China.

Conclusions
In conclusion, our study observed the offsetting effect of changes in SDG synergies and trade-offs over time and their spatial differences. To address these effects, we identified the virtuous cycle and the high-frequency indicators as crucial policy development criteria to accelerate SDG development. Exploring the dynamics of the active and passive types of SDG revealed that policies cannot be static, and the formulation of SDG development policies must be adaptive in the face of changing conditions. Enhancing the development of active synergistic SDGs while curbing the negative impact of active trade-off SDGs can contribute to overall SDG sustainable development. Promoting the

steady development of quality education, strengthening education funding, developing education infrastructure and climate regulation are all measures that can effectively lead to the development of other SDGs. Policies that promote no poverty and clean energy proactive development need to be designed to curb the trade-off effects of these proactive trade-off SDG goals on other SDGs. For example, when developing policies to build clean energy facilities in China's provinces, it is necessary to consider whether these clean energy facilities are compatible with local natural conditions along with their impact on the local ecological environment. Leveraging virtuous cycles and inhibiting active trade-offs are beneficial to control beneficial synergies from being offset by harmful trade-offs among the SDGs. It is recommended that provinces with the same virtuous cycle formulate a unified SDG development policy that can efficiently promote the common regional development while reducing development costs. By promoting the transition from material-oriented consumption to service-oriented consumption in China, strengthening the unified management of water resources, and solidly promoting the high-quality development of education, and other measures to promote the steady development of high-frequency indicators, which in turn will accelerate the positive flow of the virtuous cycle network in China and facilitate the overall sustainable development of China's SDG.This study deepened our understanding of SDG synergies and trade-offs and facilitated evidence-based policy-making. In the future, we will further update the latest SDG data to analyse the causal relationships among SDGs in China's provinces and explore the impact of the COVID-19 pandemic on the process of achieving SDGs for each province in China. Moreover, we will collect city-level SDG data and analyse the synergistic and trade-off relations at the city-level SDG in China, the virtuous cycle and the future simulation assessment of SDGs. Our results could facilitate the achievement of the 2030 Agenda in China within a limited time frame, rescuing it from failing. Meanwhile, our analytical framework could also provide lessons for other countries or assessments at different scales.

Data availability

The provincial data used in this study can be obtained from the National Bureau of Statistics via the website (http://www.stats.gov.cn/). The datasets generated during and/or analysed during the current study are not publicly available due to confidentiality issues but are available from the corresponding author on reasonable request.

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Author contributions

MC and MC conceived the study and prepared the manuscript. YL, YB and LC performed the data analysis. JZ, YC, PP, HG, BF, ZS, ZX, RZ, MEM and GL contributed to the data interpretation and revision.

Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

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Additional information

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