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Synergizing Sustainable Development Goals for Disaster Risk Reduction: Lessons from China

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Qinhan Ye: Data curation, Formal analysis, Methodology, Writing – original draft. **Junze Zhang:** Conceptualization, Funding acquisition, Writing – original draft, Writing – review & editing. **Weiyi Sun:** Data curation, Methodology. **Shihui Gao:** Data curation, Visualization. **Shuai Wang:** Funding acquisition, Supervision, Writing – review & editing. **Prajai Pradhan:** Conceptualization, Formal analysis, Writing – review & editing. **Bojie Fu:** Formal analysis, Writing – review & editing.

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Abstract

Integrating progress towards the Sustainable Development Goals (SDGs) with disaster risk—potential economic losses from natural hazards—reduction remains a critical yet daunting challenge. To address this knowledge gap, we evaluated the spatiotemporal dynamics of disaster risk across China, using a modified National Risk Index framework, with a focus on social vulnerability (i.e., susceptibility to disasters) and community resilience (i.e., capacity to adapt and recover). Spearman correlations were used to examine the magnitude and direction of relationships between SDG progress and disaster risk. Our results show that, nationally, China's disaster risk index fluctuated from being medium (11.62) in 2000 to low (3.83) in 2010, before rising again to a medium level of risk (16.22) in 2021. Crucially, the overall dynamic relationship between SDG progress and disaster risk is nonlinear. With greater progress in achieving SDGs, the disaster risk declines at first but then rebounds at the national scale, or it stabilizes at the provincial scale. We find that this pattern is driven chiefly by social vulnerability, given its similar trend to SDG progress, while community resilience increases linearly with SDG progress. Further, poverty reduction (SDG1) and quality education (SDG4) emerged as primary risk mitigators in the national scale analysis, contrasting sharply with the substantial variation in impactful SDGs among provinces. Hence, this study argues for a regionally tailored SDG prioritization strategy to prevent escalating potential economic losses from disasters triggered by natural hazards, emphasizing the dual optimization of sustainable development and risk governance frameworks.

Keywords: Disaster risk; Natural hazards; Nonlinear dynamics; Resilience; Sustainable Development Goals; Vulnerability

1. Introduction

The increasing frequency and intensity of natural hazards, such as floods, droughts, and earthquakes, caused by extreme weather events or geological processes exacerbated in part by climate change and anthropogenic factors, is severely impeding global sustainable development [1]. Over the past decade alone, the total economic losses due to all geophysical-, climate-, and weather-related disasters are about \$170 billion per year, on average, and rising [2]. Worldwide, disaster events increased from 400 occurring in 2015 to 560 in 2021, a number expected to be 40% higher in 2030 [2]. To address this monumental and escalating challenge, the United Nations not only launched the Sendai Framework for Disaster Risk Reduction (SFDRR) in 2015, but also embedded issues tied to disaster reduction in the 2030 Agenda for Sustainable Development (hereon, the “2030 Agenda”) [3,4]. Both strategies emphasize the innate, integral linkage between sustainable development and disaster risk (i.e., potential economic losses stemming from disasters triggered by natural hazards) underscoring why it is imperative to attain the Sustainable Development Goals (SDGs) sooner while also strengthening the disaster response capabilities of countries around the world [5,6].

Although the 2030 Agenda and SFDRR were launched concurrently, in terms of their practical implementation the SDGs have garnered far greater attention [7]. Much effort has gone into assessing progress towards SDGs [8–10], exploring their interconnections [11–13], and refining models to find optimal pathways of achieving them [14–16]. But this pursuit of SDGs may be disrupted by various—usually unpredictable—events, natural hazards in particular, such as floods, droughts, and hurricanes [17]. Given this persistent threat, the critical interplay between advancing SDGs and disaster risk reduction (DRR) demands broader attention. However, this important relationship remains surprisingly underexplored in current research [6,18].

Some scholars have criticized that just a few SDGs emphasize disaster risk-related aspects,

namely SDG1 (No Poverty), SDG9 (Industry, Innovation and Infrastructure), SDG11 (Sustainable Cities and Communities), and SDG13 (Climate Action) [6,19]. These goals typically reduce disaster risk via poverty reduction, risk-sensitive infrastructure, urban adaptation, or climate-related preparedness. Still, their corresponding evaluation indicators are rather simplified and may not fully capture the breadth and depth of disaster-related impacts. For example, despite being designed to mitigate the effects of climate-related disasters, past assessments of SDG13 have focused mainly on carbon emissions, thus deviating from the official indicator framework and failing to fully gauge the impact of disasters in terms of casualties and economic losses [9].

The relationship between SDGs and disaster risk has drawn recent interest and investigation [20]. For instance, some studies have illustrated how macro-scale policy instruments and public investment frameworks can be aligned with both SDG implementation and disaster preparedness objectives [21,22]. Other work has proposed methodological tools to evaluate how adaptation strategies can contribute to multiple SDG targets [23], or developed risk indices that integrate DRR with the SDGs and SFDRR frameworks [19]. While these studies certainly offer valuable conceptual insights and useful frameworks, most remain theoretical or qualitative in nature, or focus on national policy alignment and specific sectoral interventions. Quantitative empirical evidence on whether SDG progress actually contributes to DRR—particularly across spatial scales—remains scarce.

To move beyond a mainly conceptual discourse, we argue that robust quantitative analysis is essential: for assessing not only disaster risk but also its relationship with sustainable development outcomes. Various methodological approaches have been developed to assess disaster risk. Some of these rely on geospatial and statistical techniques—such as remote sensing, hazard mapping, and probabilistic modeling—to estimate exposure and potential loss patterns [25–29]. Others instead focus on the construction of composite risk indices, which

integrate multidimensional data through the use of standardized indicators and weighting schemes. These index-based approaches often rely on expert judgment or stakeholder input to select relevant indicators and define their relative importance [26,27]. A variety of disaster risk indices have been introduced over the past two decades to support risk-informed decision-making, disaster preparedness, and sustainable development planning [19,27,28]. Among them, the national risk index (NRI) devised by Zuzak et al. [29,30], provides a more comprehensive structure by incorporating expected annual losses, social vulnerability, and community resilience. This multidimensional framework allows for and fosters a more nuanced, actionable understanding of disaster risk [31]. Further, the NRI also enables consistency in application at both national and subnational scales, which is crucial for localized DRR planning and cross-regional comparisons.

To quantitatively explore the relationships between SDGs and disaster risk, our study focused on China's 31 mainland provinces (excluding Hong Kong, Macao, and Taiwan). We first refine the NRI to analyze their disaster risk from 2000 through 2021. By comparing these results with the parallel SDG progress over the same period, their relation could be elucidated. In China, over 70% of its cities and 50% of its population lie in areas vulnerable to natural hazards like geological, hydrological, and meteorological ones [32]. In 2024 alone, disasters triggered by natural hazards caused a direct economic loss of 401.11 billion RMB and impacted 94.13 million people. While there are fewer affected individuals than in the previous five years, direct economic losses have sharply risen [33]. Since its launch in 2009, the Integrated Research on Disaster Risk (IRDR) program has facilitated the establishment of a platform and network for disaster risk research in China, supporting the design of implementation pathways for the SFDRR [34]. Furthermore, China has dedicated substantial effort to attain the SDGs [35], this providing an invaluable opportunity to analyze SDG progress and DRR in tandem. In a broader context, a detailed knowledge of China's approach to balancing DRR and sustainable

development could provide useful insights for other countries and regions.

This study addresses three pressing questions: (1) What are the temporal and spatial variation characteristics of China's disaster risk from 2000 to 2021? (2) What is the relation between disaster risk and SDG progress at two scales, national and provincial? (3) Which SDGs are more effective at reducing disaster risk at either or both scales? Our main objective is to develop a data-driven framework for integrating DRR with the SDGs, one with practical implications for risk-informed policymaking. Doing so is timely as it provides policymakers with an interdisciplinary analytical tool to better integrate disaster risk management and sustainable development strategies.

2. Methods

2.1. Calculation of the disaster risk index

Our study builds upon the theoretical and methodological foundation of the NRI, which was designed to serve as a nationwide, comparable measure of disaster risk at multiple scales, where disaster risk is defined as the potential economic losses due to disasters triggered by natural hazards [31]. The NRI operationalizes disaster risk as a composite function of expected annual loss, social vulnerability, and community resilience, providing a scalable, index-based framework for assessing levels of relative risk across geographic units. It is calculated as follows:

$$\text{National Risk Index (NRI)} = \text{Expected Annual Loss} \times \frac{\text{Social Vulnerability Index}}{\text{Community Resilience Index}} \quad (\text{Eq. 1})$$

This formula reflects the current broader consensus in disaster risk science and policy—articulated in the SFDRR in particular—that risk arises from not only hazard exposure, but also from the underlying social and institutional capacities that shape a community's ability to cope with, and recover, from disasters [4].

Although expected annual loss remains a key component in quantifying the potential

economic impact of hazards, it largely reflects hazard frequency, exposure, and asset valuations [29]. As such, it provides a necessary but insufficient picture of disaster risk—especially in contexts marked by unequal development and adaptive capacity [36]. Our study adopts the tripartite structure of the NRI as a foundation while placing particular analytical emphasis on social vulnerability and community resilience.

Social vulnerability refers to the susceptibility of individuals and communities to disaster-induced harm, as shaped by socioeconomic inequalities, demographic patterns, and limited access to social services, affecting their capacity to anticipate, respond to, and recover from disasters. Following Flanagan et al. [37], the Social Vulnerability Index integrates multiple indicators—including income, age, education, housing conditions, and household structure—across several domains. In the NRI, these indicators are aggregated to yield a composite measure of relative vulnerability across counties [30].

Community resilience, in contrast, denotes the capacity of a given community to absorb, adapt to, and recover from disaster-induced harm, reflecting both its physical infrastructure and social capital [38]. The Community Resilience Index used in the NRI entails six dimensions—social, economy, institution, infrastructure, environment, and community [30]. Higher resilience scores are presumed to mitigate the adverse impacts of both frequent and low-probability disasters.

By foregrounding these two aspects, our proposed framework moves beyond a hazard-centric approach toward a people-centered, systemic understanding of disaster risk. This approach is especially critical for identifying risk asymmetries in rapidly transforming societies, where formal exposure may remain constant, yet vulnerability and resilience likely vary substantially across space and time [39].

Each component was first normalized to a [0,1] scale to ensure comparability across provinces. These normalized scores were combined, with their resulting composite value then

linearly rescaled to a range of 0 to 100, where a higher score indicates greater disaster risk. To derive the EAL, we used the multi-hazard assessment approach developed by Zuzak et al. [30], which incorporates hazard frequency, asset exposure, and historical loss rates. To ensure robustness, the estimates were further validated against historical disaster loss data [29]. Publicly available datasets were used to calculate the SVI and CRI, by following standard procedures, with data normalized, aggregated across subdomains, then compiled into single-index values representing the relative vulnerability and resilience levels, respectively (see Supplementary Material). After generating the risk scores, they were categorized into five qualitative risk levels: very low, low, medium, high, or very high. These were recalculated yearly based on the annual distribution of risk scores, thereby allowing for temporal comparisons while maintaining sensitivity to shifts in national patterns. Consequently, some provinces having the same numerical score may fall into different categories across years, depending on their overall risk distribution for that given period.

2.2. Indicator selection and data sources

Here, the methodology of the NRI was adopted and modified to assess the disaster risk across mainland China [29,30]. Specifically, indicators for the social vulnerability index and the community resilience index came from widely used indicator frameworks [37,38] and the published literature [26,28]. When choosing indicators, besides their data availability, we wanted to ensure both their academic rigor and broad applicability across different regions of China. In the preliminary selection, we identified 37 and 14 indicators of community resilience and social vulnerability, respectively. To check for potential collinearity, we ran a set of Spearman correlations on pairs of community resilience indicators, and likewise for the social vulnerability indicators. For indicator pairs with a correlation coefficient > 0.7 , we retained the indicator less correlated with other indicators. In this way, a final total of 33 indicators were

gleaned, consisting of 22 community resilience and 11 social vulnerability indicators. Details about the indicator framework, its data sources, and periods covered are provided in Table S1. Additionally, some indicators for community resilience or social vulnerability may overlap with certain SDG indicators. Such overlap was perhaps unavoidable and occurs because a given indicator could have different implications when evaluating different indices; for example, the internet penetration rate may reflect regional cooperation (SDG17), or it may indicate the resilience of community facilities.

As noted in subsection 2.1, the accuracy of Zuzak et al. [30]’s assessment of expected annual losses is evaluated via comparison with historical loss data. As well, the average annual loss is commonly used to estimate long-term losses from disasters [40]. So, to streamline the expected annual loss computation, here we utilized historical economic loss data for the expected annual loss estimation. Further, to enable a comparative analysis of disaster losses between economically advanced and less developed regions [41], the expected annual loss was assessed using the multi-year average ratio of direct economic loss to GDP for the 2000–2021 period. The expected annual loss was used as a constant when calculating the annual disaster risk index for China in 2000–2021. Hence, as per Eq. 1 above, community resilience index and social vulnerability index are the core components of China’s disaster risk index, hereon referred to as RV-DRI.

To ensure the statistical reliability, general applicability, and currency of the dataset, we mainly rely on official statistics from various sectors in China to obtain its constituent data (Table S1, S2). Overall, 12 bona-fide sources of statistics, including the *China Statistical Yearbook*, the *China Health Statistical Yearbook*, and the *China Affairs Statistical Yearbook*, were utilized in this study. We also utilized data from several published studies, including the provincial-scale Gini coefficient for China, as reported by Tian [42], and the proportion of land under cultivation, as derived from the China Land Cover Dataset (CLCD) [43]. Data for the

SDG index and individual SDG scores came from Zhang et al.'s calculations [13]. Because scores for SDG14 (Life below Water) are irrelevant in China's 20 inland provinces, so that goal was excluded from the formal analysis. The historical data for each indicator came from the 31 mainland provinces (excluding Hong Kong, Macau, Taiwan) and spanned 2000 (or the earliest available data) to 2021 (the most recent year with data available for most indicator variables). Specifically, we obtained national scale data from compiled datasets, rather than aggregating data from the provincial scale.

2.3. Data processing

Using Eq. 1, we combined the social vulnerability index, community resilience index, and expected annual loss to derive the RV-DRI. To determine community resilience and social vulnerability indices, we modified their respective methodologies used in previous research [37,38]. Their detailed calculations can be found in the Supplementary Materials. For the percentile-based classification of RV-DRI, social vulnerability index, community resilience index, and expected annual loss, for each we employed 2000–2021 data from each province [44]. To draw out distinctions contained in the data, the five defined percentiles (Table 1) were distributed unevenly [45].

Because they are simple yet also robust, the nonparametric Mann–Kendall trend test and Theil-Sen median slope are often used to detect trends in time series data [46]. When the Mann–Kendall test statistic has a P -value < 0.05 , this indicates a detected statistically significant trend, while the Theil-Sen median slope (β) value conveys the magnitude of that trend. Both methods were used here to discern temporal trends in the RV-DRI, social vulnerability index, and community resilience index at the national scale.

Table 1 Numerical ranges for the ratings of the RV-disaster risk index (RV-DRI), social vulnerability index, community resilience index, and expected annual loss, based on percentiles

of China's provincial data (from 2000 to 2021).

Rating	Percentile ranges of rating	RV-DRI	Social vulnerability index	Community resilience index	Expected annual loss
Very low	0–15%	0–1.74	0–15.0	20.69–30.57	0–5.52
Low	15–35%	1.74–7.59	15.0–35.0	30.57–34.96	5.52–18.08
Medium	35–65%	7.59–20.99	35.0–65.0	34.96–39.75	18.08–29.39
High	65–85%	20.99–41.60	65.0–85.0	39.75–43.49	29.39–37.35
Very high	85–100%	41.60–91.68	85.0–100.0	43.49–63.47	37.35–80.80

2.4. Analysis of the relationships between disaster risk and SDGs

To explore the relation between the RV-DRI and SDG index, both linear and quadratic regressions were tested [13]. The regression model with the higher R^2 and greater statistical significance (i.e., lower P -value < 0.05) was retained in the main analysis. These preliminary results (see subsection 3.2 and Figure S1 for details) indicated that the relationship of SDG index to either RV-DRI or social vulnerability was better explained by quadratic fitting (higher R^2 , P -value < 0.05), whereas linear fitting better captured its relationship to community resilience index. Hence, we adopted quadratic fitting to infer relationships between the SDG index, RV-DRI, and social vulnerability index, but used linear fitting to examine the link between the SDG index and community resilience index. Higher-order regressions were avoided to maintain parsimony and interpretability. Given this study's data availability constraints, the fitting at the national scale was based on national-scale time series data, whereas the fitting at the provincial scale utilized multi-year average data from different provinces.

The Spearman correlation coefficient (r_s) is a non-parametric measure used to assess the monotonic relationship between two ranked variables, irrespective of whether they are linearly related [47]. We use r_s to quantify the relationships in temporal data between the SDGs and disaster risk, at both provincial and national scales. Since the RV-DRI and the social vulnerability index are negative indicators, meaning higher values indicate higher disaster losses or susceptibility to disaster-induced damage, whereas community resilience is a positive

indicator, with higher values signifying stronger capacity to recover quickly from disasters, hence, we convert the RV-DRI and social vulnerability index into negative values to align all indicators in a positive direction [48]. This transformation ensures consistent indicator directionality and permits a unified analysis and comparison in the correlation analysis with the SDG index. As such, a positive r_s signifies that SDG progress is associated with a decrease in disaster risk, while a negative r_s implies that SDG progress is linked to increase in disaster risk. The absolute value of r_s represents the interaction strength, with an $|r_s| > 0.5$ considered to be a relatively strong correlation. Finally, for an $r_s > 0$, we ranked the effect of SDGs for reducing the disaster risk based on the magnitude of r_s ; conversely, for an $r_s < 0$, we ranked the effect of SDGs for augmenting the disaster risk based on the magnitude of $|r_s|$.

3. Results

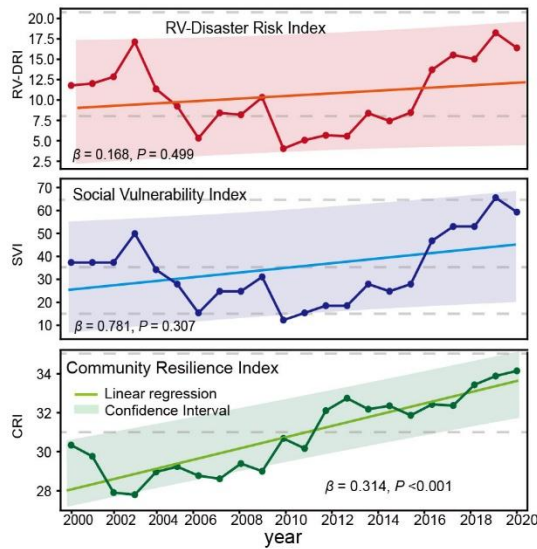
3.1. Spatio-temporal variation in the RV-DRI of China

At the national scale, our results revealed a statistically non-significant upward trend in the RV-DRI ($\beta = 0.168$, $P > 0.05$), in which the decadal pattern of disaster risk shifted over time, indicating fluctuating potential economic losses from disasters triggered by natural hazards. The RV-DRI initially decreased from a level of medium risk (11.62) in 2000 to low risk (3.83) in 2010, before returning to medium risk (16.22) in 2021. Over this ca. 20-year period, the susceptibility of social groups to disasters (i.e., social vulnerability) and the capacity of communities to adapt to and recover from adverse effects (i.e., community resilience) featured distinct patterns of change. Social vulnerability had a non-significant upward trend ($\beta = 0.781$, $P > 0.05$), falling from medium vulnerability (37.50) in 2000 to low vulnerability (12.50) in 2010, but then rising to medium vulnerability (59.38) again in 2021. Community resilience, in contrast, had a significant upward trend, increasing by about 13%, from 30.22 in 2000 to 34.20 in 2021 ($\beta = 0.314$, $P < 0.001$) (Figure 1a).

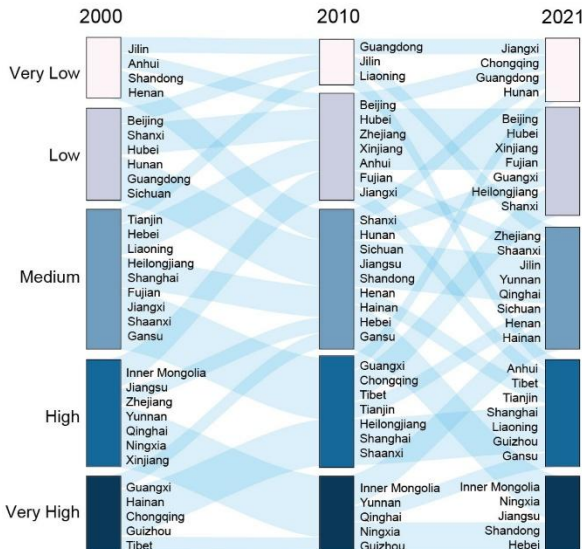
Across the provinces, those whose RV-DRI was categorized as “high” or “very high” risk fell in number from 12 to 9 over the ca. 20-year period, with more “medium” risk provinces evident

(Figure 1b). Spatially, in 2021 there was higher risk in the West of China and lower risk in its East, while those provinces classified at high or very high risk of disasters were mainly in its southwestern and northern regions (Figure S2a). However, the social vulnerability ratings changed substantially for several provinces across 2000, 2010, and 2021 (Figure 1c). Thirteen provinces made progress in reducing social vulnerability, such as Guangxi, going from “very high” in 2000 to “low” in 2021; but others, such as Guizhou, Inner Mongolia, and Tibet, consistently had “high” or “very high” social vulnerability. Three new high-vulnerability regions emerged, namely the Jiangsu, Shandong, and Hebei provinces concentrated along the eastern coast (Figure S2c).

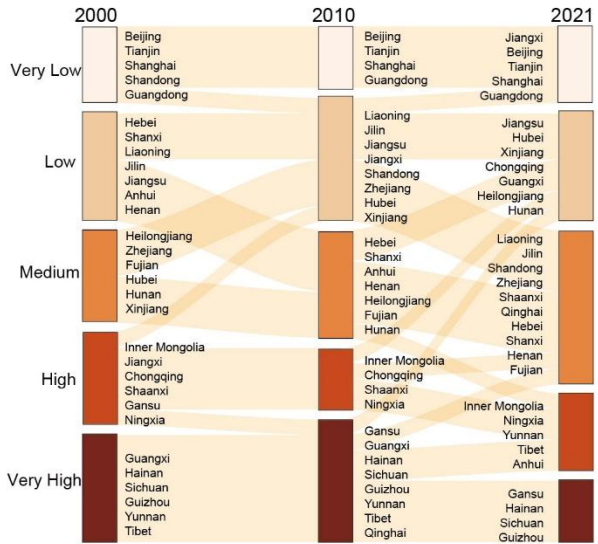
(a) National scale



(c) Social Vulnerability Index



(b) RV-Disaster Risk Index



(d) Community Resilience Index

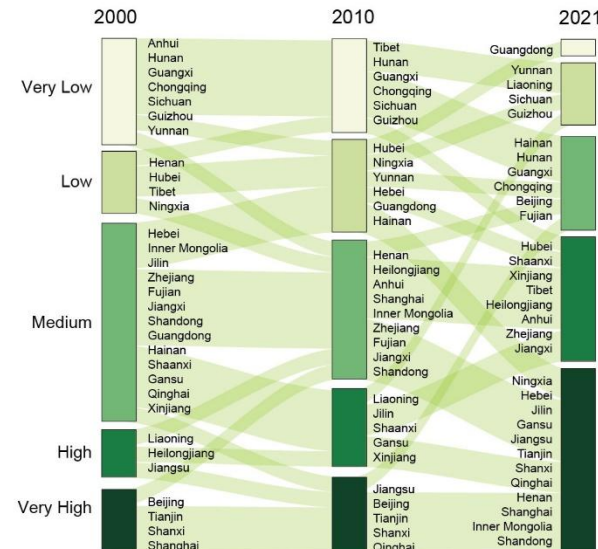


Figure 1. Spatio-temporal variation in China’s disaster risk, from 2000 to 2021. (a) Trends in the RV-disaster risk index (RV-DRI), social vulnerability index (SVI), and community resilience index (CRI) over time at the national scale. Disaster risk is expressed as the potential economic losses resulting from disasters triggered by natural hazards, with higher values indicating greater losses. Social vulnerability refers to the susceptibility of social groups to the impacts of disasters, where higher values indicate an increased likelihood of incurring adverse disaster-induced effects. Community resilience, on the other hand, denotes the capacity of communities to adapt to and recover from such adverse effects, in that higher values represent a greater ability to recover more quickly from disaster events. The β is the Theil-Sen Median slope, while the P -value is for the Mann-Kendall test statistic. The trend lines and shading are fitted linear regressions and their 95% confidence intervals, respectively. Temporal changes in the categorized RV-disaster risk index (b), social vulnerability index (c), and community resilience index (d) of China’s 31 mainland provinces.

The community resilience index generally increased, from 2000 to 2021, with the number of provinces rated in this respect as “high” or “very high” jumping to 20 from 7 (Figure 1d). Guangdong remained the sole province with “very low” community resilience, chiefly due to its limited per capita medical resources and per capita insufficient public welfare workers (Figure S2d). In terms of expected annual losses, very high values were concentrated in Gansu, Yunnan, and Hainan, with 11 provinces ranked “high” or “very high” in this respect (Figure S2b). This pattern may be ascribed to geographic conditions in these regions leading to a high frequency of disasters there, namely earthquakes and typhoons [32].

3.2. Relation between the RV-DRI and SDG index at national and provincial scales

At the national scale we uncovered a U-shaped relationship between the RV-DRI and SDG index ($R^2 = 0.73$, $P < 0.05$; Figure 2a). The fitted quadratic function reaches a minimum at an SDG index value of approximately 61, which indicated the threshold beyond which RV-DRI switched from decreasing to increasing as the SDG index rose. A similar pattern held for the social vulnerability index ($R^2 = 0.81$, $P < 0.05$), which also transitioning from a decreasing to

increasing phase at around an SDG index value of 61 (Figure 2b). Taken together, those relationships suggested that in the early stages of sustainable development, the efforts of urbanization and poverty reduction are able to reduce social groups' susceptibility to disaster-related impacts. Beyond this point, however, some SDG measures may have opposite effect on DRR. For instance, the dense construction of infrastructure in regions where natural hazards are common and intensive may have increased the vulnerability of social groups to the impacts of such events. Community resilience, in contrast, increased linearly and significantly with the SDG index ($R^2 = 0.85$, $P < 0.05$; Figure 2c). This suggested that the capacity of communities to deal with adverse effects of disasters improves steadily with sustainable development's progress. Hence, our findings suggested the vulnerability of social groups to impacts from natural hazards could play a predominant role in shaping the relationship between disaster risk and the SDG index at the national scale in China.

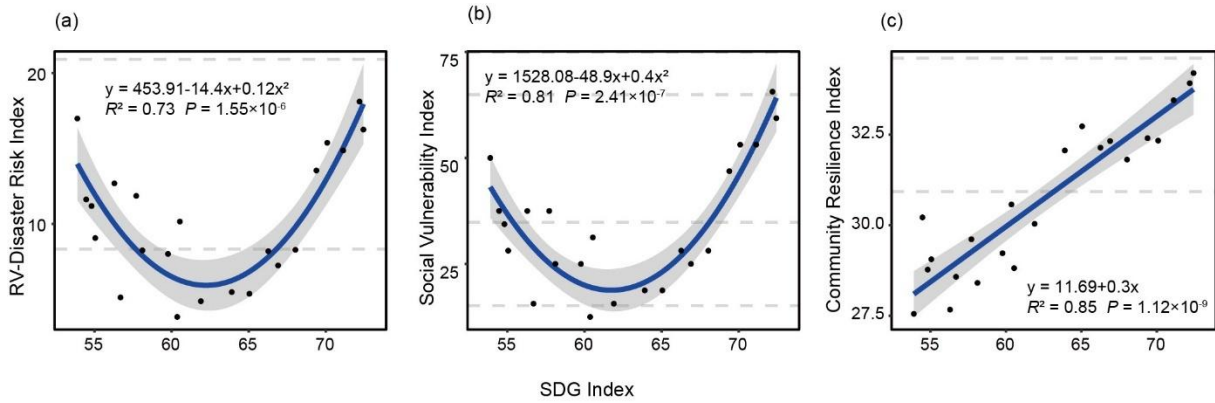


Figure 2. Relationships between the SDG index and the RV-disaster risk index (RV-DRI) (a), social vulnerability index (b), and community resilience index (c) at the national scale in China. Disaster risk is expressed as the potential economic losses resulting from disasters triggered by natural hazards, with higher values indicating greater losses. Social vulnerability refers to the susceptibility of social groups to impacts from disasters, for which higher values indicate an increased likelihood of incurring adverse disaster-induced effects. Conversely, community resilience denotes the capacity of communities to adapt to and recover from such adverse effects, in that higher values represent a greater ability to recover more

quickly from disaster events. The shaded area is the 95% confidence interval of the fitted regression.

At the provincial scale, the relationships between the SDG index and disaster risk, social vulnerability, and community resilience in China were similar to those trends at the national scale. As the SDG index increases, the RV-DRI first rises but then stabilizes ($R^2 = 0.61$, $P < 0.01$), perhaps due to the disaster risk having been already reduced to a very low level (Figure 3a). In the U-shaped relationship between social vulnerability and the SDG index ($R^2 = 0.3$, $P < 0.1$), when a certain threshold is reached (average SDG index = 65.53), social vulnerability pivots from decreasing to increasing with the SDG index (Figure 3b). Community resilience shows a significant, positive linear relationship with the SDG index ($R^2 = 0.27$, $P < 0.01$; Figure 3c), indicating that provinces with higher SDG progress tend to exhibit greater resilience. Although that R^2 value is relatively low, the chief purpose of this regression was to identify the relationship's direction. This result confirmed that community resilience strengthens with development progress, in contrast to the nonlinear behavior of both disaster risk and social vulnerability. The lower explanatory power is actually not surprising, being consistent with the expectation of considerable variation across provinces, this driven by differences in their governance, resource allocation, and baseline resilience conditions. Accordingly, at China's provincial scale, the relationship between disaster risk and SDG progress was likely influenced more by social vulnerability, given that both RV-DRI and SVI exhibit a nonlinear relationship with the SDG index, unlike community resilience which follows a more linear trajectory.

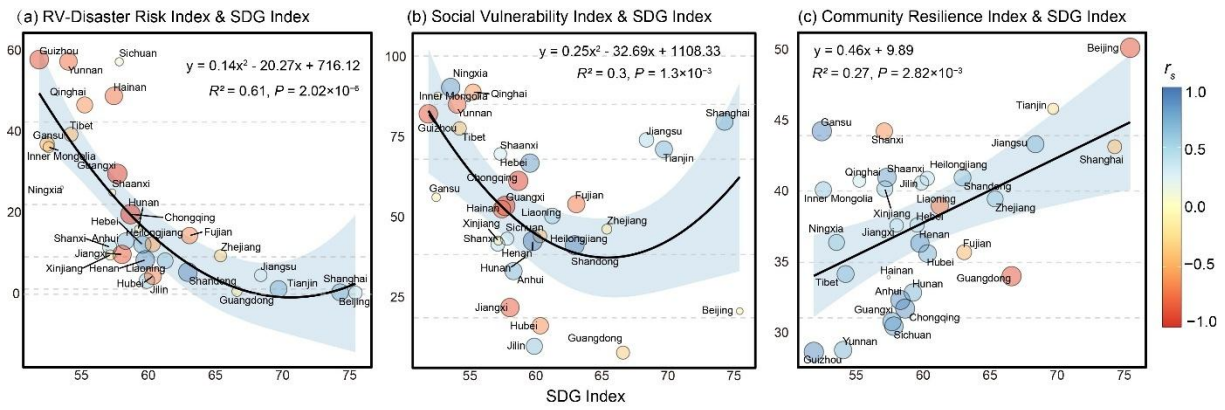


Figure 3. Relationships between the SDG index and the RV-disaster risk index (RV-DRI) (a), social vulnerability index (b), and community resilience index (c) at the provincial scale in China. Disaster risk is expressed as the potential economic losses resulting from disasters triggered by natural hazards, with higher values indicating greater losses. Social vulnerability refers to the susceptibility of social groups to impacts from disasters, for which higher values indicate an increased likelihood of incurring adverse disaster-induced effects. In contrast, community resilience denotes the capacity of communities to adapt to and recover from such adverse effects, in that higher values represent a greater ability to recover more quickly from disaster events. Points indicate multi-year averages data for each province, with their size representing the direction of the Spearman correlation coefficient (r_s) between the x-axis and y-axis variables, and their color corresponding to the direction and magnitude of the r_s . The shaded area is the 95% confidence interval of the fitted regression.

3.3. Relationship between RV-DRI and SDG scores at national and provincial scales

At the national scale, augmented scores for 14 of the 16 SDGs were associated with reductions in disaster risk (i.e., $r_s > 0$; Figure 4a); but the widespread adoption of clean energy (SDG7) and efforts to reduce inequalities (SDG10) were instead linked to a greater disaster risk (Figure 4a). This is likely because tackling inequality may entail more complex policy trade-offs; for example, narrowing the urban–rural income gap need not augment the disaster resilience of rural areas. Meanwhile, the transition to clean energy (requiring the construction of wind power systems, for instance) could introduce new, short-term environmental

disruptions that potentially amplify inherent local disaster risk.

But our results also suggested that synergistic relationships whereby the RV-DRI falls in tandem with SDG progress—has weakened over time: the number of SDGs with an $r_s > 0.5$ decreased three-fold, from 9 in 2000 to just 3 in 2021 (Figure 4a). A similar trend characterized the social vulnerability index, community resilience index, and certain SDG scores, with fewer SDGs exhibiting a strong positive correlation ($r_s > 0.5$; Figure 4b, c). Nonetheless, SDG1 (No Poverty) and SDG4 (Quality Education) generally seemed to be the most influential SDGs over the recent ca. 20-year period (Figure 4d), emphasizing the crucial role of supporting impoverished groups and enhancing educational equity for DRR on a national scale.

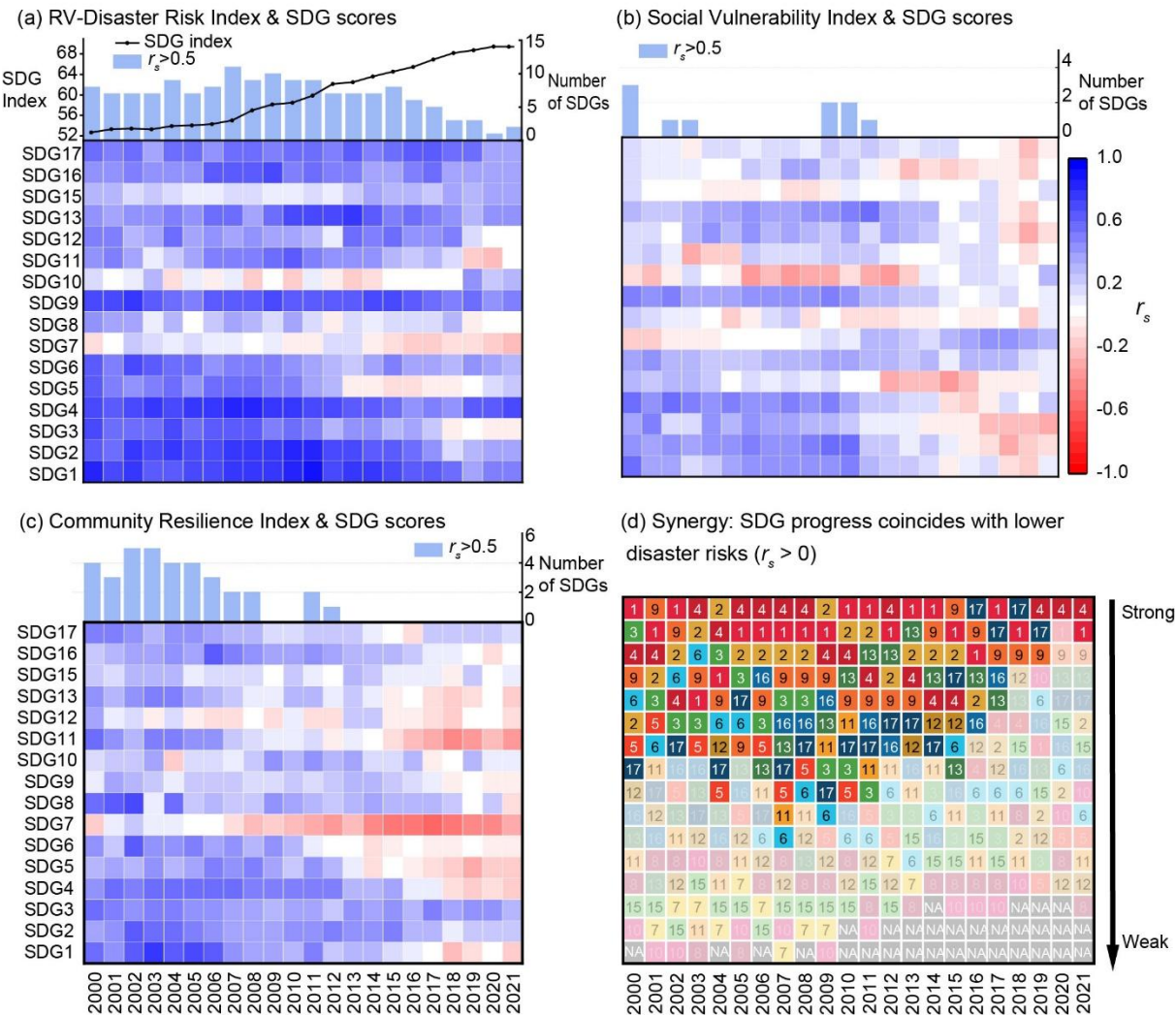


Figure 4. Relationships between 16 SDGs (excluding SDG14) and the RV-disaster risk index (RV-DRI)

from 2000 to 2021 at the national scale in China. Heatmaps for Spearman correlation coefficients (r_s) between each SDG and the RV-DRI (a), social vulnerability index (b), and community resilience index (c). Disaster risk is expressed as the potential economic losses resulting from disasters triggered by natural hazards, with higher values indicating greater losses. Social vulnerability refers to the susceptibility of social groups to impacts from disasters, for which higher values indicate an increased likelihood of incurring adverse disaster-induced effects. Community resilience denotes the capacity of communities to adapt to and recover from such adverse effects, in that higher values represent a greater ability to recover more quickly from disaster events. The line chart atop the heatmap in (a) shows the yearly national SDG index, while the bars are numbers of SDGs with an $r_s > 0.5$. (d) Rankings of the relative strength in the synergy between SDGs and disaster risk, i.e., where SDG progress coincides with a lower disaster risk. The SDGs darker in color have an $|r_s| > 0.5$; those lighter in color have an $|r_s| < 0.5$.

At the provincial scale, our analysis indicated that, as the SDG index rises, there are fewer SDGs associated with DRR and more of those linked to greater disaster risk. The threshold is reached when the average SDG index reaches 59.38, which corresponds to the SDG index of Hunan Province. For an SDG index lower than that threshold, we can see that 56% of the provinces have a higher proportion of SDGs with a strong risk-reducing influence ($r_s < -0.5$). Conversely, when the SDG index is higher than that, 64% of the provinces have a greater prevalence of SDGs associated with a strong risk-increasing influence ($r_s > 0.5$) (Figure 5a). Although SDG13 (Climate Action) is intended to lessen disaster risk, in provinces with higher SDG index levels, such as Tianjin and Shanghai, progress in meeting SDG13 (i.e., higher index value) led to a higher disaster risk there (Figure S3). This could be attributed to the implementation and effectiveness of climate action policies that vary starkly across regions. Some provinces may focus more on lowering carbon emissions than boosting their climate resilience and adaptive capacity; so, taking that narrow approach may fail to fully address the multifaceted aspects of disaster risk, particularly under climate change [49].

Likewise, the relationship between social vulnerability and the SDGs can also be analyzed using Hunan Province as a threshold (average SDG index = 59.38). When the SDG index is lower than that, we find that 63% of provinces harbor a higher proportion of SDGs with a strong influence on decreasing vulnerability ($r_s < -0.5$). Conversely, where the SDG index is higher, 57% of provinces show a greater prevalence of SDGs associated with a strong influence on increasing vulnerability ($r_s > 0.5$) (Figure 5b; Figure S4). This may be because improvements in certain SDG scores could have led, albeit temporarily, to enhanced social vulnerability; for example, faster urbanization rates may increase the population density and the population's proportion of migrants. In most cases though, community resilience tended to improve as the SDG scores increased. Still, in six provinces (e.g., Shanxi and Liaoning), multiple SDGs exerted a strong influence on decreasing resilience there (Figure 5c; Figure S5). This could be tied to local development strategies, whereby overall SDG improvements have not yet fully offset the impacts of ecological degradation.

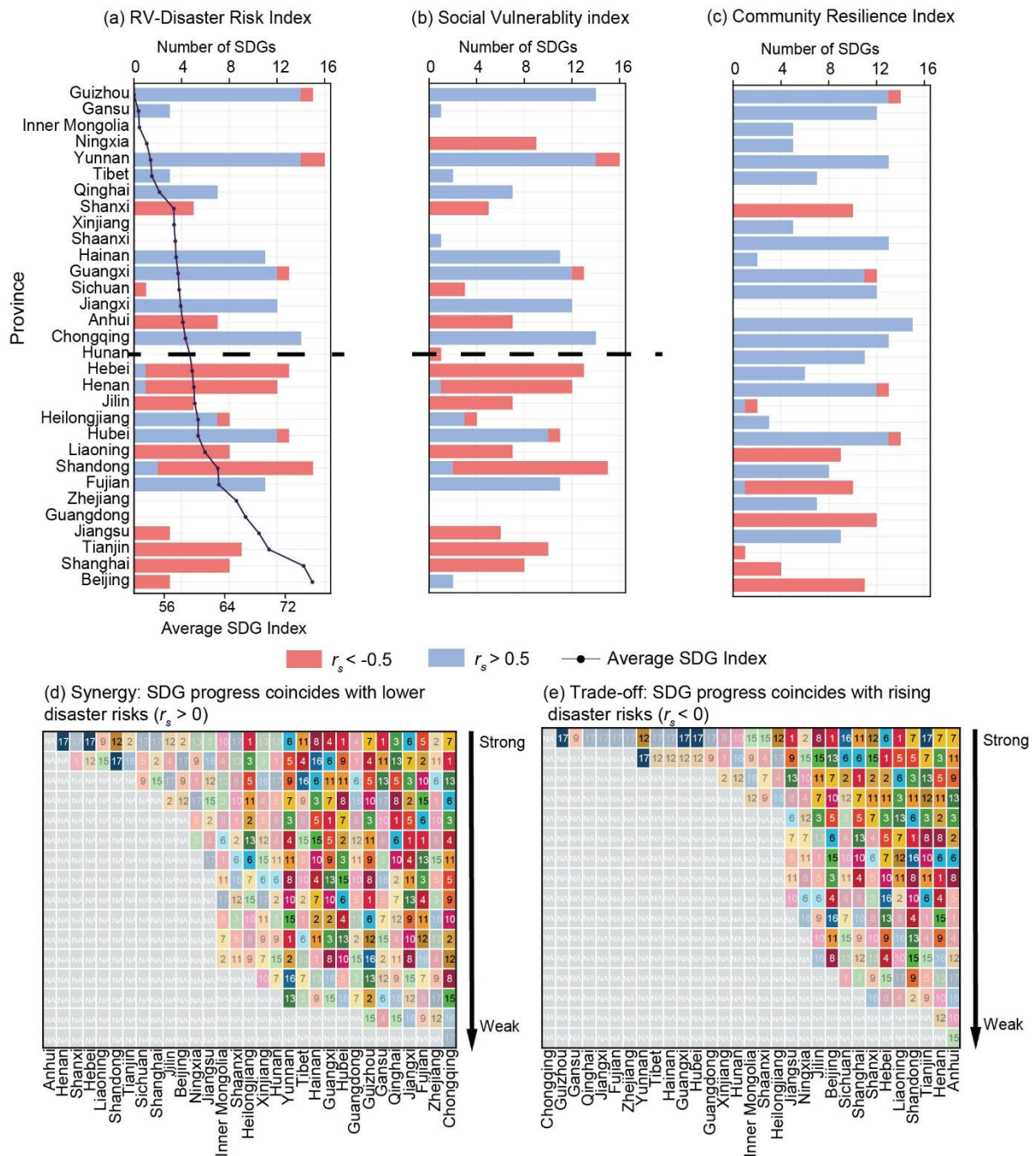


Figure 5. Relationships between the RV-disaster risk index (RV-DRI) and 16 SDG scores (excluding SDG14) at the provincial scale in China. The number of SDGs for which the RV-DRI (a), social vulnerability index (b), community resilience index (c), and SDG score have a Spearman correlation coefficient (r_s) greater than 0.5 or less than -0.5 . Provinces are sorted by the multi-year average of their SDG index. Disaster risk is expressed as the potential economic losses resulting from disasters triggered by natural hazards, with higher values indicating greater losses. Social vulnerability refers to the susceptibility of social groups to impacts from disasters, where higher values indicate an increased

likelihood of incurring adverse disaster-induced effects. By contrast, community resilience denotes the capacity of communities to adapt to and recover from such adverse effects, for which higher values represent a greater ability to recover more quickly from disaster events. (d) Rankings of the relative strength of the synergy between the SDGs and disaster risk, i.e., SDG progress coincides with lower disaster risk. (e) Rankings of the relative strength in trade-off between the SDGs and disaster risk; i.e., SDG progress coincides with greater disaster risk. The SDGs darker in color have an $|r_s| > 0.5$; those lighter in color have an $|r_s| < 0.5$.

Moreover, we found that the relation between SDGs and disaster risk varies considerably across China's provinces. Unlike at the national scale, only four provinces featured the strongest influence acting on DRR with SDG1 (No poverty) and SDG4 (Quality Education) (Figure 5d). The SDGs most influential at reducing risk across multiple provinces were SDG1, SDG6 (Clean Water and Sanitation), SDG7 (Affordable and Clean Energy), and SDG17 (Partnership for the Goals) (Figure 5d). With respect to raising disaster risk, the strongest influencing SDGs in multiple provinces were SDG1, SDG7, SDG12 (Responsible Consumption and Production), and SDG17 (Figure 5e). Notably, while progress in the other SDGs tends to lessen disaster risk, that in SDG17 often leads to an augmented disaster risk, and vice versa: when other SDGs contribute to an increased disaster risk, SDG17 usually helps to mitigate it (Figure 5d, e). This inverted duality may stem from SDG17's focus on both partnership and means of implementation, such as local government financing and taxation. For example, tax cuts in areas with scarce resources can improve living conditions there, while higher taxes in regions with robust infrastructure may reinforce their governmental capabilities and disaster preparedness [50].

To demonstrate the various impacts of SDGs on DRR, we further examined two provinces. Chongqing Province is among those with the most SDGs strongly influencing a decrease in disaster risk (Figure 5d). Besides its dense population and extensive industrialization

exacerbating environmental pressures, Chongqing has a pronounced urban–rural divide: in some underdeveloped rural areas, their vulnerability to disasters is made worse by weak social structures and an insufficient disaster response capacity [51]. Accordingly, using clean energy (SDG7) and poverty reduction (SDG1) exert a paramount influence on DRR in Chongqing. The province with the most SDGs that have a strong influence on increasing disaster risk is Shandong (Figure 5e). While its inherent disaster risk is not particularly high (Figure 1c), its coastal location renders certain assets more vulnerable to risk exposure (Figure 1c). Hence, attaining specific SDGs sooner there, such as the development of industrial infrastructure related to clean energy (SDG7), the greater participation of women in the labor force (SDG5), and the expansion of dense healthcare facilities (SDG3), may inadvertently contribute to larger potential economic losses.

4. Discussion

The plurality of relationships between sustainable development and disaster risk is a pivotal topic in academic research, with most prior studies concerned with its theoretical discussions or qualitative analyses (e.g., DeWit et al. [21] and Raikes et al. [22]). In this empirical study, however, we instead take a quantitative approach by calculating the RV-DRI for China (and its provinces), then analyzing the spatiotemporal variation in the interactions between disaster risk and the SDG index, and finally identifying which SDGs contribute most to mitigating disaster risk. Our findings thus offer valuable, timely insights into global sustainable development and disaster risk management.

4.1. The spatio-temporal variation of disaster risk in China

Our results show that China’s disaster risk initially decreased but then increased in the years 2000 through 2021. This fluctuation pattern over time suggests that the initial development successfully reduced social vulnerability, which may be associated with the efforts of the

Millennium Development Goals (MDG) in poverty reduction and infrastructure improvement. Subsequent industrialization and urban development may exacerbate the disaster risk due to increased risk exposure and potential mismanagement of social capital [52]. This finding agrees with some studies that found that social development can serve to reduce vulnerability early on, but may later deepen it due to improper allocation or mismanagement of social capital [53,54]. Yet it disagrees with other research that suggested a continuous decrease in vulnerability ensues with more social development [55,56]. That discrepancy can be explained by China's unique context of rapid urbanization and industrialization over relatively short timespan (~20 years), which has led to greater risk exposure to disasters and heightened vulnerabilities [57]. This pattern stresses the vital importance of explicitly considering the complex relationships between development and disaster risk, in turn highlighting the need for context-specific strategies to effectively manage this risk.

4.2. Nonlinear relationship between the disaster risk and the SDGs in China

Our study reveals a U-shaped relationship between SDGs index and disaster risk, at both national and provincial scales in China. For example, at the national scale in China, at first, as the SDG index increases, disaster risk decreases; but after reaching an inflection point (in this study, the threshold is an SDG index = 61), a rise in disaster risk ensues. This intriguing finding goes beyond that of traditional qualitative analyses, in which a more linear relationship between sustainability and risk reduction is presupposed or implied [17]. Our results challenge this simplistic view and indicate that how sustainable development affects disaster risk is far more complex, being jointly influenced by two societal aspects: *community resilience* (the capacity of communities to adapt to and recover from adverse effects) and *social vulnerability* (the susceptibility of social groups to impacts from disasters). This view does not imply an inherent conflict between sustainability and DRR but rather emphasizes that, inadvertently, certain initiatives targeting specific SDGs may themselves become unsustainable in practice. While

such initiatives might lessen vulnerability in the near term, they could also lead to unforeseen negative consequences during later stages of a given SDG's implementation. These unintended consequences may include heavier environmental burdens or systemic misalignments that ultimately exacerbate disaster risk [58]. Successfully implementing the SDGs requires an understanding and leveraging of these non-linear interactions [51]. However, we must acknowledge that it is not currently possible to predict how this relationship may evolve over longer timeframes. Hence, these nonlinear dynamics reported here should be seen and used as a basis for further, more detailed mechanistic analyses.

For instance, while advancements in SDG11 (Sustainable Cities and Communities) laudably seek to improve urban living conditions, rapid urbanization can strain infrastructure and resources, leaving cities more vulnerable to natural hazards such as flooding and earthquakes [59]. Similarly, progress in achieving SDG9 (Industry, Innovation, and Infrastructure) can arguably spur and fuel economic growth, though it may also drive environmental degradation and increase exposure to disaster risk due to unfettered industrial expansion. Both examples align with findings of recent research [60]: in regions prone to much geological activity the construction of dense infrastructure, while fostering economic prosperity, can induce detrimental cascading effects during natural hazards, such as earthquakes, that amplify disaster-related losses. Furthermore, this U-shaped pattern of risk underscores why caution is needed when pursuing certain SDGs and calls for the careful prioritization of those most effectively able to mitigate disaster risk in the context of local conditions.

Our study integrates conventional prioritization frameworks for SDGs in DRR through a multiscale empirical analysis. Contrary to the disproportionate emphasis on SDG13 (Climate Action) in DRR discourse [61], our results show that its direct relationship with systemic risk reduction is in fact more limited than believed. Although SDG13 effectively monitors climate-related disaster losses via standardized indicators, our RV-DRI results demonstrate that disaster

risk constitutes a composite function of both post-event impacts and pre-existing societal vulnerabilities. This subtle but powerful distinction also mirrors the spatial-temporal dissociations observed between high-loss events and chronic risk exposure across various development contexts [62].

Our national-scale analysis for China singles out SDG1 (No Poverty) and SDG4 (Quality Education) as being critical leverage points for DRR. Economic empowerment through poverty alleviation bolsters household capacity to allocate resources for disaster preparedness plans, while educational advancement strengthens both the institutional trust and technical competencies essential for recovery processes. These concurrent mechanisms corroborate established theories that wed socioeconomic development to adaptive capacity [63–65]. Subnational variability further complicates the relationships arising between SDGs and DRR. In Chongqing Province, implementation of SDG7 (Affordable and Clean Energy) correlates with reduced disaster risk, probably through decentralized energy systems which improve its critical infrastructure resilience. Shandong Province, on the other hand, is characterized by an inverted relationship, where energy infrastructure expansion seems to exacerbate ecological fragility or spatial inequalities. Such spatial heterogeneity in SDG–disaster risk interactions is why it is imperative to undertake place-based SDG operationalization, a position consistent with polycentric governance models in disaster management [59].

4.3. Policy implications for China and other regions

The nonlinear relationship between disaster risk and the SDGs highlights the need for caution when pursuing specific SDGs. It emphasizes the importance of carefully prioritizing those goals that are most effective in mitigating disaster risk, considering local conditions. Policymakers should assess the potential short-term trade-offs and long-term benefits of each SDG, ensuring that their strategies for sustainable development do not inadvertently exacerbate disaster risk. Moreover, the observed scale-dependent outcomes logically advocate for a dual-track DRR

strategy. At the macro scale, common risk factors should be identified to enhance national resilience. In parallel, regional governance requires localized risk diagnostics to properly identify context-specific vulnerability drivers—whether energy transitions amplify or mitigate risks, for instance, will depend on both regional industrial structures and ecological carrying capacities.

Those proposed approaches closely aligns with emerging paradigms advocating for development-centered disaster governance, which prioritizes root-cause vulnerability mitigation over reactive loss compensation [66]. Policymakers must therefore recalibrate their SDG implementation frameworks to better account for three interrelated dimensions: (i) the temporal disconnect between climate impacts and risk accumulation; (ii) the spatial mismatch between standardized goals and regional realities, and (iii) the structural interdependence of social development and systemic resilience. In turn, such integration demands coordinated action across administrative scales, to bridge national development agendas with subnational risk landscapes.

4.4. Limitations and prospects

Despite providing novel insights into how disaster risk and sustainable development are related, our study does have several limitations. First, the disaster risk assessment is highly sensitive to the selected indicators for social vulnerability and community resilience; though the indicators and methods used here are based on widely accepted frameworks, which may continually evolve as sustainable development broadens its reach. Second, our quantitative analysis mostly relies on bivariate regression and correlation analysis, which measure the strength of relationships but cannot unearth or distinguish the specific mechanisms underlying causal relationships, though they can point to them. Those limitations in this study may introduce some uncertainty, which could potentially affect the generalizability of our findings. Future research should strive to leverage causal multivariate hierarchical models to disentangle

complex interactions and expand risk assessments to suitably incorporate relevant socioeconomic and geopolitical dimensions [67]. Finally, our study focuses solely on the relationship between disaster risk and the SDGs, while acknowledging that numerous other types of risk also exhibit complex interdependencies with SDGs. Future research should therefore adopt a more comprehensive approach to examining the multifaceted relationships between various risk categories and the SDGs, thereby enhancing the robustness of risk assessment and management frameworks.

5. Conclusion

Taking the intricate interplay between progress towards the SDGs and disaster risk in China as a case in point, we find not only a non-linear relationship between meeting the SDGs and mitigating risk but also, with a change in spatial scale, pronounced variation in which particular goals are more helpful for disaster risk reduction. This argues for the necessity of crafting regionally tailored strategies, since local natural hazard profiles and development priorities dictate divergent SDG impacts. The apparent paradox of escalating risks amid sustained SDG progress highlights the tension between development gains and unintended consequences. Short-term economic growth often masks systemic vulnerabilities, requiring integrated policies that harmonize risk-sensitive SDG implementation with adaptive governance. To resolve inherent trade-offs, policymakers cannot but embrace holistic frameworks that simultaneously mitigate vulnerability (e.g., equitable resource distribution) and enhance resilience (e.g., climate-adaptive infrastructure), while nonetheless prioritizing those SDGs that address root causes of inequality and disaster risk exposure. By embedding vulnerability reduction and resilience-building into the 2030 Agenda, this study advocates for a radical transformative approach—one that transcends siloed development actions to foster systemic sustainability in an era of escalating climatic and anthropogenic risks.

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