

Systemic Resilience of the Sustainable Development Goals Causal Network: A Dynamic Assessment under Extreme Climate Stress Scenarios

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Abstract. Climate change threatens progress on the Sustainable Development Goals (SDGs) by exposing their deep interdependencies. This study constructs a causal network model of the SDGs and tests system resilience under five extreme climate stressors: extreme heat, extreme precipitation, drought, tropical cyclones, and wildfires—using sequential node perturbation simulations. Results indicate that the SDG network is densely connected (density, 0.346; clustering coefficient, 0.629) and performs at 0.574 baseline level. Resilience varies sharply across stressors: extreme heat triggers the fastest performance decline—its resilience curve area is 31.4% lower than drought's—indicating high cascading failure risk. Both extreme heat and tropical cyclone cause critical transitions when the first 30% of nodes are removed. Vulnerability analysis across all scenarios consistently identifies SDG 6 (Clean Water and Sanitation) and SDG 13 (Climate Action) as structural hubs—high in betweenness centrality and failure frequency—making them pivotal for system stability. These findings reveal how climate risks amplify systemic vulnerability through SDG interlinkages. The perturbation framework offers a quantitative tool to pinpoint intervention priorities and guide resilience-building governance under climate stress.

Keywords: Sustainable Development Goals (SDGs), Climate resilience, Complex networks, Cascading failures, Systemic risk

1. Introduction

Climate change is rapidly disrupting global ecological, economic, and social systems. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) confirms shape increases in extreme events—extreme heat, heavy precipitation, droughts, tropical cyclones, and wildfires—posing systemic threats to sustainable development [1]. Cocurrently, progress on the Sustainable Development Goals (SDGs) has stalled: the United Nations's 2022 SDG Report identifies climate-related risks as a primary driver of setbacks across multiple goals [2]. The 17 SDGs form a tightly coupled system defined by dynamic synergies and trade-offs [3]. For example, scaling renewable energy advances climate action (SDG 13) but may strain land and water resource (SDGs 15 and 6). Treating them as isolated targets obscures these interlinkages and weakens response strategies [4]. Yet most research still assesses goals individually, neglecting how climate

shocks propagate through the network. As a result, cascading failure pathways remain poorly mapped.

To address this, this study constructs a directed causal SDG network using empirically validated interaction data. The author simulates sequential node perturbations under five climate stressors and quantify system resilience by tracking real-time network performance decline. This reveals critical transition thresholds and identifies nodes consistently vulnerable across scenarios—especially SDG 6 (Clean Water) and SDG 13 (Climate Action)—highlighting structural leverage points. Moving beyond static, goal-by-goal analysis, the framework delivers an operational, system-level approach to strengthening global sustainability resilience amid escalating climate risk.

2. Theoretical framework

2.1. SDG interdependency studies

Recent research recognizes the SDGs as a complex, interdependent systems, not a set of standalone targets. Le Blanc framed them as a network of goals, targets, and policy feedbacks [5]; Pradhan et al. confirmed both synergies and trade-offs among goals using statistical analysis—for example, economic growth can reduce poverty but also raise resource use and environmental stress [6].

Network-based methods are now widely used to map these relationships: nodes represent goals, edges represent dependencies, and the structure reveals critical connections and risk propagation pathways [7]. Unlike linear models, networks capture coupling effects and nonlinear feedback, making them ideal for modeling development complexity. This study therefore models the SDGs as a directed dependency network to identify inter-goal linkages and trace how climate risks spread across the system.

2.2. Complex network resilience theory

Complex network resilience theory—widely used in ecological, energy, and infrastructure—measures how well interconnected systems maintain function under disturbance [8]. In such systems, failures of critical nodes can spread through connections, triggering cascading breakdowns that impair both function and structure [9].

Sequential node removal is a standard method for testing robustness and resilience: it simulates progressive node failure and tracks resulting declines in network performance [10]. The Area Under the Curve (AUC) of that performance trajectory quantifies overall resilience—the larger the AUC, the greater the system's ability to sustain function amid ongoing stress [11]. This study applies sequential removal paired with AUC analysis to quantify SDG system resilience across five extreme climate stressors.

3. Methods

3.1. Construction of the SDG causal network

To analyze how climate stress affects SDG system structure and resilience, this study build a directed causal network of 36 functional components, finer-grained than the 17 SDGs—representing core development dimensions: energy, water, food, health, ecosystems, and infrastructure [5-7]. Nodes denote these components; directed edges indicate empirically supported causal influences between them (Figure 1). This finer-grained representation more effectively captures the interaction

mechanisms among different development domains, thereby improving the resolution of the network analysis.

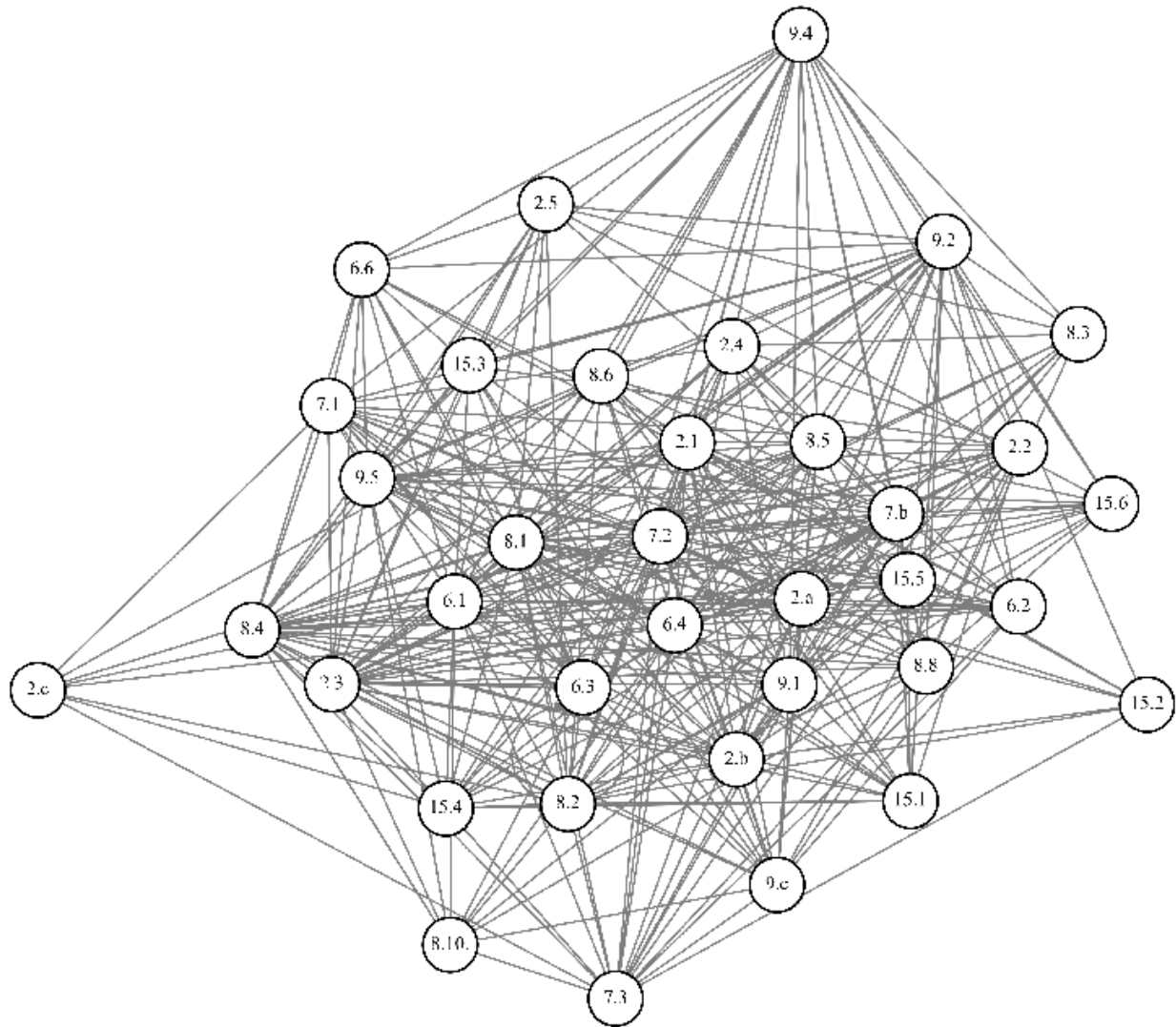


Figure 1. Topological structure of the 36-node SDG causal network

Accordingly, the network node set is defined as:

$$G=(V,E) \tag{1}$$

where $V=\{v_1, v_2, \dots, v_n\}$ denotes the set of network nodes representing the functional components associated with the Sustainable Development Goals (SDGs), and denotes the set of directed causal relationships between nodes.

The edges in the network represent causal influence relationships among different development dimensions. A directed edge is established from node (v_i) to node (v_j) if changes in v_i exert a causal influence on v_j . Formally, the directed edge is defined as:

$$e_{ij}=1 \quad (2)$$

Otherwise:

$$e_{ij}=0 \quad (3)$$

The network edges are established based primarily on interaction relationships identified in previous studies on synergies and trade-offs among the SDGs, thereby capturing the highly coupled structure of interdependencies across different development dimensions [6, 7]. Accordingly, the overall network structure can be represented by the following adjacency matrix:

$$A = [a_{ij}]_{n \times n}, \quad a_{ij} = \begin{cases} 1, & \text{if node } v_i \text{ directly influences node } v_j \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Where:

$$a_{ij} = \begin{cases} 1, & \text{if a directed edge exists from } v_i \text{ to } v_j \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

Accordingly, the SDG system is represented as a directed network consisting of 36 nodes and 436 directed edges.

3.2. Climate stress scenario design

Five climate stressors were selected—extreme heat, drought, tropical cyclones, extreme precipitation, and wildfires—because they represent the most prominent categories of climate hazards currently threatening global sustainable development today [1, 12]. Extreme heat and drought impose slow, cumulative pressure; tropical cyclones and extreme precipitation cause sudden, acute shocks; wildfires, drive coupled ecological and socioeconomic damage. Together, they span the full spectrum of climate disturbance mechanisms affecting the SDG system.

For each stressor, this research sequenced node removal by vulnerability: nodes most directly impacted, — based on the IPCC risk assessments and empirical climate impact studies—were removed first [13]. This simulates realistic, progressive degradation of the SDG network under climate stress [13].

3.3. Network performance measurement

Network performance (NP) is defined as:

$$NP = \left(\frac{N_{LWC}}{N} \right) \times \frac{1}{L} \quad (6)$$

Where N_{LWC} represents the number of nodes in the largest weakly connected component; N denotes the total number of nodes in the network; L represents the average shortest path length. This metric integrates structural connectivity and transmission efficiency. Similar composite indicators are widely adopted in complex networks resilience studies [10]. The normalized network performance is defined as:

$$NP_{\text{norm}}(t) = \frac{NP(t)}{NP_0} \quad (7)$$

where denotes the network performance under the initial (undisturbed) state, and represents the network performance after the (t)-th perturbation step.

3.4. Resilience quantification

For each climate stressor, a resilience curve was generated by tracking normalized network performance across sequential perturbations. Resilience was quantified using two complementary metrics: (1) the AUC, measuring cumulative stability during disturbance; and (2) critical threshold detection via first-order difference analysis, identifying abrupt drops in performance. The AUC is defined as:

$$AUC = \sum_{t=1}^T \frac{NP_t + NP_{t-1}}{2} \Delta t \quad (8)$$

where NP_t represents the normalized network performance at the (t)-th perturbation stage. A larger AUC indicates greater capacity to sustain function under continuous stress.

3.5. Cross-scenario vulnerability analysis

For each climate stressor, the top five removed nodes were recorded in the perturbation sequence. Nodes recurring across scenarios were flagged as structurally vulnerable. Two centrality metrics were further employed to assess their systemic roles: (1) Betweenness centrality, measuring how often a node lies on—identifying critical bridges between subsystems; (2) PageRank, quantifying a node's influence across the full network. Together, these metrics provide complementary perspectives on the systemic importance of nodes in climate-related risk propagation.

4. Results

4.1. Structural characteristics

The SDG causal network exhibits high density (0.346) and strong clustering characteristics (0.629), indicating intensive interconnections among different development dimensions. The average path length of 1.74 suggests the existence of efficient transmission pathways within the system. The baseline network performance is calculated as 0.574, reflecting a moderate level of structural cohesion.

4.2. Resilience trajectories under climate stress

As shown in Figure 2, the normalized network performance of the SDG system exhibits a declining trend under all climate stress scenarios, although the rates of degradation differ significantly among scenarios. Among them, the EHSS scenario demonstrates the most rapid decline, with network performance decreasing by more than 52% when only the first 25% of nodes have been removed.

The AUC values under different climate stress scenarios are as follows: (1) DSS: 0.71; (2) EPSS: 0.66; (3) TCIS: 0.61; (4) WDS: 0.58; (5) EHSS: 0.49. The AUC value of the EHSS scenario is approximately 31.4% lower than that of the DSS scenario, indicating that extreme heat is more likely to trigger cascading instability across interconnected development sectors.

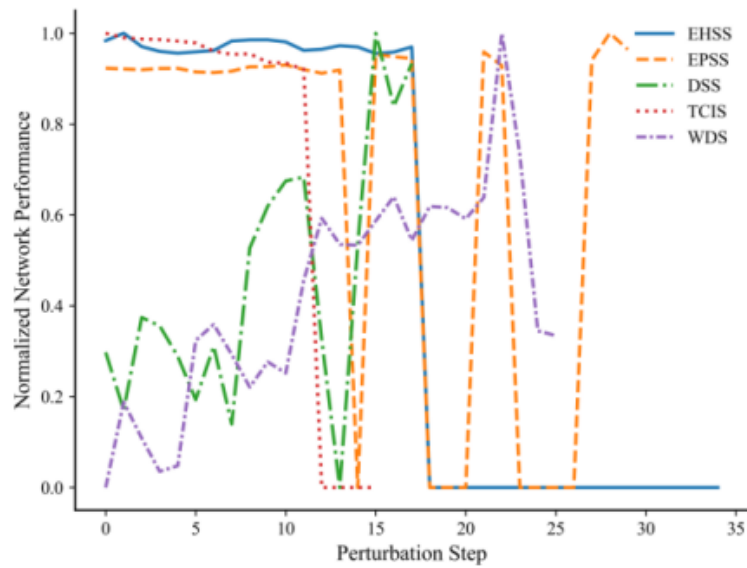


Figure 2. Decline trajectories of normalized network performance of the SDG system under five extreme climate disturbance scenarios

4.3. Critical transition thresholds

Figure 3 presents the critical transition thresholds observed under different climate stressors. Both the EHSS and TCIS scenarios exhibit pronounced performance degradation when the proportion of removed nodes reaches approximately 0.28–0.35. Among these scenarios, the EHSS demonstrates the largest decline in network performance, with a reduction of 0.17 after the removal of the 11th node, significantly exceeding the declines observed in other scenarios. This indicates that the SDG system may rapidly enter a nonlinear degradation phase following the failure of critical nodes [14].

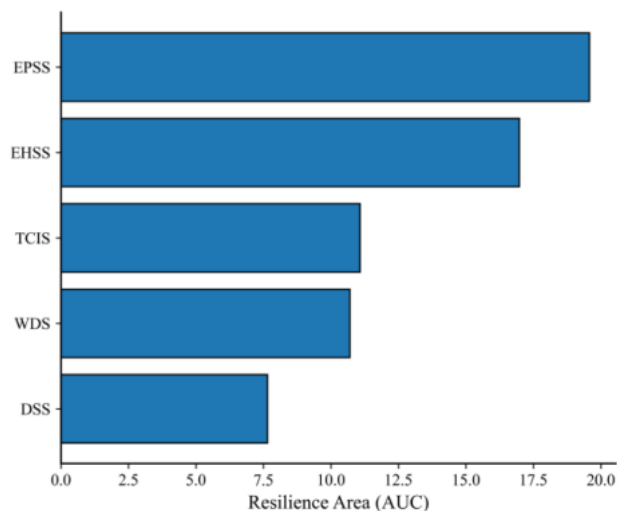


Figure 3. Comparison of critical transition thresholds of the SDG system under different climate stressors

4.4. Recurrent vulnerable nodes

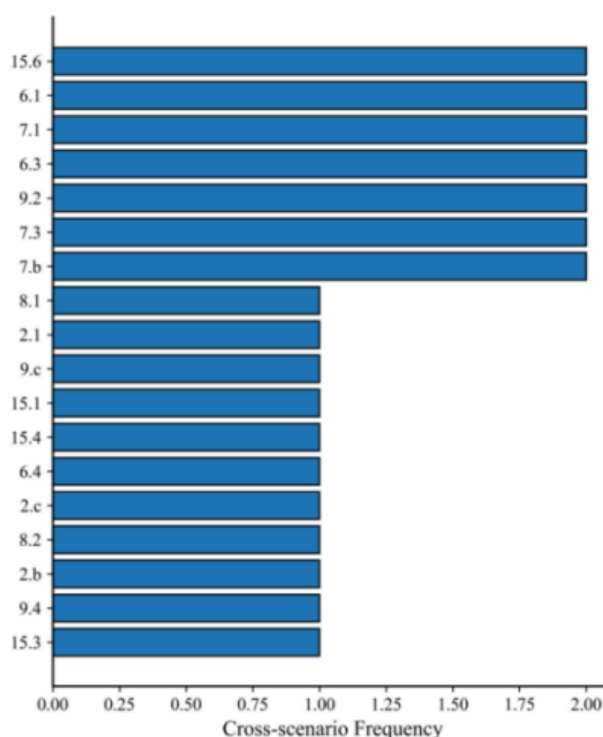


Figure 4. Frequency statistics of node failures across five climate stress scenarios

As summarized in Figure 4, SDG 6 and SDG 13 exhibit the highest occurrence frequencies among early-failing nodes across the five climate stressors. These two goals consistently appear within the early failure nodes under different climate conditions. Their high centrality positions indicate that they function as structural bridges within the network, facilitating the transmission of risks across interconnected development domains.

5. Discussion

This study shows that climate hazards differ markedly in their impact on SDG system resilience. Extreme heat causes the most severe disruption, indicating that climate risks are not uniform, but vary by propagation range, duration, and cross-sectoral coupling.

Unlike localized hazards like tropical cyclones and wildfires, extreme heat covers broader areas, persists longer, and affects more sectors simultaneously. It directly stresses health and agriculture, while also increasing energy demand, intensifying water use, and destabilizing ecosystems. These overlapping pressures create multi-point synchronous disturbance—eroding structural redundancy and buffering capacity in the interconnected SDG network, thereby accelerating cascading failure.

SDG 6 and SDG 13 consistently rank highest in failure sensitivity and centrality across all stressors. This confirms their role not as standalone goals, but as structural bridges: water systems link food, health, energy, and ecosystems; climate action influences mitigation, adaptation, energy transitions, and risk governance. Their vulnerabilities therefore propagate widely, making them critical leverage points for systemic resilience.

This finding aligns with real-world policy practices. For example, Australia's drought response has—integrating basin-scale coordination and adaptive water allocation—improved not only water security but also agricultural and energy stability. Similarly, national adaptation plans under the Paris Agreement generally emphasize coordinated climate and water governance, underscoring broad recognition of the climate–water nexus. These cases demonstrate that strengthening governance at structurally critical nodes yields amplified, cross-domain benefits.

6. Conclusion

This study develops a causal network model and simulates sequential perturbations under five representative extreme climate stressors to quantify the dynamic evolution of system resilience. Results demonstrate the SDGs form a densely interconnected, highly clustered network, reflecting strong cross-domain coupling and deep interdependence. Resilience trajectories vary significantly across stressors. Extreme heat causes the fastest performance decline and yields the lowest AUC value, indicating highest risk of cascading failure across sectors. In contrast, drought drives slower, more gradual degradation. Threshold analysis reveals critical transitions in several scenarios: after key node failure, the system rapidly shifts into nonlinear collapse. Cross-scenario analysis identifies SDG 6 and SDG 13 as structural vulnerability hotspots. This confirms water systems and climate governance are not isolated goals, but foundational nodes that stabilize the entire SDG network. Strengthening their governance and resilience amplifies system-wide robustness against climate risks.

This study makes two key contributions. First, it reframes the SDGs not as isolated goals, but as a quantifiable complex network. Second, it introduces a network perturbation framework that maps resilience trajectories, enabling identification of critical risk pathways and high-priority intervention targets.

Limitations remain. The model adopts an unweighted network, so it cannot capture variations in interaction intensity among SDG linkages. And while real-world climate hazards are often compound and probabilistic, the current framework treats them as discrete, deterministic events. Future research could incorporate weighted networks, dynamic evolution mechanisms, and stochastic disturbance models to improve the realism, adaptability, and predictive capability of resilience assessments.

References

- [1] IPCC. (2023). *Climate change 2023: Synthesis report*. IPCC. Geneva, Switzerland. doi: 10.59327/IPCC/AR6-9789291691647.
- [2] Liu, J., Mooney, H., Hull, V., et al. (2015). Systems integration for global sustainability. *Science*, 347(6225), 1258832. doi: 10.1126/science.1258832.
- [3] Gao, L., & Bryan, B. A. (2017). Finding pathways to national-scale land-sector sustainability. *Nature*, 544(7649), 217–222. doi: 10.1038/nature21694.
- [4] United Nations. (2022). *The sustainable development goals report 2022*. United Nations Publications. New York. <https://unstats.un.org/sdgs/report/2022/>
- [5] Pradhan, P., Costa, L., Rybski, D., et al. (2017). A systematic study of sustainable development goal (SDG) interactions. *Earth's Future*, 5(11), 1169–1179. doi: 10.1002/2017EF000632.
- [6] Nilsson, M., Griggs, D., & Visbeck, M. (2016). Policy: Map the interactions between Sustainable Development Goals. *Nature*, 534(7607), 320–322. <https://doi.org/10.1038/534320a>
- [7] Le Blanc, D. (2015). Towards integration at last? The Sustainable Development Goals as a network of targets. *Sustainable Development*, 23(3), 176–187. <https://doi.org/10.1002/sd.1582>
- [8] Zhou, X., & Moinuddin, M. (2017). *Sustainable Development Goals interlinkages and network analysis: A practical tool for SDG integration and policy coherence*. Institute for Global Environmental Strategies. Japan.

<https://doi.org/10.57405/iges-6026>

- [9] Fuso Nerini, F., Sovacool, B., Hughes, N., et al. (2019). Connecting climate action with other Sustainable Development Goals. *Nature Sustainability*, 2(8), 674-680. <https://doi.org/10.1038/s41893-019-0334-y>
- [10] Rockström, J., Steffen, W., Noone, K., et al. (2009). Planetary boundaries: Exploring the safe operating space for humanity. *Ecology and Society*, 14(2), 32. <http://www.jstor.org/stable/26268316>
- [11] Steffen, W., Richardson, K., Rockström, J., et al. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, 347(6223), 1259855. <https://doi.org/10.1126/science.1259855>
- [12] UNEP. (2021). *Adaptation gap report 2021: The gathering storm*. United Nations Environment Programme. Nairobi. <https://www.unep.org/resources/adaptation-gap-report-2021>
- [13] IPCC. (2022). *Climate change 2022: Impacts, adaptation and vulnerability. Contribution of Working Group II to the Sixth Assessment Report*. Cambridge University Press. <https://www.ipcc.ch/report/ar6/wg2/>
- [14] Scheffer, M., Carpenter, S., Foley, J., et al. (2001). Catastrophic shifts in ecosystems. *Nature*, 413(6856), 591-596. <https://doi.org/10.1038/35098000>