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Compound climate hazards erode energy-system resilience through transmission infrastructure

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Abstract: The rapid expansion of low-carbon electricity is increasing reliance on long-distance transmission networks that connect geographically dispersed generation with major demand centres. Yet climate hazards that are conventionally assessed in isolation can disrupt different parts of the same interconnected grid concurrently or in close succession, potentially turning otherwise distinct extremes into coupled system shocks. Here we develop an interdisciplinary source–network–load framework that couples climate hazards, engineering fragility and Monte Carlo power-system dispatch across more than 500,000 transmission lines worldwide. We show that 60–73% of global transmission lines are projected exposed to failure risk from at least one hazard by mid-century, with strongly heterogeneous vulnerabilities across regions and voltage classes. More importantly, the footprints of physically distinct wildfire, tropical-cyclone and freezing-rain hazards increasingly converge within the same transmission systems: under high emissions, the number of lines exposed to multiple hazards nearly doubles from approximately 43,000 in 2030 to 82,000 by mid-century. Concurrent failures of two or more lines, rather than isolated single-line disruptions, are far more likely to overwhelm network redundancy, accounting for 88.9–96.8% of affected customers across representative developing-country grids in China, Brazil and Southern Africa. Across these representative systems, climate-driven transmission failures generate approximately 13.5 million annual affected-customer equivalents, with only 1% of lines accounting for 31–57% of impacts. Our results reveal that interconnected grids can functionally couple and amplify geographically distinct climate hazards, making transmission resilience a prerequisite for a resilient clean-energy transition.

38 Main

39 Climate-related research on energy systems has historically focused disproportionately on
40 changes in generation potential²⁻⁴, while paying less attention to whether transmission
41 infrastructure can safely and reliably deliver this electricity. This gap is becoming increasingly
42 consequential as the global energy transition accelerates the deployment of wind and solar
43 power. High-quality renewable resources are often concentrated in deserts, offshore areas, high-
44 latitude regions and other locations far from major demand centres, increasing the spatial
45 separation between electricity generation and consumption. Climate resilience of transmission
46 infrastructure is thus becoming a prerequisite for a secure energy transition

47 As climate change accelerates, transmission networks are becoming increasingly vulnerable to
48 climate-related hazards⁵⁻⁸. Among them, wildfires (WF), tropical cyclones (TC), and freezing
49 rain (FR) pose the most widespread and damaging threats to large-scale transmission systems.
50 For instance, the 2018 Camp Fire in California ignited from faulty transmission lines and led
51 to the destruction of over 18,000 structures while causing prolonged power outages for tens of
52 thousands of homes⁹; In 2017, Hurricane Maria and subsequent TC repeatedly struck Puerto
53 Rico's grid, leaving all 3.4 million residents without electricity¹⁰; and the 2021 Texas winter
54 storm combined icing and extreme cold to collapse multiple transmission corridors across
55 states¹¹; Their combined and shifting occurrences, as warming lengthens wildfire seasons^{12,13},
56 displaces cyclone tracks poleward^{14,15}, and expands icing conditions¹⁶, mean that transmission
57 lines are increasingly exposed to hazards that were historically unexpected, and at times to
58 multiple hazards in close succession. Most infrastructure is designed against specific hazards,
59 because the physical mechanisms differ¹⁷. As hazard regimes shift and events occur
60 sequentially or concurrently, adaptation measures optimized for one hazard may inadvertently
61 increase vulnerability to another¹⁸.

62 Mitigating transmission vulnerability demands a holistic systems-thinking approach that
63 integrates multidisciplinary perspectives; grid resilience is governed not only by non-stationary
64 climate hazards but also by intrinsic engineering attributes, such as structural design standards
65 and thermal transfer capacities, which dictate structural stress tolerance and operational load-
66 carrying capabilities¹⁹. Furthermore, the topological configuration of the transmission network,
67 alongside dynamic power flow dispatch patterns, dictates how localized contingencies
68 propagate or teleconnect across the infrastructure, potentially triggering cascading failures^{19,20}.
69 While prior literature has advanced our understanding of how historical or hypothetical climate
70 extremes⁵ impact critical infrastructure^{21,22} and broader power system^{23,24}, few studies have
71 deployed a coupled framework that simultaneously internalizes the climate, engineering, and
72 operational dimensions governing grid response to environmental shocks.

73 Here, we present a comprehensive global assessment of future multi-hazard climate risks to
74 power transmission infrastructure, explicitly coupling localized asset vulnerability with
75 network-wide reliability under extreme events. We integrate a comprehensive georeferenced
76 database of more than seven million kilometres of transmission lines (above 80% of global total)
77 with climate hazard projections from multiple Earth-system model ensembles under a range of
78 socioeconomic pathways (SSP1-1.9, SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5). By
79 mapping asset-specific engineering attributes to localized climate stressors, we project future

daily failure probabilities and quantify the structural exposure of transmission corridors to three most threatening Hazards: wildfires, freezing rains and tropical cyclones, through mid-century. Beyond static physical exposures, we evaluate the systemic consequences of these disruptions, quantifying consumer electricity shortages and renewable generation curtailment when damaged corridors isolate wind, solar, and hydropower resources from demand centers. Crucially, our framework reveals how spatially and temporally distinct hazards interact consecutively or concurrently to propagate through interconnected networks, coupling generation and demand failures to severely amplify global energy system risk

Results

Emerging climate risks for global power transmission infrastructure

We quantified the spatial footprint of climate-risk exposure by identifying transmission lines whose projected failure probability (ten-year average) exceeds the mean for 2015–2025 (Supplementary figure 28). With this criterion, 253 thousand lines under the low-emission pathway (LP; 236~267 thousand; 60~68% of the network) and 274 thousand under the high-emission pathway (HP; 240~288 thousand; 61~73%) are projected to be affected by at least one hazard by mid-century. Under LP, exposure initially increases but subsequently plateaus, rising from approximately 224 thousand lines in 2030 (212~237 thousand) to 253 thousand in 2050, before remaining at approximately 250 thousand after 2050 (236~264 thousand). Under HP, the affected network expands continuously driven primarily by wildfire: wildfire-affected lines increase from 139 thousand (118~160 thousand) to 202 thousand (188~216 thousand), whereas the corresponding LP estimate stabilizes at approximately 165 thousand (148~181 thousand). Multi-hazard exposure follows the same trajectory. Under LP, the number of lines affected by at least two hazards increases from 48 thousand (39~58 thousand) to 69 thousand (54~84 thousand) and then stabilizes. Under HP, it nearly doubles from 43 thousand (30~56 thousand) to 82 thousand (65~100 thousand).

The three hazards exhibit distinct geographical patterns of risk growth. Freezing-rain risk is concentrated across the cold mid-latitudes of North America and Eurasia, particularly along mountain foothills, continental cold-air basins and climatic transition zones where subfreezing surface air can coexist with warmer layers aloft; in the most exposed corridors, particularly along the coasts of southern and northern Europe, the expected annual failure frequency exceeds 5 events yr⁻¹. Tropical-cyclone risk remains more spatially confined, with the strongest increases along cyclone-exposed coastal transmission corridors in East and South Asia and the western North Atlantic, where expected annual failures can also exceed 5 events yr⁻¹. Wildfire produces the largest and most geographically extensive transmission-risk footprint under both pathways, with prominent growth hotspots in western North America, the Mediterranean, southern Africa, South America and eastern Australia. Under HP, these fire-prone regions expand and intensify rapidly after mid-century, making wildfire the dominant driver of the widening divergence between the two pathways. After 2050, wildfire exposure encompasses approximately 202 thousand lines under HP (188~216 thousand), equivalent to more than half

119 of the global network.

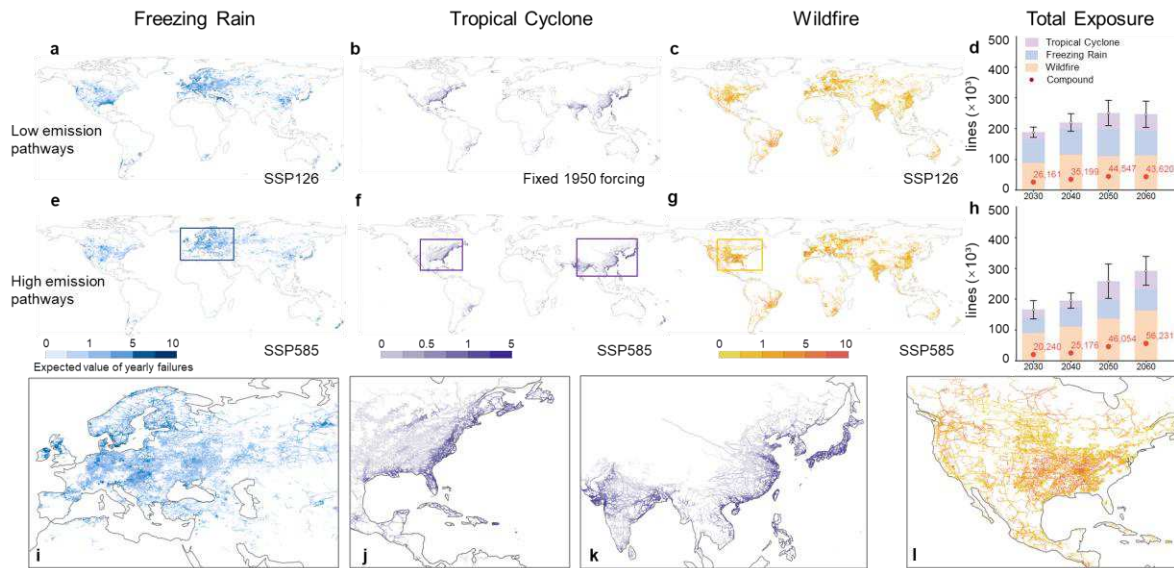


Figure 1| Global distribution and representative cases of transmission line failures induced by compound climate hazards. Spatial distribution of affected transmission lines and expected annual number of failures caused by Tropical Cyclone (TC) and Freezing Rain (FR) and wildfires under the low-emission pathway (a–c) and high-emission pathway (e–g) in 2050 (10-year average). (d and h), Global totals of affected transmission lines whose projected annual failure probability exceeds the mean value during 2015–2025. The stacked bars denote decadal means and the error bars denote ± 1 s.d. of annual values. Representative regional patterns of transmission-line exposure under different hazards: (i) Central Europe showing widespread freezing-rain risk; (j) eastern North America illustrating dense freezing-rain exposure across the U.S. Midwest and Northeast; (k) East and South Asia highlighting cyclone-related wind risks affecting coastal transmission corridors; and (l) North America showing extensive wildfire exposure.

Different sensitivities to climate-related hazards across countries

Figure 2 shows the regional and voltage-class patterns of mid-century climate-risk exposure across the global transmission network. Around 8.2~8.8 million km of hazard-specific transmission-line length is exposed by mid-century, yet the vulnerable voltage classes differ among hazards. Freezing-rain exposure is concentrated in low-voltage networks: globally, 55~59% of ≤ 110 kV lines are exposed under LP, compared with 36~40% of lines above 110 kV; in Russia, this share reaches 87.8% for ≤ 110 kV lines. This pattern suggests that local and regional lines, which are generally designed to lower mechanical loading standards, are more exposed to shifts in icing conditions. By contrast, wildfire exposure is more extensive in high-voltage corridors: under HP, 78.7% of global 330–500 kV lines and 75.9% of >500 kV lines are exposed, with particularly high densities in India’s 330–500 kV system (95.7%), China’s 330–500 kV system (81.8%) and the US 330–500 kV system (81.4%). This reflects the tendency of long-distance backbone corridors to cross sparsely populated, vegetated or semi-arid landscapes where fire weather intensifies. Tropical-cyclone wind exposure shows a third pattern, concentrating in 220 kV and higher-voltage coastal backbones: under SSP5-8.5, 49.0% of US 330–500 kV lines, 44.1% of India’s 330–500 kV lines and 44.3% of China’s 330–500

kV lines are exposed to cyclone-wind failure risk, indicating that critical transmission arteries along coastal and monsoon-affected regions are increasingly exposed to stronger storm winds. Absolute exposed length highlights where the largest climate-risk footprints occur. Freezing-rain exposure is widespread under the low-emission pathway but weakens under stronger warming. Globally, the length of lines exposed to freezing-rain failure risk declines from 3,014.0 thousand km under LP to 2,447.2 thousand km under HP, reducing the affected share from 45.4% to 36.9%. The largest low-emission footprints occur in the United States, the European Union, China and Russia, with 680.1, 625.8, 515.2 and 435.2 thousand km of exposed lines, respectively. These patterns are driven by the temperature and precipitation sensitivity of freezing rain: warming reduces exposure in many mid-latitude regions by shifting winter conditions away from the near-freezing regime required for ice accretion. The largest reductions under the high-emission pathway occur in the EU, China and the United States, where freezing-rain-exposed length falls by 177.6, 114.5 and 111.3 thousand km, respectively. Canada is the main exception, increasing from 109.1 to 125.3 thousand km, indicating a poleward persistence of freezing-rain-prone conditions in high-latitude transmission corridors.

Wildfire becomes the dominant source of mid-century transmission climate-risk exposure. Under the low-emission pathway, 4,256.2 thousand km of transmission lines are exposed to wildfire failure risk, equivalent to 64.2% of the global network. Under the high-emission pathway, this expands to 4,651.7 thousand km, or 70.1% of the network. The largest wildfire-exposure footprints occur in the residual global regions, China, the United States and the EU. Under HP, these regions reach 987.5, 825.1, 729.5 and 695.6 thousand km, respectively. India shows the highest affected share among major systems, rising from 88.0% to 94.1% of its transmission network, indicating that wildfire exposure is not confined to a few isolated corridors but becomes nearly system-wide. Increases are also substantial in the United States and the EU, where wildfire-exposed length rises by 118.6 and 102.7 thousand km, respectively. Tropical-cyclone-induced wind exposure has a smaller global footprint than freezing rain or wildfire but shows regional amplification. Globally, the length of lines exposed to cyclone-wind failure risk rises from 1,290.3 thousand km under LP to 1,385.6 thousand km under HP. The United States becomes the largest hotspot under HP, increasing from 333.6 to 402.7 thousand km, followed by China at 377.6 thousand km. India experiences the strongest relative expansion among major regions, with TC-exposed length increasing from 113.5 to 207.7 thousand km, as intensified Indian Ocean cyclones extend stronger wind hazards across coastal and near-coastal 110–500 kV transmission infrastructure. By contrast, cyclone-wind exposure decreases in several regions, including China, Brazil, Africa and the EU.

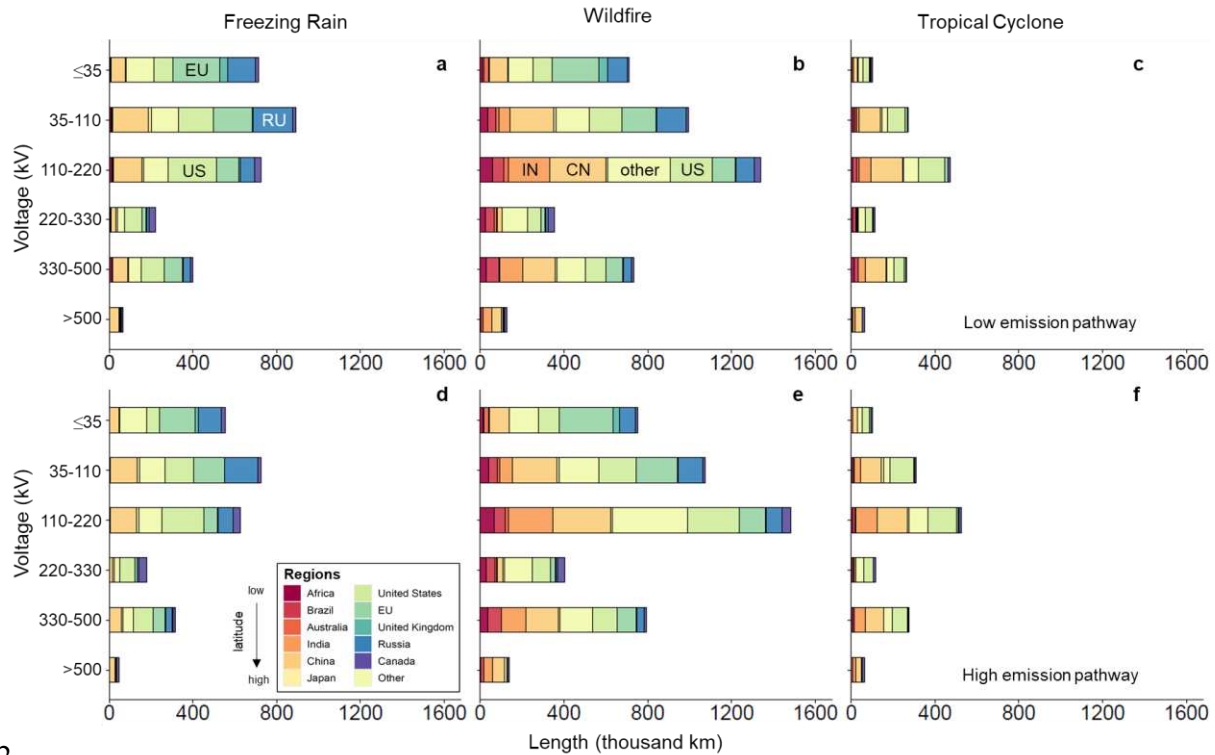


Figure 2 | Transmission line exposure to climate hazards by voltage class and regions in 2050.

Exposure of transmission infrastructure to three major hazards: Freezing Rain (FR), wildfire, and Tropical Cyclone (TC), under low-emission (LP; **a-c**) and high-emission (HP; **d-f**) scenarios. Bars represent total transmission line length ($\times 10^3$ km) exposed to each hazard, disaggregated by country and voltage class. Voltage ranges (a–b) are expressed using the interval notation “(a, b]”. The exposure-density results, normalized by total line length within each voltage class are shown in Supplementary Figure 29.

Compound climate extremes constrain transmission capacity

Figure 3 shows the monthly share of transmission capacity with failure probabilities exceeding the corresponding 2015–2025 maximum through mid-century, under both decadal-average conditions and the most severe year. Climate change are shifting historically distinct hazard regimes spatially closer, and compound climate hazards increasingly strike large fractions of transmission capacity within the same season, creating recurrent transmission bottlenecks in major electricity systems. Averaged across the three power-grid systems in different climate zones, the share of monthly affected capacity increases from 3.8% in 2020–2030 to 8.9% in 2030–2040 and 9.5% in 2040–2050 under the low-emission pathway (LP). Under the high-emission pathway (HP), the corresponding share rises from 4.2% to 8.8% and 10.1%. From 2040 to 2050, exposure increases by a further 1.3 percentage points under HP, more than twice the 0.6-percentage-point increase under LP. Nevertheless, low emissions do not eliminate substantial transmission risk. By 2040–2050, the mean affected-capacity share still reaches 6.9–11.7% across the three systems under LP. Risks are much greater during sporadic extreme months. In the most severe years, peak monthly exposure during 2040–2050 reaches 21.4–65.3% of system capacity in Spain, with critical exposure (where failure probability rises by more than

one percentage point) reaching 28.5%, highlighting potentially system-constraining episodes that are obscured by decadal averages.

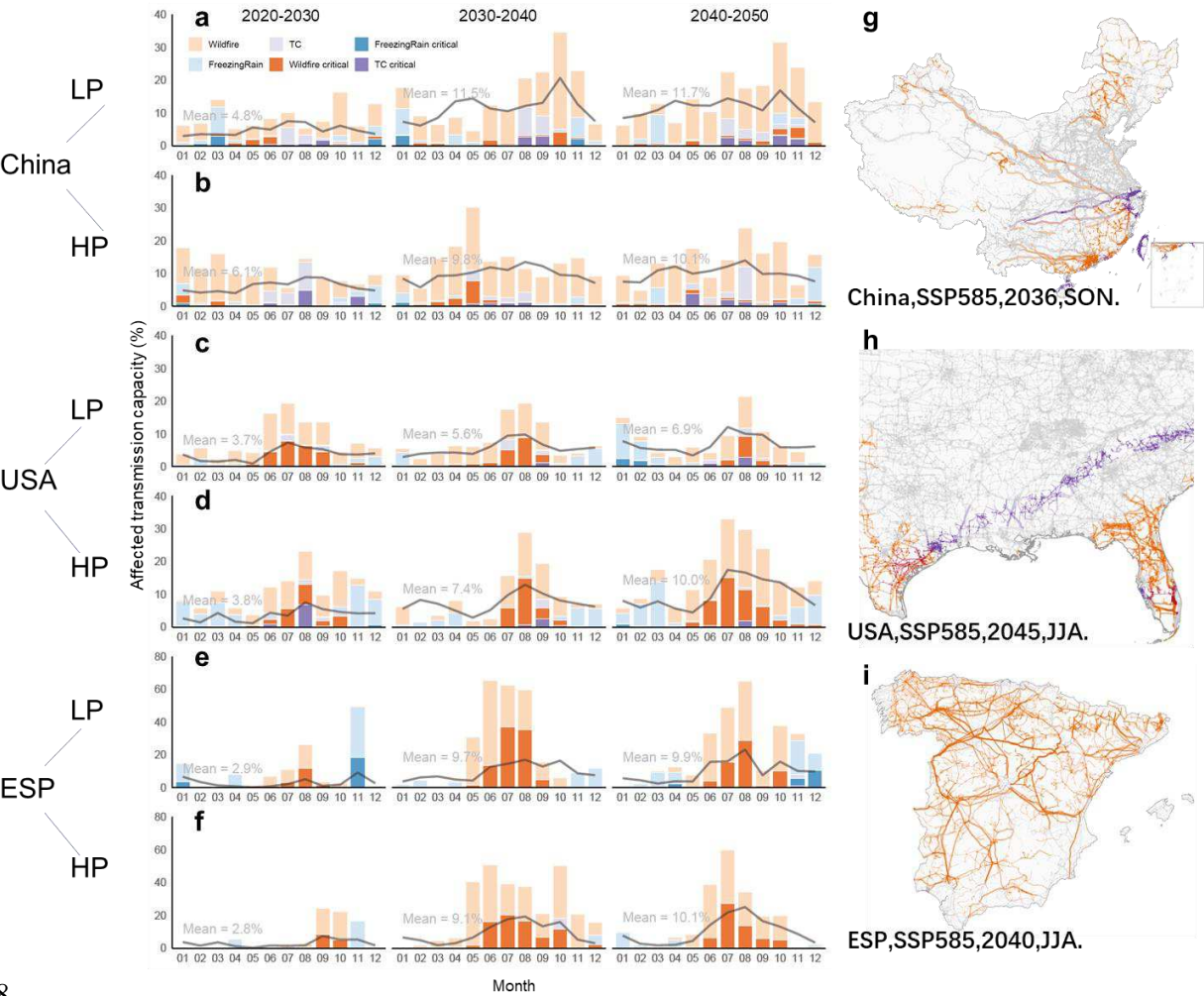


Figure 3 | Monthly and spatial patterns of compound climate risks to transmission capacity. a–f, Monthly distribution of projected transmission-capacity risk across three representative power-grid systems under low-emission pathway (LP) and high-emission pathway (HP) for three future periods: 2020–2030, 2030–2040, and 2040–2050. A line is classified as affected when its monthly mean failure probability exceeds the corresponding 2015–2025 period maximum by an absolute probability increment of at least 10^{-4} (0.01 percentage points). The grey line shows the monthly affected-capacity share averaged across all years within each decade, while bars show the most severe year pattern. Darker segments in stacked bars denote critical risk, defined as transmission capacity for which the monthly mean failure probability exceeds the 2015–2025 period maximum by at least 10^{-2} (1 percentage point). g–i, Examples of spatially explicit transmission corridors exposed to compound climate risks in China, the United States, and Spain under SSP585. Colored transmission segments indicate climate-risk-exposed lines and the width shows transmission capacity.

The dominant hazard and its seasonal window differ markedly among power systems. Wildfire-affected capacity share across the three systems increases from 2.3% in 2020–2030 to 7.6% in 2040–2050 under HP, accounting for three-quarters of total projected exposure in 2050. Even under LP, wildfire exposure also increases substantially, from 2.0% to 6.7%, but largely

stabilizes after 2030–2040. Wildfire risk is concentrated from June to October in the United States and Spain, generally peaking in July or August, whereas in China it extends across a broader spring-to-autumn window and overlaps with tropical-cyclone exposure during summer. Spain is particularly dominated by wildfire: in the most severe month of 2030–2040, 65.5% of transmission capacity is affected under LP, exceeding the 50.8% peak under HP. This event-scale reversal shows that low-emission pathways can still contain extreme individual hazard. Freezing rain generates a distinct cold-season risk window, primarily between November and March (in these three Northern Hemisphere countries). Its cross-system mean exposure under LP increases from 1.2% to 2.1%, slightly higher than the 1.8% projected under HP in 2040–2050; severe freezing-rain months alone can affect nearly half of Spain’s transmission capacity. Tropical-cyclone risk contributes less than 1% across the three systems. However, its concentration in a small number of summer months produces larger episodic impacts, affecting up to 10% of Chinese transmission capacity, 2% of Spain in sporadic extreme months, while negligible in other European countries.

The spatial patterns further show that these risks are correlated along transmission corridors rather than dispersed among isolated assets (Fig. 3g–i). In China, exposed lines extend across the densely interconnected eastern and southern power systems and along long-distance interregional corridors, with tropical-cyclone risk concentrated near the southeastern coast and wildfire risk distributed more broadly across inland and coastal networks. In the United States, exposure converges along Gulf and Atlantic coastal networks and major corridors connecting the southern, central and eastern systems. In Spain, wildfire exposure covers much of the national transmission network, including multiple parallel routes crossing the interior and connecting major coastal load centres. A notable low-exposure area appears around Madrid, where several key 132- and 400-kV circuits are underground, preserving critical transmission capacity serving the capital. Elsewhere, simultaneous exposure of adjacent or parallel lines reduces the ability of power flows to be rerouted after an individual disturbance, thereby eroding network redundancy and contingency margins. Compound climate extremes can therefore transform failures that would be absorbed individually through meshed-network redundancy or redispatch into correlated corridor-level constraints, increasing the likelihood that local asset risks propagate into regional transmission bottlenecks and power-supply deficits.

Disproportionate impacts from small subset of corridors in developing countries

To determine how risk exposure translates into societal consequences, we further conducted large ensembles of Monte Carlo simulations of line failures and network dispatch, quantifying the resulting customer impacts. Power-shortage impacts were highly concentrated in a small subset of transmission lines, particularly in developing-region grids with uneven connectivity and limited redundancy. Across representative developing power grids of China, the Southern African Power Pool (SAPP) and Brazil, climate-driven transmission failures generated 13.5 million customers experiencing power shortages per year, with only 1% of lines accounting for 31–57% of this expected burden. The degree of concentration varied markedly with network

structure. In SAPP, lines providing the sole topological connection between parts of the network represented only 14.6% of all lines but accounted for 88.1% of expected resident impacts. In Brazil, such lines comprised 28.9% of the network and accounted for 49.9% of impacts, rising to 63.3% and 74.2% within the 35–110-kV and 110–220-kV classes, respectively. By contrast, they represented only 1.4% of China's more highly meshed network and accounted for 7.0% of impacts, consistent with its more highly meshed structure and greater availability of alternative transmission routes.

Impacts become less frequent but more severe with increasing voltage, yet the greatest expected annual burden (considering both frequency and impact) arises from different voltage classes depending on each grid's structure. In China, lines operating at ≥ 500 kV failed in only 0.043% of Monte Carlo simulations, compared with 0.093–0.127% for lines below 110 kV. Yet when a ≥ 500 -kV line failed, it accounted for shortages affecting 142,708 customers on average, approximately six times the 21,883–23,759 customers associated with failures below 110 kV. Brazil showed the same broad rare-but-severe tendency: the mean failure frequency is 0.153% at ≥ 500 kV, compared with 0.237–0.443% below 110 kV, whereas the conditional (when failed) customer impact rose from 3,309 customers at ≤ 35 kV and 17,156 at 35–110 kV to 35,620 at ≥ 500 kV.

Expected customer impact nevertheless peaks below the highest voltage class, and the dominant tier differed among grids. In China, 220–500 kV lines contributed 5.85 million customer impacts per year, or 60.9% of line-attributed exposure, whereas ≥ 500 kV lines contributed 16.7%. SAPP was dominated by 110–220 kV lines, which contributed 0.665 million events per year (59.5%); each failure in this tier affected an event-weighted mean of 28,973 customers, four times the 7,269 attributed to a 220–500 kV failure. Brazil was also centred on its sub-transmission and regional backbone: 110–220 kV lines contributed 1.19 million events per year (43.4%), followed by 220–500 kV lines at 0.755 million (27.4%) and 35–110 kV lines at 0.532 million (19.3%). Together, the 35–220 kV tiers accounted for 62.7% of Brazil's expected line-attributed impact. Nominal voltage therefore defines only a broad severity envelope; topology determines the voltage tier at which failure likelihood and network-mediated consequence intersect. Low- and medium-voltage corridors were consequently not benign. The highest-ranked Brazilian asset was a 138 kV line: it failed in 2.65% of monthly simulations, affecting 220,391 customers on average per year. A 66 kV SAPP line similarly ranked fourth in that system, affecting 53,277 customers per year. These apparent outliers reveal critical bottleneck corridors that provide effective connection between major load centres and the wider grid.

Concurrent failures amplified these topological vulnerabilities. Draws containing at least two failed lines accounted for 96.8% of affected customers in China, 88.9% in SAPP and 90.8% in Brazil. Brazilian draws with three to five concurrent failures affected as many as 7.28 million customers, while China's maximum increased from 2.70 million under a single-line failure to 8.23 million when more than ten lines failed. The location and combination of failed assets also matter. The spatial corridors in Fig. 4 identify locations where concurrent losses can exhaust

redundancy across serial or parallel paths. High-impact lines were spatially clustered: 61.3%, 53.8% and 41.7% of the top 1% in China, SAPP and Brazil, respectively, shared a terminal with another top-ranked line, compared with voltage-matched random expectations of 21.6%, 18.5% and 10.7%. It defines a compact priority set for targeted hardening, corridor diversification and enhanced monitoring.

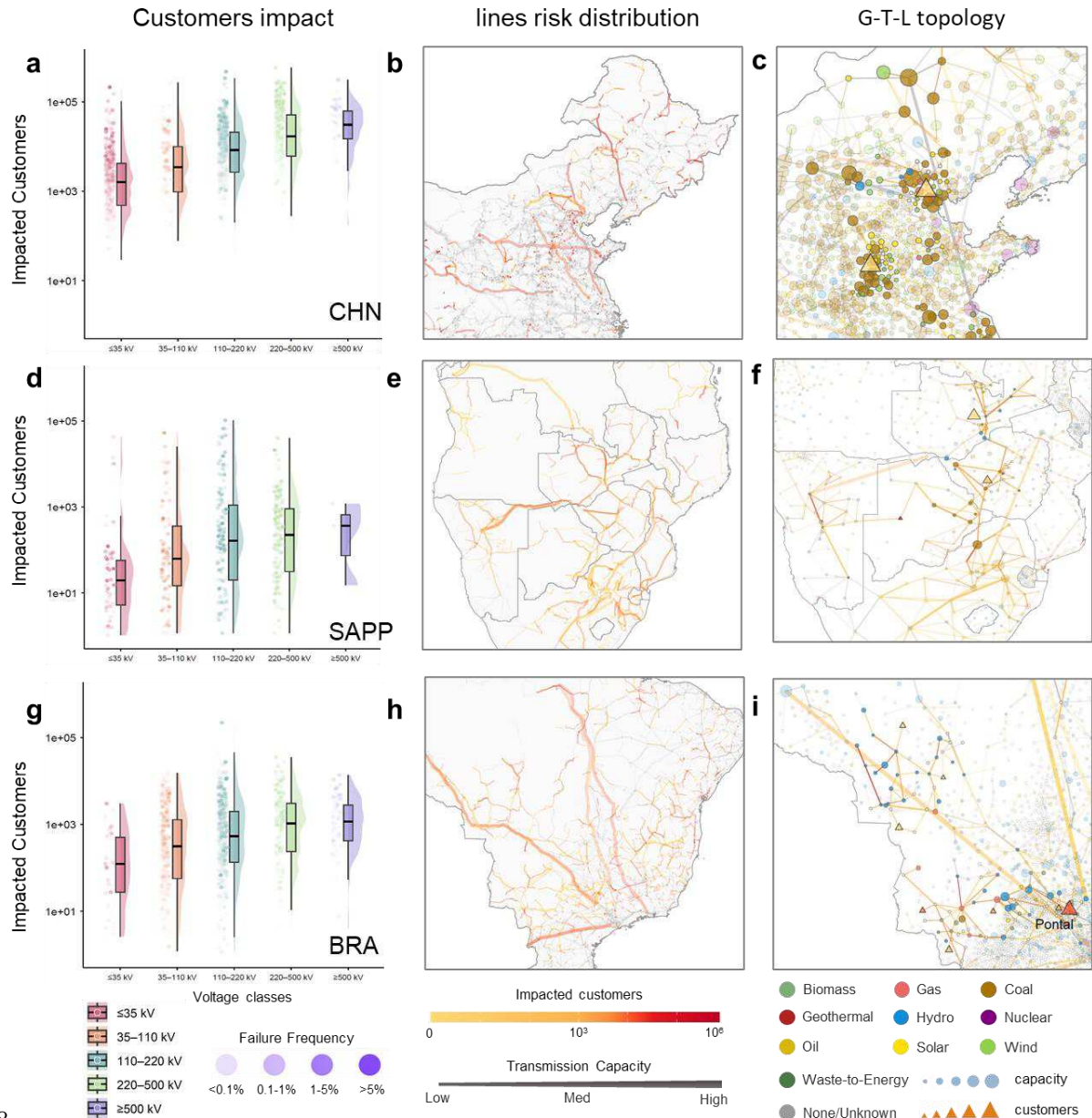


Figure 4| Customer exposure caused by simultaneous transmission-line disruptions in generation–transmission–load networks. a,d,g, Distributions of expected annual affected customers attributed to climate-exposed transmission lines across voltage classes in China, the Southern African Power Pool (SAPP), and Brazil. Points represent individual transmission-line records, boxplots summarize the median and interquartile range, and shaded distributions show the spread of affected customers on a logarithmic scale. Voltage classes range from ≤ 35 kV to ≥ 500 kV. b,e,h, Spatial distribution of climate-exposed transmission corridors in the three systems. Line colors indicate expected customer impact from low to high. c,f,i, County-level structure of the corresponding GTL (generation units, transmission links,

and load nodes) networks. Generation nodes are colored by fuel type, including biomass, geothermal, oil, gas, hydro etc., and the size represents capacity. Where multiple generation units are aggregated at the same node, the dominant fuel type by capacity is shown. Triangles indicate load nodes experiencing load shedding; their size represents the expected number of affected residents, while colours from yellow to red indicate increasing frequency of power shortages.

Discussion and policy implications

Our findings demonstrate that anthropogenic climate change is doing more than merely intensifying single-hazard extremes; it is fundamentally restructuring the spatiotemporal architecture of risk within global power transmission networks. The escalation of multi-hazard, sequential, and teleconnected events demonstrates that traditional engineering and governance frameworks built around isolated, local hazards, are no longer sufficient for managing 21st-century power systems²⁵. Understanding multi-hazard interactions is essential because the governance and recovery of sequential or concurrent disasters are far more complex than those of single events^{18,26}. Managing a single wildfire season, for example, can rely on targeted vegetation control and emergency repair protocols. In contrast, when wildfires are followed by typhoons, or when FR precedes a cyclone season, restoration and resource allocation become exponentially more difficult²⁷. Infrastructure that has only partially recovered from one event is more vulnerable to the next, while emergency crews, supply chains, and financial mechanisms face overlapping demands. Moving forward, our results offer three critical implications for future-proofing electricity grid resilience under accelerated climate-related hazards.

First, risk governance should shift from hazard-centric asset protection towards system-level, differentiated resilience planning. Regulators should establish a three-dimensional design framework based on climatic zone, voltage class and topological importance. Strategic corridors that enable inter-regional power exchange or connect major energy bases with load centres—such as interstate interconnectors in the United States—should receive priority reinforcement, with wind, icing and fire-resistance requirements raised above general national standards (for example by extending design return periods to 100 years or longer). Design and maintenance protocols should reflect regional hazard regimes, particularly in emerging hotspots where future risks exceed those anticipated from historical experience—for example, by strengthening icing resistance and de-icing capacity in northern Europe and other high-latitude regions. For ultra-high-voltage backbones spanning multiple climatic zones, standards should further account for sequential hazards and cumulative physical degradation along different sections of the same corridor. Designating these high-risk corridors enables targeted policy interventions rather than diffuse infrastructure spending

Second, resilience planning must recognize that otherwise unrelated extremes can become teleconnected through the power network. A local hazard may appear manageable in isolation, yet spatially distant events can simultaneously disable parallel corridors while elevated demand or reduced generation further erodes system flexibility. The grid can therefore connect, propagate, and amplify hazards conventionally treated as independent. Early-warning systems

should move beyond isolated meteorological forecasts towards network-aware models that anticipate correlated outages, transmission congestion and downstream electricity deficits across regions.

Third, safeguarding electricity supply requires geographically distributed and technologically diverse generation portfolios, with planning priorities guided by potential impacts on customers and essential services. Large energy bases and long-distance transmission should be complemented by distributed renewables, storage and other local resources near load centres, creating a dual system of local supply and regional mutual support. Inter-regional corridors should also draw on complementary generation and flexible capacity, rather than depend on a single resource whose output may collapse during droughts, wind lulls or other climate extremes. This multi-point supply structure would allow receiving regions to maintain critical loads through local and neighbouring resources when major generation bases or long-distance corridors are disrupted, preventing localized failures from escalating into widespread socioeconomic disruption.

While this study establishes an integrated framework for assessing compound climate risks to power transmission systems, several structural limitations and uncertainties merit discussion. First, the infrastructure network is treated as static. Although the power-plant database integrates multiple sources and includes facilities under construction or planned, detailed future transmission expansion, retirement and reinforcement plans are not represented. The results therefore quantify future climate risks to a largely present-day network configuration rather than predict the performance of the power systems that will ultimately operate under those climates. This assumption may overestimate vulnerability where substantial grid hardening occurs, but could underestimate exposure arising from network expansion into hazard-prone regions.

Second, system operation is represented using a simplified network-flow dispatch model rather than full AC power-flow and dynamic stability simulations. This abstraction preserves computational feasibility across global networks, multiple climate scenarios and multidecadal timescales, but does not resolve phase angles, reactive power, voltage stability, protection-system responses or sub-second-to-minute operational dynamics. Relatedly, the model captures the cascading propagation of climate-induced capacity constraints and power deficits, but not cascading failures themselves. Processes such as overload-induced line tripping, frequency instability, grid islanding and system-wide collapse are therefore not explicitly simulated. As a result, the modeled network presents higher operational flexibility and resilience than would occur during real-time, rapidly evolving climate shocks.

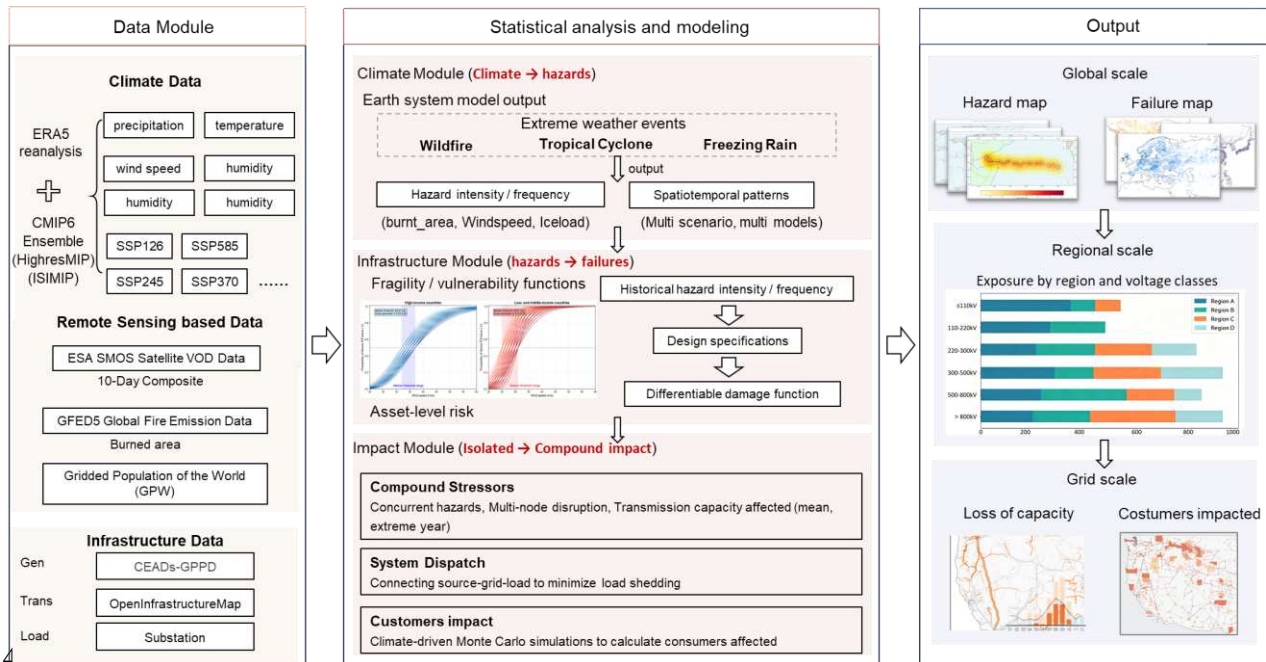
Despite these limitations, our core conclusions remain robust. Because the model represents a highly flexible network and does not simulate the full dynamics of cascading failure, the estimated disruptions should be interpreted as conservative. The emergence of substantial risks even under these optimistic assumptions indicates that the identified vulnerabilities are structurally embedded in transmission networks. Assessing such risks over decadal timescales is essential for anticipatory adaptation, given the long service lives and substantial planning, permitting and construction lead times of transmission infrastructure. Our results therefore provide a policy-relevant and actionable baseline for targeted reinforcement, contingency

planning and climate-resilient power-system development.

In conclusion, increasingly compound and teleconnected climate risks require a shift from protecting individual assets against isolated hazards to governing interconnected power systems for system-wide resilience. Understanding how climate extremes interact across space, time and network topology is therefore not only an engineering challenge but also a socioeconomic imperative. Embedding multi-hazard dynamics and network interdependencies into grid planning and operation will be essential to securing a reliable, resilient and equitable global energy transition under a changing climate.

Methods

Our methodology integrates three core modules to simulate the impacts of climate change on climate-related hazards, on power infrastructure, and the broader power system and electricity gap (Extended Data Figure 1). The climate module translates climate projections under different SSP scenarios into spatially explicit hazard intensity fields for wildfire, freezing rain (FR), drought, and Tropical Cyclones (TC). The infrastructure module overlays these hazard fields with geo-referenced transmission and generation datasets, incorporating engineering attributes to estimate hazard-specific fragility, failure probabilities, and associated power generation deficits. The impact module links these physical disruptions to system-level outcomes: it accounts for cooling-demand surges during heat events, and embeds line failures into a simplified economic dispatch model to simulate power flow rerouting, network congestion, unserved demand, and curtailed renewable generation. The validation part is in Supplementary Information Section 4. Together, these modules provide an integrated framework for tracing how climate hazards propagate from physical infrastructure damage to system-wide and socio-economic consequences.



Extended Data Figure 1 Schematic diagram of the methodological framework.

1.1 Climate module: derivation of multiple climate-related risk indices in grid cells

The module integrates multi-model climate projections with hazard-specific physical indicators to characterize the temporal evolution and spatial distribution of three major climate hazards affecting transmission infrastructure: freezing rain (FR), tropical cyclones (TC), and wildfires. Future climate projections were obtained from the Coupled Model Intercomparison Project Phase 6 (CMIP6) and the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP). The three hazards were simulated through a common climate-hazard framework but using hazard-specific process representations. Freezing rain was identified from the joint thermodynamic and precipitation conditions required for precipitation formation and phase transition; tropical cyclones were characterized using storm tracks derived from CMIP6 HighResMIP simulations; and wildfire exposure was obtained from process-based fire-model simulations driven by CMIP6 climate forcing. This design allowed each hazard to be represented using the climate variables, spatial and temporal resolutions, and model configurations most appropriate to its governing physical processes.

Because different hazard-specific models provide projections under different socioeconomic scenarios, we harmonized available experiments into two representative emission pathways: a low-emission pathway (LP; including SSP1-1.9, SSP1-2.6, and control experiments depending on data availability) and a high-emission pathway (HP; SSP5-8.5). For each grid cell and time step, hazard-specific indices were derived to represent the intensity or occurrence potential of each HAZARDS. Rather than directly applying raw climate variables, we constructed physically informed hazard indicators that reflect the mechanisms controlling infrastructure exposure. For each hazard type, the resulting index was subsequently spatially associated with transmission lines through geographic overlay and used as the climate forcing input for infrastructure failure-risk modelling.

1.1.1 Freezing rain

FR is a hazardous form of winter precipitation that occurs when raindrops fall through a layer of subfreezing air near the ground and freeze upon contact with surfaces. FR typically occurs during the winter or early spring months, particularly from December to February in the Northern Hemisphere^{28,29}. It is most common in mid-latitude regions where warm air aloft interacts with cold air near the surface. Freezing rain events are identified based on the characteristic vertical thermal structure and precipitation-phase physics governing their formation. Freezing rain typically occurs under a “warm-over-cold” profile, in which a melting layer aloft overlies a shallow subfreezing layer near the surface. In this configuration, hydrometeors melt into liquid raindrops within the warm layer and subsequently become supercooled as they fall through the near-surface cold layer, freezing instantaneously upon contact with exposed surfaces.

To operationalize this mechanism, we diagnose freezing-rain-favorable conditions using near-surface air temperature (T_{as}), air temperature at 850 hPa (T_{a850}), and precipitation-phase variables derived from climate model outputs. A given day is classified as conducive to freezing rain when all of the following criteria are simultaneously satisfied:

$$T_{850} > 0^{\circ}\text{C}$$

$$-3^{\circ}\text{C} < T_{2m} < 0^{\circ}\text{C}$$

$$P_{\text{rain}} = P_{\text{total}} - P_{\text{snow}} > 0$$

These criteria jointly characterize atmospheric conditions favourable for freezing rain formation. Under such conditions, we further estimate rainfall intensity and associated ice accretion thickness based on physically derived relationships (see Section 1.2.1 for a detailed calculation example). A freezing rain event is ultimately diagnosed when the simulated ice accretion exceeds a predefined threshold, reflecting the onset of infrastructure-relevant icing impacts.

1.1.2 Wildfire

Wildfire hazard is characterized using outputs from the ISIMIP ensemble of global fire models. We primarily employ results from the ELM-ECA model³⁰, which explicitly represents key fire processes including ignition, spread, and human suppression, enabling a more mechanistic representation of climate–fire interactions. This process-based formulation is particularly suited for capturing the response of wildfire activity to compound climate extremes, which is central to this study. Wildfire hazard is quantified using the simulated burned area fraction at each grid cell and time step, representing the proportion of land area affected by fire. This metric integrates the combined effects of climatic drivers (e.g., temperature, precipitation, and vapor pressure deficit), fuel availability, and human intervention, and thus provides a physically grounded indicator of wildfire intensity and spatial extent.

To account for structural model uncertainty, we further incorporate simulations from the CLASSIC fire model as an alternative representation. CLASSIC adopts a more empirical formulation of burned area based on climate and vegetation constraints, which provides a comparatively conservative estimate of wildfire risk. Results based on CLASSIC are used to assess the robustness of our findings to model structural differences.

1.1.3 Tropical cyclone

Tropical cyclone (TC) hazards are identified using six-hourly tropical-cyclone tracks downloaded from CMIP6 HighResMIP experiments. To ensure relevance for infrastructure risk assessment, we retain only storms with maximum sustained wind speeds exceeding 17 m s^{-1} , corresponding to the tropical storm threshold. This filtering excludes weak disturbances while preserving events with potential engineering impacts on power infrastructure. Storm tracks are detected using established feature-tracking algorithms, including TRACK³¹ and TempestExtremes³². Both approaches identify tropical cyclones based on coherent dynamical signatures, including closed circulation structures, minima in sea-level pressure, and sustained wind speed thresholds, and output time-resolved storm center positions and intensity metrics.

As TC tracks are represented as vector trajectories, a spatial transformation is required to enable integration with gridded risk analysis. For each storm track, we construct a gridded exposure field by assigning an influence radius R (typically 100–300 km) around each time-resolved storm center location, representing the spatial extent of damaging winds. The resulting

wind fields are aggregated over time to produce monthly, grid-level indicators of TC exposure, including (i) event frequency and (ii) maximum wind intensity. A grid cell is classified as exposed to tropical cyclone impact when the simulated wind speed exceeds the design threshold of transmission infrastructure. The final output is a spatially explicit TC hazard dataset at a unified resolution, which is subsequently overlaid with transmission network data to quantify exposure intensity and potential disruption risk (Supplementary Figure 33 to 34).

1.1.4 Compound supply–demand climate stressors (drought, low wind–solar, and heatwaves)

In addition to transmission-related hazards, we consider a set of climate extremes that primarily affect the generation (source) and demand (load) sides of the power system, including drought, low wind–solar resource conditions (or *dunkelflaute*), and heatwaves. Power system risks are inherently systemic and often arise from the concurrence of shocks across the source–network–load nexus; for example, transmission failure can coincide with elevated electricity demand during heatwaves, or hydropower deficit during drought. Such compound conditions can amplify system stress beyond what would be inferred from transmission failures alone.

Given that the primary focus of this study is on transmission infrastructure risk, these additional hazards are incorporated in a simplified manner and are not analysed in detail in the main text. Detailed formulations of these extreme-event identification methods and their quantified impacts on generation capacity and electricity demand are provided in the Supplementary Information Section 2 and Supplementary Information Section 4.2. Their identification follows a threshold-based approach commonly adopted in climate impact studies. Specifically, drought conditions are diagnosed using discharge anomalies relative to historical baselines; low wind–solar conditions are identified based on concurrent deficits in near-surface wind speed and surface solar radiation below climatological percentiles; and heatwaves are defined as consecutive days exceeding high-percentile temperature thresholds (e.g., the 95th or 97.5th percentile) for a minimum duration. These diagnostics are applied consistently across climate model outputs to generate spatially explicit indicators of generation shortfalls and demand surges. Although simplified, incorporating these stressors is essential for capturing the co-occurrence of multi-dimensional risks in the power system.

A remaining limitation is that the hazard-specific ensembles do not contain identical climate-model members. The climate variables and model resolutions required to simulate freezing rain, tropical cyclones and wildfire are not consistently available from the same CMIP6 models; tropical-cyclone tracks, in particular, were obtained from a separate HighResMIP ensemble, whereas wildfire projections additionally depend on process-based fire models. We therefore maximized model overlap where possible and used multi-model ensemble estimates to reduce dependence on any individual model. Nevertheless, when hazards are derived from different climate-model realizations, their joint occurrence does not represent a fully synchronized evolution of the climate system. The framework captures shared responses to the same emission pathway and identifies overlapping infrastructure exposure, but it does not explicitly preserve

all event-scale physical dependencies among hazards—for example, relationships mediated by common circulation anomalies or sequential interactions between cyclones, vegetation conditions and wildfire. The compound-risk results should therefore be interpreted as estimates of multi-hazard exposure and potential coincidence rather than as a fully coupled probabilistic simulation of cross-hazard dependence.

1.2 Infrastructure module

1.2.1 Power infrastructure failure probability

Engineering design resilience was parameterized using climatic-action return periods derived from international overhead-line standards (IEC 60826)³³ and Supplementary Data Table 1. Because different hazards impose fundamentally different physical stresses on transmission infrastructure, hazard-specific failure models were applied. Tropical-cyclone risk was represented primarily through extreme wind speed and the associated wind-load response, whereas freezing-rain risk was modelled using ice accretion and combined wind–ice loading. Wildfire risk, for which structural design standards generally do not prescribe an equivalent climatic return period, was instead characterized using fire exposure relative to historically experienced conditions.

(1) Freezing rain

FR poses significant risks to infrastructure and human activities^{34,35}. Glaze ice accumulation can increase mechanical loading on overhead power lines and transmission towers, potentially leading to line outages. To assess the failure probability of transmission lines under freezing rain events, we developed an integrated framework that combines meteorological forcing, ice-accretion estimation, transmission-line exposure mapping, and empirical failure-probability assessment. The framework includes four key steps: (1) estimating historical ice accretion, (2) deriving design ice thickness, (3) simulating future ice accretion, and (4) assessing transmission-line failure probability.

A range of models has been developed to estimate ice accretion on overhead conductors during freezing-rain events using meteorological inputs. These models differ in their representation of physical processes, empirical assumptions, and data requirements. Examples include the Chaine model³⁶, the Meteorological Research Institute (MRI) model³⁷, the Makkonen freezing rain model³⁸, and the Cold Regions Research and Engineering Laboratory (CRREL) model³⁹. For long-term, large-scale simulations, we employ a simplified freezing rain model⁴⁰ that assumes a uniform radial ice thickness (R_{eq}) on transmission lines. The formula is as follows:

$$R_{eq} = \frac{1}{\rho_i \pi} \sum_{j=1}^N \left[(P_j \rho_0)^2 + (3.6 V_j W_j)^2 \right]^{1/2}$$

where P_j represents the precipitation rate (in mm/h), $W_j = 0.067 P_j^{0.846}$ represents the liquid water content (in g/m^3), and V_j represents the wind speed (in m/s) during the j th hour of a continuous N -hour FR event. ρ_i and ρ_0 represent the densities of ice and water, respectively.

To estimate design ice thickness at a specified return period, we fitted the historical ice-accretion series in each grid cell using a Gumbel distribution. The Gumbel distribution^{41–43} is widely used for extreme value analysis and is well suited for estimating rare meteorological extremes. In this section, we applied the Gumbel distribution to model extreme ice accretion and estimate the design ice thickness for each segment of global transmission line networks. Specifically, historical ice-thickness records were fitted to the distribution, and return-period-based design values were derived to represent the level of ice loading that each line segment is expected to withstand. The cumulative distribution function of the Gumbel distribution $F(x)$ is given by:

$$F(x) = \exp\{-\exp[-(x - b)/a]\}$$

Where x represents the annual maximum ice accretion thickness, a is the scale parameter, and b is the location parameter. These parameters are derived from the historical ice thickness data as follows:

$$a = \frac{\sqrt{6}}{\pi} \times \sigma = \frac{\sigma}{1.28255}$$

$$b = E(x) - 0.45005\sigma = \mu - 0.45005\sigma$$

Where μ and σ represent the mean and standard deviation of historical ice cover thickness, respectively.

The return level corresponding to a return period T can then be estimated as:

$$x_T = b - a \ln \left[-\ln \left(1 - \frac{1}{T} \right) \right]$$

where x_T represents the design ice thickness associated with a T -year return period. For example, x_{50} and x_{100} indicate the ice thickness expected to be exceeded, on average, once every 50 and 100 years, respectively. In this study, these return-period values were used to define the design ice-loading threshold for each transmission line segment, following international or country-specific transmission-line design standards (which assign different return periods according to the voltage class, functional importance, and reliability requirement).

By integrating design ice thickness estimates and future projections of ice accretion, we applied an empirical failure-probability model to assess the risk of freezing-rain-induced outages across grid cells. The model relates infrastructure vulnerability to the ratio between projected ice accretion and the design ice-loading threshold, thereby quantifying the potential risk to power grid facilities under different icing conditions. The empirical model of failure probability⁴⁴ is defined as follows:

$$P_{failure} = \begin{cases} 0 & , \quad m \leq M \\ \exp \left[\frac{0.6931(m - M)}{4M} \right] - 1 & , \quad M < m < 5M \\ 1 & , \quad m \geq 5M \end{cases}$$

where m and M represent the predicted ice accretion thickness and the design ice thickness, respectively. This empirical model effectively captures the nonlinear relationship between ice accretion thickness and the probability of power grid failure, aiding in the identification of high-risk areas.

Meteorological variables, including precipitation rate, wind speed, near-surface temperature, and upper-atmosphere temperature, were obtained from the ERA5 reanalysis dataset at a spatial resolution of $0.5^\circ \times 0.5^\circ$ for the historical period. Based on these inputs, historical ice-accretion thickness was calculated for each grid cell from 1980 to 2023. To assess future risks to power transmission infrastructure, ice-accretion thickness was further simulated for 2024–2079 under two Shared Socioeconomic Pathways, SSP1-2.6 and SSP5-8.5.

(2) Wildfire

Unlike hazards such as freezing rain or tropical cyclones, for which failure probabilities can be derived from the relationship between hazard intensity and infrastructure design thresholds (e.g., icing thickness or wind speed limits), wildfire impacts lack well-defined engineering design criteria. Instead, failures are primarily driven by direct exposure to fire fronts, thermal damage, and safety-related operational shutdowns. Therefore, we approximate failure probability using the burned area fraction, which directly reflects the likelihood that transmission assets are affected within a given grid cell. Intuitively, a higher fraction of burned area corresponds to a greater probability that the line segment is directly affected by fire or subject to operational shutdown.

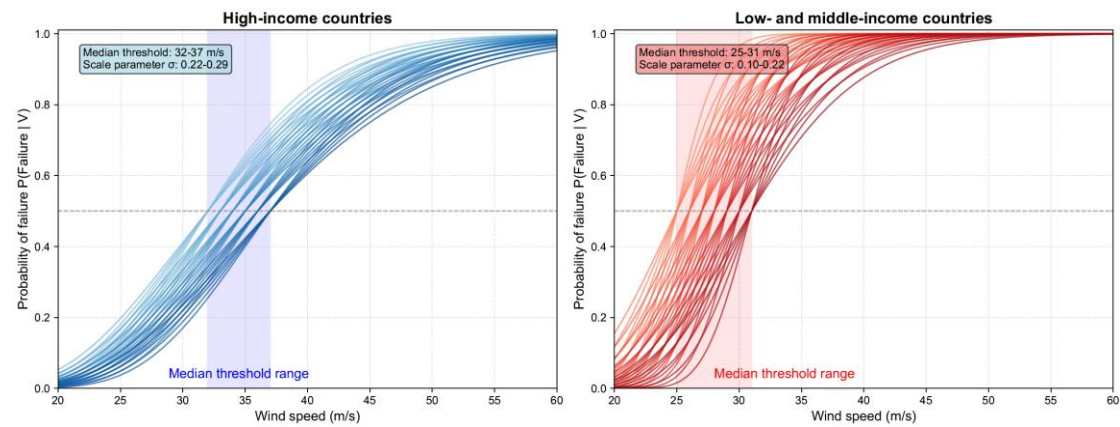
(3) Tropical cyclone

By integrating engineering vulnerability analysis with climate model projections, we achieved a dynamic assessment of future tropical cyclone (TC) risks. The research framework comprises three core components: (1) collection and calibration of regionally differentiated fragility curves for transmission lines, (2) processing of tropical cyclone wind fields based on CMIP6 HighResMIP multi-model ensembles, and (3) quantification and spatial mapping of global transmission network failure probabilities.

We review the fragility curves documented in the existing literature that characterize the impact of strong winds on transmission lines. Existing methodological approaches fall primarily into two categories: one fits continuous fragility curves based on simulation-observation comparative experiments and statistical methods^{45,46}; the other employs a threshold-based approach for binary failure/safe classification⁴⁷. This chapter synthesizes the wind resistance thresholds and fragility curve parameters obtained from previous studies, and further incorporates the engineering design standards of representative countries to perform regionally calibrated adjustments to the fragility curves. The calibrated curves adopt a lognormal cumulative distribution function and feature differentiated median wind speed thresholds—defined as the wind speed at which the failure probability reaches 50% in the cumulative distribution function. Based on the empirical statistical analysis of historical typhoon wind speeds and failure events by Thomas et al.⁴⁷, and considering the inherent uncertainty in parameter estimation, the median wind speed threshold for high-income countries is taken within a certain interval around 35 m/s, while that for low- and middle-income countries is taken within a certain interval around 30 m/s. Accordingly, the failure probability function is expressed as follows:

$$P(Failure|V) = \Phi \left[\frac{1}{\beta} \ln \left(\frac{V}{MVT} \right) \right]$$

where V represents wind speed, MVT represents median wind speed threshold and β is the scale parameter (logarithmic standard deviation of the fragility function corresponding to the damage state). These parameters were compiled from existing literature based on engineering experiments. Uncertainty analysis is conducted within specific ranges (Extended Data Figure 2).



Extended Data Figure 2. TC damage functions for Low-Income and High-Income countries

Using tropical cyclone track data from the CMIP6 HighResMIP⁴⁸ multi-model ensembles, which includes maximum wind speed values at each track point, we interpolated the discrete track point winds into a global gridded wind speed distribution. By integrating simulation results from multiple models, we constructed gridded wind speed fields for TCs under future scenarios, with a spatial resolution of $0.5^{\circ} \times 0.5^{\circ}$. By inputting the processed tropical cyclone wind fields into the calibrated fragility curves, we computed failure probabilities for transmission lines worldwide. Combined with a high-resolution global transmission line distribution database, spatial overlay analysis was employed to generate future scenario-based tropical cyclone risk maps for transmission infrastructure, providing evidence for resilient infrastructure planning.

International standards and utility practices commonly prescribe enhanced protection, higher reliability classes, or special design assessments for extra-high-voltage and system-critical transmission assets. To approximate this additional capacity to withstand historically experienced hazards, lines operating above 500 kV were assigned an elevated historical tolerance threshold. Specifically, their simulated failure probabilities were adjusted relative to the 99.9th percentile of the corresponding baseline-period hazard distribution.

1.2.2 Loss of power generation

In addition to transmission disruptions, climate extremes can directly impair electricity generation capacity. To capture these effects, we estimate generation losses across major power sources using physically informed approach that links climate stressors to technology-specific performance reductions.

For hydropower, generation losses are associated with drought-induced reductions in water availability. Grid-level runoff and infrastructure-level dam reservoir anomalies are mapped to

plant locations, and generation capacity is scaled according to deviations from historical mean conditions using empirical response relationships. For wind and solar power, output variability is directly driven by resource availability; generation is therefore adjusted based on deviations in near-surface wind speed and surface solar radiation, respectively, relative to climatological baselines. Periods of low wind and solar resources are explicitly identified and applied as constraints on renewable generation. Detailed formulations of the hazard–impact relationships and parameter choices are provided in the Supplementary Information Section 2.

1.2.3 Climate induced demand surge

Historically, the most significant impact of climate risk on the demand side, often leading to power shortages, is the surge in cooling demand during heat waves. It can coincide with transmission-related hazards such as wildfires and tropical cyclones, substantially increasing system stress by simultaneously elevating demand and raising the likelihood of transmission line failures. Therefore, this study models cooling demand. Residential cooling demand was calculated using the CHILLD⁴⁹ (Cooling and Heating Global Energy Demand model) initially developed by the International Institute for Applied System Analysis (IIASA). This global-daily scale model reasonably simplifies building physics and allows for a reliable estimation of building cooling and heating demand with a reduced demand for input data and computational load. The framework of the CHILLD model is presented by the following three core formulas, which incorporates climate conditions, building characteristics, technological factors, and occupancy behaviors to compute the final energy demand for space cooling:

$$T_{bal,m} = T_{sp} - \frac{g_{sol,m} + g_{int}}{H_{tr} + H_{ve}}$$

$$VDD_m = \sum_{d=1}^{dm} (T_d - T_{bal,m})^+$$

$$E_m = \frac{(H_{tr} + H_{ve}) \times f_{op} \times VDD_m \times f_{fl}}{\eta_c}$$

The process of the it starts with calculating the balance temperature $T_{bal,m}$ (°C), referring to the temperature at which cooling is required for buildings. CHILLD model calculates the balance temperature from indoor setpoint temperature T_{sp} (°C), monthly heat gain from solar heat sources $g_{sol,m}$ (W), heat gain from internal heat sources g_{int} (W), and heat transfer coefficient by transmission H_{tr} and ventilation H_{ve} (W/°C). Then, the balance temperature, along with daily mean outdoor temperature T_d (°C) are used to calculate variable degree days VDD_m (°C) for a given month. VDD has a similar conception to traditional degree-days, except VDD is based on the analytically calculated balance temperature, while the degree-days method assumes an arbitrarily fixed balance temperature, which may not accurately reflect the energy demand in different locations (Huang & Gurney, 2016). Finally, final energy demand for a given

day is calculated from VDD_d , H_{tr} , H_{ve} , daily operation time fractions for cooling f_{op} , the cooled floor space f_{fl} (m^2), and the efficiency of cooling system η_c . The equations are implemented on a global grid cell of $0.5^\circ \times 0.5^\circ$ and on a daily resolution.

1.3 Power-system dispatch under extreme-weather shocks

1.3.1 Network representation

To propagate asset-level climate shocks through interconnected power systems, we formulated a capacity-constrained linear dispatch model. Each node i represents a city or aggregated regional power system, and each edge represents a transmission corridor. The formulation retains the network mechanisms that can be resolved consistently at global scale—generation adequacy, transfer limits, congestion, rerouting and islanding—without assuming unavailable line-reactance, voltage or phase-angle data. Node-level variables and parameters are defined as follows:

- C_i and g_i : available generation capacity and dispatched generation at node i (MW)
- D_i and LS_i : electricity demand and involuntary load shedding at node i (MW)
- c_i and λ_i : variable generation cost and the penalty assigned to unserved load (USD MWh^{-1})

For each connected pair of nodes i and j , f_{ij} denotes signed power transfer into node i from node j , with $f_{ij} = -f_{ji}$, and T_{ij} denotes the usable transfer capacity (MW).

1.3.2 Dispatch objective and constraints

For each time step, dispatch is obtained by solving a linear program that minimizes variable generation cost and involuntary load shedding:

$$\min \sum_i (c_i g_i + \lambda_i LS_i)$$

subject to:

$$g_i + LS_i - D_i + \sum_j f_{ij} = 0 \quad \forall i$$

$$|f_{ij}| \leq T_{ij} \quad \forall (i, j)$$

$$0 \leq g_i \leq C_i \quad \forall i; \quad 0 \leq LS_i \leq D_i \quad \forall i$$

The load-shedding penalty λ_i is set sufficiently above all marginal generation and transfer costs, so feasible demand is served before generation cost is minimized. Renewable technologies, which have the lowest variable costs, are therefore dispatched preferentially; unused climate-available renewable output is recorded as curtailment.

Network topology is partitioned into predefined synchronous or interconnection regions. Putative AC links between asynchronously operated regions are removed, whereas documented high-voltage direct-current links and controlled interties are retained with capacity constraints and transfer penalties. This treatment prevents unrealistic unconstrained coupling while preserving physically available cross-region transfers. Because Kirchhoff's voltage law is not imposed, the formulation is a network-constrained transport dispatch rather than an AC or linearized DC power-flow model.

1.3.3 Climate-shock implementation and counterfactual comparison

Climate stressors enter exogenously by modifying three sets of model inputs at each matched seasonal time step:

- Source-side shocks (generation), such as drought-induced hydropower loss: $C'_i = C_i(1 - \alpha_i)$.
- Network-side shocks (transmission), in which physical damage reduces usable transfer capacity: $T'_{ij} = T_{ij}(1 - \gamma_{ij})$.
- Load-side shocks (demand), such as heatwave-induced cooling demand: $D'_i = D_i(1 + \beta_i)$, where α_i , γ_{ij} and β_i denote the fractional reduction in available generation, fractional reduction in transmission capacity and fractional increase in demand, respectively.

The model is evaluated under three configurations:

- Baseline (no-climate-shock) case. Demand, generator availability and transmission status are fixed at their historical seasonal conditions. Because demand and generation vary seasonally, separate baselines are solved for each quarter.
- Transmission-only shock case. Climate-driven transmission outages are imposed while generation availability and demand remain at their matched baseline values.
- Compound source–network–load shock case. Co-occurring or teleconnected stressors are imposed jointly—for example, drought-related generation loss in a supply region, transmission outages along connecting corridors and heatwave-driven demand growth in a load centre. The resulting network representation integrates spatially explicit generation assets, electricity-demand nodes and transmission corridors, while accounting for future climate-dependent energy-resource endowments (Supplementary Fig. 4&5)

Each shocked solution is paired with the corresponding seasonal baseline. We report only non-negative increments in load shedding and renewable curtailment relative to that baseline, rather than absolute energy imbalances. This paired counterfactual design reduces sensitivity to incomplete coverage of small generators and regional lines and prevents pre-existing inventory inconsistencies from being attributed to climate shocks.

The model does not resolve reactive power, bus voltages, phase angles, protection actions or sub-hourly stability, and therefore does not simulate cascading blackouts. At the global scale, however, it provides a consistent estimate of how climate-driven changes in generation availability, transmission capacity and demand alter network-feasible transfers, load shedding and renewable curtailment. Results are consequently interpreted as comparative indicators of system stress and propagation potential rather than operational power-flow forecasts.

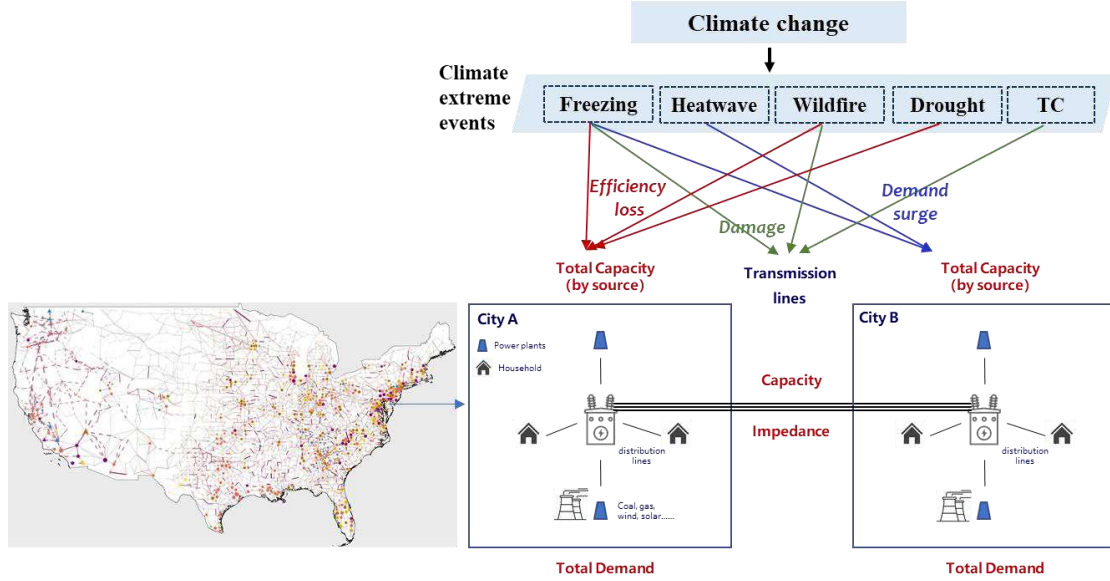


Figure 5 | Climate-shock propagation through the capacity-constrained dispatch model. The schematic links climate-related hazards to generation availability, transmission capacity and electricity demand. These inputs are updated before network-constrained redispatch, and the shocked solution is compared with a matched seasonal baseline to quantify incremental load shedding and renewable curtailment. Interconnected nodes allow locally imposed shocks to propagate through congestion, rerouting and islanding. The schematic is conceptual; the optimization represents capacity-constrained transfers and does not resolve voltage or phase-angle dynamics.

1.3.4 Estimating affected customers

To quantify the customer consequences of climate-induced transmission failures, we converted post-disruption load shedding into affected-customer equivalents at the node level and then attributed these impacts to individual failed transmission lines. For each Monte Carlo (1320 times simulations in total) realization and monthly time step, failed transmission lines were removed from the network and dispatch model was solved on the residual grid. The additional climate-induced load shedding at node i was calculated relative to the corresponding no-failure baseline dispatch:

$$\Delta LS_{i,t,r} = \max(LS_{i,t,r}^{\text{shock}} - LS_{i,t}^{\text{base}}, 0),$$

where t denotes month and r denotes Monte Carlo realization. The nodal shortage fraction was then defined as:

$$s_{i,t,r} = \min \left[\max \left(\frac{\Delta LS_{i,t,r}}{D_{i,t}}, 0 \right), 1 \right],$$

where $D_{i,t} = EC_{2019,i} + \Delta AC_{i,t}$ is the electricity demand used for normalization, including baseline electricity consumption and additional cooling demand. Nodes with shortage fractions below 5% were not counted as materially affected considering potential adaptation strategies, and the affected-customer equivalent at node i was calculated as:

$$A_{i,t,r} = \begin{cases} P_i s_{i,t,r}, & s_{i,t,r} > 0.05, \\ 0, & s_{i,t,r} \leq 0.05, \end{cases}$$

where P_i is the population assigned to node i . This conversion assumes that the fraction of

electricity demand not served is proportional to the fraction of customers affected within the node.

Transmission failures do not affect only their endpoints. Their consequences depend on whether power can be rerouted considering load capacity, whether local network islands emerge, and how much load shedding occurs within the affected parts of the system. To quantify the relative importance of individual transmission lines under climate-driven outages, we developed a network-flow-informed, component-aware allocation approach. Node-level affected customers are attributed to failed transmission lines using the topology of the post-failure network. The affected-customer equivalents were first aggregated within each post-failure component c :

$$A_{c,t,r} = \sum_{i \in c} A_{i,t,r}.$$

Each failed line was then mapped to the post-failure component or components containing its two endpoints. Within each component, affected-customer equivalents were allocated across incident failed lines according to their baseline powerflow (F_l^{base}) weights:

$$w_{l,c} = \frac{F_l^{\text{base}}}{\sum_{k \in \mathcal{L}_c} F_k^{\text{base}}},$$

where $\mathcal{L}_c$ is the set of failed lines incident to component c . The attributed customer impact of line l in realization r and month t was therefore:

$$A_{l,t,r} = \sum_{c \in \mathcal{C}_l} w_{l,c} A_{c,t,r},$$

where $\mathcal{C}_l$ is the set of post-failure components adjacent to line l . Finally, the annual affected-customer equivalent attributed to line l was calculated by averaging across Monte Carlo realizations (R) and summing across the 12 months of each year:

$$A_{l,y}^{\text{annual}} = \sum_{t \in y} \frac{1}{R} \sum_{r=1}^R A_{l,t,r}.$$

This metric integrates both the probability that a line fails under climate-driven outage sampling and the conditional severity of customer disruption when that line participates in a disrupted network state. It should therefore be interpreted as an expected annual customer-impact contribution attributed to each transmission line, rather than the marginal causal effect of independently removing that line. Because impacts are summed across monthly realizations, the metric represents annual affected-customer equivalents and may count repeated disruptions affecting the same population in different months.

This approach captures two common network-mediated failure mechanisms. First, if a failed line disconnects a downstream subnetwork, the resulting island may contain several cities beyond the two terminal nodes of the failed line; affected customers within the island (rather than only the line itself spatially linked nodes) are therefore attributed to the boundary failed lines. Second, if several failed lines lie along the same transmission corridor, the customer impact within the disrupted component is shared among these corridor lines according to their

baseline power-flow weights, reflecting their relative contribution to normal power transfer.

References

1. Fuso Nerini, F., Adshead, D., Thacker, S., Pant, R. & Hall, J. W. Breaking the cycle of underinvestment in climate-resilient energy infrastructure. *Nat Energy* 1–2 (2025) doi:10.1038/s41560-025-01868-9.
2. Liu, L. *et al.* Climate change impacts on planned supply–demand match in global wind and solar energy systems. *Nat Energy* **8**, 870–880 (2023).
3. Gutiérrez, C. *et al.* Future evolution of surface solar radiation and photovoltaic potential in Europe: investigating the role of aerosols. *Environ. Res. Lett.* **15**, 034035 (2020).
4. Wan, W., Zhao, J., Popat, E., Herbert, C. & Döll, P. Analyzing the Impact of Streamflow Drought on Hydroelectricity Production: A Global-Scale Study. *Water Resources Research* **57**, e2020WR028087 (2021).
5. Bennett, J. A. *et al.* Extending energy system modelling to include extreme weather risks and application to hurricane events in Puerto Rico. *Nat Energy* **6**, 240–249 (2021).
6. Forzieri, G. *et al.* Escalating impacts of climate extremes on critical infrastructures in Europe. *Global Environmental Change* **48**, 97–107 (2018).
7. Tavares da Costa, Ricardo, Krausmann, Elisabeth, & Hadjisavvas, Constantinos. *Impacts of Climate Change on Defence-Related Critical Energy Infrastructure*. (Publications Office of the European Union, 2023).
8. Lifelines: The Resilient Infrastructure Opportunity. <https://doi.org/10.1596/978-1-4648-1430-3> (2019) doi:10.1596/978-1-4648-1430-3.
9. Vahedi, S. *et al.* Wildfire and power grid nexus in a changing climate. *Nat Rev Electr Eng* <https://doi.org/10.1038/s44287-025-00150-0> (2025) doi:10.1038/s44287-025-00150-0.
10. Kwasinski, A., Andrade, F., Castro-Sitiriche, M. J. & O’Neill-Carrillo, E. Hurricane Maria Effects on Puerto Rico Electric Power Infrastructure. *IEEE Power Energy Technol. Syst. J.* **6**, 85–94 (2019).
11. Flores, N. M. *et al.* The 2021 Texas Power Crisis: distribution, duration, and disparities. *J Expo Sci Environ Epidemiol* **33**, 21–31 (2023).
12. Abatzoglou, J. T. *et al.* Climate change has increased the odds of extreme regional forest fire years globally. *Nat Commun* **16**, 6390 (2025).
13. Abatzoglou, J. T. & Williams, A. P. Impact of anthropogenic climate change on wildfire across western US forests. *Proc. Natl. Acad. Sci. U.S.A.* **113**, 11770–11775 (2016).
14. Kossin, J. P., Emanuel, K. A. & Vecchi, G. A. The poleward migration of the location of tropical cyclone maximum intensity. *Nature* **509**, 349–352 (2014).
15. Studholme, J., Fedorov, A. V., Gulev, S. K., Emanuel, K. & Hodges, K. Poleward expansion of tropical cyclone latitudes in warming climates. *Nat. Geosci.* **15**, 14–28 (2022).
16. Jeong, D. I., Cannon, A. J. & Zhang, X. Projected changes to extreme freezing precipitation and design ice loads over North America based on a large ensemble of Canadian regional

- climate model simulations. *Nat. Hazards Earth Syst. Sci.* **19**, 857–872 (2019).
17. Karagiannakis, G., Panteli, M. & Argyroudis, S. Fragility Modeling of Power Grid Infrastructure for Addressing Climate Change Risks and Adaptation. *WIREs Climate Change* **16**, e930 (2025).
 18. Simpson, N. P. *et al.* Adaptation to compound climate risks: A systematic global stocktake. *iScience* **26**, (2023).
 19. Stürmer, J. *et al.* Increasing the resilience of the Texas power grid against extreme storms by hardening critical lines. *Nat Energy* **9**, 526–535 (2024).
 20. Ji, C. *et al.* Large-scale data analysis of power grid resilience across multiple US service regions. *Nat Energy* **1**, 16052 (2016).
 21. Koks, E. E. *et al.* A global multi-hazard risk analysis of road and railway infrastructure assets. *Nat Commun* **10**, 2677 (2019).
 22. Verschuur, J., Koks, E. E. & Hall, J. W. Systemic risks from climate-related disruptions at ports. *Nat. Clim. Chang.* **13**, 804–806 (2023).
 23. Mühlhofer, E., Bresch, D. N. & Koks, E. E. Infrastructure failure cascades quintuple risk of storm and flood-induced service disruptions across the globe. *One Earth* **7**, 714–729 (2024).
 24. Xu, L. *et al.* Resilience of renewable power systems under climate risks. *Nat Rev Electr Eng* **1**, 53–66 (2024).
 25. Verschuur, J. *et al.* Quantifying climate risks to infrastructure systems: A comparative review of developments across infrastructure sectors. *PLOS Climate* **3**, e0000331 (2024).
 26. Matthews, T., Wilby, R. L. & Murphy, C. An emerging tropical cyclone–deadly heat compound hazard. *Nat. Clim. Chang.* **9**, 602–606 (2019).
 27. *Surviving a Catastrophic Power Outage.* <https://www.cisa.gov/resources-tools/resources/niac-catastrophic-power-outage-study> (2020).
 28. Cortinas, J. A Climatology of Freezing Rain in the Great Lakes Region of North America. *Monthly Weather Review* (2000).
 29. Wen, Q. H., Wan, D., Dong, Q., Yan, Y. & Zhang, P. Improved freezing rain forecast using machine learning. *Weather and Climate Extremes* **44**, 100690 (2024).
 30. Zhu, Q. *et al.* Representing Nitrogen, Phosphorus, and Carbon Interactions in the E3SM Land Model: Development and Global Benchmarking. *Journal of Advances in Modeling Earth Systems* **11**, 2238–2258 (2019).
 31. Hodges, K., Cobb, A. & Vidale, P. L. How Well Are Tropical Cyclones Represented in Reanalysis Datasets? <https://doi.org/10.1175/JCLI-D-16-0557.1> (2017) doi:10.1175/JCLI-D-16-0557.1.
 32. Ullrich, P. A. & Zarzycki, C. M. TempestExtremes: a framework for scale-insensitive pointwise feature tracking on unstructured grids. *Geoscientific Model Development* **10**, 1069–1090 (2017).
 33. IEC 60826:2017. <https://webstore.iec.ch/en/publication/33148>.
 34. Gao, J. Analysis and assessment of the risk of snow and freezing disaster in China.

- International Journal of Disaster Risk Reduction* **19**, 334–340 (2016).
35. McCray, C. D., Atallah, E. H. & Gyakum, J. R. Long-Duration Freezing Rain Events over North America: Regional Climatology and Thermodynamic Evolution. *Weather and Forecasting* (2019).
 36. Chaîné, P. M. & Castonguay, G. *New Approach to Radial Ice Thickness Concept Applied to Bundle-like Conductors*. (1974).
 37. MRI. *Ontario Hydro Wind and Ice Loading Model*. (1977).
 38. Makkonen, L. Modeling power line icing in freezing precipitation. in *Proceedings of the 7th International Workshop on Atmospheric Icing of Structures* (Chicoutimi, Canada, 1996).
 39. Jones, K. F. *Ice Accretion on Overhead Lines*. (1996).
 40. Jones, K. F. A simple model for freezing rain ice loads. *Atmospheric Research* **46**, 87–97 (1998).
 41. Coles, S. G. & Tawn, J. A. Modelling Extreme Multivariate Events. *Journal of the Royal Statistical Society Series B: Statistical Methodology* **53**, 377–392 (1991).
 42. Muis, S., Verlaan, M., Winsemius, H. C., Aerts, J. C. J. H. & Ward, P. J. A global reanalysis of storm surges and extreme sea levels. *Nat Commun* **7**, 11969 (2016).
 43. Liu, Y. X., Sheng, C. & Hong, H. P. Fitting generalized Pareto distribution based on the expected order statistics and its application for ice accretion hazard mapping. *Structural Safety* **101**, 102297 (2023).
 44. Lin, J., Bao, M., Liang, Z., Sang, M. & Ding, Y. Spatio-temporal evaluation of electricity price risk considering multiple uncertainties under extreme cold weather. *Applied Energy* **328**, 120090 (2022).
 45. Raj, S. V., Bhatia, U. & Kumar, M. Cyclone preparedness strategies for regional power transmission systems in data-scarce coastal regions of India. *International Journal of Disaster Risk Reduction* **75**, 102957 (2022).
 46. Bennett, J. A. *et al.* Extending energy system modelling to include extreme weather risks and application to hurricane events in Puerto Rico. *Nat Energy* **6**, 240–249 (2021).
 47. Hall, J. *et al.* Tropical cyclone risk to global electricity supply. Preprint at <https://doi.org/10.21203/rs.3.rs-4650238/v1> (2024).
 48. Roberts, M. J. *et al.* Projected Future Changes in Tropical Cyclones Using the CMIP6 HighResMIP Multimodel Ensemble. *Geophysical Research Letters* **47**, (2020).
 49. Mastrucci, A., van Ruijven, B., Byers, E., Poblete-Cazenave, M. & Pachauri, S. Global scenarios of residential heating and cooling energy demand and CO2 emissions. *Climatic Change* **168**, 14 (2021).

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Author contributions

Dabo Guan and Yida Sun designed the study. Yida Sun conducted the research, collected and processed the data, performed the analyses, and drafted the manuscript. Wendong Wei, Yuanbo Yu and Yitao Jian collected and processed the meteorological data and contributed to data visualization and manuscript preparation. Ning Zhang provided guidance on power-system modelling and contributed to model development. Gesang calculate cooling demand part. Wendong Wei also advised on the estimation of electricity generation. Yufeng Zhou processed the tropical-cyclone dataset. Wendong Wei and Hui Lu guided the uncertainty and validation analyses. Ramit Debnath, Steven J. Davis, Qiang Zhang and Kebin He contributed to reviewing and revising the manuscript and figures. All authors reviewed and approved the final manuscript.

Data availability

Multi-model meteorological forcing and hazard simulations were obtained from several climate-data archives. Bias-adjusted daily meteorological variables and wildfire simulations were obtained from the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP), while the original CMIP6 outputs are available through the Earth System Grid Federation. Tropical-cyclone tracks were obtained from the CMIP6 HighResMIP tropical-storm-track archive hosted by the Centre for Environmental Data Analysis. Socio-economic data for the different SSP scenarios is derived from IIASA: <https://secure.iiasa.ac.at/web-apps/ene/SspDb/>. Global transmission line and substation data are sourced from Open Infrastructure Map: <https://openinframap.org/>. Power plant data are compiled from multiple sources, including the Global Energy Monitor World Electric Power Plants (WEPP) database and additional publicly available datasets, and harmonized into a unified global infrastructure database. Population data used to estimate potentially affected customers were obtained from the Gridded Population of the World, Version 4 (GPWv4): <https://www.earthdata.nasa.gov/data/projects/gpw>.

Code availability

Model code updated to the scenarios described in this publication is also available for download at Zenodo <https://doi.org/10.5281/zenodo.22771567>.

Competing interests

The authors declare no competing interests.

Extended data figures and tables

Extended Data Table 1 CMIP6 global climate models used in the climate-hazard assessment

GCMs	Centre	Country/region
GFDL-ESM4	NOAA Geophysical Fluid Dynamics Laboratory	United States
IPSL-CM6A-LR	Institut Pierre-Simon Laplace	France
MPI-ESM1-2-HR	Max Planck Institute for Meteorology	Germany
MRI-ESM2-0	Meteorological Research Institute, Japan Meteorological Agency	Japan

UKESM1-0-LL	Met Office Hadley Centre and NERC partners	United Kingdom
CMCC-CM2-SR5	Euro-Mediterranean Center on Climate Change	Italy
CMCC-ESM2	Euro-Mediterranean Center on Climate Change	Italy
NorESM2-MM	NorESM Climate Modelling Consortium	Norway
EC-Earth3-Veg-LR	EC-Earth Consortium	European consortium
MPI-ESM1-2-LR	Max Planck Institute for Meteorology	Germany

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