

# Supplementary Materials for

## Compound climate hazards erode energy-system resilience through transmission infrastructure

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### The PDF file includes:

Supplementary Sections 1 to 5

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References

## 1. Power system Infrastructure Dataset building

### 1.1 Power Generation units

Existing global power generation databases are often characterized by significant heterogeneity, format inconsistency, and attribute sparsity. To mitigate these issues, we establish a robust workflow for multi-source data fusion, cleansing, and harmonization. By synthesizing open-source and commercial datasets, we constructed a high-resolution baseline dataset for photovoltaic, wind, and hydro units. The specific procedures are detailed as follows:

(1) Multi-Source Data Aggregation: we integrated disparate datasets from Global Energy Monitor (GEM), the World Electric Power Plants Database (WEPP), Rystad Energy, and the World Resources Institute (WRI) into a unified structure. And the source of the relevant data has been added as Source and Source ID fields to facilitate subsequent searching and comparison.

(2) Pre-processing and Validity Screening: Essential quality control filters were applied to ensure data integrity. Entries lacking critical spatial-temporal or physical attributes—specifically commissioning year, geolocation (latitude/longitude), installed capacity, or wind turbine counts—were systematically excluded.

(3) Data Deduplication: A hybrid approach combining spatial proximity and attribute similarity (capacity/name) was employed to detect potential duplicates, which were indexed with a duplicate\_id. Following a "human-in-the-loop" manual validation process, redundant records were flagged in the isDeleted field to ensure uniqueness.

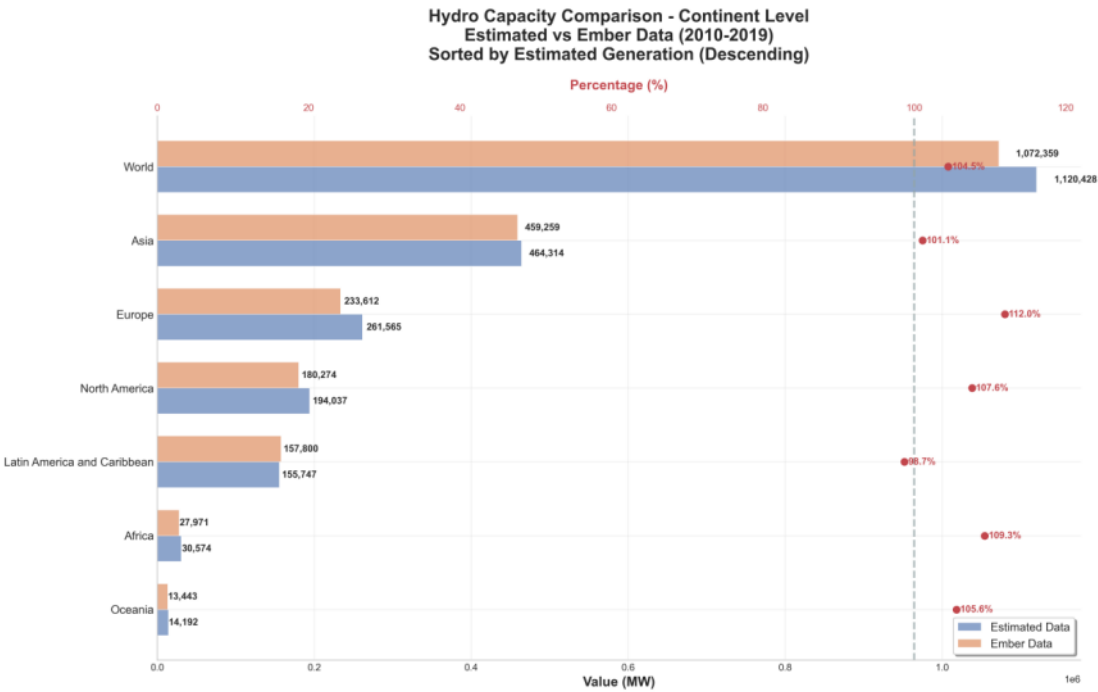
(4) Completeness Scoring Model: A scoring metric was devised to quantify information richness. Each record was graded based on the completeness of its metadata and technical parameters, with higher scores indicating a higher density of valid information.

(5) Hierarchical Aggregation: Statistical analysis of installed capacity was performed at the national level, stratified by the assigned data completeness scores.

(6) Benchmarking and Adaptive Selection: The dataset was calibrated against 2020 public benchmarks to verify coverage. A priority-based selection algorithm was employed, where high-scoring records were preferentially retained and lower-scoring records were added iteratively until the dataset's total capacity converged with authoritative public statistics. Ultimately, the installed capacity of our power unit dataset covers more than 77% of the global total amount.

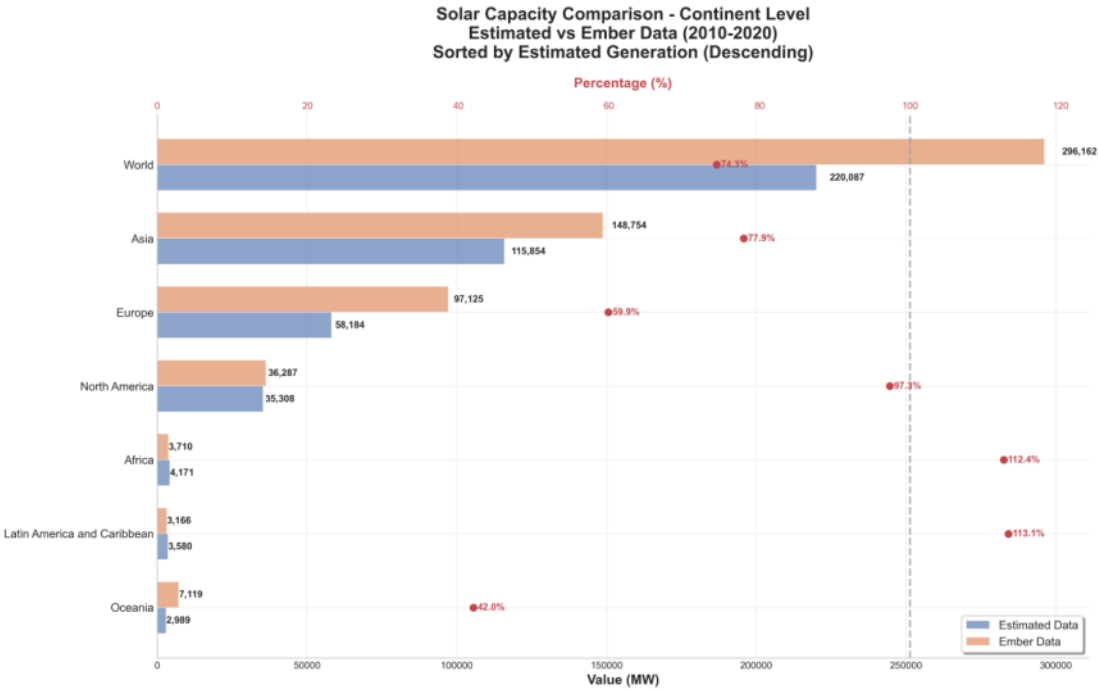
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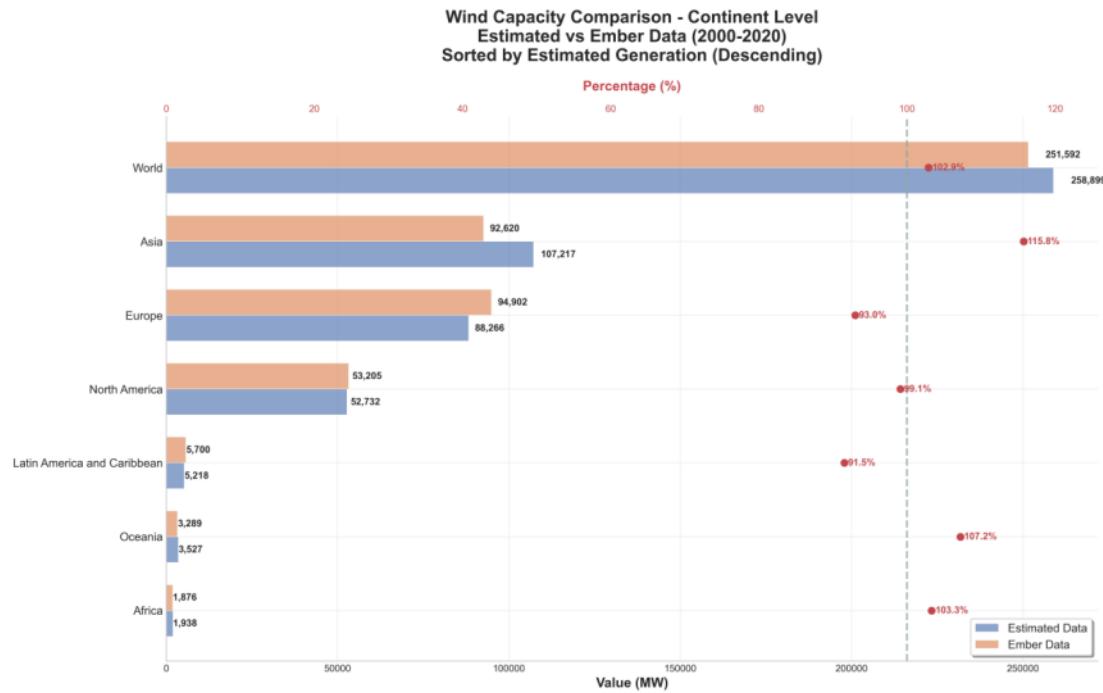
41 Supplementary Figure 1 Comparison of hydropower installed capacity between database and public data.



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43 Supplementary Figure 2 Comparison of photovoltaic installed capacity between database and public data.





Supplementary Figure 3 Comparison of wind power installed capacity between database and public data.

## 1.2 Transmission lines Engineering-informed estimation of transmission line capacity

Transmission-line and substation geometries and attributes were obtained from Open Infrastructure Map export. Open Infrastructure Map is a thematic view of infrastructure mapped in OpenStreetMap, covering electricity, telecoms, oil, and gas infrastructure. The exported powerline and substation layer provides geospatial geometries and associated OSM-derived attributes such as voltage, circuits, cables, frequency, operator, and location. To convert geospatial transmission line inventories into physically meaningful network constraints, we developed an **engineering-informed capacity estimation framework** that links line voltage, length, and circuit configuration to maximum power transfer capability. This approach enables scalable representation of transmission capacity in large-scale power system and climate-risk models, where detailed line design data are typically unavailable.

### Data pre-processing and imputation of missing attributes

Because the dataset is derived from volunteered geographic information, we applied additional pre-processing to repair fragmented geometries and impute missing engineering attributes where necessary. Transmission line attributes, including maximum operating voltage  $U$ , frequency  $f$ , and number of circuits  $n_c$ , were extracted from a global geospatial database. For lines with missing voltage, circuit, or cable attributes but with an available line name, we manually searched public line-specific information, including utility documents, grid maps, project descriptions, and other publicly accessible engineering references. When the line identity could be confirmed, the corresponding voltage level and circuit information were assigned manually. This step was used only for identifiable named transmission lines and was intended to reduce reliance on generic assumptions for major assets. Only when both database metadata and line-name-based manual searches were insufficient did we apply conservative engineering default rules. For missing voltage

values, we inferred a representative voltage class from the repaired line length, using typical voltage-distance relationships in transmission planning. The default rule was applied as follows: lines of at least 500 km were assigned 500 kV; 250-500 km, 400 kV; 120-250 km, 330 kV; 70-120 km, 220 kV; 40-70 km, 132 kV; 20-40 km, 110 kV; 10-20 km, 66 kV; 3-10 km, 35 kV; 1-3 km, 11 kV; and less than 1 km, 4 kV. These inferred values were used only as fallback estimates and were flagged separately from directly observed or manually verified voltage values. All imputed attributes were retained with diagnostic flags, including whether the voltage was directly reported, manually verified, or inferred from line length.

We also tagged transmission records that were unlikely to be directly exposed to surface weather and climate hazards. Specifically, lines whose “location” field indicated underground, underwater, undersea, duct, tunnel, indoor, covered, ceiling, or similar sheltered configurations were tagged during climate-exposure analysis. Overhead, overground, outdoor, surface, bridge, rooftop, and aboveground records were retained because these configurations may remain exposed to wind, precipitation, heat, wildfire, icing, flooding, or other weather-related hazards.

### Capacity of AC transmission

For alternating current (AC) transmission lines, the maximum transferable power  $P_{\max}$  was estimated as the minimum of four engineering constraints:

$$P_{\max} = n_c \cdot \min(P_{\text{eco}}, P_{\text{th}}, P_{\Delta V}, P_{\text{stab}}) \quad (1)$$

where  $n_c$  is the number of circuits.

#### (1) Economic current limit

The economically reasonable transmission capacity is given by

$$P_{\text{eco}} = \sqrt{3} U A J \quad (2)$$

where  $A$  is the conductor cross-sectional area and  $J$  is the allowable current density, reflecting standard overhead line design practice.

#### (2) Thermal (ampacity) limit

The thermal limit is defined as

$$P_{\text{th}} = \sqrt{3} U I_{\max} \quad (3)$$

where  $I_{\max}$  is the maximum permissible conductor current before overheating.

#### (3) Voltage drop constraint

To ensure acceptable voltage quality, particularly for low- and medium-voltage networks, a voltage drop limit was imposed:

$$P_{\Delta V} = \frac{\alpha U^2}{(R + X \tan \phi) L} \quad (4)$$

where  $R$  and  $X$  are the line resistance and reactance per unit length,  $\phi$  is the power factor angle,  $L$  is line length, and  $\alpha$  represents the maximum allowable relative voltage drop (set to 10%).

#### (4) Steady-state stability limit

For long-distance AC transmission, the steady-state power-angle stability constraint was approximated as

$$P_{\text{stab}} = \frac{U^2}{XL} \sin(\delta_{\text{max}}) \quad (5)$$

where  $\delta_{\text{max}}$  is the maximum permissible power angle, set to 10°-30° following standard stability criteria.

Voltage-specific conductor parameters ( $A, I_{\text{max}}, R, X$ ) were assigned based on representative overhead line designs for each voltage class. Where multiple circuits were present, capacities were scaled proportionally. In addition to transmission lines, transformers connecting different voltage levels are represented as network branches linking nodes of different nominal voltages. Because transformer-level engineering parameters are generally unavailable in large-scale geospatial datasets, their transfer capability is approximated by the typical capacity of substations at the corresponding voltage levels. In practice, transformer branch capacity is set equal to the smaller of the capacities of the connected voltage classes, ensuring that inter-voltage transfers remain consistent with the physical limits of the transmission network.

#### Capacity of HVDC

For high-voltage direct current (HVDC) transmission lines, transfer capacity is assigned based on typical engineering designs of large-scale HVDC projects. We adopt a voltage-based lookup table derived from representative HVDC transmission systems widely deployed in long-distance interregional power transmission.

Each HVDC line is assigned a nominal transfer capacity according to its voltage level (Supplementary Table 3). The estimated capacities represent upper-bound steady-state transfer limits rather than operational dispatch constraints. While the framework does not resolve AC power flows or dynamic contingencies, it provides a physically grounded and computationally tractable representation of transmission capacity, suitable for system-level assessments of power system resilience, vulnerability, and climate-risk propagation.

Supplementary Table 1 Typical capacities of representative HVDC lines.

| Voltage Level | Region              | Capacity (MW) | Typical Line Name                                   |
|---------------|---------------------|---------------|-----------------------------------------------------|
| ±320 kV       | China               | 1000          | Xiamen Island ±320 kV HVDC Project                  |
| ±320 kV       | India               | 2000          | Pugalur–Thrissur ±320 kV HVDC Link                  |
| ±320 kV       | Europe (UK)         | 1200          | Caithness–Moray ±320 kV HVDC Link                   |
| ±320 kV       | Germany             | 900           | SylWin1 ±320 kV HVDC Offshore Link                  |
| ±320 kV       | Denmark/Netherlands | 700           | COBRA Cable ±320 kV HVDC Interconnection            |
| ±500 kV       | China               | 3000          | Gezhouba–Shanghai ±500 kV HVDC Transmission Project |

| <b>Voltage Level</b> | <b>Region</b> | <b>Capacity (MW)</b> | <b>Typical Line Name</b>                                                    |
|----------------------|---------------|----------------------|-----------------------------------------------------------------------------|
| <b>±500 kV</b>       | China         | 3200                 | Xiluodu Right Bank–Guangdong ±500 kV Double-circuit HVDC Project            |
| <b>±500 kV</b>       | India         | 1500                 | Rihand–Delhi ±500 kV HVDC Link                                              |
| <b>±500 kV</b>       | US            | 3100                 | Pacific Intertie Expansion                                                  |
| <b>±500 kV</b>       | Europe        | 1000                 | MONITA (Montenegro–Italy) ±500 kV HVDC Link                                 |
| <b>±500 kV</b>       | South Korea   | 3000                 | Bukdangjin–Godeok ±500 kV HVDC Link                                         |
| <b>±500 kV</b>       | Egypt         | 3000                 | Egypt–Saudi Arabia ±500 kV HVDC Interconnection (BADR-TABA2)                |
| <b>±660 kV</b>       | Pakistan      | 4000                 | Matiari–Lahore ±660 kV HVDC Transmission Line Project                       |
| <b>±800 kV</b>       | China         | 8000                 | Yazhong–Jiangxi ±800 kV UHV DC Transmission Project                         |
| <b>±800 kV</b>       | China         | 8000                 | Jinsha River Upstream–Hubei ±800 kV UHVDC Transmission Project              |
| <b>±800 kV</b>       | Brazil        | 5000                 | Brazil Northeast ±800 kV UHVDC Transmission Project (Graça Aranha–Silvânia) |
| <b>±800 kV</b>       | India         | 6000                 | Raigarh–Pugalur ±800 kV HVDC Link[citation:11]                              |
| <b>±1100 kV</b>      | China         | 12000                | Changji–Guquan ±1100 kV UHV DC Transmission Project                         |

131 Supplementary Table 2 Typical capacities of representative AC lines.

| <b>Voltage Level</b> | <b>Region</b>    | <b>Typical Capacity (MW)</b> | <b>Typical Line Name</b>                                                                          |
|----------------------|------------------|------------------------------|---------------------------------------------------------------------------------------------------|
| <b>35 kV</b>         | China            | 50                           | Yilong Zhongba 35 kV Power Transmission and Transformation Project (Nanchong, Sichuan)            |
| <b>110 kV</b>        | China            | 150                          | Zhoushan Penglai–Shenjiawan 110 kV Transmission Line Project                                      |
| <b>220 kV</b>        | China            | 400                          | Hetian Rare Metal Industrial Park 220 kV Power Transmission and Transformation Project (Xinjiang) |
| <b>330 kV</b>        | China            | 400                          | Liujiaxia–Tianshui–Guanzhong 330 kV EHV Transmission Project (Liu-Tian-Guan Line)                 |
| <b>345 kV</b>        | USA              | 400-800                      | Western Spirit Wind 345 kV Gen-Tie Transmission (New Mexico)                                      |
| <b>400 kV</b>        | Europe (Ireland) | 1200                         | North-South 400 kV AC Power Interconnection (Ireland)                                             |

| <b>Voltage Level</b> | <b>Region</b>           | <b>Typical Capacity (MW)</b> | <b>Typical Line Name</b>                                                           |
|----------------------|-------------------------|------------------------------|------------------------------------------------------------------------------------|
| <b>400 kV</b>        | Europe (Portugal-Spain) | 1000                         | Portugal–Spain Northern 400 kV Power Interconnection (Viana do Castelo–Pontevedra) |
| <b>400 kV</b>        | Turkey                  | 1000                         | Dardanelles Strait 400 kV AC Submarine Cable Crossing                              |
| <b>400 kV</b>        | South Africa            | 1000-2000                    | Medupi–Spitskop 400 kV Transmission Line                                           |
| <b>400 kV</b>        | Germany                 | 1000-1200                    | 380 kV AC Backbone (German Transmission Grid)                                      |
| <b>500 kV</b>        | China                   | 1000-3000                    | Three Gorges–Guangdong 500 kV AC Transmission Project                              |
| <b>500 kV</b>        | USA                     | 1500-4500                    | Tehachapi Renewable Transmission Project (California)                              |
| <b>500 kV</b>        | Brazil                  | 1500-2000                    | Rio–Lagos 500 kV Transmission Line (Guanabara Project)                             |
| <b>500 kV</b>        | Vietnam                 | 2500-5000                    | Quang Trach–Pho Noi 500 kV Circuit-3 Transmission Line                             |
| <b>500 kV</b>        | Argentina-Brazil        | 1100                         | Garabi 500 kV AC Interconnector (Rincon de Santa Maria–Ita)                        |
| <b>500 kV</b>        | USA                     | 1500                         | TransWest Express 500 kV AC Segment (Utah–Nevada)                                  |
| <b>750 kV</b>        | China                   | 2000-2200                    | Guanting–Lanzhou East 750 kV Power Transmission Demonstration Project              |
| <b>765 kV</b>        | India                   | 2200-4000                    | Vindhyachal–Varanasi 765 kV Transmission Line                                      |
| <b>765 kV</b>        | USA                     | 2200-2400                    | AEP 765 kV Transmission System (Ohio Valley)                                       |
| <b>1000 kV</b>       | China                   | 5000                         | Jindongnan–Nanyang–Jingmen 1000 kV UHV AC Pilot Demonstration Project              |
| <b>1000 kV</b>       | China                   | 9500                         | Huainan–Wannan–Zhebei–Shanghai 1000 kV UHV AC Double-Circuit Transmission Project  |

132 Supplementary Table 3 Representative overhead transmission line parameters by voltage class. Typical  
133 conductor configurations and electrical parameters used to estimate transmission capacity for each  
134 voltage level. Values represent standard overhead line designs commonly adopted in extra-high- and  
135 ultra-high-voltage transmission systems.

| Voltage class <sup>1,2</sup> | Voltage range (kV) | Typical conductor configuration | Effective cross-section A <sup>3,4</sup> (mm <sup>2</sup> ) | Max current I <sub>max</sub> <sup>5-7</sup> (A) | Resistance R <sup>3,8</sup> (Ω km <sup>-1</sup> ) | Reactance X <sup>9</sup> (Ω km <sup>-1</sup> ) |
|------------------------------|--------------------|---------------------------------|-------------------------------------------------------------|-------------------------------------------------|---------------------------------------------------|------------------------------------------------|
| MV (Medium Voltage)          | 1-20               | Single conductor                | 70                                                          | 225                                             | 0.46                                              | 0.36                                           |
| MV (Medium Voltage)          | 20-36              | Single conductor                | 150                                                         | 366                                             | 0.22                                              | 0.37                                           |
| HV (High Voltage)            | 36-110             | Single conductor                | 150                                                         | 372                                             | 0.22                                              | 0.37                                           |
| HV (High Voltage)            | 110-230            | Single conductor                | 300                                                         | 569                                             | 0.11                                              | 0.38                                           |
| EHV (Extra High Voltage)     | 230-400            | Twin bundle                     | 2 × 300                                                     | 1138                                            | 0.056                                             | 0.31                                           |
| EHV (Extra High Voltage)     | 400-800            | Twin bundle                     | 2 × 400                                                     | 1306                                            | 0.042                                             | 0.32                                           |
| UHV (Ultra High Voltage)     | 800-1100           | Quad bundle                     | 4 × 400                                                     | 2612                                            | 0.021                                             | 0.3                                            |
| UHV (Ultra High Voltage)     | >1100              | Six-bundle                      | 6 × 400                                                     | 3990                                            | 0.014                                             | 0.28                                           |

136 Supplementary Table 4 Global engineering assumptions applied consistently across all transmission lines.

| Parameter       | Symbol | Value                  | Description                                 |
|-----------------|--------|------------------------|---------------------------------------------|
| Power factor    | cosφ   | 0.85-1.0               | Voltage-dependent typical operating range   |
| Current density | J      | 0.9 A mm <sup>-2</sup> | Economically optimal design current density |

|                       |                 |         |                                     |
|-----------------------|-----------------|---------|-------------------------------------|
| Max voltage deviation | $\alpha$        | 10%     | Allowable steady-state voltage drop |
| Max power angle       | $\delta_{\max}$ | 10°-30° | Steady-state stability constraint   |
| Nominal frequency     | f               | 50 Hz   | System operating frequency          |

Supplementary Table 5 Voltage-dependent minimum line length thresholds used to correct fragmented or implausibly short GIS line geometries.

| Voltage range (kV) | Minimum representative length (km) |
|--------------------|------------------------------------|
| $\leq 3$           | 1                                  |
| 3-6                | 4                                  |
| 6-10               | 6                                  |
| 10-35              | 20                                 |
| 35-110             | 50                                 |
| 110-220            | 100                                |
| 220-330            | 200                                |
| $> 330$            | 300                                |

Notes on applicability: The parameters summarized here represent **engineering-typical values** rather than line-specific designs.

## 2. Compound supply-demand climate stressors

### 2.1 Hydro capacity

This section assesses the impact of drought on hydropower output by evaluating deviations in river discharge and reservoir water levels from their long-term historical baselines.

Hydropower generation can be calculated using the following equation:

$$E_{\text{hydro}} = \min(\eta \rho g Q_{t,\text{turb}} H_t, N_{\text{installed}}) \cdot \Delta t \quad (6)$$

where  $\eta$  denotes the hydropower coefficient,  $\rho$  is the density of water,  $g$  is the acceleration due to gravity,  $Q_{t,\text{turb}}$  is rate of water flow through the pipe and turbine,  $H_t$  is the hydraulic head,  $N_{\text{installed}}$  is the installed (rated) generation capacity of the hydropower plant, and  $\Delta t$  represents the selected time interval.

In this study, the hydropower calculation model considers only conventional hydropower facilities, namely run-of-river and reservoir-based plants, and excludes pumped-storage hydropower stations. For the computation of hydraulic head, because the database lacks head information for some plants, we estimate missing values by approximating the elevation difference between each plant's location and its downstream flow-direction point. Using a digital elevation model, we extract elevation and slope information globally. The elevation at the next downstream grid cell, determined by the local slope direction, is subtracted from the elevation of the plant's location to approximate the hydraulic head at that site.

$$H_{dam} = H_{source} - H_{target} \quad (7)$$

Here,  $H_{source}$  denotes the elevation at the hydropower plant source location, and  $H_{target}$  represents the elevation at the slope-derived downstream flow-direction grid cell. For plants lacking maximum head data in the database, we supplement the missing values using the following expression:

$$H_{max} = 0.92H_{dam} \quad (8)$$

Method varies by hydropower plant type. For run-of-river plants, we adopt the expression to calculate hydraulic head:

$$H_t = \gamma H_{max} \quad (9)$$

with  $\gamma = 0.68$  representing a globally calibrated parameter. For reservoir-based hydropower plants, reservoir storage induces additional regulation effects, requiring a correction to the hydraulic head. The adjusted head can be computed using<sup>10</sup>:

$$H_t = H_{max} \left( \frac{S_t}{S_{max}} \right)^\beta \quad (10)$$

where  $S_t$  denotes the actual reservoir storage,  $S_{max}$  represents the maximum reservoir storage (estimated from long-term historical records), and  $\beta = 0.9229$  is a regression parameter linking variations in storage to variations in hydraulic head. This parameter is drawn from the GRanD technical documentation. The hydropower generation losses associated with drought-induced events can be assessed by comparing historical and future generation levels and calculating their differences.

## 2.2 Wind and solar capacity

The word Dunkelflaute<sup>11</sup> was coined by combining two German words “Dunkelheit” (darkness) and “Windflaute” (windless) to describe heavy overcast skies and weak wind conditions. These meteorological events can last from a few hours to a few consecutive days. Similar to windgust events, fluctuations in wind speed can also lead to low-wind conditions, including prolonged periods of calm or light breezes. When coupled with persistently overcast skies or limited daylight causing low solar irradiance, both wind and photovoltaic power generation experience simultaneous sharp declines. Here, we define such extreme weather events as Dunkelflaute.

To identify and quantify the impact of Dunkelflaute events, we analyze results by overlaying wind speed and solar irradiance parameter data from previous GCMs at coinciding timestamps. One straightforward approach is to directly specify the conditions for low irradiance and low wind speed. For example, A grid location is considered to experience a Dunkelflaute event if its daily average wind speed falls below the turbine cut-in wind speed (4 m/s) and the surface solar radiation is drops below 50% of normal levels or  $\leq 50 \text{ W/m}^2$ .

To facilitate a more systematic assessment of the impacts of Dunkelflaute on power generation loss, we adopt an alternative quantitative method. Analogous to the hydrological definition of drought, we identify whether photovoltaic and wind power outputs during a given period fall below a threshold derived from the multi-year mean output within a historical moving window. If the output falls below the threshold, the period is classified as a energy drought. When both wind drought and

solar drought occur simultaneously, the interval is defined as a Dunkelflaute event. Specifically, a drought event can be defined as follows:

$$D_{solar}(t) = \begin{cases} 1, & \text{if } E_{solar}^{future}(t) \leq \alpha E_{solar}^{hist}(t) \\ 0, & \text{else} \end{cases} \quad (11)$$

$$D_{wind}(t) = \begin{cases} 1, & \text{if } E_{wind}^{future}(t) \leq \alpha E_{wind}^{hist}(t) \\ 0, & \text{else} \end{cases} \quad (12)$$

$$D_{df}(t) = \begin{cases} 1, & \text{if } D_{solar}(t) = 1 \text{ and } D_{wind}(t) = 1 \\ 0, & \text{else} \end{cases} \quad (13)$$

where the variables  $D_{solar}(t)$ ,  $D_{wind}(t)$ ,  $D_{df}(t)$  indicate whether a given day  $t$  qualifies as a solar drought, a wind drought, or a Dunkelflaute event.  $\alpha$  denotes the chosen percentile-based threshold; here we use 5%, 10%, and 30% to represent different drought severities.  $E_{solar}^{hist}(t)$ ,  $E_{wind}^{hist}(t)$  represents the climatological benchmark derived from the multi-year mean within a historical moving window. We use 31 years of data (1980-2010) and apply a 31-day window, yielding 961 values whose mean is adopted as the historical reference. This benchmark is computed using the following expression:

$$\bar{E}_{hist}(t) = \frac{1}{31 \times 31} \sum_{y=1980}^{2010} \sum_{d=t-15}^{t+15} E_{hist,d,y} \quad (14)$$

Based on this, we quantify the dual impacts of low wind speed and weak solar irradiance to assess the combined effects of Dunkelflaute events on wind and photovoltaic power generation. Historical long-term average data from 1980 to 2010 are used as the baseline to evaluate the impact of Dunkelflaute events on power generation losses under future climate change conditions from 2025 to 2080.

Photovoltaic power generation is primarily constrained by solar irradiance. Under low-light conditions, typically occurring in winter or on cloudy days, reduced temperatures further diminish the efficiency of solar panels. Other meteorological parameters, such as wind speed, also indirectly affect photovoltaic output. Therefore, this study employs Equation 14-16 to comprehensively evaluate multiple parameters and estimate the final photovoltaic power generation. Following previous efforts, we take solar radiance, ambient temperature and wind speed as input and simulate PV power generation per 1 m<sup>2</sup> of PV panel ( $E_{PV}$ ):

$$E_{PV} = I \times \eta_{PV} \quad (15)$$

where  $I$  is the solar radiance on the PV module per m<sup>2</sup> (W m<sup>-2</sup>) and  $\eta_{PV}$  is the efficiency of the PV module, which is influenced by weather conditions. Parameter  $\eta_{PV}$  can be computed as:

$$\eta_{PV} = \eta_{panel} \times \left( 1 + \gamma \times (T_{panel} - T_{STC}) \right) \quad (16)$$

where  $\eta_{panel}$  is the assumed panel efficiency under standard conditions (17%);  $\gamma$  is the typical efficacy response of monocrystalline silicon solar panels ( $-0.005 \text{ } ^\circ\text{C}^{-1}$ );  $T_{STC}$  is the panel temperature under standard conditions (25  $^\circ\text{C}$ ); and  $T_{panel}$  is the panel temperature corrected with temperature, irradiation and wind:

$$T_{\text{panel}} = c_1 + c_2 \times T + c_3 \times I + c_4 \times V \quad (17)$$

where  $c_1$  is 4.3 °C;  $c_2$  is 0.943;  $c_3$  is 0.028°C m<sup>2</sup> W<sup>-1</sup>;  $T$  is ambient temperature (°C);  $I$  is the solar radiance on the PV module (W m<sup>-2</sup>); and  $c_4$  is -1.528 °C s m<sup>-1</sup> and  $V$  is the surface wind speed (m s<sup>-1</sup>). Therefore, when  $T_{\text{panel}}$  surpass  $T_{\text{STC}}$ , the declined panel efficiency would further reduce  $E_{\text{PV}}$ .

Fluctuations in wind speed directly influence wind power generation. When wind speeds fall below the turbine cut-in speed (e.g., 4 m/s), wind turbines cannot generate sufficient torque to initiate rotation, resulting in zero power output.

To calculate the actual wind power generation, note that wind speeds obtained from GCMs typically represent near-surface measurements at 10 meters. These values must be extrapolated to the hub height of wind turbines ( $h_{\text{hub}}$ ) using the conversion Equation 17.

$$V_{\text{hub}} = V_{10} \left( \frac{h_{\text{hub}}}{10} \right)^\alpha \quad (18)$$

where  $\alpha$  is 1/7, and  $V_{\text{hub}}$  is the wind at the hub height of the wind turbine.

By integrating open-source databases and commercial data from The Wind Power, we compiled a database of turbine power curves encompassing over 800 wind turbine designs and mathematical models. Based on the manufacturer, model, and power specifications of actual turbines and wind plant database, we classify the turbine power-curve parameters in our database into five categories (super tiny, tiny, medium, large, and ultra-large) based on the empirical distribution of installed wind-farm capacities as well as rotor diameter and hub height. Within each group, we select the median turbine power curve as the representative curve, and use this curve to compute the corresponding estimated power generation, as Supplementary Table 6.

Supplementary Table 6 Grouping Parameter Table of Wind Turbine Power Curve

| Group         | Diameter(m) | Height(m) | Capacity(kW) |
|---------------|-------------|-----------|--------------|
| <b>tiny</b>   | 31          | 40        | 250          |
| <b>small</b>  | 62          | 70        | 1200         |
| <b>medium</b> | 86          | 75        | 2000         |
| <b>large</b>  | 103         | 95        | 2500         |
| <b>xlarge</b> | 128         | 105       | 5000         |

To capture the intra-day variability of wind resources more accurately, we employ a direct simulation approach rather than static probability distributions. Using 3-hourly wind speed time-series data derived from CMIP6 files, the instantaneous Capacity Factor is calculated by substituting the wind speed directly into the corresponding turbine power curve:

$$CF_t = \frac{P_{\text{curve}}(V_t)}{P_{\text{rated}}} \quad (19)$$

where  $P_{\text{rated}}$  is the rated capacity of the turbine. Given the 3-hour temporal resolution, each day

contains eight discrete simulation steps ( $t=1, 2, \dots, 8$ ). To facilitate long-term spatiotemporal analysis and align with daily climate variables, the 3-hourly  $CF$  values are integrated and averaged to generate a daily mean Capacity Factor ( $CF_{daily}$ ):

$$CF_{daily} = \frac{1}{8} \sum_{t=1}^8 CF_t \quad (20)$$

In subsequent analyses, each grid cell or site is matched to its designated group, enabling the estimation of long-term potential wind-power output under future climate conditions.

### 2.3 Cooling demand and Heatwave

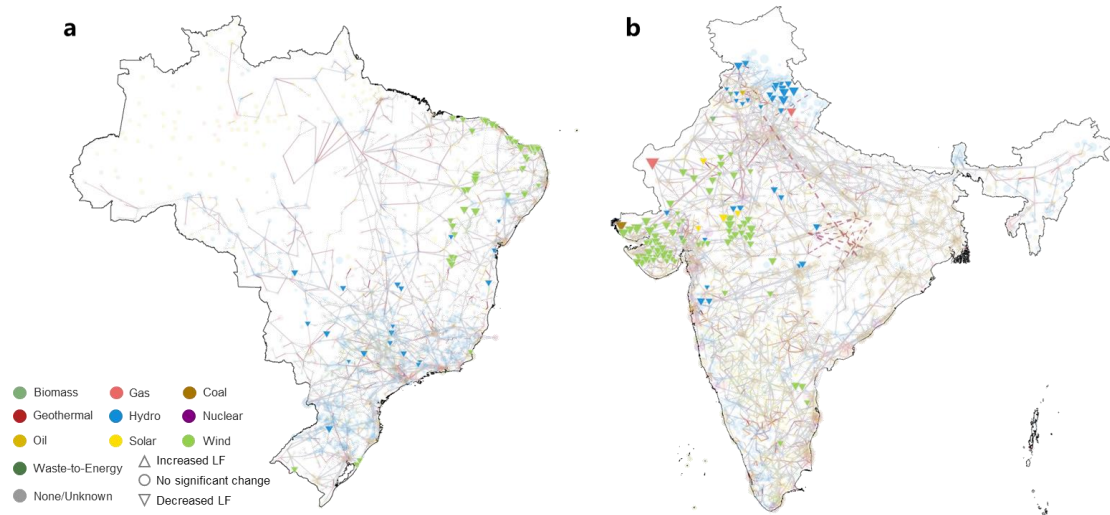
To quantify climate-induced demand surges, we focus on temperature-driven increases in electricity consumption associated with cooling demand during heatwaves. Heatwave events are identified using a threshold-based approach, defined as consecutive days with daily temperatures exceeding high-percentile thresholds (e.g., the 95th or 97.5th percentile relative to a historical baseline).

The corresponding increase in electricity demand is estimated using the CHILLD<sup>12</sup> (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 three core formulas. The model uses three equations to incorporate climate conditions, building characteristics, technological factors, and occupancy behaviors to compute the final energy demand for space cooling. 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<sup>13</sup>. 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<sup>2</sup>), and the efficiency of cooling system  $\eta_c$ . The equations are implemented on a global grid cell of  $0.5^\circ \times 0.5^\circ$  and on a daily resolution.

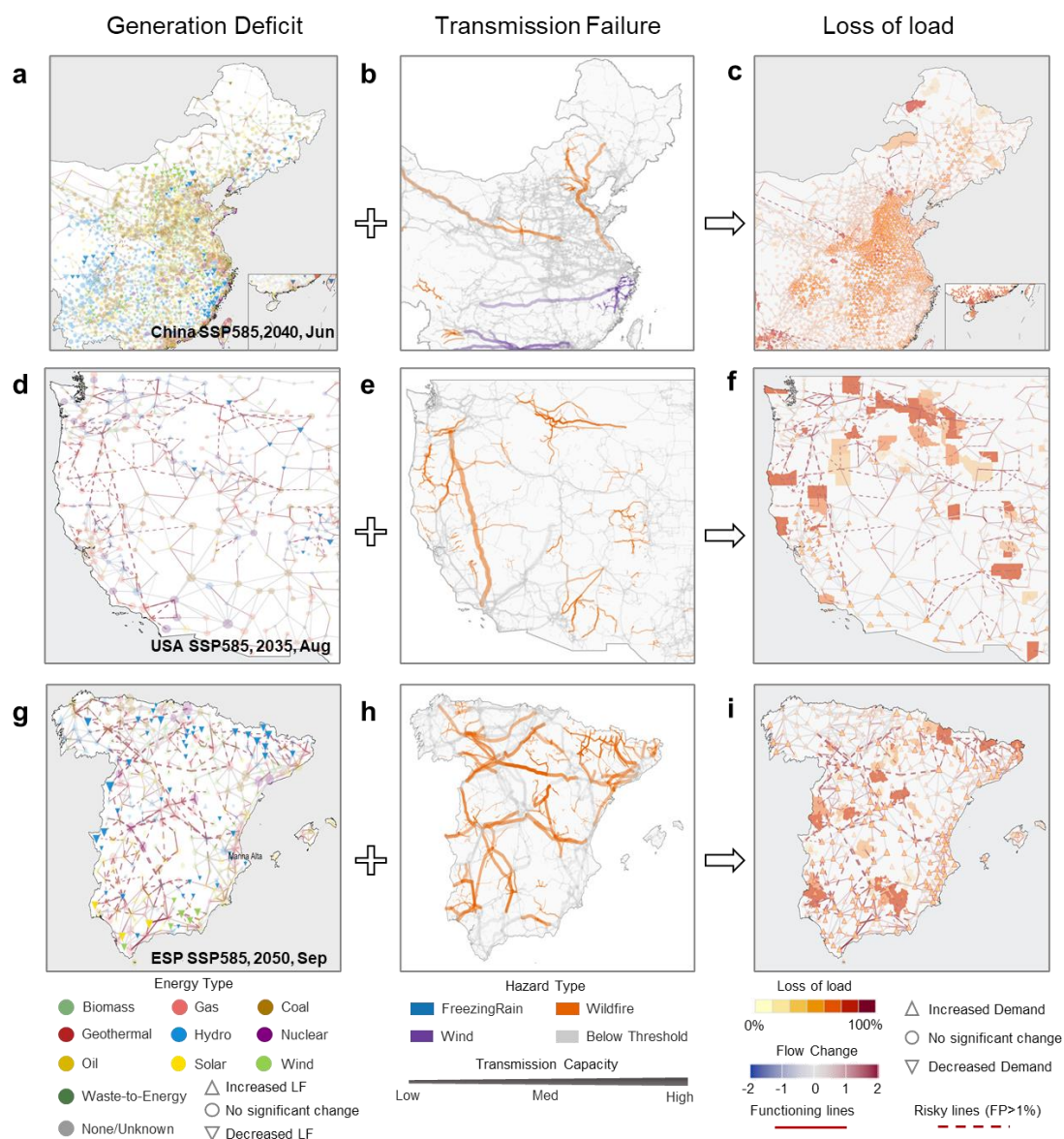
$$T_{bal,m} = T_{sp} - \frac{g_{sol,m} + g_{int}}{H_{tr} + H_{ve}} \quad (21)$$

$$VDD_m = \sum_{d=1}^{dm} (T_d - T_{bal,m})^+ \quad (22)$$

$$E_m = \frac{(H_{tr} + H_{ve}) \times f_{op} \times VDD_m \times f_{fl}}{\eta_c} \quad (23)$$



Supplementary Figure 4 Climate-resource-informed power-grid topologies in representative developing countries. Prospective power-system networks for Brazil (a) and India (b) integrate existing transmission infrastructure and generation assets with the spatial distribution of future climate-dependent energy-resource potential. Colours denote generation technologies, while symbols distinguish different categories of generation assets as defined in the legend. Upward-pointing triangles indicate increased plant load factors, downward-pointing triangles indicate decreased load factors, and circles indicate no substantial change relative to the corresponding season in the baseline period. Dashed segments indicate transmission lines with monthly failure probabilities exceeding 1%.



Supplementary Figure 5 Propagation of compound climate shocks through national power systems. Representative extreme months under SSP5–8.5 are shown for China in June 2040 (a–c), the United States in August 2035 (d–f), and Spain in September 2050 (g–i). a,d,g, Climate-induced generation deficits, with colours indicating generation technologies and symbols showing changes in plant load factors. Upward-pointing triangles indicate increased plant load factors, downward-pointing triangles indicate decreased load factors, and circles indicate no substantial change relative to the corresponding season in the baseline period. b,e,h, Transmission-line failures associated with freezing rain, wildfire and tropical cyclones; line width represents transmission capacity, and dashed segments indicate lines with monthly failure probabilities exceeding 1%. c,f,i, Resulting loss of load and changes in power flows after system redispatch. Colours indicate the share of load lost and the magnitude and direction of flow changes, while symbols denote changes in nodal electricity demand.

### 3. Uncertainty analysis

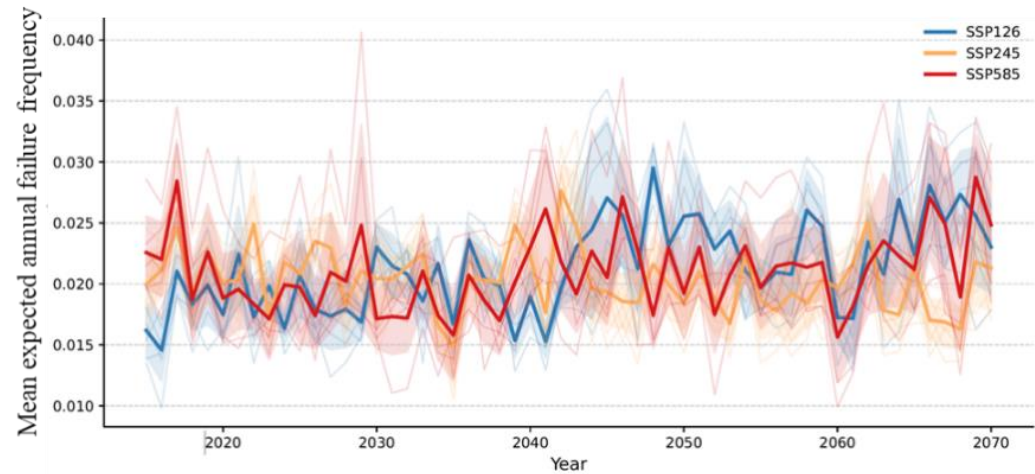
| Module                          | Uncertainty source                                                |           | Alternative settings                                                                                                                   |
|---------------------------------|-------------------------------------------------------------------|-----------|----------------------------------------------------------------------------------------------------------------------------------------|
| Climate-hazard module           | Earth system model                                                |           | Climate models listed in Extended Data Table 1                                                                                         |
|                                 | Freezing-rain threshold                                           | ice-load  | Threshold defined relative to the baseline-period ice-load distribution: mean, 70th percentile, 90th percentile, or maximum            |
|                                 | Tropical-cyclone speed threshold                                  | wind-     | 20, 25, or 30m s <sup>-1</sup>                                                                                                         |
|                                 | Wildfire burnt-area-fraction threshold                            |           | Threshold defined relative to the baseline-period burnt-area-fraction distribution: mean, 70th percentile, 90th percentile, or maximum |
| Infrastructure-fragility module | Structural design return period                                   |           | 30, 50, or 100 years                                                                                                                   |
|                                 | Spatial representation of engineering design standards            | design    | Spatially uniform design standards or regionally heterogeneous design standards                                                        |
|                                 | Component fragility function                                      | fragility | Alternative fragility functions shown in Extended Data Fig. 2                                                                          |
|                                 | Historical reference statistic for excess failure probability     | failure   | Future failure probabilities expressed relative to the baseline-period mean, 90th percentile, or maximum                               |
| Network-propagation module      | Secure transmission-line loading limit                            |           | 70%, 75%, or 80% of nominal line capacity                                                                                              |
|                                 | Population-driven adjustment of future cooling electricity demand |           | 0%, 10%, 50%, or 100% of the projected population-driven increase in cooling demand included                                           |
|                                 | Load-shedding threshold                                           | event     | An event is identified when unserved electricity demand exceeds 1%, 3%, or 5% of total demand                                          |
|                                 | Dispatch objective                                                |           | Minimum-cost economic dispatch or minimum-impedance power-flow allocation                                                              |
|                                 | Treatment of committed and planned generation capacity            |           | Planned generation projects included or excluded                                                                                       |

315 **Notes:** FR denotes freezing rain and TC denotes tropical cyclone. Population projections can  
316 substantially alter future cooling electricity demand, particularly in regions experiencing rapid population  
317 growth or decline. We therefore vary the proportion of the projected population-driven cooling-demand  
318 increment incorporated into the model from 0% to 100%, rather than treating the population effect as  
319 deterministic.

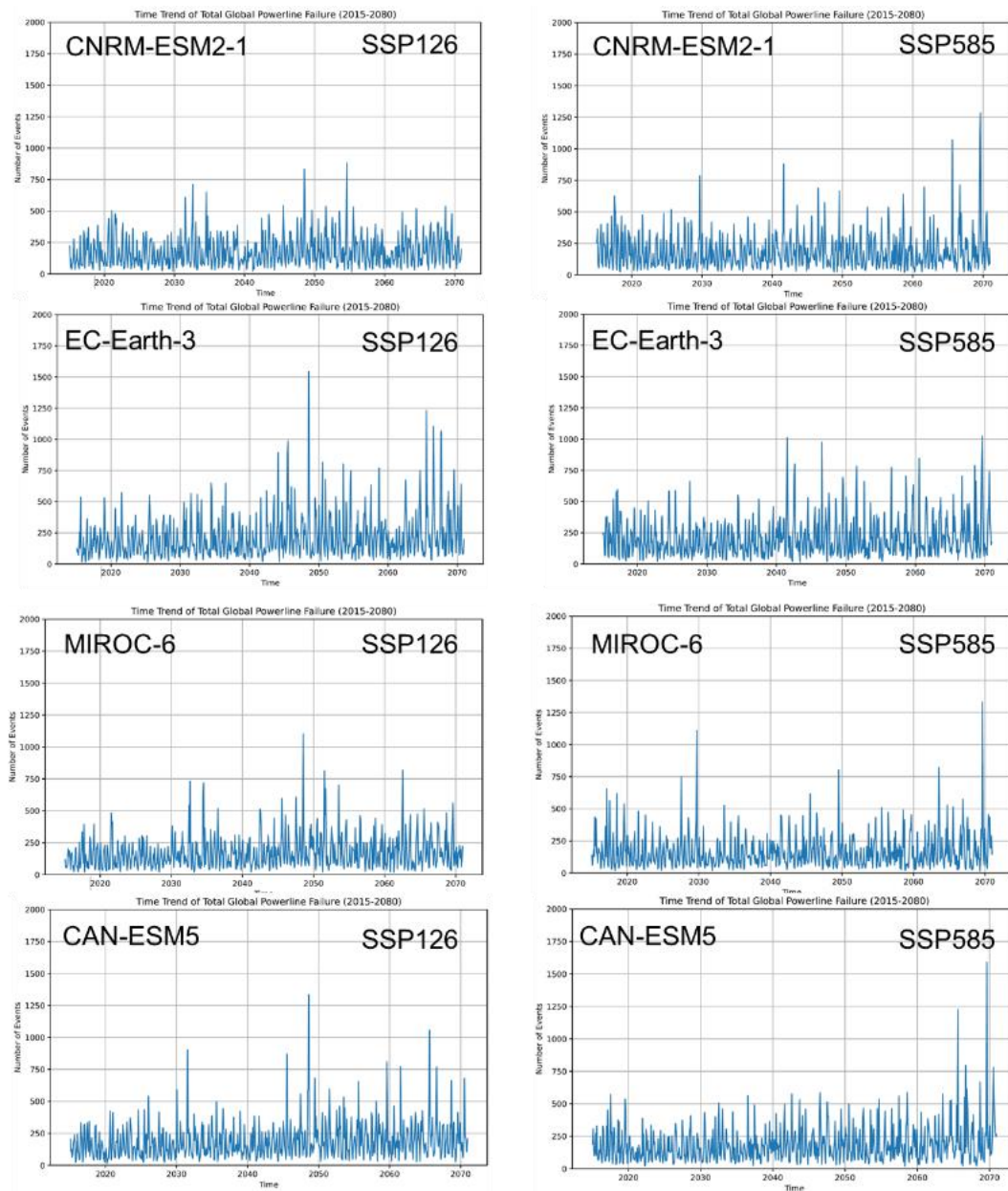
320 Extreme climate events exhibit stochastic variability and model-dependent characteristics, estimates

of transmission-line failure probabilities are subject to considerable uncertainty. Most analysis therefore uses multi-model ensemble means to characterize the central tendency of projected changes. But averaging climate variables across models can smooth or suppress extremes that occur at different times and locations, in this part we did not identify extreme weather events from multi-model-mean climate fields. Instead, we independently detected freezing-rain, wildfire, and tropical-cyclone events within each climate model and calculated the corresponding transmission-line failure-probability patterns before any ensemble averaging. The main text presents the multi-model mean of these model-specific failure estimates. The results for each model are shown in this section to quantify inter-model uncertainty and assess the robustness of the principal findings.

For freezing-rain-induced failure risk, individual climate-model simulations exhibit noticeable interannual variability but broadly consistent long-term behavior. Across models, failure probabilities remain relatively stable or increase gradually from the historical period to the mid-century future, while differences between emissions scenarios are comparatively limited. Inter-model uncertainty is primarily associated with the magnitude of short-term fluctuations and the timing and severity of extreme years, whereas the long-term trends show greater convergence. These results indicate that the broad spatial patterns and long-term evolution of freezing-rain-related failure risk are relatively consistent across climate models, although substantial uncertainty remains at the individual-year scale.



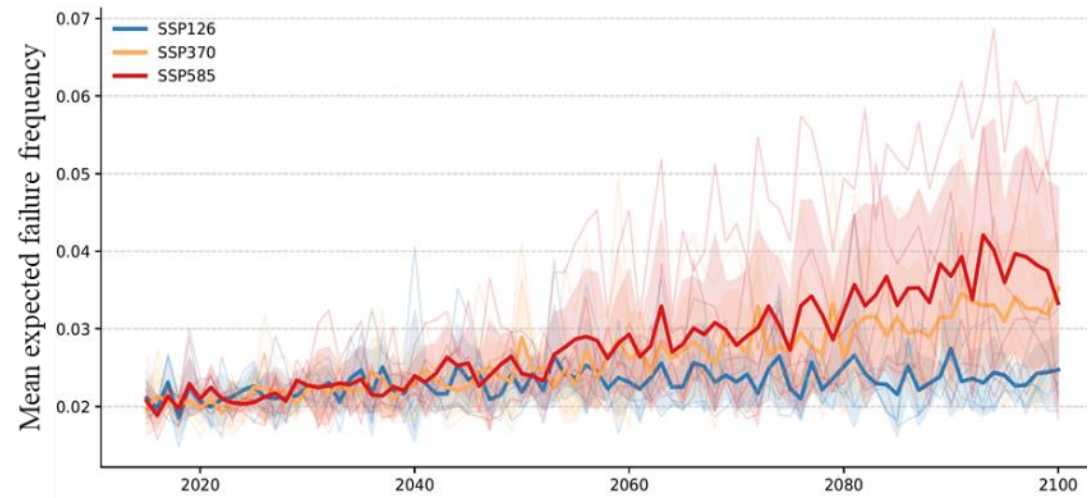
Supplementary Figure 6 Ensemble average of expected annual failure frequencies across transmission lines induced by freezing rain.



Supplementary Figure 7 Ensembles of expected monthly failure frequencies across transmission lines induced by freezing rain

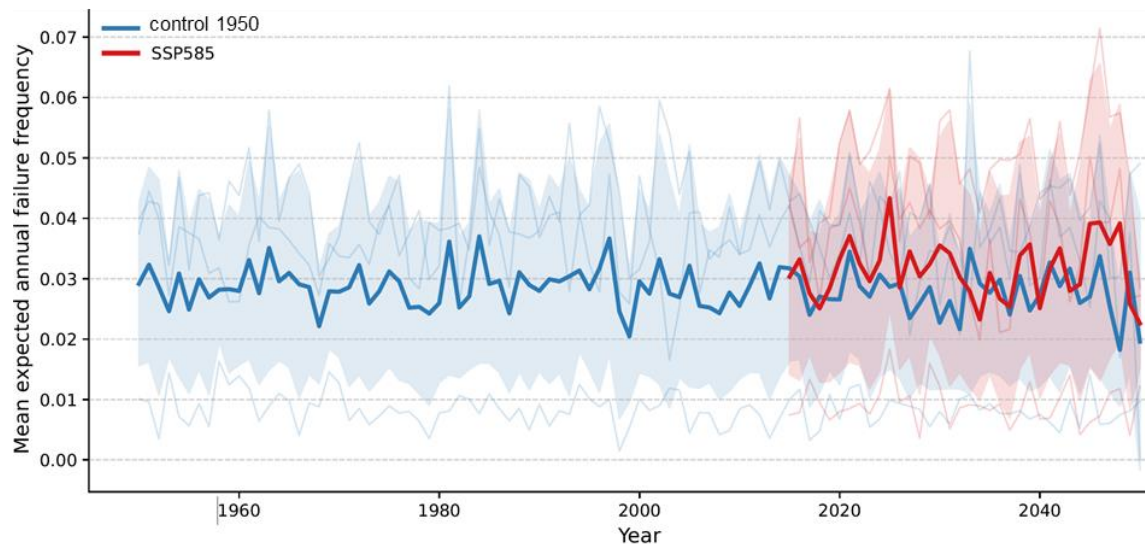
Compared with freezing rain, wildfire simulations involve substantially greater uncertainty because they depend on complex processes governing both natural and anthropogenic ignitions, fuel availability, and fire spread. Nevertheless, the climate models consistently project an increase in wildfire-induced transmission-line failure probability, with risks rising systematically from lower- to higher-emissions pathways. The magnitude and rate of increase vary considerably across scenarios and models, but projected risks are markedly higher under the high-emissions pathway. Inter-model dispersion also increases over time under high emissions, producing a progressively widening uncertainty range, particularly during the second half of the century. This divergence indicates that wildfire risk is sensitive to internal climate variability, model parameterizations, and model-specific representations of the compound effects of drought and extreme heat. Despite these uncertainties, the consistent direction of change across models provides robust evidence that

wildfire-induced transmission-line failure risk will increase substantially under continued high emissions.



Supplementary Figure 8 Ensemble average of expected annual failure frequencies across transmission lines induced by wildfire

For tropical cyclones, uncertainty is dominated by pronounced differences among climate models. During the historical period, the large inter-model spread reflects the inherent difficulty of simulating tropical-cyclone genesis, intensity, frequency, and trajectories. In future projections, the multi-model ensemble indicates that tropical-cyclone-induced transmission-line failure probability is generally higher under the high-emissions pathway than under the low-emissions control pathway. However, the magnitude of this response varies considerably: some models project a clear upward trend, whereas others show comparatively limited changes. These differences largely arise from model-specific representations of future changes in cyclone intensity, occurrence frequency, and storm tracks. At the ensemble level, particularly when comparing emissions scenarios, the results nevertheless indicate an overall intensification of tropical-cyclone-related transmission risk under high emissions, suggesting a consistent directional increase in the potential threat to power networks. However, because relatively few climate models currently provide tropical-cyclone simulations at sufficiently high spatial resolution, this global-scale trend should be interpreted cautiously. Greater emphasis should therefore be placed on the regional-scale results presented in the main analysis.



Supplementary Figure 9 Ensemble average of expected annual failure frequencies across transmission lines induced by tropical cyclones

The disaster-resistance design standards of transmission lines strongly influence their failure frequency under future extreme weather. To assess the extent to which infrastructure adaptation and reinforcement could mitigate risks from consecutive and spatially concurrent hazards, we constructed a high-resilience scenario in which the hazard tolerance of all transmission lines was increased relative to the baseline design standards. Specifically, the design ice-load return period was increased by 10% for freezing-rain hazards, and the extreme-wind-speed resistance threshold was increased by 10% for tropical cyclones. For wildfire, transmission lines were assumed to withstand hazard-induced failure intensities up to the 95th percentile of the historical-period distribution. This scenario therefore represents an engineering strategy that accounts for most hazard conditions already experienced during the historical period. A line was classified as being at risk only when its projected exposure and associated failure intensity exceeded the corresponding enhanced design threshold.

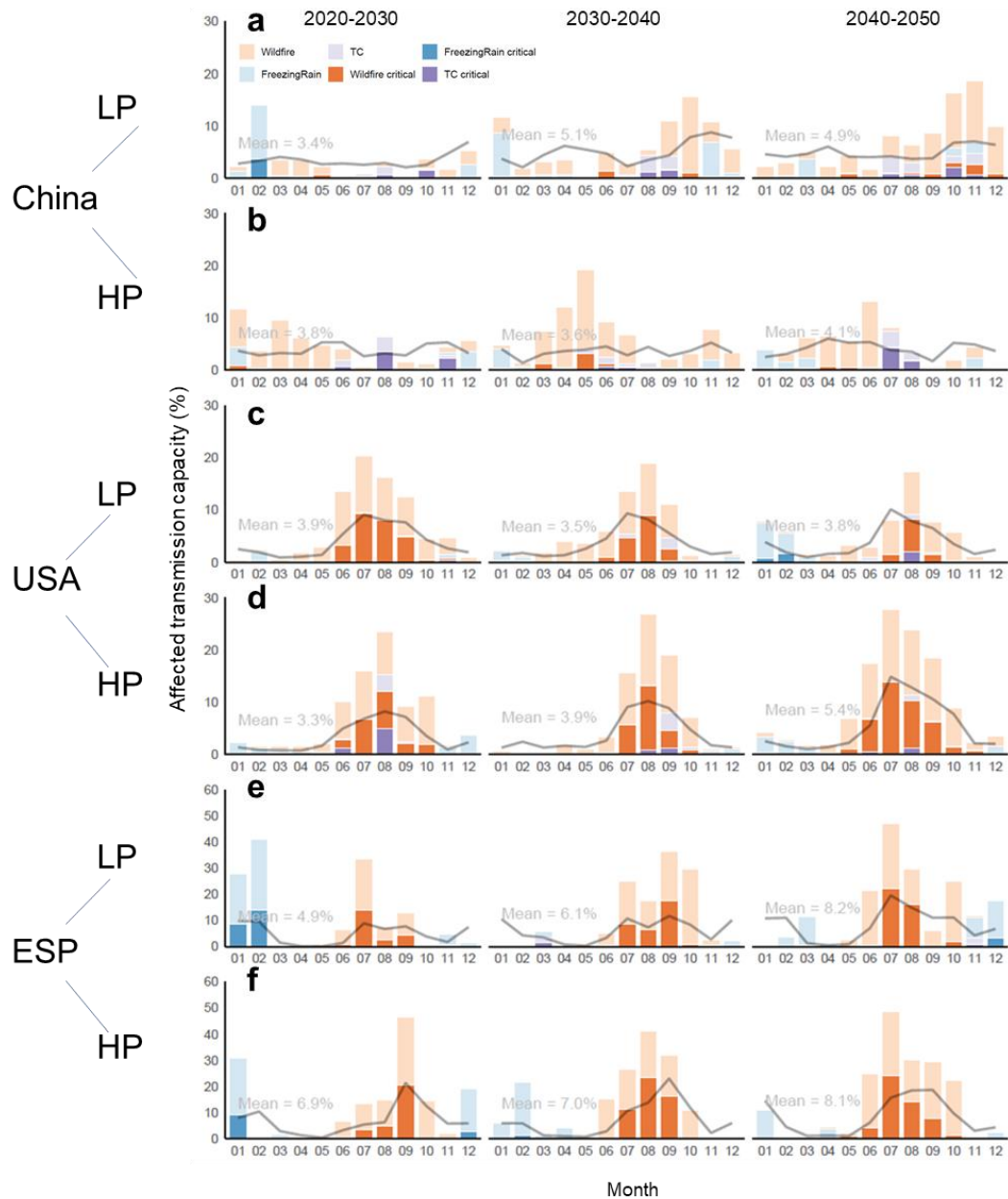
The results indicate that higher engineering resilience cannot completely eliminate the climate-driven increase in transmission-line failure risk, but can substantially reduce system exposure to consecutive and spatially concurrent hazards. By mid-century, the number of transmission lines exposed to consecutive hazards decreases from approximately 25,000 under the baseline-resilience scenario to approximately 17,000 under the high-resilience scenario—a reduction of approximately one third. Thus, strengthening disaster-resistance standards can substantially limit the spatial extent of weather-related disruptions and reduce the burden placed on grid operation, maintenance, and post-disaster restoration. Nevertheless, the mean interval between consecutive failures remains largely unchanged at approximately 1.4 months, indicating that reinforcement primarily reduces the number of exposed lines rather than materially changing the temporal clustering of hazard events.

The benefits of enhanced resilience vary markedly across regions. The United States exhibits the largest reduction, with the mean number of affected lines decreasing from approximately 4,000 to 2,000. This suggests that raising design thresholds based on the upper range of historically observed hazards could avoid a substantial proportion of foreseeable failures. In contrast, improvements are

404 limited in countries such as Spain, where the number of affected lines changes only marginally. This  
405 regional heterogeneity points to a more challenging reality: in some regions, future extreme hazards  
406 are projected to move substantially beyond the range of historical experience, generating  
407 unprecedented risks. Under such conditions, conventional engineering standards calibrated  
408 primarily against historical hazard distributions may no longer provide adequate protection.  
409 Forward-looking, climate-informed dynamic risk assessment and adaptive design measures are  
410 therefore required.

411 The mitigating effect of engineering reinforcement is even more pronounced for spatially concurrent  
412 hazards. Because these events can simultaneously disrupt multiple transmission corridors, their  
413 systemic significance extends beyond individual line failures to an increased probability of  
414 contingencies exceeding the power system's N-2 security criterion. Under the high-resilience  
415 scenario, the share of transmission capacity simultaneously affected declines substantially across  
416 multiple countries. By mid-century, the mean concurrently affected capacity in China and the United  
417 States decreases from approximately 6-9% under baseline resilience to 3-6% under high resilience.  
418 In Spain, India, and Brazil, the corresponding share declines from approximately 11-32% to 8-17%.  
419 These results demonstrate that increasing line tolerance to ice loading, extreme winds, and wildfire  
420 exposure can effectively attenuate the synchronized impacts of spatially concurrent hazards across  
421 transmission networks.

422 Substantial risks nevertheless persist during the most extreme months, with pronounced differences  
423 among countries. In China, even during the most severely affected month, the share of capacity  
424 exposed to high-intensity failure risk remains below 5%, indicating that engineering reinforcement  
425 can effectively constrain systemic risk. In the United States, although the mean affected-capacity  
426 share decreases substantially, continued intensification of wildfire risk causes the share in extreme  
427 months to remain as high as approximately 15%. In Spain, the extreme-month affected-capacity  
428 share declines from approximately 35% to 23%; despite this considerable reduction, the residual  
429 systemic risk remains high. These residual risks arise because some transmission lines are exposed  
430 to hazard intensities beyond both historical experience and existing design envelopes. Consequently,  
431 even the strong assumption that all lines can withstand nearly all historically observed hazards is  
432 insufficient to eliminate the impacts of future climate change. This finding underscores the need to  
433 move beyond exclusively history-based design standards toward adaptive engineering strategies  
434 explicitly informed by projected future climate extremes.



**Supplementary Figure 10 Monthly and spatial patterns of compound climate risks to transmission capacity under high resilience scenario.** 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 show transmission capacity.

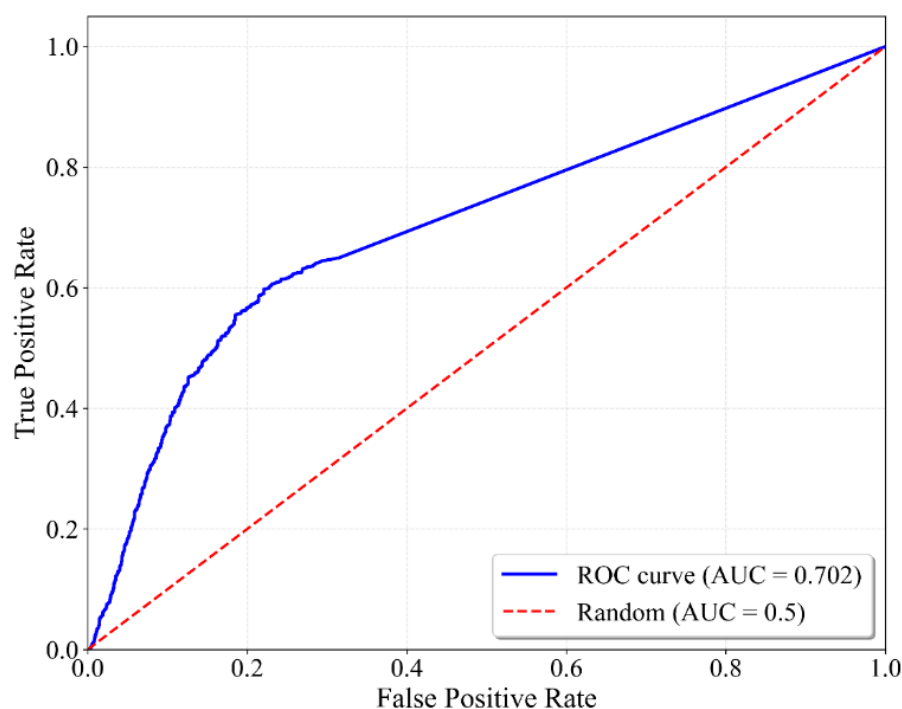
## 4. Validation

### 4.1 Validation of extreme weather events and infrastructure failure

The underlying wildfire and tropical-cyclone datasets—burned-area fractions and cyclone tracks, respectively—were generated using established and extensively evaluated modelling systems. Independently revalidating these upstream models is beyond the scope of this study; their performance and validation procedures are documented in the original publications cited in methods part. This section thus focuses on evaluating the model's performance in simulating freezing rain events from two dimensions: prediction accuracy and temporal trends, using the 6-hourly 0.1° gridded freezing rain observation dataset for China from 2000 to 2019 (Supplementary Table 8) as the benchmark. For prediction accuracy, the freezing rain identification threshold was set at 0.1 mm. By comparing the model simulations with observations, we found that 47% of the freezing rain events identified by the model were actually observed (precision), whereas 59.9% of the observed freezing rain events were successfully captured by the model (recall). Overall, the model achieved a comprehensive classification accuracy of 73.1% for freezing rain events, with an F1 score of 52.7%. In addition, the area under the ROC curve (AUC) was 0.70 (Supplementary Figure 11), visually demonstrating the model's ability to discriminate between the occurrence and non-occurrence of freezing rain under the given threshold.

Supplementary Table 8 2000-2019 6-hour 0.1° resolution freezing rain dataset in China

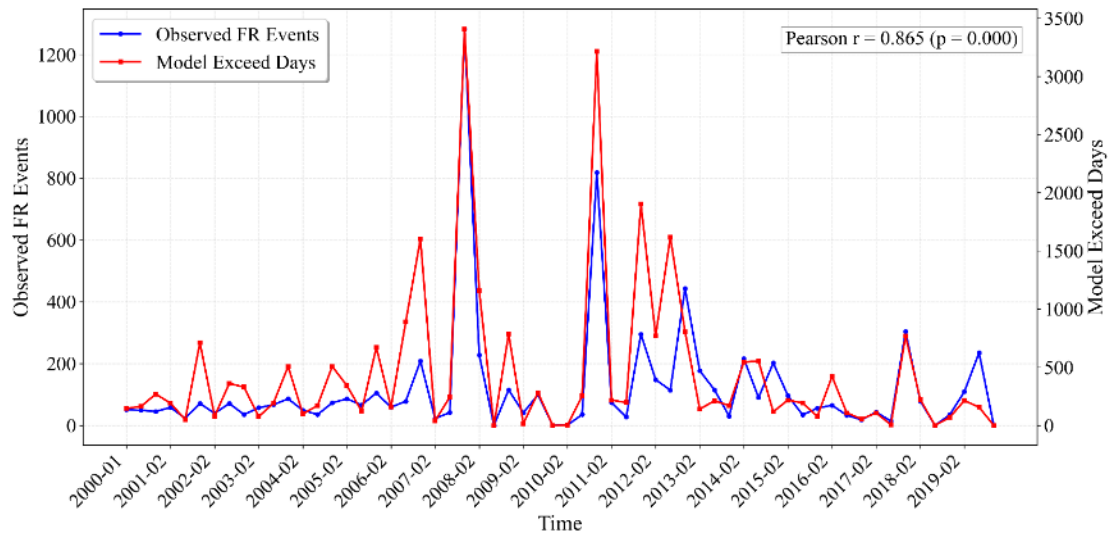
| year | month | day | hour | latitude | longitude | FR    | name         |
|------|-------|-----|------|----------|-----------|-------|--------------|
| 2001 | 12    | 16  | 20   | 24.1     | 115.3     | FALSE | Southern     |
| 2012 | 2     | 10  | 20   | 26.4     | 112.8     | FALSE | Central      |
| 2011 | 1     | 27  | 8    | 27       | 106       | TRUE  | Southwestern |
| 2014 | 2     | 28  | 20   | 31.8     | 114.1     | TRUE  | Central      |
| 2003 | 12    | 3   | 20   | 28.8     | 105.8     | FALSE | Southwestern |
| 2011 | 1     | 13  | 8    | 27       | 106       | TRUE  | Southwestern |
| 2012 | 2     | 9   | 8    | 35.2     | 109.9     | FALSE | Northwestern |
| 2008 | 1     | 22  | 2    | 26.7     | 110.6     | TRUE  | Central      |
| 2012 | 12    | 11  | 8    | 23.1     | 107.1     | FALSE | Southern     |
| 2014 | 12    | 12  | 20   | 43.4     | 128.2     | FALSE | Northeastern |
| 2000 | 12    | 11  | 8    | 30.2     | 116.1     | FALSE | Southeastern |
| 2000 | 2     | 14  | 2    | 28.2     | 109.7     | FALSE | Central      |
| 2000 | 1     | 8   | 20   | 29.3     | 120.2     | FALSE | Southeastern |
| 2008 | 2     | 10  | 20   | 27.3     | 112.7     | TRUE  | Central      |
| 2001 | 2     | 24  | 2    | 29.3     | 107.8     | FALSE | Southwestern |



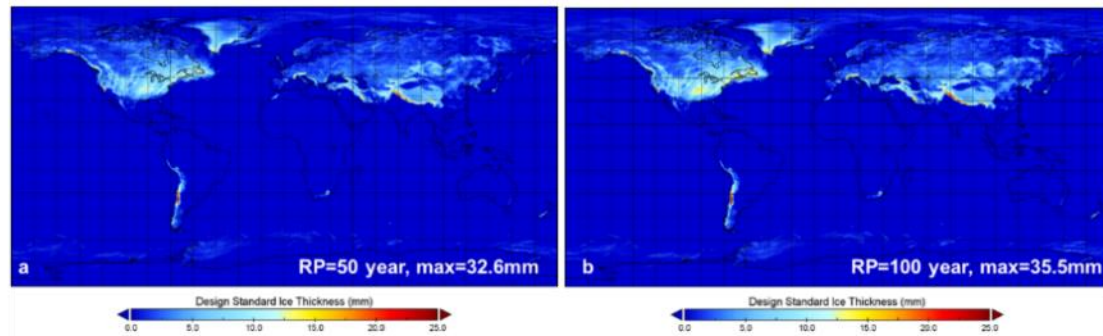
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468 Supplementary Figure 11 ROC curve of freezing rain prediction

469 For the temporal trend validation, we aggregated the monthly number of freezing rain events from  
 470 the observation dataset at each grid cell over the period 2000-2019, and compared this against the  
 471 model-simulated monthly number of days with ice accretion thickness exceeding the threshold over  
 472 the same period. The validation was restricted to the winter months (December, January and  
 473 February), consistent with the temporal coverage of the freezing rain observation dataset used. As  
 474 shown in Supplementary Figure 12, the simulated results exhibit strong interannual consistency with  
 475 the observed freezing rain event frequency (Pearson correlation coefficient  $r = 0.865$ ,  $p = 0.000$ ),  
 476 indicating that the model effectively reproduces the temporal fluctuation characteristics of freezing  
 477 rain events. In terms of the time series morphology, the observed and simulated peaks coincided  
 478 synchronously during years with high freezing rain frequency, such as 2008 and 2011, further  
 479 corroborating the model's reliability in the temporal dimension.



Supplementary Figure 12 Validation of freezing rain time trend in winter months (December, January and February)



Supplementary Figure 13 ice load design standard under different return period.

Beside the time series validation, to evaluate the model's capability in simulating typical hazards and transmission line failures, we conducted a retrospective validation using the ice storm event that affected Heilongjiang Province in November 2023. According to official damage records, this event resulted in the outage of 1 line at 500 kV, 3 lines at 220 kV, 2 lines at 110 kV, 27 lines at 66 kV, 1 line at 35 kV, and 399 lines at 10 kV. In addition, 3 substations at 110 kV, 38 at 66 kV, and 4 at 35 kV were rendered inoperable, affecting approximately 13,749 distribution transformer units and 966,400 end-users.

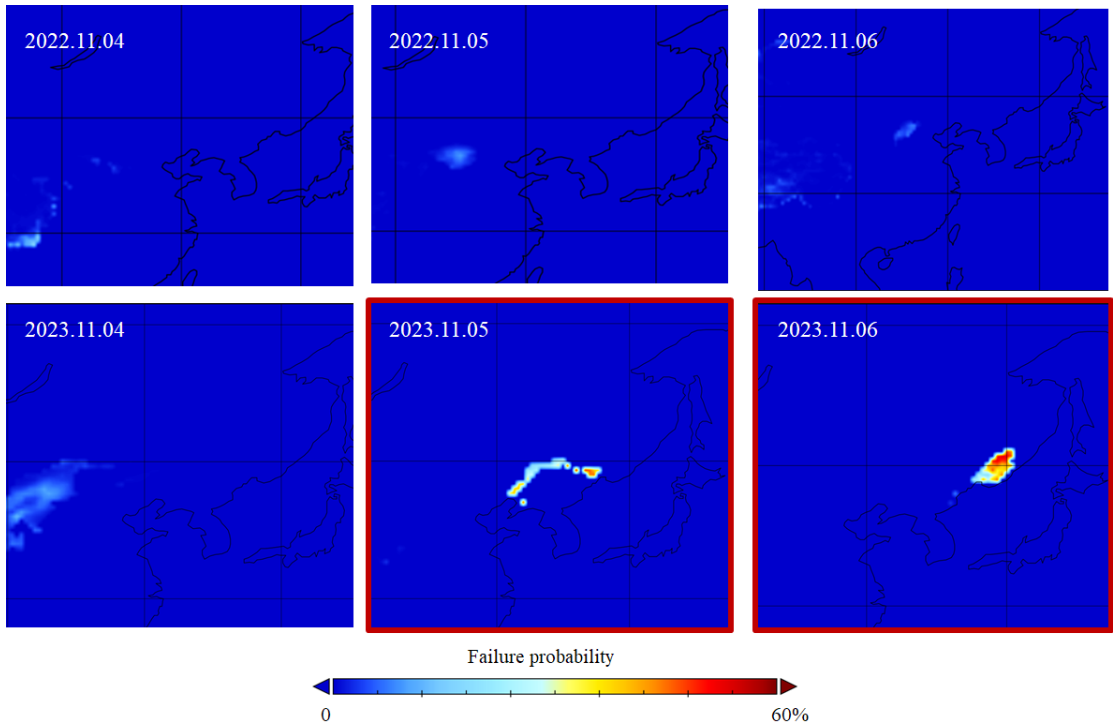
The model was forced by ERA5 reanalysis meteorological data to simulate the event retrospectively. The simulation successfully captured the freezing-rain episodes on November 5-6, 2023, over the cities of Harbin, Mudanjiang, and Changchun, with estimated ice accretion thicknesses ranging from 1 to 10 mm across the affected regions. Based on the simulated ice loads and the fragility functions, a total of 754 transmission lines were identified with failure probabilities exceeding 1%.

Among these, 34 lines (24.5% of the simulated 500-kV lines), 89 lines (10.2% of 220-kV lines), and 631 lines (8.8% of lines at 66 kV and below) exceeded the 10% probability threshold. Spatially, lines with failure probabilities above 30% were predominantly located along the Harbin-Mudanjiang corridor and the eastern peri-urban areas of Changchun, which aligns closely with the

regions reported to have sustained the most severe infrastructure damage during the actual event.

In terms of the distribution of failure probabilities, approximately 62% of the high-risk lines (469 lines) exhibited failure probabilities in the range of 10%-20%, 21% (158 lines) in the 20%-30% range, and 17% (127 lines) above 30%. This probabilistic structure mirrors the observed damage pattern, wherein a large number of low-voltage distribution lines were affected while only a limited number of high-voltage transmission lines were brought offline.

Further spatial overlay analysis between the simulated high-risk lines (failure probability > 10%) and the documented outage records indicates that approximately 70% of the actually failed lines were successfully captured within the model's high-risk set.



Supplementary Figure 14 Transmission line failure risk simulation against the November 2023 Ice Storm in Heilongjiang, China

## 4.2 Validation of climate affected power generation

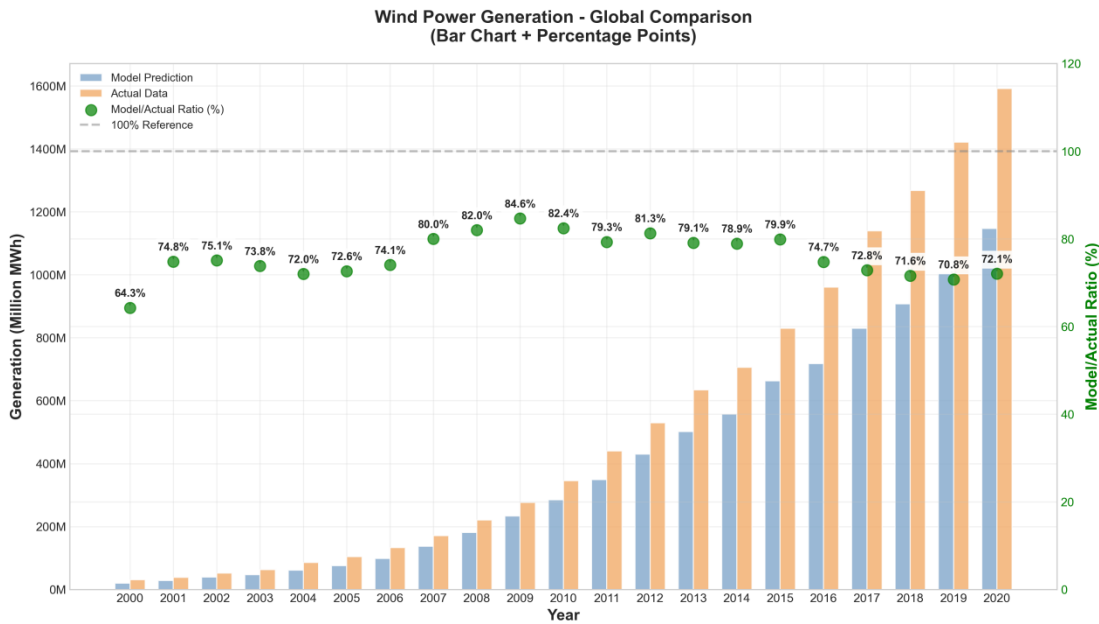
To validate the reliability of the electricity generation calculation framework, this study used historical meteorological data from 2000 to 2024 for predictive simulations, maintaining an identical computational workflow to that used for future scenario projections. The model-derived capacity factors and total electricity generation were compared against publicly available statistics from sources such as Ember and ENTSO-E at national, continental and global scales. This consistency ensures that the validation results can genuinely reflect the accuracy of the model in estimating electricity generation and capacity factors driven by meteorological parameters.

The results indicate that the model is capable of reproducing interannual variability and long-term trends with stable temporal consistency. Although amplitude deviations exist in certain local regions, no systematic drift is observed. These discrepancies may arise from limitations in the accuracy of the reanalysis meteorological data, biases introduced by interpolating meteorological data to power

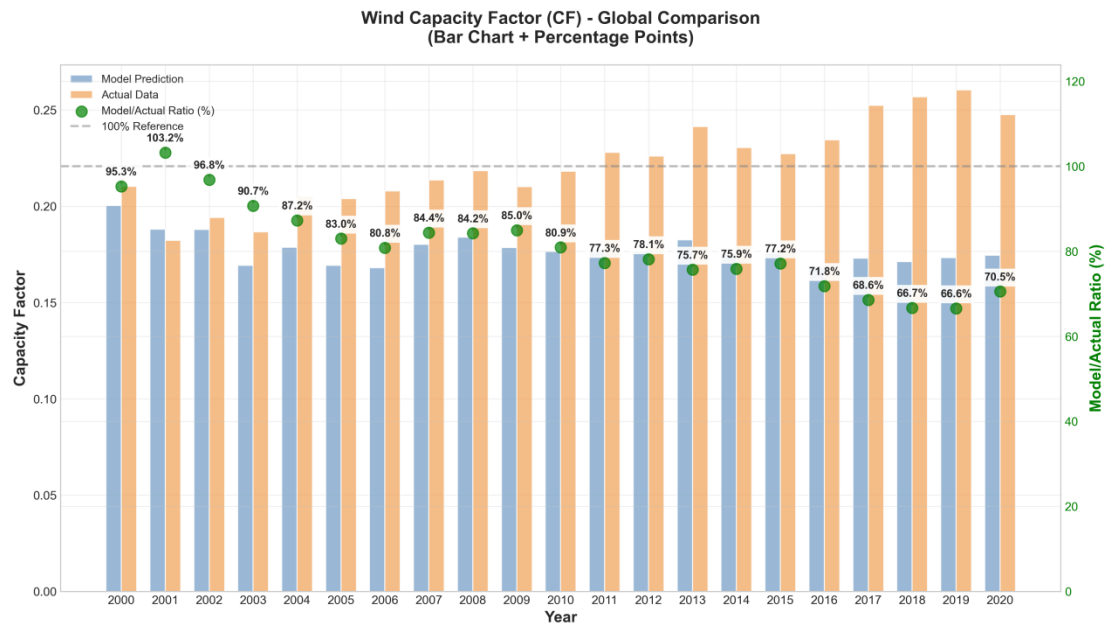
plant locations, and differences in statistical definitions across various data sources. Nevertheless, these deviations do not compromise the model's ability to capture relative change trends. The comparison between the model outputs and the public benchmark data is presented below.

### 4.2.1 Wind

For wind power, the model was driven by the historical near-surface 10m wind speed parameter from ERA5, incorporating a medium turbine power curve. The historical electricity generation results from 2000 to 2020 calculated by our prediction model are presented in Supplementary Figure 15. At the global level, the simulated results generally cover more than 70% of the total generation reported in public datasets, with minor deviations in certain years. At the continental level, the simulations also reach approximately 80% of the public benchmark values. In addition, we compared the capacity factor (calculated as electricity generation divided by installed capacity and annual hours) against public data standards, with the corresponding results shown in Supplementary Figure 16. At both the global and continental scales, the simulated capacity factors cover approximately 80% of the public dataset values over the multi-year time series, further demonstrating the accuracy of the model configuration.

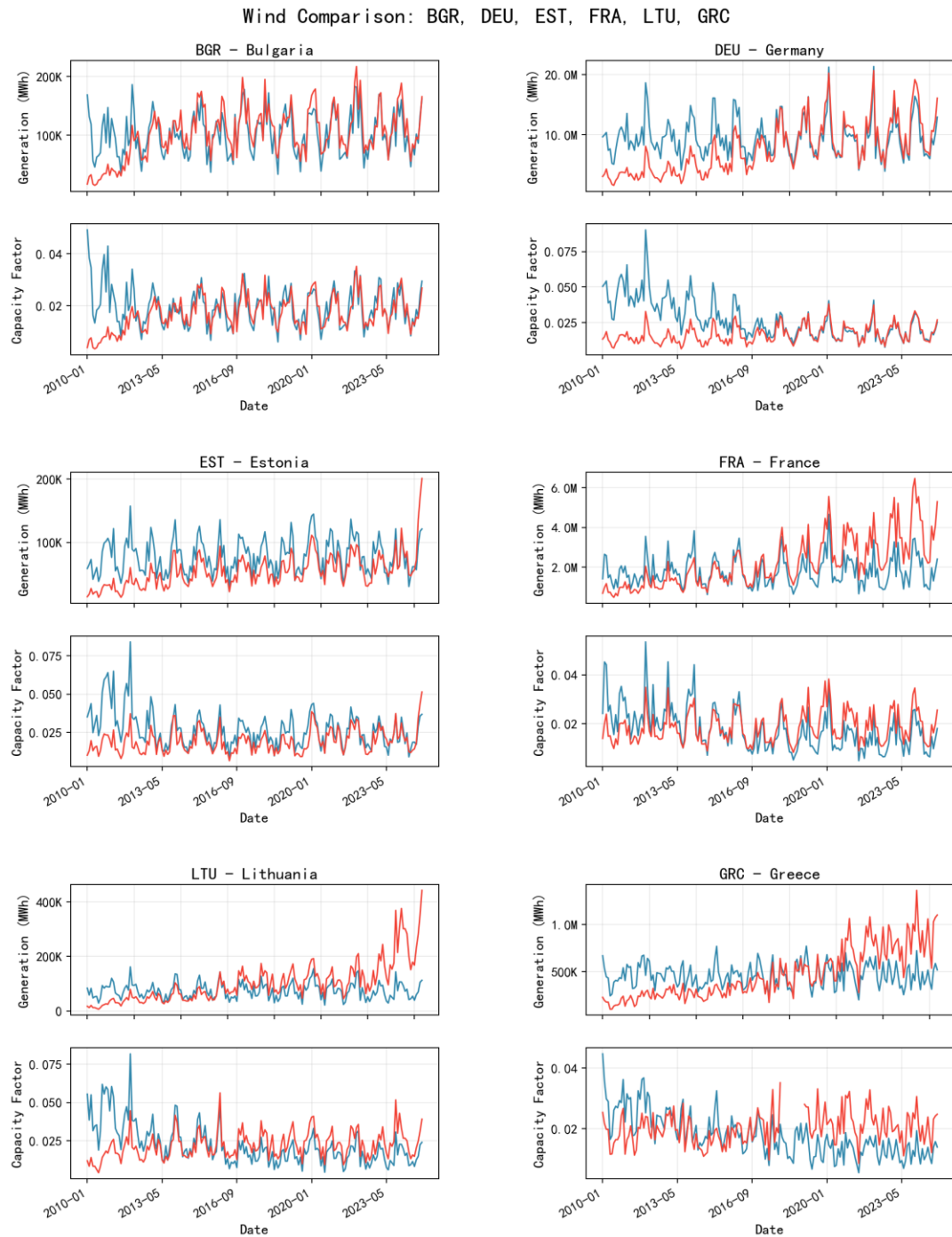


Supplementary Figure 15 Comparison of annual global wind power generation between model calculations and public data.



Supplementary Figure 16 Comparison of annual global wind capacity factor between model calculations and public data.

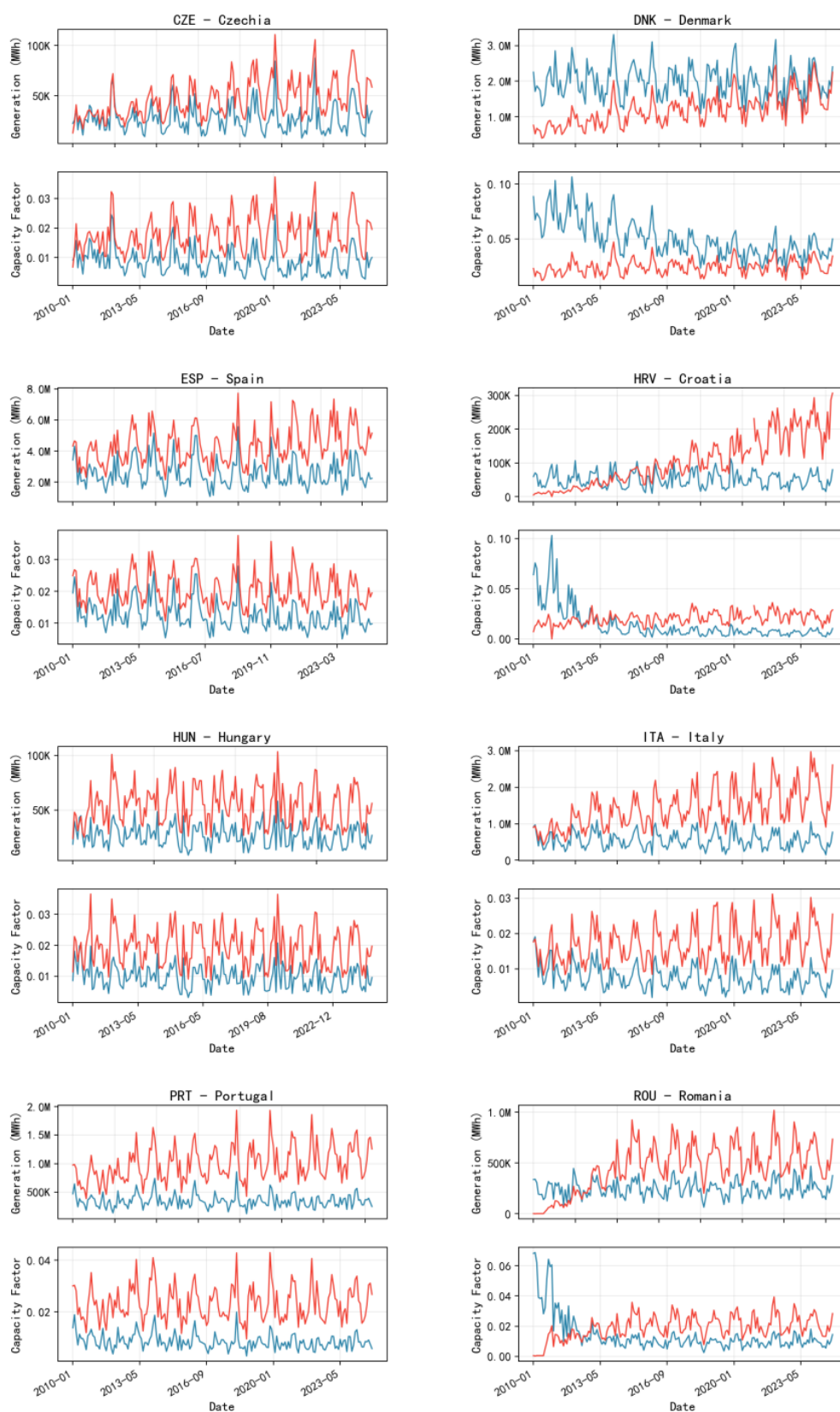
In addition, given that annual data may mask intra-annual variability and that interannual installed capacity growth could confound the assessment of overall trends, we further plotted monthly electricity generation and installed capacity data as line charts over the corresponding time series (Supplementary Figure 17Supplementary Figure 18). Owing to limitations in the availability of monthly public data, we used the monthly electricity generation and installed capacity data from ENTSO-E for this analysis, covering approximately 30 countries or regions in Europe. Despite this relatively limited geographic scope, the results show that the wind power model captures monthly variations in both electricity generation and capacity factor remarkably well for countries such as Bulgaria, Germany, Estonia, France, Greece and Lithuania, with model outputs nearly identical to the observations in some cases. For countries including Czechia, Denmark, Spain, Croatia, Italy, Hungary, Portugal and Romania, the model-simulated monthly generation and capacity factors are slightly lower than the observed values, yet the month-to-month variability is still well reproduced. In a few cases, such as Finland, while the simulated capacity factors are generally consistent with observations, notable discrepancies in electricity generation are observed in certain years, which can be attributed to the absence of newly added generating facilities during the study period in the installed capacity database.



562

563 Supplementary Figure 17 Comparison of monthly electricity generation and capacity factor trends  
 564 between model calculations and public data at the national level (Bulgaria, Germany, Estonia, France,  
 565 Greece, Lithuania)

# Wind Comparison: CZE, DNK, ESP, HRV, HUN, ITA, PRT, ROU



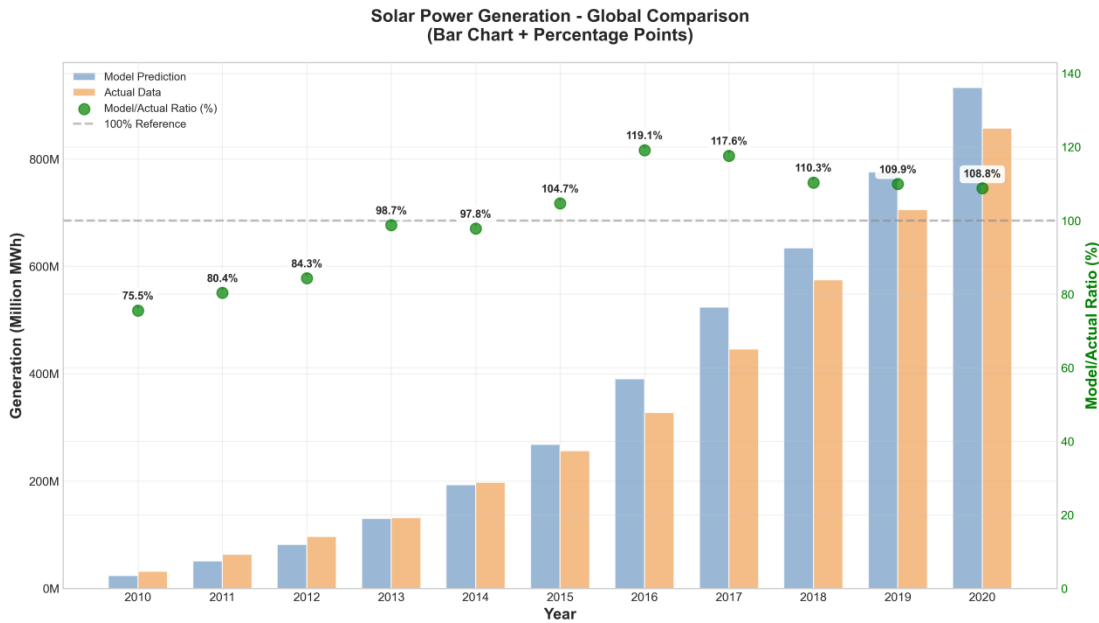
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567 Supplementary Figure 18 Comparison of monthly electricity generation and capacity factor trends  
568 between model calculations and public data at the national level (Czechia, Denmark, Spain, Croatia,  
569 Italy, Hungary, Portugal, Romania)

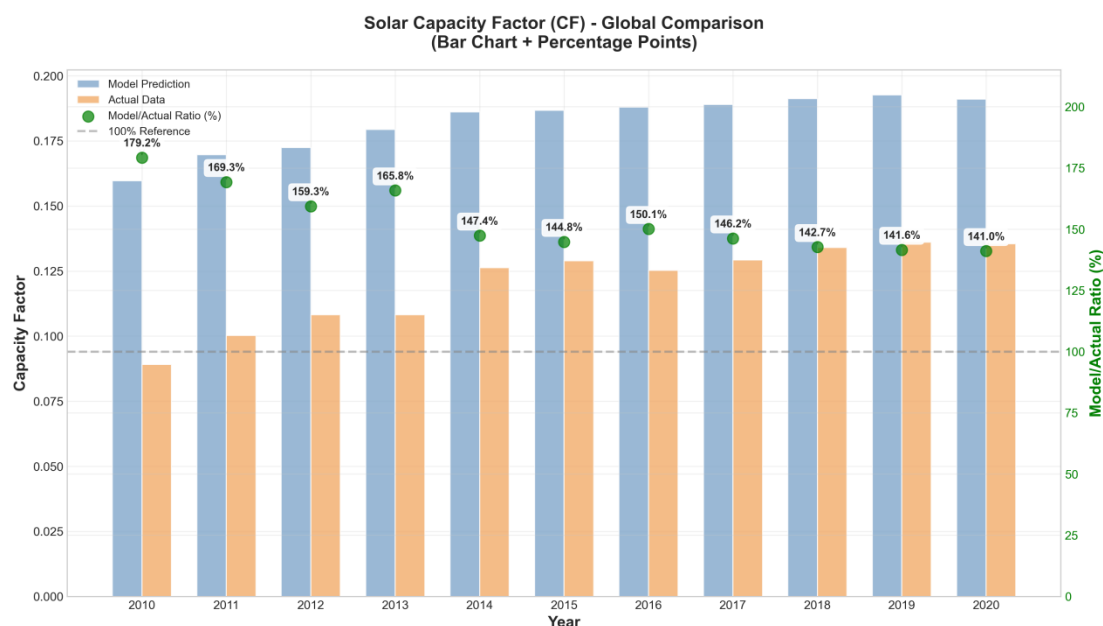
#### 4.2.2 Solar

For photovoltaic (PV) power, the model was driven by historical solar radiation, temperature and wind speed parameters from ERA5. Given that global PV installed capacity was relatively limited before 2008 and that discrepancies across different statistical sources could introduce substantial distortions and biases, the historical period from 2010 to 2020 was selected for comparative analysis. The simulated electricity generation results are presented in Supplementary Figure 19. At the global level, the model-calculated generation is approximately 110% of the public data, while at the continental level it generally ranges from 110% to 120%, with the exception of Europe, where it accounts for approximately 80% of the public benchmark. This discrepancy for Europe is attributable to the relatively lower total installed capacity in our database for this region, which is only about 60% of that reported in public datasets.

In addition, we compared the capacity factor (calculated as electricity generation divided by installed capacity and annual hours) against public data standards, with the corresponding results shown in Supplementary Figure 20. Globally, the capacity factor from our model is approximately 150% of that derived from public data; at the continental level, the model results generally range between 110% and 150% of the public benchmarks. Although the capacity factor is somewhat overestimated, which could in principle be adjusted by tuning the corresponding coefficients in the generation model, we did not apply such proportional adjustments, given the insufficient installed capacity in our database. As a result, the current simulated electricity generation already falls within a reasonable range relative to public benchmarks.



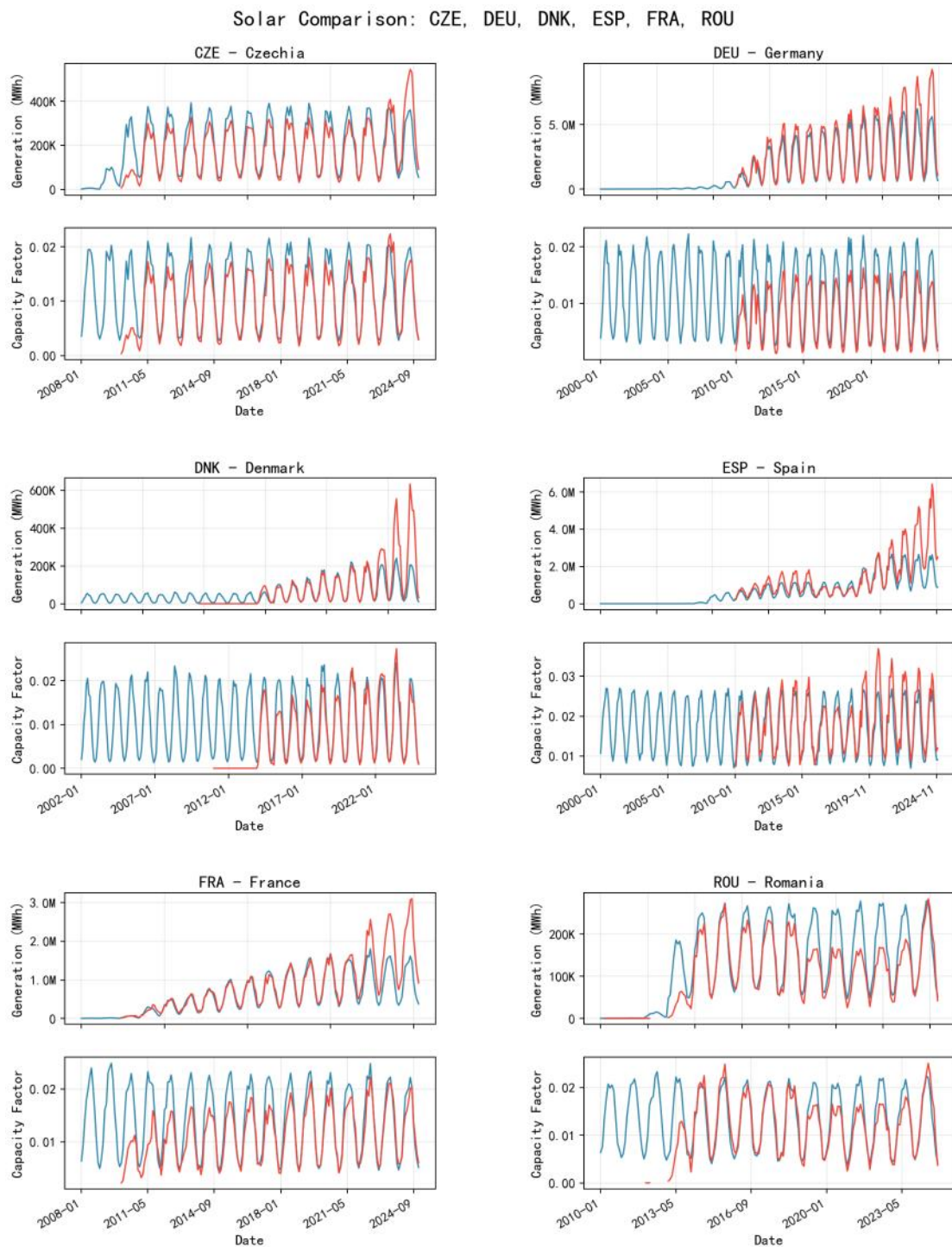
Supplementary Figure 19 Comparison of annual global PV electricity generation between model calculations and public data.



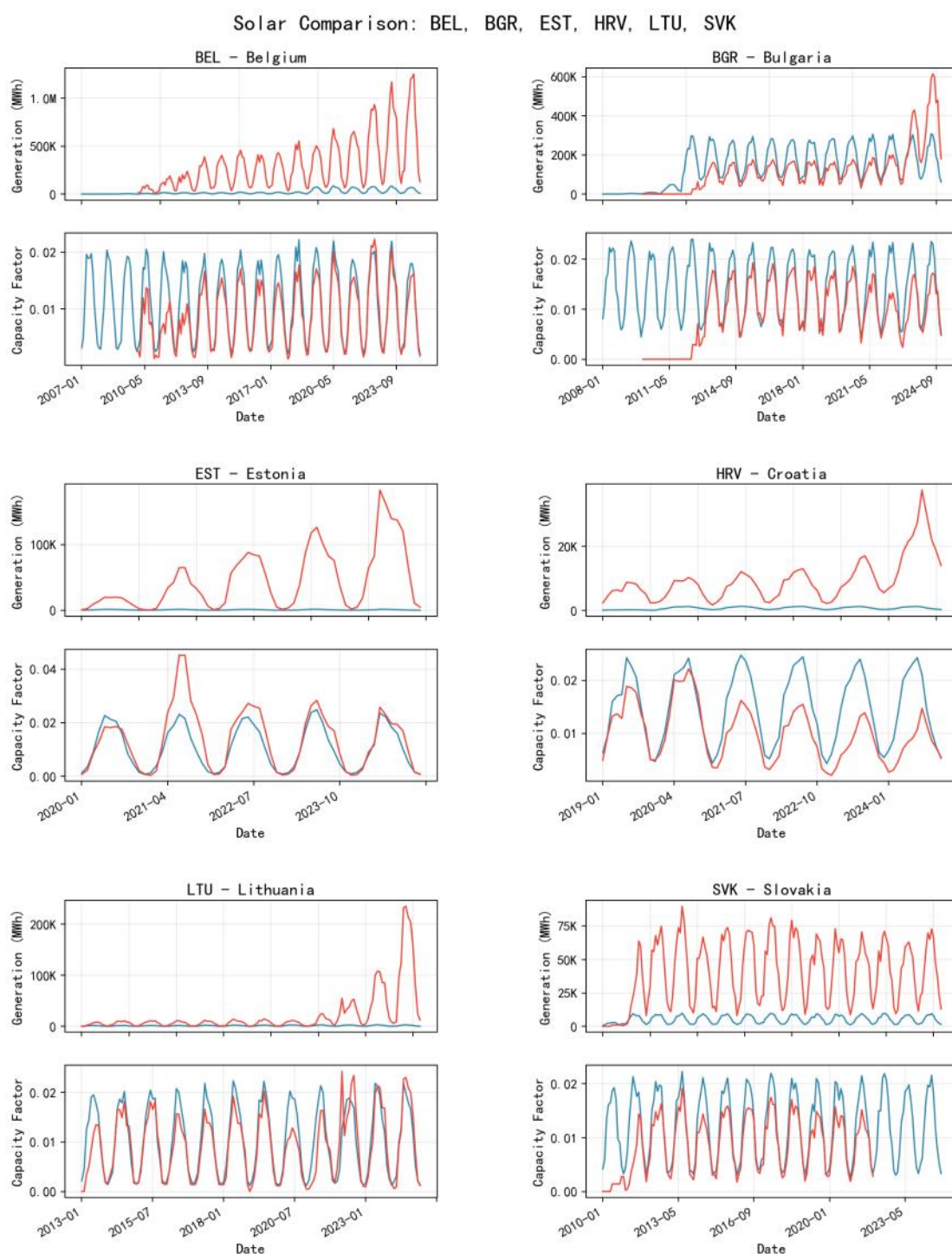
593

594 Supplementary Figure 20 Comparison of annual global PV capacity factor between model calculations  
 595 and public data.

596 Similarly, we further plotted monthly electricity generation and installed capacity data as line charts  
 597 over the corresponding time series (Supplementary Figure 21Supplementary Figure 22). The results  
 598 show that the PV model captures monthly variations in both electricity generation and capacity  
 599 factor remarkably well for countries such as Czechia, Germany, Denmark, Spain, France and  
 600 Romania, with model outputs nearly identical to the observations in some cases. For countries  
 601 including Belgium, Bulgaria, Estonia, Croatia, Lithuania and Slovakia, while the simulated capacity  
 602 factors are generally consistent with observations, notable discrepancies in electricity generation are  
 603 observed in certain years, which can be attributed to the absence of newly added generating facilities  
 604 during the study period in the installed capacity database, resulting in underestimated generation.



Supplementary Figure 21 Comparison of monthly electricity generation and capacity factor trends between model calculations and public data at the national level (Czechia, Germany, Denmark, Spain, France, Romania)



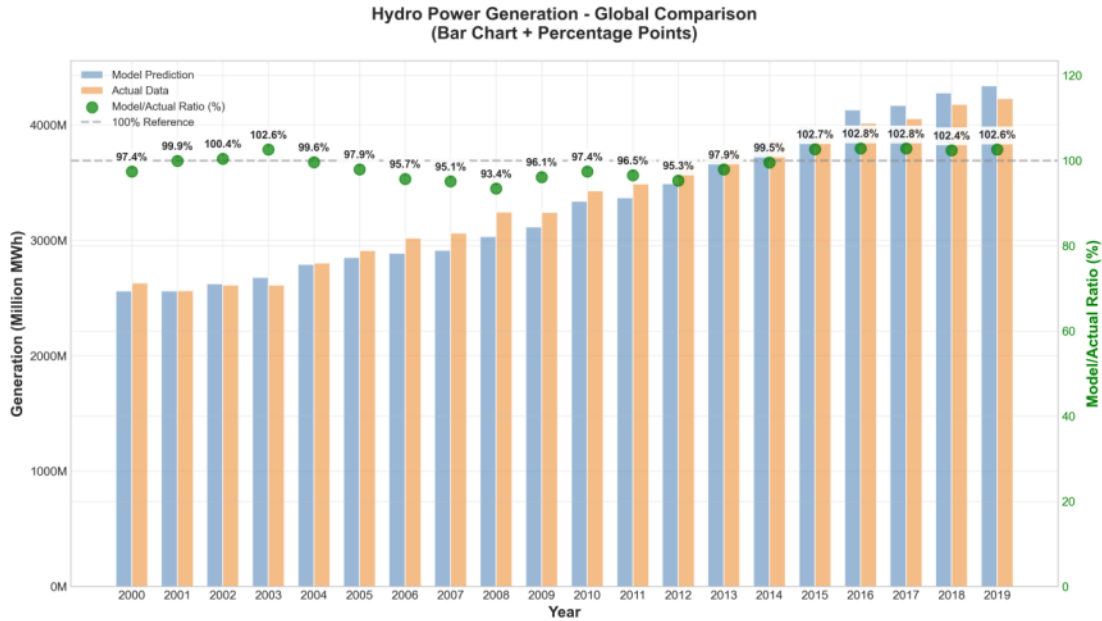
609

610 Supplementary Figure 22 Comparison of monthly electricity generation and capacity factor trends  
 611 between model calculations and public data at the national level (Belgium, Bulgaria, Estonia, Croatia,  
 612 Lithuania, Slovakia)

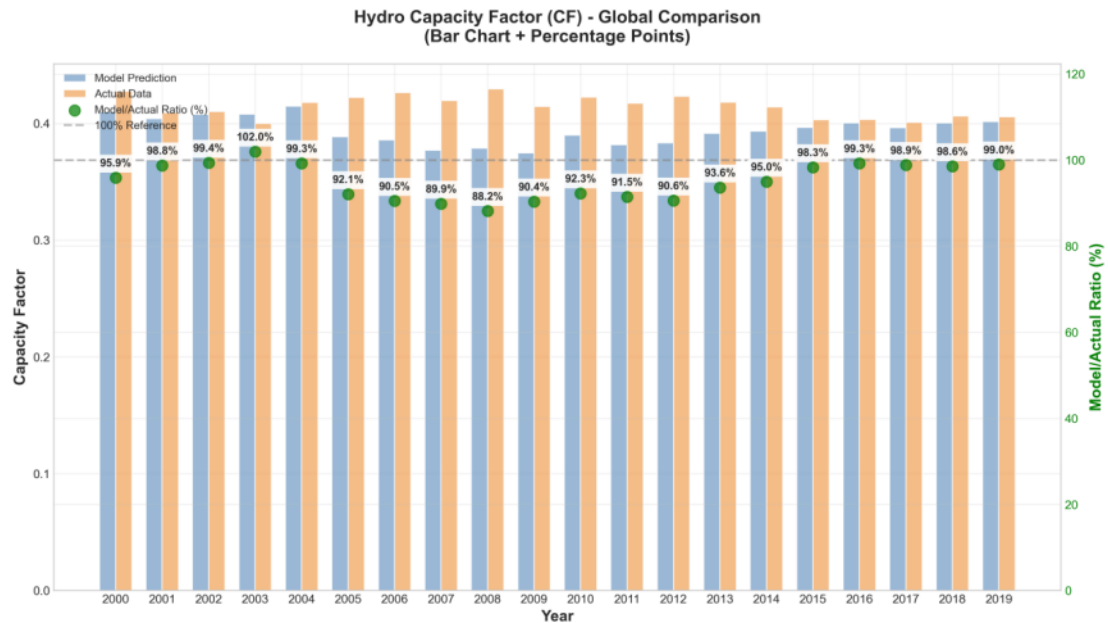
### 613 4.2.3 Hydro

614 For hydropower, the model was driven by historical runoff and reservoir capacity parameters from  
 615 ERA5. The historical electricity generation results from 2000 to 2019 calculated by our prediction  
 616 model are presented in Supplementary Figure 23. At the global level, the simulated total generation  
 617 is generally close to that reported in public datasets, with an overall mean absolute error of no more

than 5%. At the continental level, the simulations also achieve approximately 100% of the public benchmark values, with the exception of Oceania, where the proportion is about 80%. In addition, we compared the capacity factor (calculated as electricity generation divided by installed capacity and annual hours) against public data standards, with the corresponding results shown in Supplementary Figure 24. At the global level, the mean capacity factor from our model is generally consistent with the public datasets. At the continental level, the installed capacity proportions also range from approximately 90% to 100% of the public benchmarks, indicating that the overall model performance is in good agreement with historical validation.



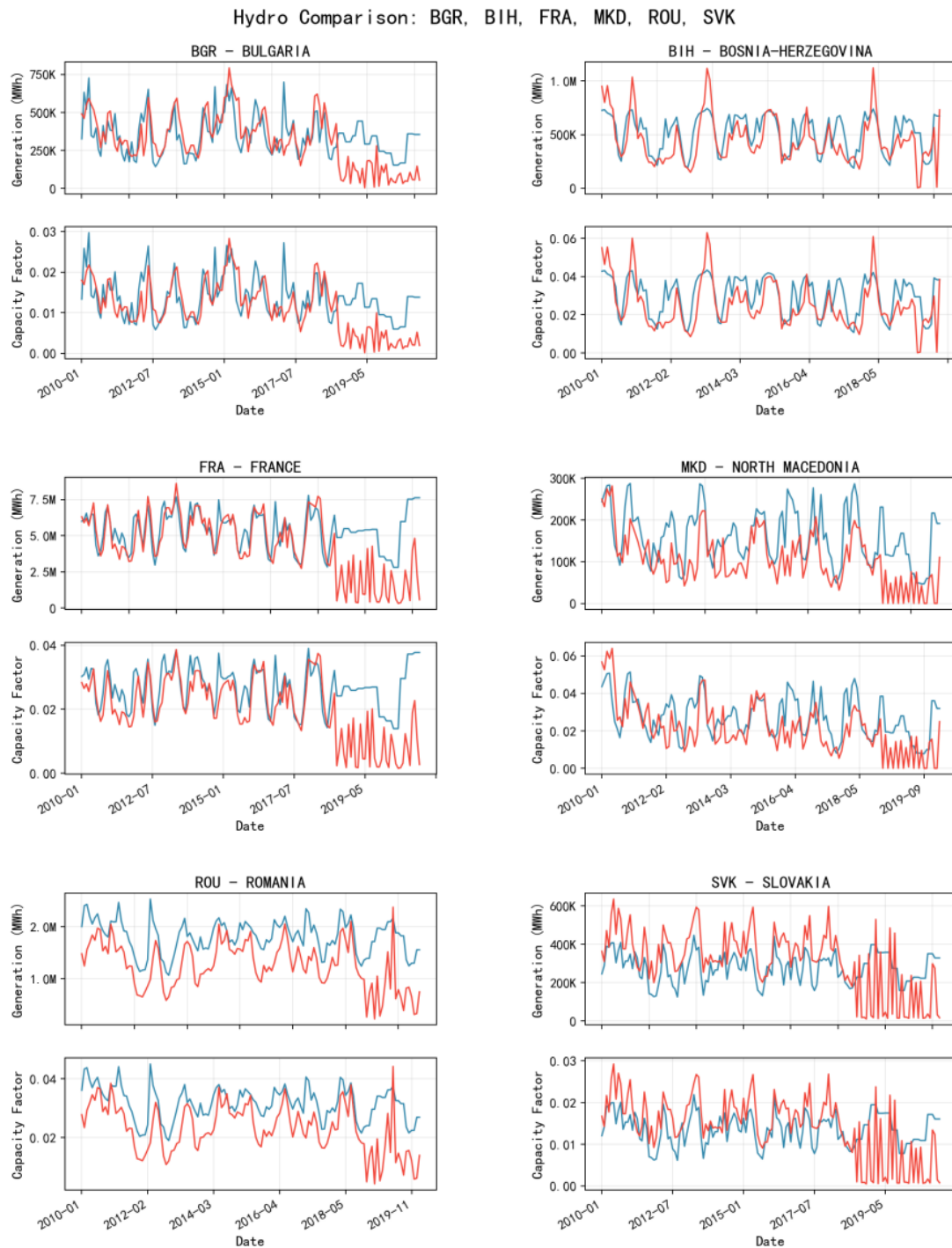
Supplementary Figure 23 Comparison of annual global hydropower generation between model calculations and public data.



629

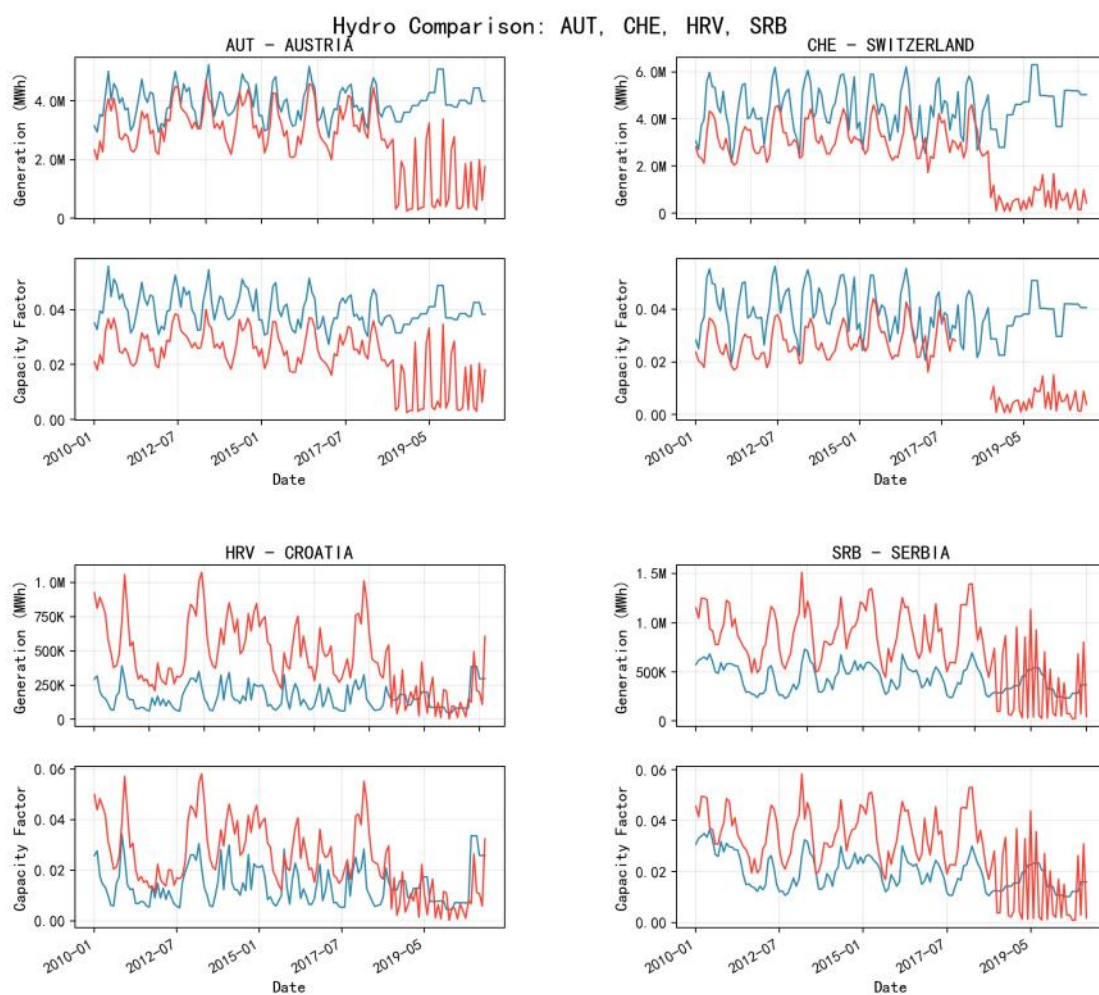
630 Supplementary Figure 24 Comparison of annual global hydropower capacity factor between model  
 631 calculations and public data.

632 Similarly, we further plotted monthly electricity generation and installed capacity data as line charts  
 633 over the corresponding time series (Supplementary Figure 25Supplementary Figure 26). The results  
 634 show that the hydropower model captures monthly variations in both electricity generation and  
 635 capacity factor remarkably well for countries such as Bulgaria, Bosnia-Herzegovina, France, North  
 636 Macedonia, Romania and Slovakia, with model outputs nearly identical to the observations in some  
 637 cases. For countries including Austria, Switzerland, Croatia and Serbia, although the simulated  
 638 monthly hydropower generation and capacity factors are slightly higher or lower than the observed  
 639 values, the month-to-month variability is still well reproduced, further demonstrating the scientific  
 640 robustness of the model. At the same time, we acknowledge that the trends for certain countries or  
 641 regions are less accurately captured, which may be attributable to deviations in head height or the  
 642 inherent limitation that the hydropower model cannot simply generalize the operational  
 643 characteristics of all individual hydropower plants. Examples include Slovenia and Sweden, as  
 644 shown in Supplementary Figure 27.

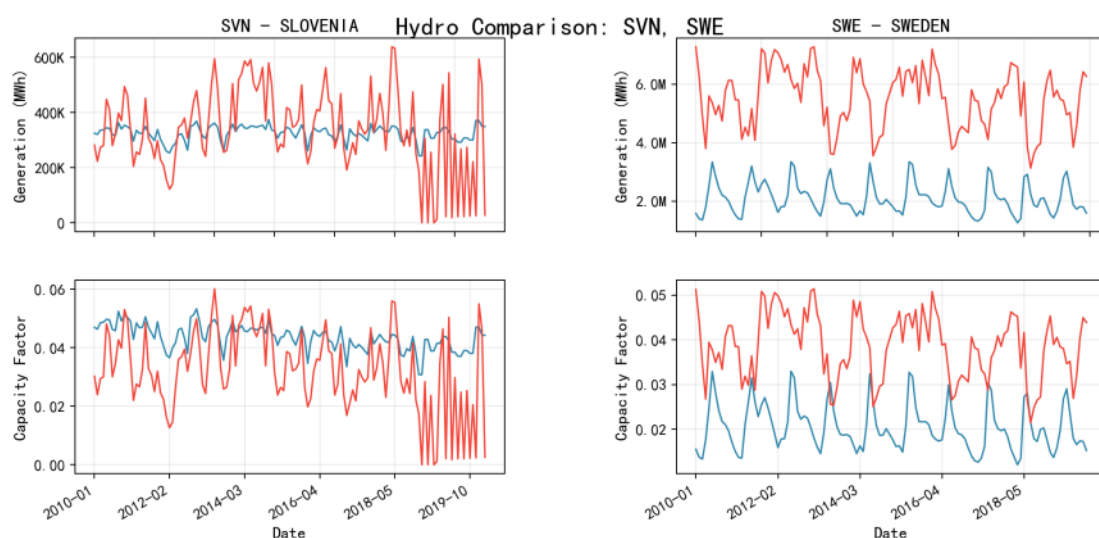


645

646 Supplementary Figure 25 Comparison of monthly electricity generation and capacity factor trends  
 647 between model calculations and public data at the national level (Bulgaria, Bosnia-Herzegovina,  
 648 France, North Macedonia, Romania, Slovakia)



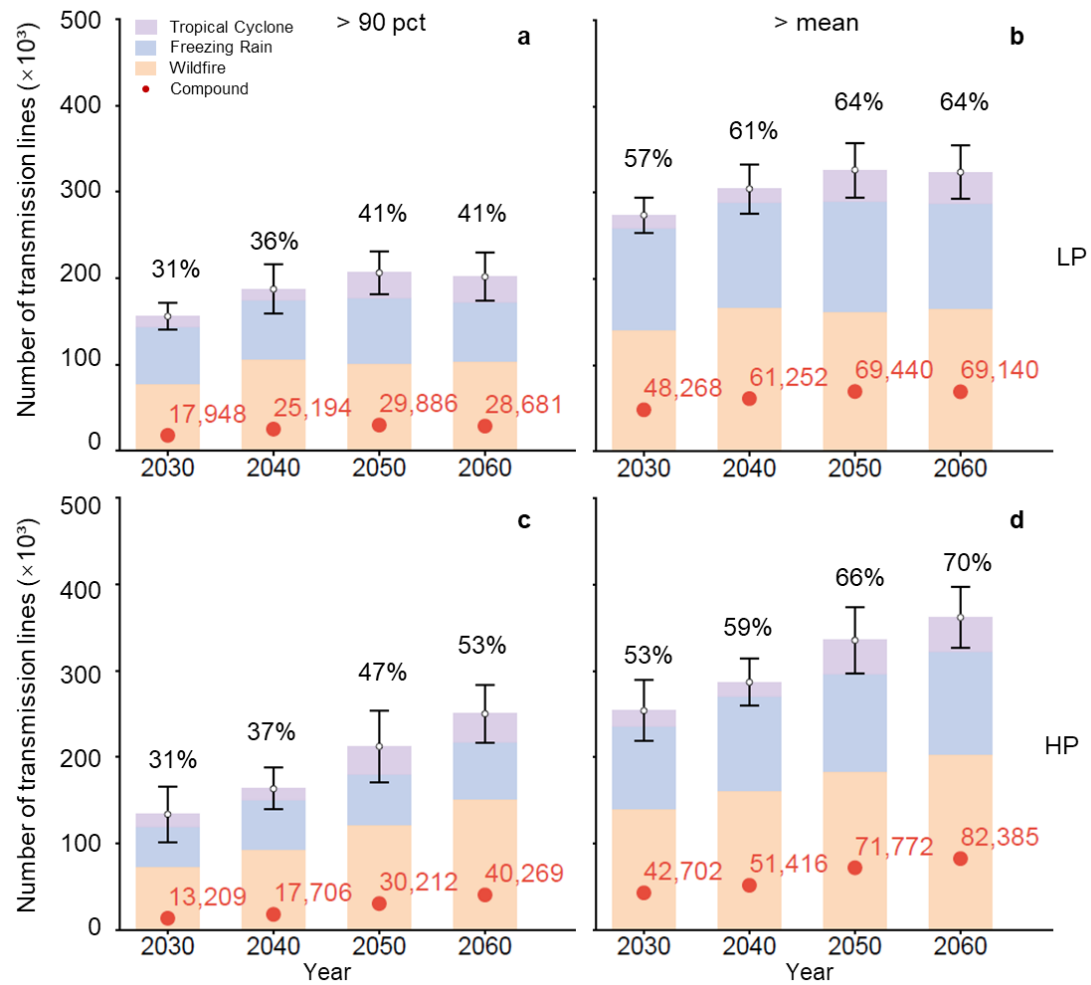
Supplementary Figure 26 Comparison of monthly electricity generation and capacity factor trends between model calculations and public data at the national level (Austria, Switzerland, Croatia, Serbia)



Supplementary Figure 27 Comparison of monthly electricity generation and capacity factor trends between model calculations and public data at the national level (Slovenia, Sweden)

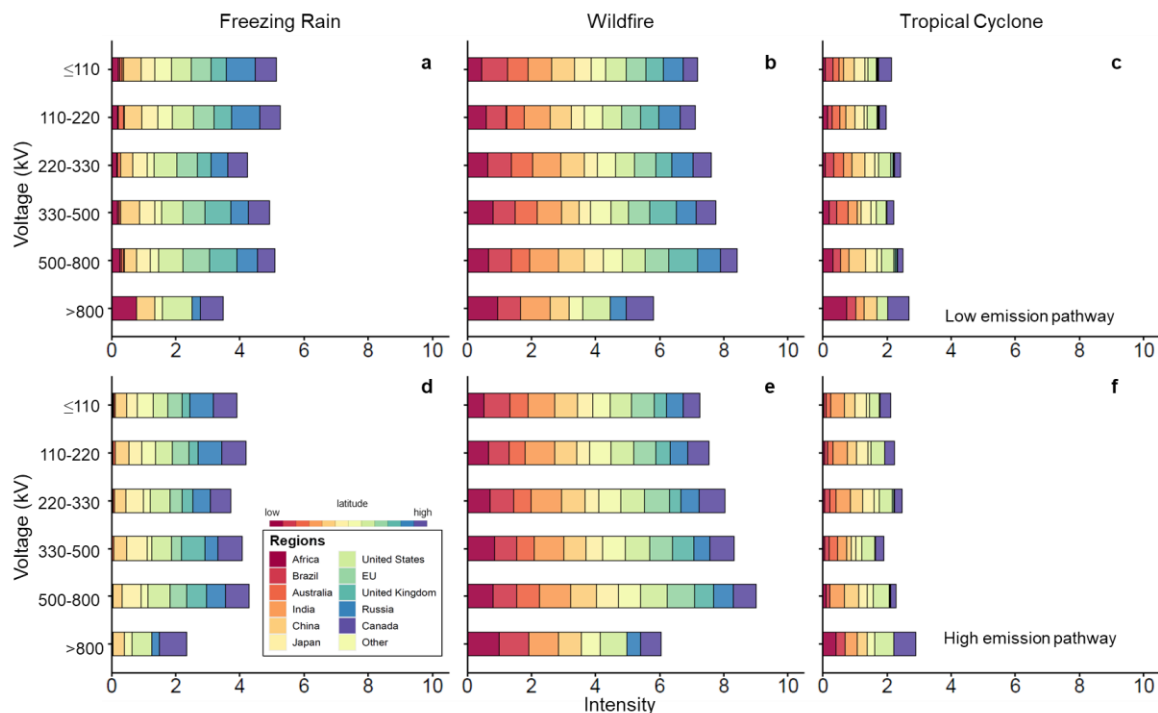
## 5. Other supplementary results

656 **5.1 Transmission lines under different risk levels**



657

658 Supplementary Figure 28 Global totals of affected transmission lines in mid-century whose projected  
659 annual failure probability exceeds the 90pct value (a,c) and mean value (b,d) of baseline period of 2015–  
660 2025.



Supplementary Figure 29 Transmission line exposure intensity to climate hazards by voltage class and representative countries in 2050. Exposure of transmission infrastructure to three major hazards—FR, wildfire, and TC—under low-emission (SSP1-1.9; top) and high-emission (SSP5-8.5; bottom) scenarios. Bars represent the exposure intensity, defined as the ratio of hazard-exposed transmission line length to the total transmission line length within each country. Voltage ranges (a-b) are expressed using the interval notation “(a, b]”.

To distinguish climate-driven risk intensification, we calculated a regional risk-growth density (besides the absolute length in Maintext) for each hazard and voltage class. This metric is defined as increasing-risk length divided by the total transmission-line length in the same region and voltage class, reducing the influence of differences in mapped infrastructure length among countries and regions. At the global scale, normalized exposure confirms a strong hazard transition by mid-century. Freezing-rain risk-growth density declines from 45.4% under SSP1-1.9 to 36.9% under SSP5-8.5, whereas wildfire increases from 64.2% to 70.1% and tropical-cyclone wind increases from 19.5% to 20.9%. Thus, the similar total hazard-specific exposed length across the two pathways masks a compositional shift: high emissions reduce the spatial prevalence of increasing freezing-rain failure probabilities but make wildfire risk growth more widespread and slightly expand the relative footprint of cyclone-wind risk.

Freezing-rain density highlights regions where icing risk remains climatically persistent after normalization by network size. Under SSP1-1.9, Russia, the United States, the EU and Canada have the highest regional densities, with 76.5%, 68.7%, 65.9% and 62.9% of their networks showing increased freezing-rain failure probability by the 2050s. Under SSP5-8.5, freezing-rain density declines in most regions, especially the United Kingdom, the EU, Africa, the United States and China, consistent with warming-driven reductions in near-freezing precipitation environments. However, the decline is not universal. Canada increases from 62.9% to 72.2%, and Japan increases slightly from 46.6% to 48.7%, indicating that high-latitude or maritime winter climates can remain

within, or move into, temperature regimes conducive to freezing-rain risk growth. Wildfire risk-growth density is substantially higher and more spatially pervasive. Under SSP1-2.6, India already has the highest wildfire density, with 88.0% of its transmission network showing increased wildfire failure probability. China, Brazil, Russia, Africa, Australia, the EU and the United States all exceed 60%. Under SSP5-8.5, wildfire density rises to 94.1% in India, 73.7% in both China and the United States, 73.3% in the EU, 72.0% in Africa, 71.9% in Canada and 71.5% in Brazil. These values indicate that wildfire risk growth is not confined to isolated fire-prone corridors; in many regions it becomes a near-system-wide stressor. The density perspective is particularly important for India, Africa and Brazil, where absolute exposed lengths are smaller than in China, the United States or the EU, but a large fraction of the network experiences increasing wildfire risk. Tropical-cyclone wind has a smaller normalized footprint globally, but density analysis reveals strong regional concentration. Under LP, cyclone-wind risk-growth density is highest in China, the United States, Japan, Canada, Australia, India and Brazil, ranging from 23.3% to 36.7%. Under SSP5-8.5, India shows the largest increase, rising from 24.4% to 44.7%, followed by the United States, which increases from 33.7% to 40.7%. China remains highly exposed, although its density declines from 36.7% to 33.7%. Japan and Canada remain moderately exposed, at 32.6% and 28.3%, respectively. By contrast, cyclone-wind density declines in Brazil, Africa, Australia, the EU and the United Kingdom. These patterns indicate that cyclone-related transmission risk growth is not spatially uniform; it is shaped by the overlap between storm-track changes, coastal exposure and the regional layout of transmission corridors. The normalized results also alter the regional ranking compared with absolute exposed length. Large systems such as China, the United States and the EU dominate absolute exposed length because they contain extensive transmission networks. However, density metrics reveal smaller or medium-sized systems where risk growth is proportionally more widespread. For example, India has a smaller absolute wildfire-exposed length than China or the United States, but has the highest wildfire risk-growth density under both pathways. Canada has a modest total network length relative to the United States, China or the EU, but it ranks first for freezing-rain density under SSP5-8.5 and has one of the highest overall hazard-specific densities. Voltage-class normalization further shows that increasing risk is not limited to low-voltage networks. For freezing rain,  $\leq 110$  kV systems have the highest global density, ranging from 56.5% under SSP1-1.9 to 45.0% under SSP5-8.5 because of the conservative designing standard cannot stand the changing climate. Wildfire has the strongest high-voltage signal:  $\geq 330$  kV lines have a global risk-growth density of 71.9% under SSP1-2.6 and 78.3% under SSP5-8.5. This indicates that wildfire risk growth increasingly affects strategic long-distance corridors, not only local or radial lines. Cyclone-wind risk also has a pronounced high-voltage component, with  $\geq 330$  kV density remaining around 27–28% globally and reaching 49.4% in the United States, 42.6% in India and 39.8% in China under SSP5-8.5.

## 5.2 Consecutive risk patterns in typical countries

As climate change alters the spatial distributions of different extreme weather hazards, regions that were historically exposed to relatively distinct hazard regimes increasingly overlap. Consequently, a growing number of transmission lines may experience multiple types of hazards within short periods. Under both low- and high-emissions pathways, the number of transmission lines exposed to consecutive hazards increases toward mid-century, while the time separating successive events

generally shortens under high emissions. We define consecutive hazards as two or more qualifying hazard events affecting the same transmission line within a three-month window.

Under the low-emissions pathway, approximately 36,438 transmission lines globally are exposed to consecutive hazards in 2030, with an uncertainty range of 30,180–40,373 lines. By 2050, this number increases to approximately 39,100 lines (33,524–47,385), equivalent to an increase of around 4% per decade. The uncertainty intervals reflect the results obtained when the hazard-induced failure-probability threshold is varied from 1% to 5%. The proportion of affected lines in the global network increases from approximately 8% to 10%, suggesting that, by mid-century, around one-tenth of mapped transmission lines could experience multiple high-intensity climate hazards within a three-month period. The mean interval between successive hazards fluctuates between approximately 1.3 and 1.5 months, although its fitted temporal trend remains broadly stable and increases slightly. For individual sequences, the interval between distinct hazards can be only one to two months—potentially shorter than the time required for infrastructure inspection, repair and operational recovery—thereby increasing stress on power-system operation.

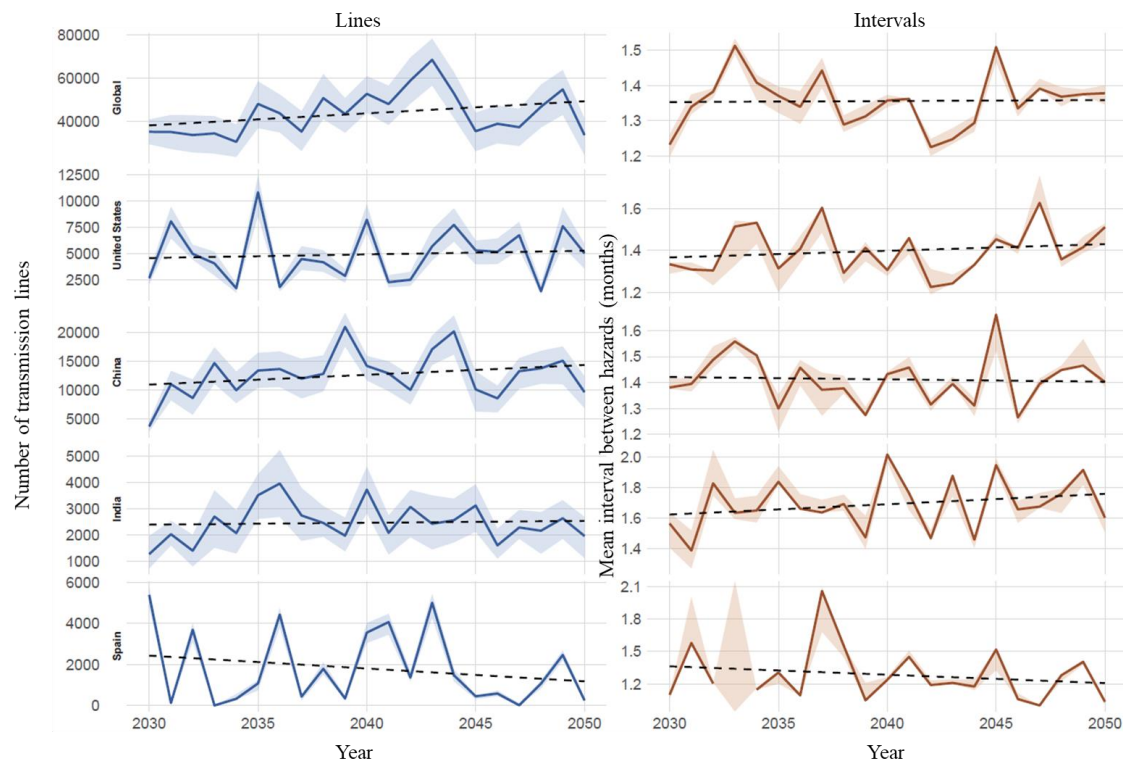
Under the high-emissions pathway, the number of lines exposed to consecutive hazards increases much more rapidly, from approximately 29,000 in 2030 to around 72,000 in 2050. This increase indicates that extreme climate hazards become increasingly clustered at timescales relevant to grid operation. The fitted mean interval between successive events also declines, from approximately 1.35 to 1.30 months. Although annual estimates fluctuate, the regional results show a broadly consistent contrast between emissions pathways: consecutive-hazard risks stabilize under low emissions but increase persistently and substantially under high emissions.

Under the low-emissions pathway, approximately 4,000 transmission lines in the United States, 7,500 in China and 3,000 in India experience consecutive hazards each year. Transitions between different hazard types further complicate risk management because each hazard may require distinct preparedness, maintenance and restoration measures. In China, the most common heterogeneous sequence combines tropical cyclones and wildfires, with less frequent wildfire–freezing-rain sequences. A representative seasonal progression consists of tropical-cyclone winds during summer (June–August), elevated wildfire risk during the subsequent dry season, and freezing rain in late winter or early spring. In extreme years, the number of such cross-hazard transitions approaches 1,000, indicating that the same transmission corridors may experience repeated and heterogeneous climate stresses across seasons.

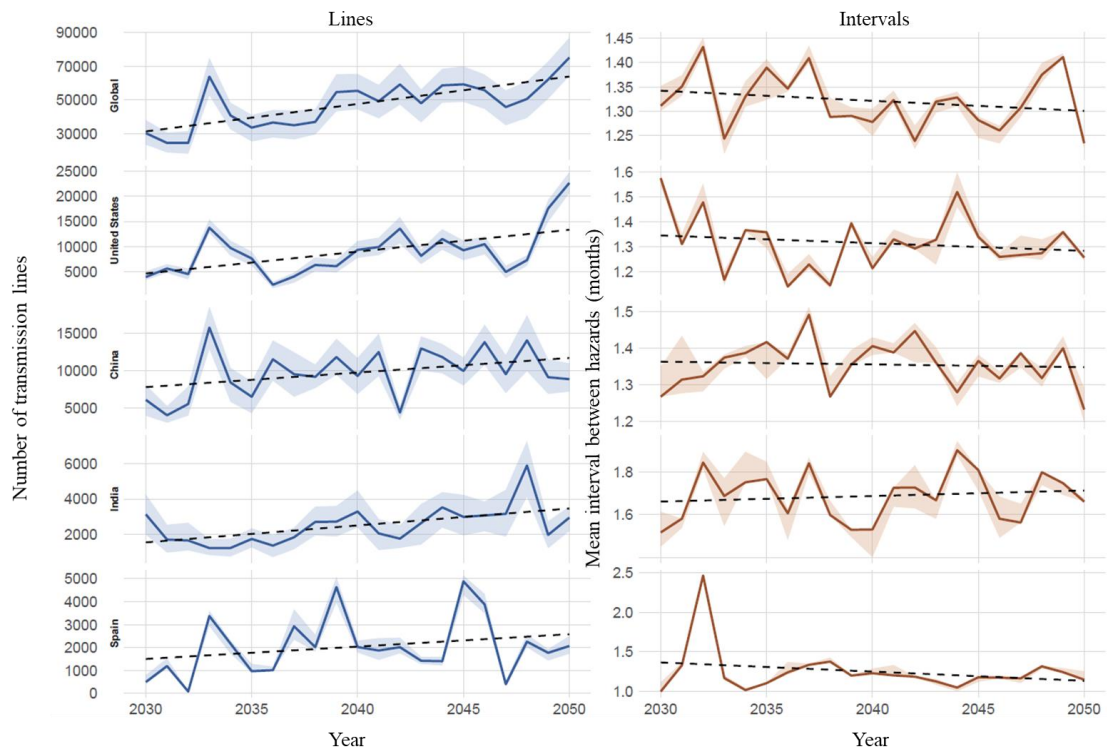
In India, wildfire–tropical-cyclone sequences dominate, largely because projected wildfire exposure expands across much of the country. Central and northern India emerge as major hotspots, where increasing wildfire exposure overlaps with the inland extension of tropical-cyclone-related winds. In severe years, the number of wildfire–tropical-cyclone transitions reaches approximately 1,000–1,500. In the United States, the most common consecutive-hazard combinations are wildfire–tropical-cyclone and wildfire–freezing-rain sequences, together occurring approximately 600–1,800 times per year. These patterns reflect the pronounced climatic heterogeneity of the continental United States. Whereas wildfire risk has historically been concentrated in the western United States, future projections indicate substantial increases across central and southeastern regions, extending wildfire exposure into areas also affected by freezing rain and tropical cyclones. Tropical-cyclone-related winds remain concentrated primarily along the Atlantic and Gulf coasts. A single transmission line could therefore experience freezing rain in January, wildfire exposure in June and

tropical-cyclone winds in August, subjecting the same infrastructure to multiple types of stress within one year.

Under the high-emissions pathway, both the scale and interannual variability of consecutive hazards increase further. The annual number of affected transmission lines rises in the United States, India and China, with the most pronounced increase occurring in India. Distinct peaks emerge in individual years, indicating that multiple hazard transitions can become concentrated within the same operating period. This growth is driven mainly by increases in wildfire–tropical-cyclone and tropical-cyclone–wildfire transitions, consistent with the projected extension of wildfire seasons and intensification or redistribution of extreme-wind hazards under continued warming. Transitions involving freezing rain and either of the other hazards remain less common. However, freezing-rain-related sequences do not disappear; instead, their spatial distributions shift progressively into new regions..

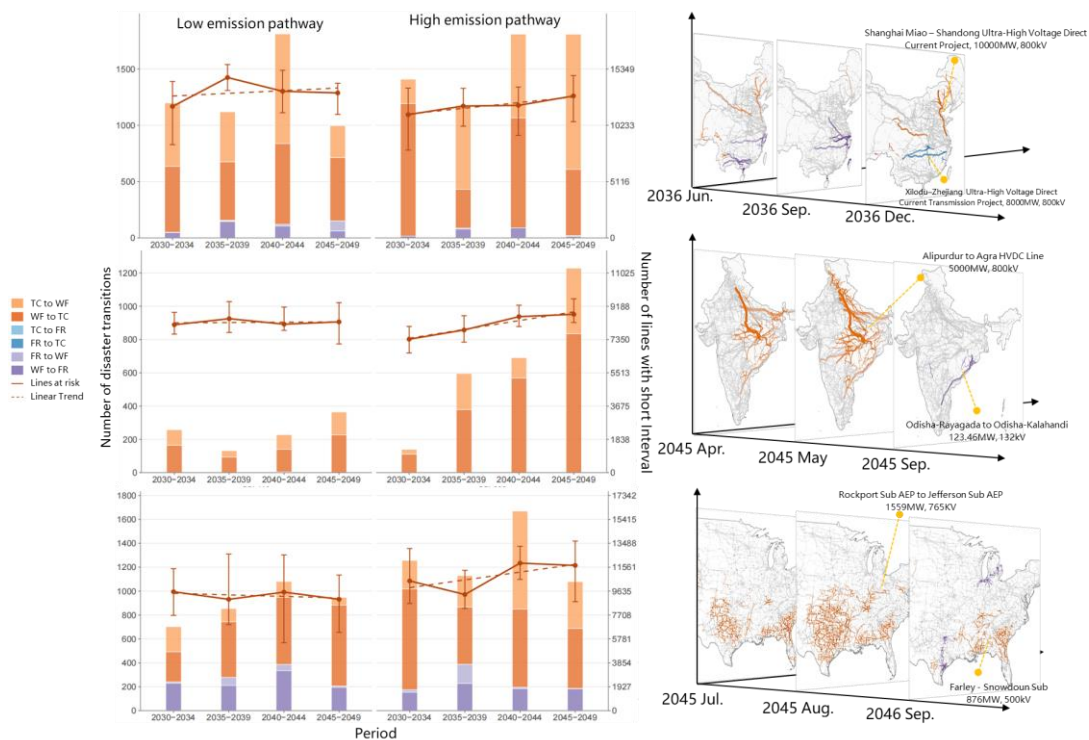


Supplementary Figure 30 Temporal characteristics of consecutive climate hazards affecting transmission networks under low emission pathway. Annual number of transmission lines exposed to consecutive hazards (left) and the mean interval between consecutive hazard occurrences (right) at the global level and in the United States, China, India and Spain during 2030–2050. Consecutive exposure is defined as a transmission line being affected more than once within a three-month period. Solid lines show the central estimates, dashed lines indicate temporal trends, and shaded bands represent uncertainty arising from varying the failure-probability threshold between 1% and 5%.



793

794 Supplementary Figure 31 Temporal characteristics of consecutive climate hazards affecting  
 795 transmission networks under high emission pathway. Annual number of transmission lines exposed to  
 796 consecutive hazards (left) and the mean interval between consecutive hazard occurrences (right) at the  
 797 global level and in the United States, China, India and Spain during 2030–2050. Consecutive exposure  
 798 is defined as a transmission line being affected more than once within a three-month period. Solid lines  
 799 show the central estimates, dashed lines indicate temporal trends, and shaded bands represent  
 800 uncertainty arising from varying the failure-probability threshold between 1% and 5%.

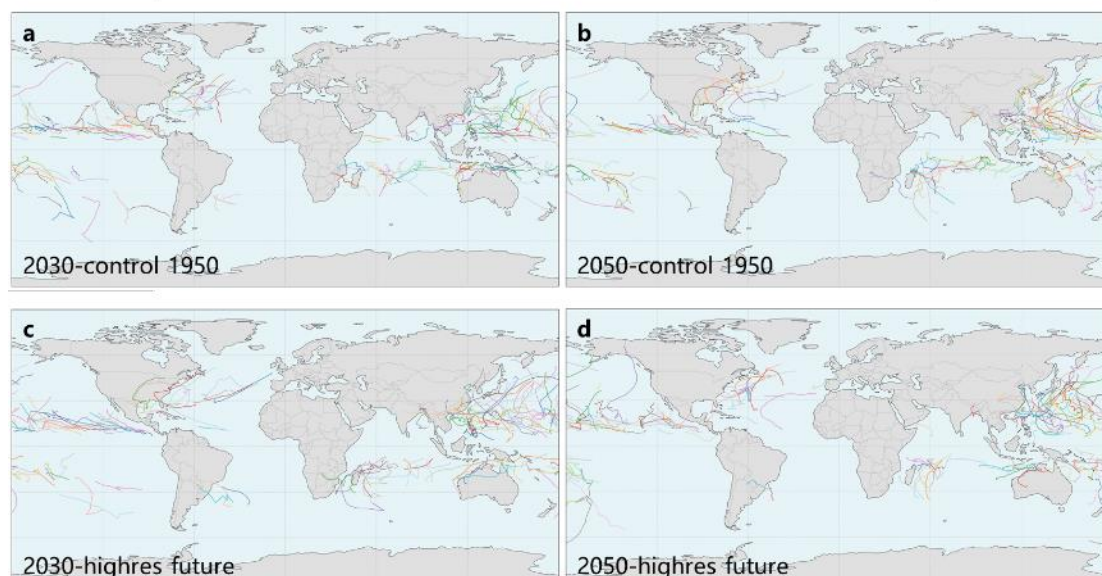


Supplementary Figure 32 Annual exposure of transmission lines to consecutive and heterogeneous hazards under low- and high-emission pathways in China, India and United States.

### 5.3 Tropical cyclone tracks patterns

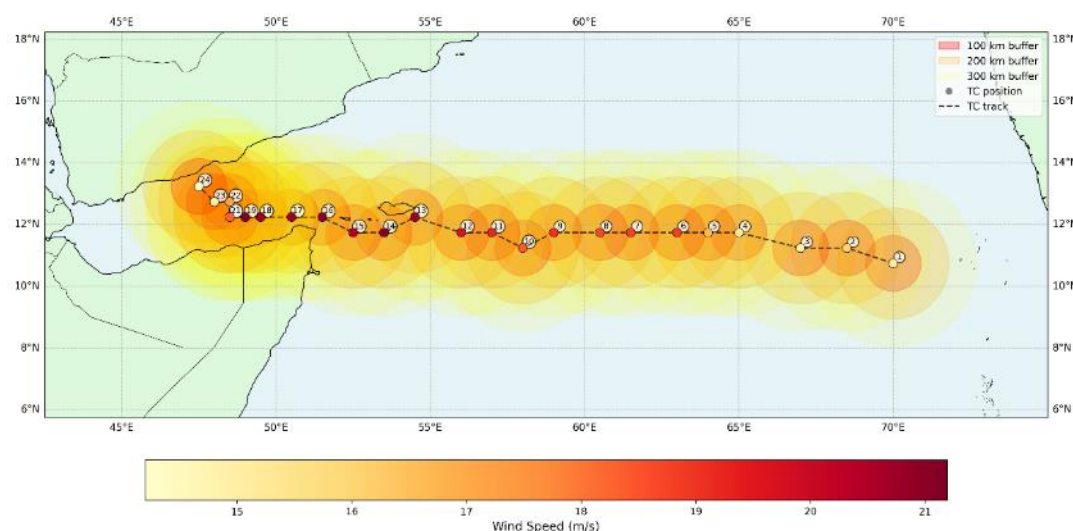
Supplementary Figure 33 shows the simulated global tropical cyclone tracks under two scenarios for the years 2030 and 2050: the control-1950 scenario (panels a-b), which is based on the 1950 climatological conditions, and the highres-future scenario (panels c-d), which reflects future projections under the SSP585 scenario at high resolution.

In terms of spatial distribution, the western North Pacific and the North Atlantic emerge as the core regions of TC activity. Under the control-1950 scenario, the track density is relatively uniform across ocean basins in 2030 (panel a), while by 2050 (panel b), the track density in the western North Pacific increases notably, accompanied by a slight dispersion in other basins. In contrast, under the highres-future scenario, the tracks in the eastern North Pacific and North Atlantic display longer extensions in 2030 (panel c); by 2050 (panel d), the track density increases substantially in the western North Pacific, around Australia and in the North Atlantic, with more complex trans-basin tracks, indicating that both the spatial extent and track complexity of TC activity intensify over time.



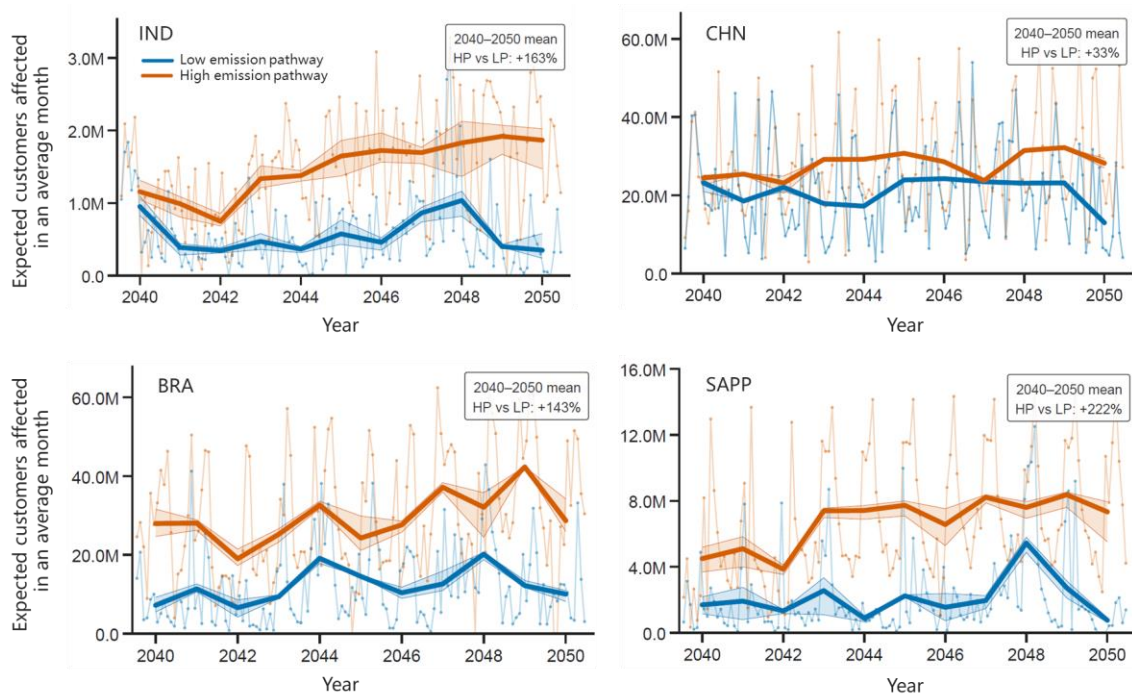
Supplementary Figure 33 Simulated global tropical cyclone tracks under the control-1950 (a-b) and highres-future (c-d) scenarios for 2030 and 2050.

Supplementary Figure 34 illustrates the wind speed buffer zones along a representative tropical cyclone track in the northwestern Indian Ocean. The numbered points along the track denote wind speed recording locations, with colors corresponding to wind speed magnitudes as indicated by the color bar. Centred at each recording point, concentric buffer zones of 100 km, 200 km and 300 km radii are delineated to characterize the spatial extent of wind speed decay. The red-to-yellow gradient within the buffer zones visually represents the decrease in wind speed from the cyclone centre outward, quantitatively depicting the spatial distribution characteristics of the TC wind field.



Supplementary Figure 34 Schematic diagram of wind speed buffer zones along a tropical cyclone track.

## 5.4 Projected impacted customers under compound hazards



Supplementary Figure 35 Projected trends in monthly customer impacts in four typical developing power grids under low- and high-emission pathways. Fine points and thin lines show the monthly number of affected customers averaged across Monte Carlo realizations, capturing seasonal and interannual variability. Thick lines show the mean monthly impact for each year, calculated by averaging across the 12 months and Monte Carlo realizations; shaded bands represent the 5th–95th percentile range across realizations. Blue and orange indicate the low-emission pathway (LP) and high-emission pathway (HP), respectively. Insets report the percentage difference between HP and LP in their mean impacts during 2040–2050.

## 5.5 Carbon implications of climate-induced transmission disruptions

Climate hazards can affect power-sector emissions not only by directly damaging infrastructure, but also by altering the feasible operation of the power system. When climate-driven failures temporarily remove transmission lines from the network, the effective network topology and transfer capacity change, constraining power exchanges between generation and demand centres. These constraints can prevent the system from maintaining its least-cost dispatch. Network-induced carbon penalty is therefore created, whereby the remaining electricity is produced at higher cost and with higher carbon intensity.

We quantified this effect using the Monte Carlo dispatch simulations by comparing each hazard-disrupted realization with its corresponding intact-network baseline for the same month. Because transmission failures can also reduce total electricity generation through unserved demand, changes in total emissions alone do not provide an appropriate measure of the carbon consequence of network disruption. For example, total emissions may decline following a severe outage simply because less electricity is supplied. We therefore calculated generation carbon intensity.

The simulations reveal a clear carbon penalty from transmission disruption in most representative systems under the high-emission scenario. Averaged across the 2040–2050 simulations, generation carbon intensity increased from 373.8 to 377.6 kg CO<sub>2</sub>e per MWh in China (+1.03%), from 188.3 to 190.4 kg CO<sub>2</sub>e per MWh in Brazil (+1.16%), from 581.6 to 584.2 kg CO<sub>2</sub>e per MWh in India

(+0.45%), and from 589.9 to 592.1 kg CO<sub>2e</sub> per MWh in Australia (+0.39%). Generation-cost intensity increased concurrently by approximately 0.60%, 0.78%, 0.22%, and 0.29%, respectively. The simulated cross-country pattern of carbon intensity is broadly consistent with observed differences among national power systems, with India, Australia and China exhibiting substantially higher carbon intensity than hydro- and renewable-dominated Brazil. The absolute simulated values, however, are not intended to reproduce reported national-average carbon intensities exactly. Observed grid-average intensities are approximately 560 kg CO<sub>2e</sub> per MWh in China, around 60–120 kg CO<sub>2e</sub> per MWh in Brazil, approximately 630–650 kg CO<sub>2e</sub> per MWh in India, and around 550–560 kg CO<sub>2e</sub> per MWh in Australia. Differences between these reported values and our simulations arise from several factors, including the spatial and technological coverage of the generation database, assumed plant-level emission factors and operating costs, the representation of transmission constraints, temporal aggregation, and the optimization-based dispatch assumptions. We therefore interpret the model primarily in terms of the relative change between intact and hazard-disrupted networks under otherwise identical system assumptions, rather than as a reconstruction of observed national emission inventories.

These relatively small long-term averages mask substantially stronger effects during individual extreme months. Monte Carlo-mean monthly carbon-intensity increases reached approximately 14.5% in China, 7.6% in India, 6.2% in Australia, and 4.5% in Brazil, while corresponding generation-cost penalties reached 8.2%, 6.2%, 4.5%, and 3.3%, respectively. Climate-driven network failures can therefore create short-lived but pronounced periods in which electricity becomes simultaneously more expensive and more carbon intensive.

Expressed using the network-induced carbon penalty defined above, these dispatch distortions correspond to approximately 13.1 Mt CO<sub>2e</sub> per year in China, 4.0 Mt CO<sub>2e</sub> per year in India, 1.5 Mt CO<sub>2e</sub> per year in Brazil, and 0.5 Mt CO<sub>2e</sub> per year in Australia during 2040–2050 under the high-emission simulations. These quantities are not changes in total power-sector emissions because outages may simultaneously suppress electricity consumption and generation. Instead, they represent the additional emissions associated with producing the remaining electricity under a less carbon-efficient dispatch configuration.

Importantly, the direction and magnitude of this effect depend on which transmission corridors fail, rather than simply on the number or aggregate capacity of failed lines. South Africa provides a counterexample: its mean carbon intensity decreases slightly under the high-emission simulations, from 601.6 to 599.1 kg CO<sub>2e</sub> per MWh (−0.49%), although individual months still show increases of more than 5%. Similarly, among the systems for which both low- and high-emission simulations are available, India changes from an approximately neutral or slightly negative mean carbon-intensity response under the low-emission case (−0.05%) to a clear positive penalty under the high-emission case (+0.45%), whereas Australia exhibits a positive penalty under both scenarios (+0.57% and +0.39%, respectively).

Thus, the carbon consequences of transmission disruption do not scale mechanically with aggregate hazard severity. Instead, they emerge from the interaction between the spatial location of transmission failures, network topology, and the geographic distribution, marginal costs, and carbon intensities of available generation resources. Failures of strategically important corridors may prevent low-cost and low-carbon electricity from reaching demand centres, forcing the dispatch model to rely more heavily on locally available generators. Conversely, failures in other parts of the network may reduce access to carbon-intensive generation or primarily result in load shedding,

producing little or even negative change in average carbon intensity.

Supplementary Data Table 1 Representative return periods for climatic design actions in overhead transmission-line standards and utility specifications

| Source                                      | Line class or voltage                                                                                                                                   | Hazard                       | Design return period, (T) (years) |
|---------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------|-----------------------------------|
| IEC 60826:2017 <sup>14</sup>                | Temporary lines, some wood-pole lines, or lines of limited importance                                                                                   | Wind, ice and combined       | ~25                               |
| IEC 60826:2017 — Reliability level 1        | Ordinary permanent transmission lines                                                                                                                   | Wind, ice and combined       | 50                                |
| IEC 60826:2017 — Reliability level 2        | Important lines; earlier IEC implementation guidance suggests lines above 230 kV, or lower-voltage lines providing a principal or sole source of supply | Wind, ice and combined       | 150                               |
| IEC 60826:2017 — Reliability level 3        | Critical lines, particularly major lines above 230 kV that provide a principal or sole supply and whose failure would have serious consequences         | Wind, ice and combined       | 500                               |
| EN 50341-1:2012 <sup>15</sup> , Europe      | Overhead lines within the standard's scope; final reliability level determined through National Normative Aspects                                       | Extreme wind and extreme ice | 50                                |
| China, GB 50545-2010 <sup>16</sup>          | 110–330 kV AC lines, including large crossings                                                                                                          | Wind, ice and combined       | 30                                |
| China, GB 50545-2010                        | 500–750 kV AC lines, including large crossings                                                                                                          | Wind, ice and combined       | 50                                |
| China, GB 50665-2011 <sup>17</sup>          | 1,000 kV AC overhead lines                                                                                                                              | Wind, ice and combined       | 100                               |
| China, GB 50790-2013 <sup>18</sup>          | ±800 kV HVDC overhead lines                                                                                                                             | Wind, ice and combined       | 100                               |
| United States, IEEE NESC 2023 <sup>19</sup> | Grade B construction                                                                                                                                    | Extreme wind without ice     | 100                               |
| United States, IEEE NESC 2023               | Grade C construction                                                                                                                                    | Extreme wind without ice     | 50                                |
| United States, IEEE NESC 2023, Rule 250D    | Structures subject to extreme ice with concurrent wind                                                                                                  | Ice plus concurrent wind     | 50                                |
| United States, ASCE                         | Transmission-line structures                                                                                                                            | Extreme wind and extreme     | 100 recommended                   |

| Source                                                                     | Line class or voltage                                                                                                          | Hazard                 | Design return period, (T) (years)                                        |
|----------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|------------------------|--------------------------------------------------------------------------|
| Manual 74, 4th ed. <sup>20</sup>                                           | generally                                                                                                                      | ice/combined ice–wind  | basis                                                                    |
| Australia/New Zealand, AS/NZS 7000 implementation by TasNetworks           | Existing 110 kV line assessment, Security level I, 50-year working life                                                        | Wind                   | 50                                                                       |
|                                                                            | New 110 kV lines or existing 220 kV assessment, Security level II                                                              | Wind                   | 100                                                                      |
|                                                                            | New 220, 275 and 330 kV lines and new DC lines up to 500 kV, Security level III                                                | Wind                   | 200                                                                      |
| Australia, Powerlink Queensland specification                              | General new transmission lines, Security level III                                                                             | Wind                   | AS/NZS 7000 level III                                                    |
|                                                                            | 500 kV network and new interstate interconnectors                                                                              | Wind                   | 300                                                                      |
| Canada, CSA C22.3 No. 60826:19 (R2023) <sup>21</sup>                       | Transmission lines generally, nominally 45 kV and above                                                                        | Wind, ice and combined | 50-year Canadian reference maps; higher IEC reliability levels available |
| Japan, JEC-5101:2022 <sup>22</sup>                                         | Transmission towers; importance incorporated through reliability and load conversion factors rather than a simple voltage rule | Wind                   | 50-year target reliability                                               |
|                                                                            | Transmission towers and conductors                                                                                             | Wet-snow/ice accretion | 50                                                                       |
| Brazil, federal transmission-planning requirement—project-specific example | Critical sections of 230 kV lines crossing the Jacuí River                                                                     | Wind                   | 250                                                                      |

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