

The risk to renewable electricity from volcanic eruptions

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Abstract

Weather-dependent renewable energy systems are increasingly exposed to climate variability, yet the consequences of rare, high-impact climate shocks for renewable electricity supply remain poorly understood. Here we use a volcanic eruption the size of the 1815 Tambora one as a analogue for an abrupt climate disruption caused by stratospheric aerosols, combining climate simulations with renewable resource and cost-based impact estimates to assess impacts on global wind and solar power. We find a concurrent global decline in wind and solar resources, with a mean reduction of 3.6% persisting for up to 20 months. Under present-day infrastructure, these anomalies correspond to an estimated 213.5 TWh loss in renewable electricity generation—comparable to California's annual electricity consumption in 2024—and USD 9.0 billion in associated cost-based losses. Impacts are regionally heterogeneous and reveal a marked decoupling between physical sensitivity and system exposure. South America and Africa exhibit the largest mean resource reductions, whereas Asia incurs the largest absolute generation losses because of its concentrated installed capacity. Our results identify major volcanic aerosol forcing as a previously underexplored source of renewable electricity risk and highlight the importance of incorporating low-frequency climate shocks into long-term energy planning and assessments of aerosol-based climate intervention.

Introduction

Renewable energy is central to the global transition away from fossil fuels, helping to meet growing electricity demand while advancing decarbonization goals^{1,2}. In particular, wind and solar power are expanding rapidly and are projected to account for 95% of all renewable capacity additions through 2030 (ref. 3). As their share in power systems increases, however, electricity supply becomes increasingly sensitive to climate variability^{4,5}. The 2021 Texas blackout during a severe winter storm illustrated how abrupt climate-related disruptions can cascade through power systems with high renewable penetration, with major social, economic and health consequences^{6,7}. This underscores the need to quantify how climate variability, including low-probability, high-impact events, may affect renewable electricity generation in order to design energy systems that are both sustainable and resilient.

Considerable attention has been devoted to understanding how climate variability and extreme events affect wind and solar resources across spatial and temporal scales^{8–14}. Large-scale modes of climate variability, such as the El Niño–Southern Oscillation (ENSO), modulate key meteorological drivers of renewable energy production^{15–17}. Extreme weather events, including tropical cyclones, heatwaves and floods, can also disrupt wind and solar generation through abrupt changes in wind speed, cloud cover and surface radiation, posing growing challenges for energy infrastructure and system reliability^{18–20}. Recent studies have highlighted the increasing occurrence of wind–solar shortage events, in which low wind speeds and reduced solar radiation coincide, as an emerging threat to energy security^{21,22}. Yet most previous studies have focused on the climatological characterization of variability and compound events, and quantitative assessments have remained regionally limited^{14,19}. As a result, a key gap

remains in how large-scale climate forcings propagate through renewable resources to influence electricity supply, particularly within a framework that connects physical climate responses to energy-system-relevant impacts.

Here we address this gap by developing an assessment framework that combines large-ensemble climate simulations across different background states with renewable resource modelling and economic evaluation to quantify climate-related risks to renewable electricity supply. Volcanic forcing provides a particularly useful test case because it represents a strong externally imposed perturbation superimposed on internal climate variability, while also offering a physically grounded analogue for aerosol-based climate intervention, including stratospheric aerosol injection (SAI), proposed to offset global warming^{22–28}. Large explosive eruptions inject substantial amounts of sulfur dioxide into the stratosphere, where it forms sulfate aerosols that can persist for up to two years and perturb Earth's radiative balance, reducing surface solar radiation and altering near-surface winds^{29–33}. In line with this, recent work has shown a robust two-year global reduction in near-surface wind speed after major eruptions, corresponding to an estimated $\sim 9.2\%$ decline in global wind resources, although these assessments have so far remained largely confined to the resource level³⁴.

As a case study, we focus on the 1815 Tambora eruption as a representative low-probability, high-impact perturbation. The eruption occurred in April (hereafter Apr0), with stratospheric aerosol loading peaking in Aug0. We show that a Tambora-like event would produce pronounced and spatially heterogeneous disruptions in renewable energy resources through coupled radiative and dynamical responses. When translated to present-day infrastructure, these resource anomalies correspond to an estimated 216.9 TWh reduction in renewable electricity generation over the subsequent 20 months—equivalent to $\sim 4.9\%$ of current global annual production—and to substantial cost-based losses. The persistence of these reductions over nearly two years suggests a form of stress that would be difficult to offset through storage alone, given that most deployed storage systems are designed primarily for short-term balancing. More broadly, our framework highlights a transferable way to assess renewable-energy risks associated with extreme climate perturbations, with implications for the design of more resilient low-carbon energy systems and for broader evaluations of aerosol-based climate intervention.

Results

Widespread suppression of global renewable resources

Following the eruption onset in Apr0, both global wind power density (WPD) and solar power density (SPD), averaged over land areas excluding Antarctica, decline significantly (Fig. 1). The largest anomalies occur in Aug0, when WPD decreases by 2.0 W m^{-2} and SPD by 1.5 W m^{-2} , corresponding to reductions of 8.1% and 4.7% relative to climatology, respectively. Climatological WPD and SPD both exhibit pronounced seasonality, with WPD peaking during boreal winter and SPD during boreal summer (Supplementary Fig. 1). The volcanic response of WPD is likewise strongly seasonal: reductions intensify during boreal summer, weaken through autumn, become negligible in winter, and then re-emerge the

following spring, persisting until Oct1. By contrast, SPD recovers more gradually and remains suppressed until Nov1.

These results indicate a sustained and temporally coherent reduction in both wind and solar resources, despite their differing seasonal recovery characteristics. Given the persistence of these anomalies, we define Apr0 to Nov1 as the primary analysis period. Over this 20-month interval, global mean monthly WPD decreases by 1.3 W m^{-2} , equivalent to 4.9% relative to climatology, while SPD declines by 0.8 W m^{-2} , or 2.5%.

Climatologically, solar resources are most abundant at low latitudes and decrease towards the poles, whereas wind resources are concentrated in the mid-latitudes and peak at high latitudes (Supplementary Fig. 2). Following the eruption, SPD reductions show strong spatial coherence across latitudes (Figs. 2b,d), consistent with large-scale radiative forcing by volcanic aerosols. WPD responses, by contrast, are much more regionally heterogeneous (Figs. 2a,c), with widespread reductions across the mid-latitudes and simultaneous increases at high latitudes, especially over northern Eurasia and northwestern Europe. Although the mid-latitudes are not the climatological centres hot-spots of wind resource, they experience the largest absolute reductions and hence the largest proportional declines (Fig. 2c). The high-latitude increases coincide with strengthened circulation anomalies that are most pronounced during D0JF1 (Supplementary Fig. 3), and this regional contrast contributes to the partial wintertime recovery in global-mean WPD (Fig. 1).

Taken together, these results reveal a geographically extensive but regionally differentiated reduction in renewable energy resources. Solar resources decline coherently across much of the globe, whereas wind responses are spatially heterogeneous. Their combined effect is particularly pronounced in the subtropics, where concurrent declines in both resources may increase the likelihood of compound renewable shortfalls.

Robustness of volcanic resource impacts across diverse climate states

To examine the robustness of the renewable-energy response, we assess how volcanic perturbations interact with two contrasting background climate states: a strong warming scenario and the El Niño phase of ENSO, representing a high-emission anthropogenic climate background and a dominant mode of natural variability, respectively^{35,36}. The temporal evolution of post-Tambora anomalies in WPD and SPD remains broadly similar to that in the baseline experiment, with the main differences occurring in wintertime WPD responses after the eruption (Supplementary Fig. 3). Under warming, the winter reduction in WPD recovers more strongly, whereas under El Niño conditions the rebound is weaker.

Spatially, the response patterns remain broadly consistent with those in the baseline experiment, and differences among climate states are statistically insignificant across most global land areas (Supplementary Fig. 4). In the warming background, WPD shows widespread increases over northern

high latitudes and modest decreases over the mid-latitudes, while SPD exhibits mixed changes with relatively weak reductions in the tropics and subtropics (Supplementary Figs. 4a,b). Under El Niño conditions, WPD reductions are more pronounced across the mid-latitudes, whereas the high-latitude increases are weaker; SPD also shows somewhat stronger reductions in the tropics and subtropics (Supplementary Figs. 4c,d).

Overall, these results suggest that the suppression of renewable resources following a Tambora-like eruption is qualitatively robust across the climate states examined here, although the regional expression of the response varies. These regional differences may have implications for infrastructure siting and capacity planning, which deserve further investigation.

Systemic energy generation deficits

To assess the implications of these resource anomalies for electricity supply, we translate volcanic-induced changes in wind and solar resources into potential generation losses under present-day infrastructure. Following the regional classification of the International Renewable Energy Agency (IRENA), global land areas are grouped into seven regions (Supplementary Fig. 5), and regional generation losses are estimated by combining relative changes in renewable resources with regional electricity-generation statistics. Spatially, relative changes in WPD evaluated over wind-rich areas (Fig. 3a)—identified using a resource-based exposure framework that restricts the analysis to grid cells with high climatological wind potential (see Methods)—show pronounced and spatially heterogeneous reductions. The largest declines occur in South America, Africa and Oceania, although localized increases persist at high latitudes. By contrast, SPD reductions (Fig. 3b), evaluated across all land areas, are more spatially uniform, with widespread but comparatively modest decreases across most regions. These contrasting patterns are also evident in the regional means (Fig. 3c): wind resources exhibit substantial interregional variability, whereas solar reductions are more consistent, with regional mean declines generally close to 2%. South America emerges as the most physically sensitive region, with wind and solar reductions of 11.6% and 3.8%, respectively, followed by Africa (10.6%) and Oceania (6.9%) for wind.

These pronounced but uneven resource reductions do not translate directly into proportional losses in electricity generation. Instead, when mapped onto present-day infrastructure, the resulting generation impacts are strongly shaped by the uneven spatial distribution of installed capacity, producing markedly different regional outcomes.

As shown in Fig. 4, Asia experiences the largest total generation loss, whereas Africa incurs only 6.5 TWh, among the smallest regional losses, owing to its comparatively limited installed renewable capacity. A similar contrast is seen for solar generation: despite the relatively even spatial distribution of post-Tambora SPD reductions, Asia again shows the largest absolute loss, followed by Europe and North America, while losses in Africa, Eurasia and Oceania remain modest. Because Asia currently hosts the largest wind and solar generation capacity worldwide, it experiences the greatest cumulative reduction in

renewable electricity generation, amounting to 109.8 TWh (74.8 TWh from wind and 35.0 TWh from solar). In Europe, by contrast, although onshore wind generation reaches 508.9 TWh—nearly half of Asia's level³⁷—enhanced wind resources in northern Europe partly offset declines farther south, resulting in substantially smaller wind-generation losses than in Asia.

Overall, these results indicate that a Tambora-like eruption could produce substantial and uneven reductions in renewable electricity generation (~ 213.5 TWh globally over 20 months), an amount comparable to California's total annual electricity consumption, with impacts determined not only by the magnitude of the physical resource anomaly but also by the spatial distribution of installed infrastructure. This reveals a clear decoupling between physical resource sensitivity and exposure of the current energy system. Because our estimates are based on 2024 infrastructure, they should be interpreted as present-day reference impacts rather than fixed future outcomes. However, given the continued expansion of renewable deployment—and the fact that global renewable capacity in 2024 remains below 40% of the 11.17 TW required by 2030 to align with decarbonization targets^{37,38}—comparable resource reductions in a more renewable-dependent future could translate into substantially larger generation impacts.

Associated economic exposure and risk

To estimate the economic implications of reduced renewable electricity generation, we use regionally aggregated Levelized Cost of Electricity (LCOE) data from IRENA³⁹. Because comprehensive and publicly available electricity-cost data are not reported consistently across all regions, we adopt the lowest available regional LCOE values to derive a conservative estimate of cost-based losses (see Methods)^{38,40}. Based on 2024 values, a Tambora-scale eruption corresponds to an estimated global loss of up to USD 9.0 billion over the 20-month impact period. Regional losses reflect the combined influence of installed capacity and electricity costs. In Africa, relatively limited installed capacity constrains the loss in electricity generation, but comparatively high electricity costs still yield an estimated loss exceeding USD 358.7 million (Fig. 5). In Asia, by contrast, lower LCOEs associated with more mature wind and solar technologies partly moderate the economic effect, yet the large generation deficit still translates into an estimated loss of nearly USD 3.8 billion.

These results suggest that, even under conservative assumptions, volcanically induced reductions in renewable generation could generate substantial economic exposure, with regional losses shaped by both infrastructure distribution and cost structure. Continued technological progress has sharply reduced renewable LCOEs—by around 90% for solar and 70% for onshore wind between 2010 and 2024³⁹—which may lessen the cost associated with a given unit of lost generation. At the same time, growing reliance on weather-dependent renewable electricity could increase the broader system relevance of such disruptions. Taken together, these findings indicate that future eruptions of comparable magnitude could still impose substantial financial and operational stress on increasingly renewable-dependent power systems.

Underlying physical mechanism in the global renewable energy response

The reduction in near-surface wind speed following tropical volcanic eruptions is primarily linked to a weakening of the Hadley circulation, which suppresses subtropical subsidence and reduces the downward transfer of momentum to the surface³⁴. By contrast, enhanced surface winds at high northern latitudes are dynamically associated with a strengthening of the Arctic polar vortex (Supplementary Fig. 6)^{27,41}. This strengthening arises from an increased stratospheric meridional temperature gradient caused by tropical stratospheric warming, a well-established feature of the first winter after major volcanic eruptions^{42–44}, and helps explain the enhanced wind energy during DJF1 (Fig. 1).

In respect to solar energy, direct radiative attenuation caused by stratospheric volcanic aerosols is substantially modulated by concurrent changes in cloud cover. To separate these effects, we decompose surface downward shortwave radiation into an aerosol-driven clear-sky component and a residual cloud-related component. This analysis shows that the direct aerosol effect, expressed as an Apr0–Nov1 mean reduction of 8.9 W m^{-2} in surface downward shortwave radiation, is partly offset by a positive contribution of 3.2 W m^{-2} associated with reduced cloud cover. The spatial pattern and magnitude of these cloud-related flux anomalies closely track changes in total cloud cover (Supplementary Fig. 7), highlighting the importance of cloud–radiation feedbacks in shaping the global SPD response. This compensating effect indicates that, although the volcanic aerosol layer imposes a widespread solar deficit, associated thermodynamic and dynamical adjustments in the troposphere—expressed here as reduced cloudiness—partially mitigate the resulting decline in solar power potential.

Taken together, these results show that volcanic impacts on wind and solar resources arise through distinct but interconnected dynamical and radiative pathways. Volcanic aerosols directly suppress solar resources by reducing surface shortwave radiation, while also indirectly altering the distribution of wind resources through changes in atmospheric thermal structure and circulation. These circulation changes additionally suppress convection and cloud cover, offsetting part of the aerosol-induced reduction in solar radiation. The pronounced seasonality, regionality and temporal lag in these mechanisms help explain the spatially heterogeneous renewable-energy responses identified here. More broadly, they illustrate how large-scale natural perturbations can introduce persistent and spatially uneven stresses into increasingly weather-dependent energy systems, reinforcing the importance of incorporating such disturbances into long-term energy planning and resilience assessment.

Discussion and Conclusions

Our results show that a Tambora-scale tropical eruption could produce a substantial and prolonged reduction in global wind and solar resources, with peak declines reaching 6.1% and effects persisting for up to 20 months. When mapped onto present-day infrastructure, these anomalies correspond to an estimated cumulative loss of 216.9 TWh in renewable electricity generation and USD 9.2 billion in cost-based losses. Although the global-mean response remains broadly similar across the ENSO and

warming states examined here, the associated generation and economic impacts are highly heterogeneous across regions. Wind resources show a marked contrast between subtropical declines and high-latitude increases, whereas solar resources are reduced across most land areas, with the subtropics experiencing the strongest concurrent losses. Asia incurs the largest absolute generation and cost-based losses, reflecting its concentrated installed capacity and growing dependence on renewable electricity. By contrast, South America and Africa emerge as the regions most physically sensitive to wind-resource reductions. Although current installed capacities in these regions remain comparatively limited, this sensitivity may be relevant for future infrastructure siting and long-term capacity planning.

This analysis is subject to several important limitations, including the relatively coarse model resolution, simplified representation of boundary-layer processes, and an idealized mapping between resource anomalies and present-day energy infrastructure. In addition, the regional patterns identified here are based on a single climate model and should therefore not be interpreted as precise regional forecasts. Multi-model assessments will be needed to better constrain the magnitude and spatial structure of these responses. Even so, the framework developed here provides a quantitative and transferable basis for quantifying the impact of large-scale climate perturbations on future renewable electricity supply.

Our results highlight a decoupling between physical resource sensitivity and exposure of the current energy system, and they underscore the importance of considering low-probability, high-impact disturbances in long-term energy planning. This includes not only major volcanic eruptions, but also aerosol-based climate interventions such as SAI. At the same time, the comparison should be interpreted with caution. Proposed SAI deployments would involve substantially weaker but more sustained forcing than a Tambora-scale eruption, producing a semi-persistent stratospheric aerosol layer rather than an impulsive perturbation. Nevertheless, previous studies suggest that even more moderate aerosol forcing can alter renewable energy resources, including robust reductions in global solar power potential and regionally heterogeneous changes in wind power^{45–47}. In this sense, our study provides the first step towards quantifying how large-scale aerosol perturbations may interact with increasingly weather-dependent energy systems. These interactions point to an important but still underexplored trade-off, whereby aerosol-based climate intervention could unintentionally suppress renewable electricity generation and thereby complicate decarbonization pathways. Integrated assessments that jointly consider climate mitigation and energy-system resilience will therefore be important in evaluating the feasibility of ambitious targets in global energy transitions toward net-zero carbon emissions.

Methods

CESM model simulation

We use CESM1.2, a fully coupled Earth system model comprising the Community Atmosphere Model version 5 (CAM5), the Community Land Model version 4 (CLM4), the Parallel Ocean Program version 2 (POP2) and the Community Ice Code version 4 (CICE4)⁴⁸, to perform the volcanic sensitivity experiments. The model resolution is approximately 2° (1.9° latitude × 2.5° longitude) for the atmosphere

and land, $\sim 1^\circ$ for the ocean and sea ice (gx1v6 grid with a displaced Greenland pole), and 0.5° for river routing. Previous CESM-CAM5 studies have shown that the model is able to reproduce a range of observed and reconstructed climate features with reasonable fidelity^{49–51}.

We first establish a pre-industrial baseline climate using an 1850 control simulation with fixed greenhouse-gas concentrations, aerosols, ozone and solar irradiance. After spin-up from equilibrium conditions, the model is integrated for 100 years, followed by an additional 30-year extension to sample internal variability. Each year of this 30-year segment is then used as an initial condition to generate a 30-member ensemble, with and without the Tambora volcanic forcing reconstructed by Gao et al.⁵² The temporal and spatial evolution of the imposed Tambora aerosol forcing is shown in Supplementary Fig. 8.

To assess the influence of anthropogenic warming on volcanic impacts, we further perform experiments under a high-emission background climate using the RCP8.5 scenario, which represents a strong warming pathway with a radiative forcing of 8.5 W m^{-2} by 2100^{53,54}. Starting from the final year of the historical twentieth-century simulation (2005), CESM1.2 is integrated under RCP8.5 to 2080 to establish the warmed baseline state. This simulation provides the background climate for the future volcanic perturbation experiments. Ten simulations initialized on 1 January of each year from 2070 to 2079 are extended through 2080, from which three representative cases corresponding to distinct ENSO phases are selected. For each case, ten different temperature perturbations are applied to generate initial-condition ensembles. Volcanic sensitivity experiments are then conducted for a total of 30 realizations, with and without Tambora forcing.

To ensure consistent temporal alignment across all experiments, we define the eruption year as Year 0. Months within the eruption year are denoted using the “Mon0” convention; for example, Apr0 refers to April of the eruption year and May0 to May of the same year. Months in the following year are labelled accordingly (for example, Jan1 for January of Year + 1). This notation is used throughout the study for compositing model responses, calculating climatologies and deriving relative changes. An El Niño-like response is defined as a case in which the Apr0–Nov1 Niño3.4 anomaly exceeds one standard deviation of the corresponding control (Ctrl) ensemble distribution, yielding five members. Unless otherwise stated, results are presented as composited, area-weighted anomalies relative to the corresponding control simulations. The impact of volcanic aerosols is quantified as the difference between the ensemble means of simulations with and without volcanic forcing.

Wind power density

Wind energy resources are approximated as a function of instantaneous wind speed U ^{55, 56}. When the wind speed exceeds the cut-in threshold (U_{min}) but remains below the rated wind speed (U_c), the instantaneous wind power density (WPD) is defined as:

$$WPD = \frac{1}{2} \rho U^3 \# (1)$$

where ρ is the air density.

Wind power output remains constant once rated capacity is reached and drops to zero when wind speed exceeds the cut-out threshold (U_{max}). Following the specifications of the GE Vernova GE 2.5–103 onshore wind turbine (rated at 2.5 MW), which has been widely adopted in previous studies^{36,40}, the cut-in, rated and cut-out wind speeds are set to 3 m s^{-1} , 12 m s^{-1} , and 25 m s^{-1} , respectively. Assuming a hub height of 100 m, WPD is calculated from the 100 m wind speed (U_{100}) as:

$$WPD = \begin{cases} 0, & U_{100} < U_{min} \text{ or } U_{100} > U_{max} \\ \frac{1}{2} \rho U_{100}^3 & U_{min} \leq U_{100} \leq U_c \\ \frac{1}{2} \rho U_c^3 & U_c < U_{100} \leq U_{max} \end{cases} \quad \# (2)$$

Because the model output provides wind speed at 10 m height (U_{10}), wind speed at hub height is extrapolated using the standard power-law wind profile^{34,36,55}:

$$U_{100} = U_{10} \times \left(\frac{z_{100}}{z_{10}} \right)^\alpha \quad \# (3)$$

where α is the wind shear exponent, taken here as 1/7, and z_{100} and z_{10} denote the heights of 100 m and 10 m, respectively.

Solar power density

Solar energy resources are evaluated from incident solar irradiance while accounting for the effects of ambient temperature and wind speed on photovoltaic (PV) conversion efficiency. Following established approaches^{11,56,57}, solar power density (SPD) is defined as:

$$SPD = I \times \eta_{PV} \quad \# (4)$$

where I is the solar irradiance on the PV module, and η_{PV} is the effective panel efficiency after temperature correction, given by:

$$\eta_{PV} = \eta_{panel} \times [1 + \gamma \times (T_{panel} - T_{STC})] \quad \# (5)$$

where $\eta_{panel} = 17\%$ is the nominal panel efficiency under standard test conditions (STC), $\gamma = -0.005 \text{ }^\circ\text{C}^{-1}$ is the temperature coefficient typical of monocrystalline silicon panels, and $T_{STC} = 25 \text{ }^\circ\text{C}$ is the panel temperature under STC. The panel temperature (T_{panel}) is estimated empirically from ambient conditions as:

$$T_{panel} = c_1 + c_2 \times T + c_3 \times I + c_4 \times U_{10} \quad \# (6)$$

where T is ambient air temperature, U_{10} is near-surface wind speed at 10 m, and the empirical coefficients are $c_1 = 4.3 \text{ }^\circ\text{C}$, $c_2 = 0.943$, $c_3 = 0.028 \text{ }^\circ\text{C}/(\text{W}/\text{m}^2)$, and $c_4 = 1.528 \text{ }^\circ\text{C}/(\text{m}/\text{s})$.

Estimation of regional renewable resource changes and generation losses

To characterize regional differences in the response of renewable energy resources to volcanic forcing, we divide global land areas excluding Antarctica, where energy statistics are unavailable, according to the regional classification used by IRENA. IRENA reports nine regions: Africa, Asia, Central America and the Caribbean, Europe, Eurasia, Middle East, North America, Oceania and South America. Because installed capacities in the Middle East and in Central America and the Caribbean are much smaller than those in the other regions, we merge these regions to simplify the analysis and better align the classification with continental geography. Specifically, the Middle East is grouped with Asia, and Central America and the Caribbean is grouped with North America. The resulting analysis therefore uses seven regions: Africa, Asia, Eurasia, Europe, North America, Oceania and South America (Supplementary Fig. 5).

Using the most recent regional electricity-generation data for wind and solar power in 2024⁵⁸, we estimate potential generation losses from the regional mean relative changes in WPD and SPD. For solar power, this approach is applied directly because SPD responses are comparatively spatially uniform within regions. For wind power, however, directly averaging WPD changes across all land grid cells would introduce substantial bias because wind responses are much more spatially heterogeneous. In addition, globally consistent grid-level data on actual wind turbine installations are not available, and existing infrastructure reflects not only climatic suitability but also socio-economic, policy and land-use constraints. We therefore adopt a resource-based exposure approach to represent potential wind-generation areas.

Specifically, potential wind-generation regions are identified using a threshold annual mean wind speed of 6 m s^{-1} at 100 m height, following previous studies^{59,60}. To align this threshold-based definition with the model framework, we first calculate the fraction of global land area exceeding 6 m s^{-1} in the Global Wind Atlas (GWA; Supplementary Fig. 9a). This yields 50.6% of global land area, representing regions with wind conditions suitable for turbine deployment. We then identify the top 50.6% of land grid cells with the highest annual mean WPD in the control simulation as representative wind-rich areas in our model-based analysis (Supplementary Fig. 9b). Regional onshore wind-generation losses are estimated by applying the mean relative WPD changes over these selected wind-rich grid cells to the corresponding regional generation totals, while solar-generation losses are estimated from the mean relative SPD changes over all land grid cells in each region.

2024 regional installed capacity and electricity generation

Regional installed-capacity data are taken from *Renewable capacity statistics 2025* (ref. 37), which provides comprehensive statistics on renewable power-generation capacity over the past decade. In this dataset, renewable power-generation capacity is defined as the maximum net generating capacity of power plants and other installations that use renewable energy sources to produce electricity,

representing the capacity installed and connected by the end of the calendar year³⁷. These data are compiled from multiple sources, including the IRENA questionnaire, official national statistics, industry association reports, other published reports and news articles. In this study, we use the most recent available data, for 2024, on onshore wind capacity and total wind capacity, as summarized in Supplementary Tables 1 and 2.

Regional electricity-generation data are obtained from the Ember *Electricity Data Explorer*, which reports country-level wind and solar electricity generation for 2024 (ref. 58). Because the Ember dataset reports total wind generation, onshore wind generation is estimated by scaling total wind generation according to the regional shares of onshore and offshore installed wind capacity (Supplementary Table 1). Based on the annual generation totals, cumulative electricity generation over the 20-month response period is then estimated from the corresponding monthly mean values.

2024 LCOE estimation

The most recent available Levelized Cost of Electricity (LCOE) data are taken from *Renewable Power Generation Costs in 2024* (ref. 39), which documents the continued decline in the costs of utility-scale solar photovoltaic (PV) and onshore wind power. LCOE is defined as the discounted lifetime cost of a power-generation system divided by its discounted lifetime electricity production^{38,40,61}:

$$LCOE = \frac{\sum_{t=1}^N \frac{I_t + O_t}{(1+r)^t}}{\sum_{t=1}^N \frac{E_t}{(1+r)^t}} \quad \# (7)$$

where I_t is capital investment in year t , and O_t is the operation and maintenance cost in year t , E_t is electricity generation in year t , r is the discount rate, and N is the project lifetime.

To estimate region-specific cost-based losses associated with volcanic-induced reductions in renewable electricity generation, we use a capacity-weighted aggregation approach. The IRENA report provides weighted-average regional LCOE values for onshore wind and solar power in 2024 for Africa, Central America and the Caribbean, Eurasia, Europe, North America, Oceania, Other Asia, Other South America, Brazil, China, India and the United States. To match the regional classification used in our installed-capacity analysis, we aggregate these subregional LCOE values using weights based on each subregion's onshore wind installed capacity in 2024 (Supplementary Table 2). Regional cost-based losses are then estimated by multiplying the corresponding generation losses by the aggregated regional LCOE values.

Declarations

Data availability

CESM model results used for analysis in the study are publicly available at the Zenodo repository: <https://doi.org/10.5281/zenodo.20122569>.

Installed wind and solar capacity data were obtained from the *Renewable Capacity Statistics 2025* report published by International Renewable Energy Agency and are publicly available at: <https://www.irena.org/Publications/2025/Mar/Renewable-capacity-statistics-2025>.

Renewable electricity cost data were obtained from the *Renewable Power Generation Costs in 2024* report published by International Renewable Energy Agency and are publicly available at: <https://www.irena.org/Publications/2025/Jun/Renewable-Power-Generation-Costs-in-2024>.

Electricity generation data were obtained from the Ember Electricity Data Explorer and are publicly available at: <https://ember-energy.org/data/electricity-data-explorer/>.

Code availability

The analytical scripts used in this study can be accessed at the Zenodo repository: <https://doi.org/10.5281/zenodo.20122569>. Data processing, analyses, and visualizations were performed using MATLAB (R2024b) and Python (3.13.2).

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Figures

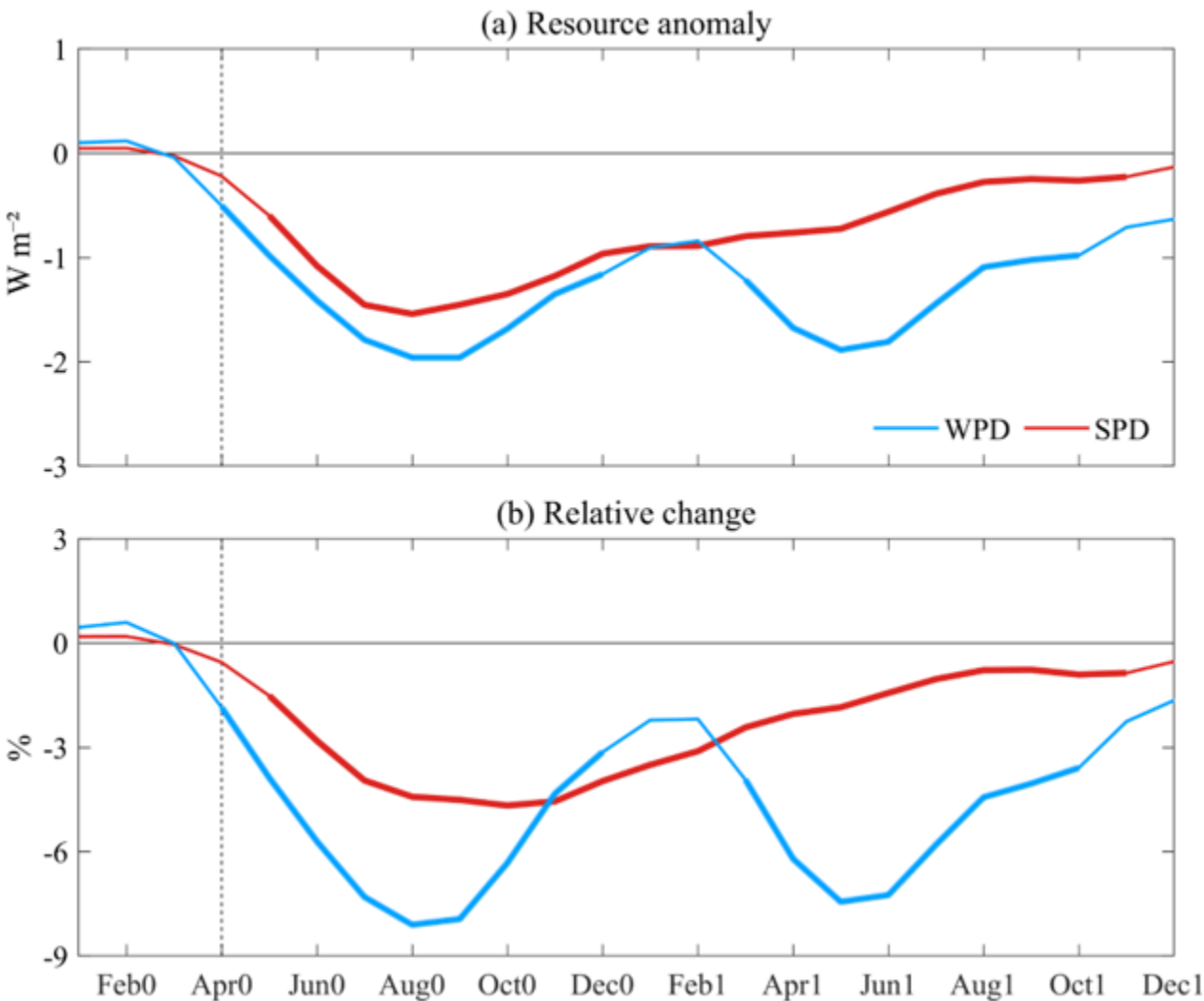


Figure 1

Global land-mean responses of wind and solar resources to the 1815 Tambora eruption. **a**, Monthly anomalies in wind power density (WPD; blue, W m^{-2}) and solar power density (SPD; red, W m^{-2}), averaged over global land areas excluding Antarctica. **b**, Relative changes in WPD (blue) and SPD (red), expressed as percentages relative to the corresponding monthly climatology in the control simulation for each ensemble member. All values are shown as 3-month running means. Bold lines denote anomalies that are significant at the 95% confidence level based on a two-tailed Student's *t*-test.

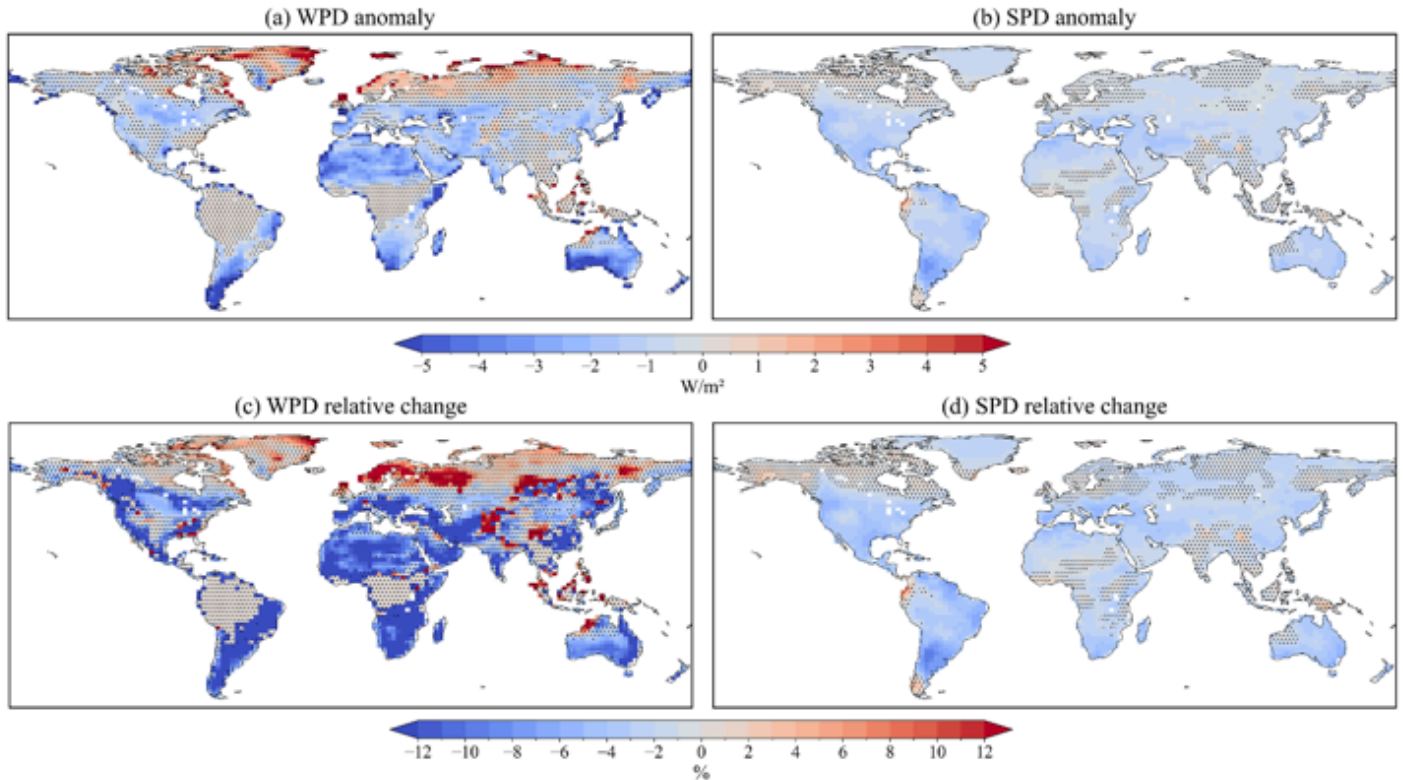


Figure 2

Spatial responses of wind and solar resources to the 1815 Tambora eruption. Spatial distribution of WPD (**a**, **c**) and SPD (**b**, **d**) responses over land areas, averaged over Apr0-Nov1. **a**, **b** Absolute anomalies. **c**, **d** Relative changes. Stippling indicates regions where the response is not significant at the 95% confidence level based on a Student's *t*-test.

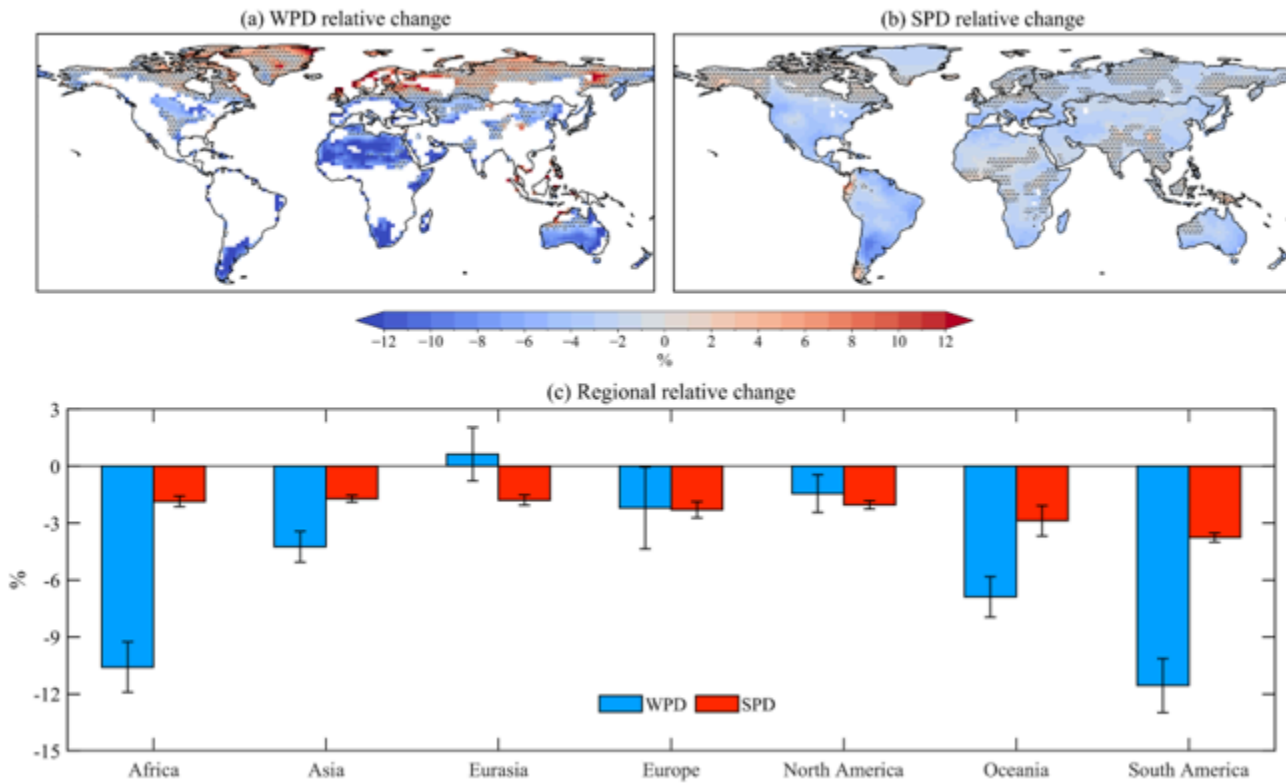


Figure 3

Regional responses of wind and solar resources following the 1815 Tambora eruption. **a**, Spatial distribution of relative changes in WPD over selected wind-rich regions representing potential wind turbine installation areas, averaged over Apr0–Nov1. **b**, Relative changes in SPD over all land areas for the same period. Stippling in **a** and **b** indicates regions where the response is not significant at the 95% confidence level based on a Student's *t*-test. **c**, Regional mean relative changes in WPD and SPD (%). Bars show the ensemble mean, and error bars denote ± 1 standard error across ensemble members.

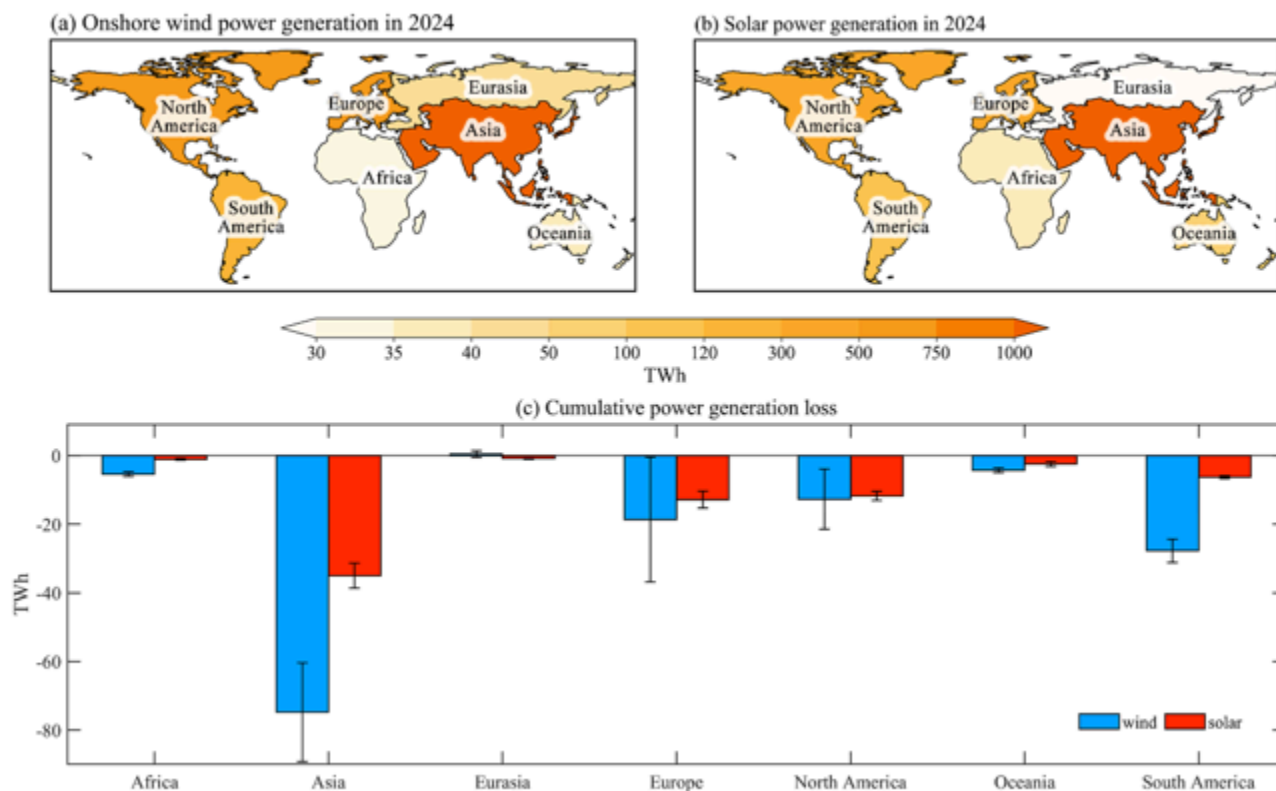


Figure 4

Regional responses of wind and solar electricity generation to the 1815 Tambora eruption. **a,b**, Regional annual electricity generation from onshore wind (**a**) and solar (**b**) in 2024, based on EMBER⁴⁴. **c**, Cumulative regional losses in wind (blue) and solar (red) electricity generation over Apr0–Nov1. Bars show the ensemble mean, and error bars denote ± 1 standard error across ensemble members. Cumulative generation losses are estimated using 2024 regional electricity-generation data.

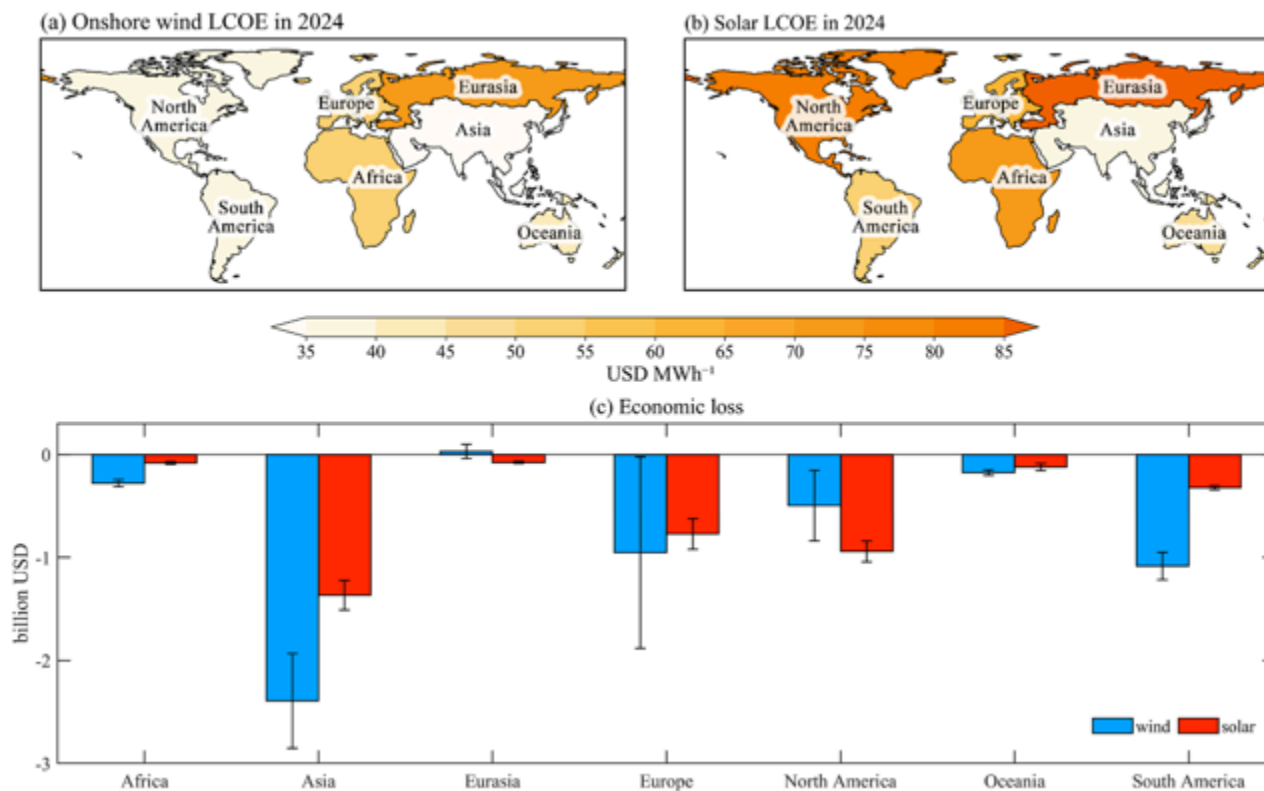


Figure 5

Regional cost-based losses associated with wind and solar electricity generation following the 1815 Tambora eruption. **a,b**, Regional Levelized Cost of Electricity (LCOE) for onshore wind (a) and solar (b) in 2024, based on IRENA⁴⁷. **c**, Cumulative regional cost-based losses associated with wind (blue) and solar (red) electricity generation over Apr0–Nov1. Bars show the ensemble mean, and error bars denote ± 1 standard error across ensemble members. Cost-based losses are estimated using 2024 regional LCOE values.

Supplementary Files

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