

Global renewable zone classification to map deployment constraints and opportunities

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Physical Sciences - Article

Keywords: renewable energy, zone classification, wind power, solar power, resource assessment, renewable planning

Posted Date: August 18th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10285044/v1>

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Additional Declarations: There is **NO** Competing Interest.

Global renewable zone classification to map deployment constraints and opportunities

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Abstract

The global energy transition requires an unprecedented scale of wind and solar power deployment across diverse geographies[1]. The time-variability and location-dependence of renewables [2] means that achieving deep decarbonisation through very high renewable shares raises more difficult challenges than those faced so far [3]. Addressing them will require location-specific strategies, yet most studies examine only a few wealthy regions [4] or disparate aspects [5–9], leaving the global picture fragmented and at risk of lock-in to suboptimal build-out [10]. Here we show that constraints on wind-solar-only deployment are recurrent worldwide, identified with a unified global renewable zone classification in analogy to the Köppen–Geiger climate zones [11–13]. Land that is abundant in both resources and temporally reliable is scarce; long-duration storage is a nearly universal requirement; demand centres are systematically misaligned with the best resources, a legacy of dense settlement in fertile, sheltered valleys whose topography suppresses generation; and these patterns are not reducible to climate. Grouping countries reveals four distinct deployment groups with frontrunners whose strategies may transfer to similar countries. Our globally consistent classification offers a shared reference across the energy, climate, geography and policy communities, facilitating knowledge transfer among regions that face similar constraints.

Keywords: renewable energy, zone classification, wind power, solar power, resource assessment, renewable planning

30 Main

The clean energy transition requires deploying wind and solar capacity at an unprecedented scale across highly diverse geographic settings [1]. Existing power systems have been able to absorb variability from variable renewable energy (VRE) generators with traditional dispatchable power plants, and to some extent, short-duration battery storage. However, achieving deep decarbonisation through very high VRE shares presents qualitatively different challenges [3], apparent among which is that the system must itself manage two fundamental properties of wind and solar energy: their temporal variability and location dependency [2]. This emphasizes the focus on planning grid capacity, balancing infrastructure, deployment speed, and coordination [14, 15], which vary dramatically by country, depending on resource availability, demand distribution, and existing infrastructure [16]. Furthermore, fragmented or poorly coordinated policy and planning for renewable deployment can risk locking in suboptimal build-out [10].

Yet globally, these challenges are still addressed separately. Existing energy system studies predominantly focus on Europe, the United States, and China [4], leaving many important areas of the world understudied. When taking a broader geographic focus, studies remain limited to specific aspects of the problem, e.g., by quantifying resource adequacy [5, 6], resource complementarity [7], supply–demand mismatches at global scale [8], and single-technology typologies [9]. The result is fragmented information that does not bridge different communities, calling for the need for a shared communication tool for planning across scientific, policy, and financial audiences worldwide.

Here we build a unified, communicable framework for the renewable transition globally: a global renewable zone classification (Fig. 1), inspired by the Köppen–Geiger climate classification [11, 12], which encodes complex climate processes into discrete, globally comparable zones that non-specialists can read from a single map [13]. The resulting map uses gridded data at 0.25° resolution and integrates three planning-critical dimensions: (i) long-term wind and solar resource abundance derived from global atlases [5, 6]; (ii) temporal balancing requirements quantified via storage-duration metrics capturing annual energy deficits [17] in optimal mixes of wind–solar capacity deployment; and (iii) spatial balancing needs assessed through the correlation between resource availability and electricity demand, proxied by built-up surface area [18].

Across these dimensions, we identify three recurrent constraints: low resource quality, long-duration storage requirements, and spatial misalignment between resource and demand that necessitates long-distance transmission. These constraints are widespread across the globe, intensifying as systems approach very high renewable shares. While countries currently leading the transition are often experimenting as they go along [19, 20], accelerating and completing the energy transition will benefit from planning rather than retrofitting after an initial rapid build-out [10]. To illustrate this, we group countries into four clusters with distinct characteristics and shared constraints, and identify within each cluster a frontrunner whose strategy, lessons, and caveats are most relevant to the others.

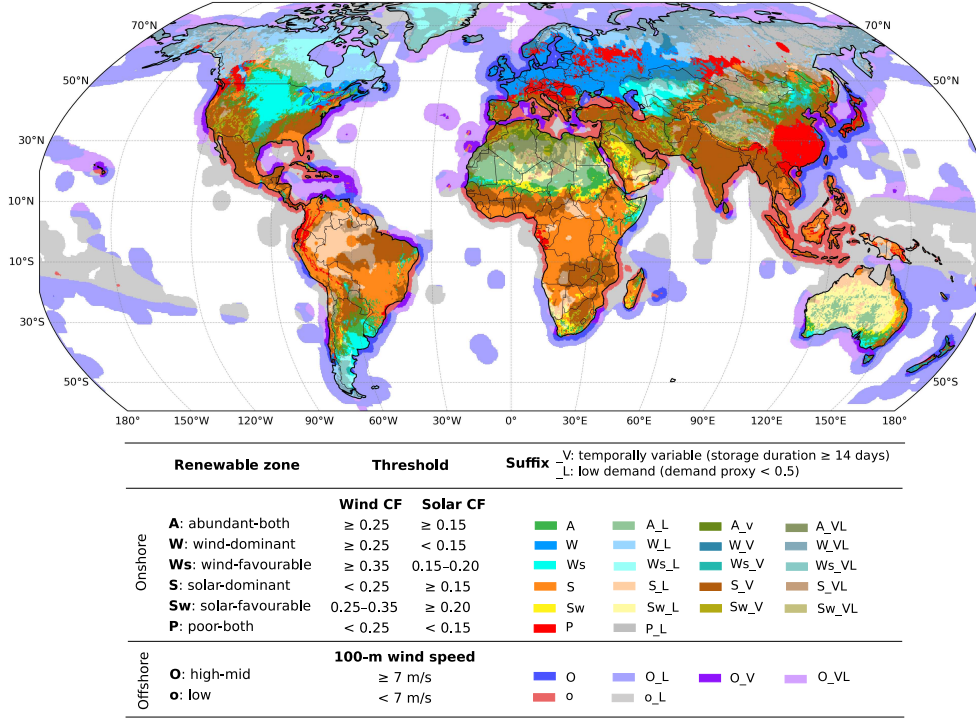


Fig. 1 Global renewable zones. Primary categories indicate dominant resource configuration along with the thresholds for selecting criteria (CF: capacity factor). Suffixes: *_V*, temporally variable (require long storage duration of at least 14 days); *_L*, low demand (demand proxy normalised p95 below 0.5). Note that temporal variability is not considered in poor zones (P and o). Poor-both regions with high electricity demand are rendered in red, highlighting the renewable–population mismatch. For the separate maps of each component (abundance, storage duration, demand proxy), see Extended Data Figs. A3, A4. For the choice and sensitivity of thresholds, see Methods, Extended Data Table A1, and the interactive web application at <https://www.renewablezones.org/>.

Climate explains only one-fifth of renewable zone variance

We classify the global land surface into renewable zones by evaluating wind and solar capacity factors against thresholds, resulting in a spatial distribution that broadly reflects atmospheric circulation patterns (Fig. 1). Comparison with the Köppen–Geiger climate classification [13] confirms that certain climate classes are strong predictors of renewable abundance, but climate class overall only explains 21% of renewable zone variance (Cramér’s $V = 0.45$, $V^2 = 0.21$, Fig. 2b,c), while topographic complexity, mesoscale meteorology, and local land-surface characteristics account for the remaining 79%. Our renewable zone framework captures this heterogeneity directly by incorporating high-resolution resource data from the Global Wind and Solar Atlases [5, 6] (see Methods and Extended Data Fig. A1 for comparison with climatology ERA5-only classification).

More than half (56%) of land is only abundant in one resource. Solar-dominant zones (group S, orange) cover 33% of land area, concentrated in the tropics and subtropics (30°S–30°N) where persistent sunlight and weak winds under Hadley circulation favour photovoltaics, including the Sahara, Arabian Peninsula, Australian interior, and southwestern United States (Fig. 2a; complete statistics in Extended Data Table A1,A2). Tropical climates (Köppen class A) exhibit 91% correspondence with solar-dominant, making this the most predictable pairing (Fig. 2b,c). Wind-dominant zones (group W, blue, 23% of land) are concentrated above 45°N where strong westerly winds prevail: this covers north- and western Europe, the Canadian prairies, and the North American Great Plains. Polar climates (Köppen class E) predict wind dominance with 50% accuracy, driven by strong meridional pressure gradients and polar jet dynamics.

Regions abundant in both resources are rare. Group A (Abundant-both, green) covers only 14% of land, found where favourable atmospheric conditions coincide with strong solar irradiance: the North American Great Plains, Patagonia, sub-Saharan Africa’s wind corridor, northeast China, and southern Australia. Dry climates (class B) show the highest prevalence of abundant-both zones (33%) with minimal cloud cover and open terrain favouring both resources and virtually no poor-both regions, making them valuable despite typically low local electricity demand.

Temperate and continental climates (C, D) exhibit the greatest heterogeneity, with renewable zones varying dramatically across similar climate classes. Continental regions (D) contain disproportionately large poor-both areas (group P, grey), where neither wind nor solar resources meet moderate abundance thresholds, due to orographic influences discussed below.

Offshore zones show abundant wind resources along mid-latitude coastlines, driven by unobstructed oceanic winds and strong pressure gradients. More critically, equatorial offshore regions near the Intertropical Convergence Zone (ITCZ) show systematically poor wind resources (in grey and red, Fig. 1), creating fundamental deployment challenges for tropical coastal nations that have limited offshore wind as a domestic resource alternative.

Scarcity of abundant and reliable resource zones

Resource abundance alone does not determine deployability. Temporal variability governs whether resources can reliably supply electricity year-round or require substantial energy storage to bridge the gap between generation and demand. We quantify this as the storage duration required for an optimally mixed wind–solar system to maintain a constant supply (Extended Data Fig. A5), evaluated over 1995–2025, capturing both shorter-term weather and longer-term seasonal variability [17], with the latter being crucial in energy systems with very high VRE shares [3]. Globally, the required storage duration with an optimal wind-solar mix averages 13 days (range: 3–88 days) when minimising for the average deficit, with almost everywhere requiring at least 7-day storage (99.6%, Extended Data Fig. A3b). This duration is beyond what battery storage normally can offer, indicating the needs for alternative long-duration storage almost anywhere on Earth.

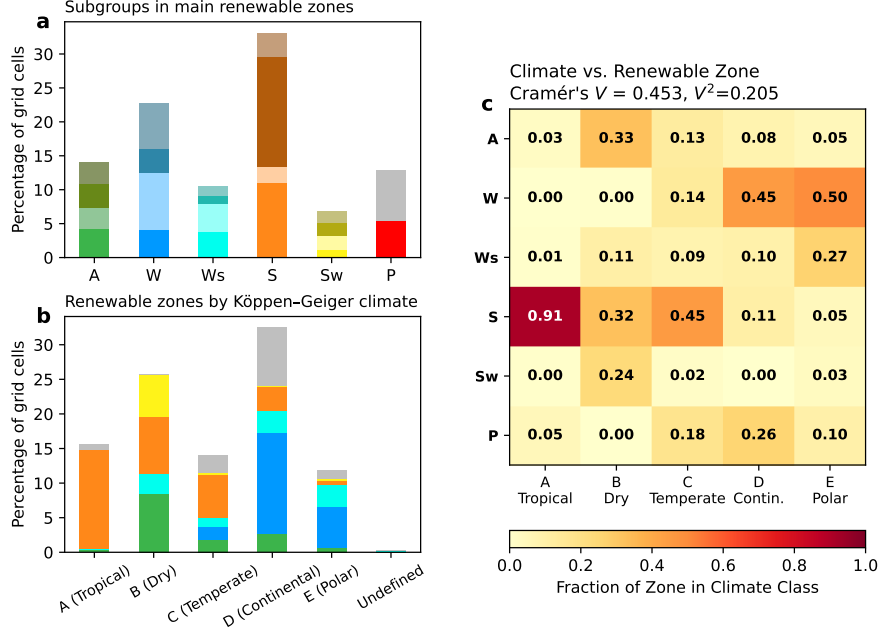


Fig. 2 Quantitative distribution of the renewable zones. (a) Percentage of global land grid cells in each renewable group. (b) Renewable zone composition within each Köppen-Geiger climate class. Colour codes follow Fig. 1. (c) Cramér's V matrix showing the association between renewable zones and climate classes. Values are normalised by column to show the fraction of each renewable zone found within a specific climate class. For detailed statistics of renewable zones and subgroups, see Extended Data Table A2.

While wind and solar generation exhibit natural anti-correlation in many regions and provide temporal complementarity [7], the strength of this complementarity varies dramatically. Low storage requirements (under 10 days) can reflect strong wind-solar complementarity [7] with low seasonality, e.g., tropical regions, or robust seasonal anti-correlation between winter wind and summer solar peaks, e.g., central Australia, Patagonia, and the North American Great Plains (Fig. 1). These regions offer favourable contexts for renewable-dominated grids, as weekly-scale storage can bridge generation-demand gaps. On the other hand, storage requirements exceed 25 days across Iran, Afghanistan, Pakistan, northern India, and western China despite locally abundant solar resources. These areas experience South and East Asian monsoon systems with strong seasonal variability in cloudiness and winds, coupled with complex orographic influences from extensive mountain ranges such as the Himalayas, Zagros and Alborz Mountains. Fossil fuels currently dominate electricity generation in these regions [21].

Combining temporal variability with resource abundance reveals the scarcity of regions that are both abundant and reliable (Fig. 1). Nearly half of the abundant-both area (6 of 14 percentage points) experiences high temporal variability (suffix ‘ V ’ in Fig. 1). This leaves merely 8% of global land with both abundant and temporally reliable year-round resources.

Several solar-dominant regions, namely western North America, Asia Minor, the Middle East, and northern India, possess inadequate wind complementarity, requiring long-duration storage. California illustrates this challenge clearly, where the optimal mix is wind-heavy ($\alpha > 0.7$, see Methods) despite comparatively poor wind resources (CF < 0.25). The state currently operates 22.4 GW solar capacity alongside only 8.4 GW wind (2026) [19], supported by rapid battery storage growth (12.5 GW installed, 2025 [22]). This resource-imbalanced portfolio has forced the system operator CAISO to curtail up to 919 GWh monthly during spring (February–May) [19] when solar oversupply coincides with low demand and limited storage capacity.

Fertile valleys and the renewable–population mismatch

Grid cells combining high demand with poor-both resources (group P) are highlighted in red in Fig. 1, revealing systematic spatial mismatches between resource and demand, e.g., eastern China, the western United States, and southern-central Europe. Of 178 countries analyzed, 78 (44%) contain poor-resource high-demand zones; 36 (20%) have more than 10% of territory in this category (Extended Data Table A3). These areas share common environmental attributes: 64% of affected countries show mean elevation lower than 657 m and 88% have precipitation above 810 mm yr^{−1} (Fig. 3). Three latitude-dependent groups emerge: (1) Equatorial zones below 20°N/S (in dark purple, Congo, Indonesia, Vietnam, Philippines, Ecuador, Colombia) with above 2000 mm yr^{−1} precipitation where ITCZ dynamics suppress winds and enhance clouds; (2) Alpine valleys above 40°N/S (in green, Austria, Switzerland, Slovenia, Romania) with orographic sheltering at 500–1500 m; (3) East Asian monsoon regions 20–40°N/S (in turquoise, China, Japan, Taiwan) with 1500–3000 mm yr^{−1} precipitation plus 10–30% aerosol-driven solar losses [23].

We propose that this systematic spatial mismatch arises from the historical co-location of dense human settlement with geographic conditions that favoured intensive agriculture: fertile alluvial soils, reliable freshwater from orographic or monsoonal precipitation, and wind-sheltered valley microclimates enabled early civilisation in the Yangtze and Yellow River valleys, the Rhine–Danube–Po corridor, the Ganges–Brahmaputra delta, and the Congo Basin [24, 25]. The same historically advantageous topographic and climatic conditions suppress VRE generation by disrupting horizontal flow and enhancing cloudiness through orographic lifting [26], which reduces wind potential and negatively affects surface solar irradiance even with favourable solar angles at low latitudes.

Country-level constraints clustered into four distinct deployment strategies

To translate the renewable classification for national planning, we aggregate three zone-derived metrics per country: resource quality (the higher of wind or solar score per grid cell, Extended Data Fig. A6), storage duration for an optimally mixed

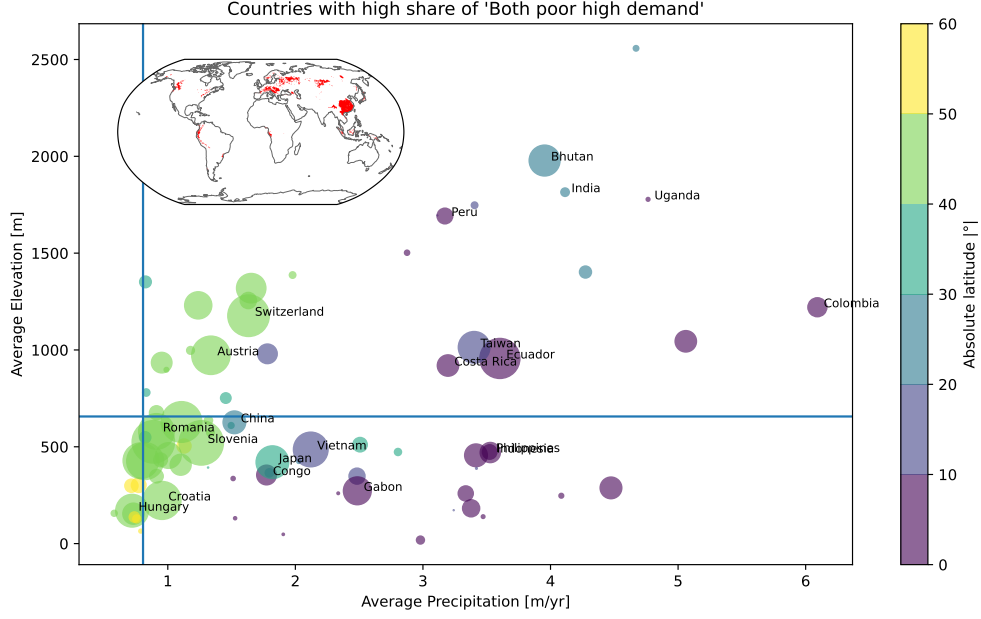


Fig. 3 Environmental attributes of the renewable–population mismatch. Each marker represents a country with a share of poor-both high-demand grid cells, positioned by mean elevation and mean annual precipitation of those cells. Electricity demand for each grid cell is proxied by the distance-weighted sum of built-up surface area within a 2° radius, using the Global Human Settlement Layer [18] (see Methods). Marker size indicates the fraction of national territory in the poor-both high-demand subgroup; colour indicates absolute latitude. Blue lines mark global averages (657 m elevation; 810 mm yr^{-1} precipitation). Three groups of countries are clearly seen by their colours: equatorial countries in purple ($\leq 20^\circ\text{N/S}$), monsoonal countries in blue ($20 - 40^\circ$), and Alpine/Carpathian countries in green ($\geq 40^\circ$). Affected areas are marked in red in the map, same as shown in Fig. 1. A full country list is provided in Extended Data Table A3.

wind–solar supply, and resource–demand spatial alignment (Spearman rank correlation between grid-cell resource and demand proxy, Extended Data Fig. A7). K-means clustering on these normalised metrics identifies four coherent clusters (Fig. 4; full list in Extended Data Table A4) with distinct distributions of renewable zones (Extended Data Fig. A8).

No country has favourable conditions in all three dimensions (Table 1). We discuss each cluster in order of decreasing overall favourability for deep decarbonisation, highlighting frontrunner countries with the highest current VRE shares, and how their deployment strategies align with the cluster’s characteristic constraints. Most countries with high VRE shares are currently in Europe, but we also discuss countries outside Europe when possible.

Across all clusters, country size plays a key role for strategy: large mismatched countries (USA, China, Australia) require domestic transmission backbones, while small countries (Denmark, Netherlands, Belgium) achieve equivalent outcomes

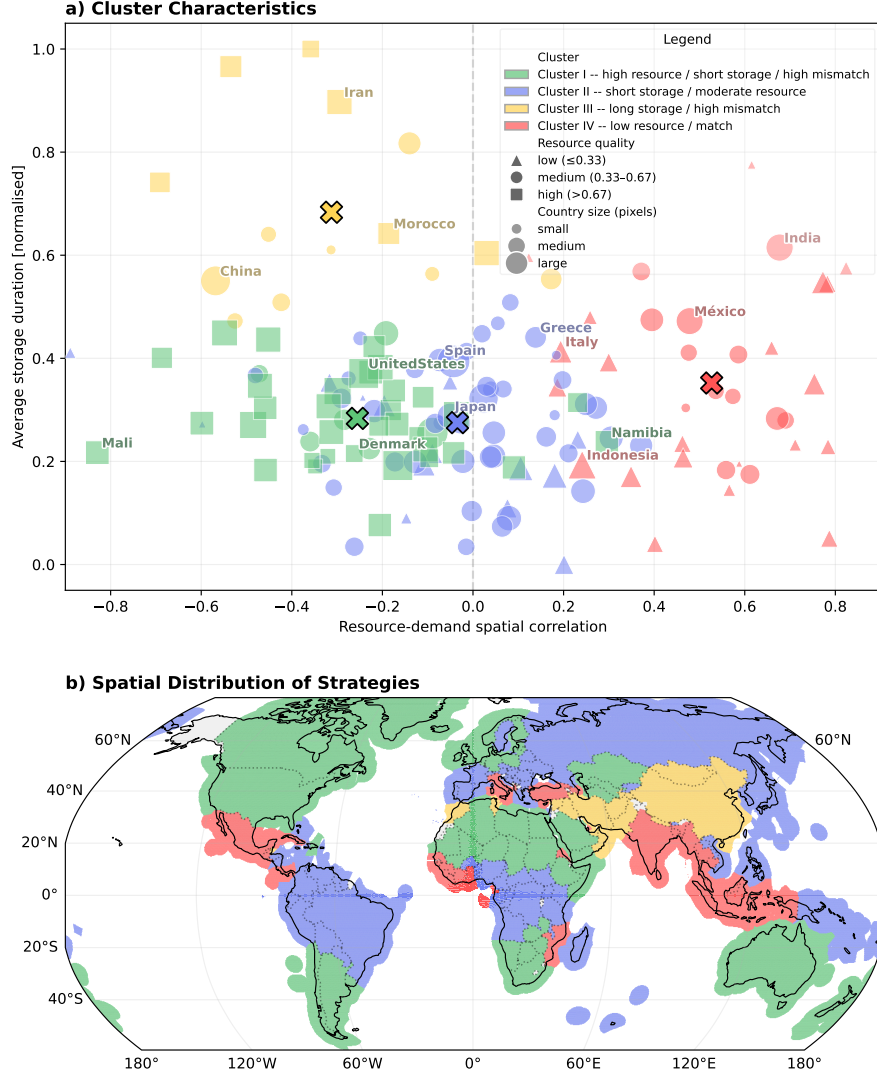


Fig. 4 Clusters of countries for deployment strategies (a) Scatter plot based on their resource-demand spatial correlation (x-axis), storage duration (y-axis), and resource quality (shape of markers), all normalised. Clusters are numbered in the order of their overall favourability for VRE deployment, see main text. Centroids of clusters are marked as **X**s; Size of markers shows the countries' size by pixels (including maritime regions) (b) Map with countries coloured by their corresponding clusters. Countries with fewer than 64 pixels ($2^\circ \times 2^\circ$) are excluded to keep the spatial correlation meaningful, resulting in 158 countries considered. Contested areas and overseas territories disconnected from a country's primary grid are excluded (see Methods).

through cross-border interconnection. The cluster framework identifies which countries face structurally similar bottlenecks, helping countries identify which frontrunner strategies could be adapted to their own local context.

Table 1 Four clusters of country-level deployment groups. Resource quality, storage duration (days), and resource–demand correlation (ρ) are cluster-centroid values on normalised scales. VRE shares are wind + solar as percentage of electricity generation (2024 data from Ember [30], Eurostat [27] and 2023 data from IEA country profiles [37]). See Extended Data Table A4 for the full country list and Extended Data Fig. A8 for renewable zone distributions per cluster.

Cluster	Characteristics	Frontrunners	Caveats
I: Abundant resources, transmission-bound (42 countries)	Resource quality 0.81; 13% abundant-both; strong wind–solar complementarity (storage 8–12 d). <i>Bottleneck:</i> spatial mismatch ($\rho = -0.26$) makes transmission the binding constraint.	Denmark 69% VRE (2024) [27]: world-leading offshore wind, dense interconnection to neighbours [28].	Multi-country energy droughts across inter-connected European grids occur at least twice annually [29]. USA (17% VRE, 2024 [30]): fragmented Western/Eastern/-Texas grids contributed to 2021 Texas freeze [31].
II: Moderate resources, mild mismatch (66 countries)	Resource quality 0.38; high single-resource (W, S) but also the highest poor-both share (P, 13%). Mild mismatch ($\rho = -0.03$), short storage. <i>Bottleneck:</i> no single severe constraint; coordination across wind–solar balance and inter-connection is key.	Spain 43% VRE (2024) [27]: balanced wind–solar portfolios with cross-border interconnection.	Spain–France interconnections congested 68% of the time [32]. April 2025 Iberian blackout highlighted the need for grid-forming inverter standards in high-VRE systems [33].
III: Good resources, highly constrained (14 countries)	Resource quality 0.66; 22% abundant-both, 35% solar-dominant. Longest storage (>20 d) and strongest mismatch ($\rho = -0.31$). <i>Bottleneck:</i> simultaneous need for long-duration storage and long-distance transmission.	Morocco 20% VRE (2023): 580 MW Noor Ouarzazate CSP* with molten-salt thermal storage [34]. China 18% VRE (2024 [30]): storage with 50 GW pumped hydro [35]; transmission with 45 UHV* lines (~340 GW) spanning 2000+ km [36]	UHV-scale transmission requires centralised planning and state financing, limiting direct transferability.
IV: Co-located but low resource (36 countries)	Resource quality 0.26 (lowest); 36% solar-dominant, virtually no good wind. Resources and demand co-located ($\rho = +0.53$). <i>Bottleneck:</i> scaling generation itself; finance and grid modernisation are the priority.	Italy 22% VRE (2024 [27]): lags EU peers, remains a major fossil fuel importer [37]. India 11% VRE (2025): third-largest VRE market by 2026 [38], but demand growing faster than supply [30].	Single-source solar dominance creates duck-curve and ramping challenges [39]. Low-wind offshore technologies [40] could be beneficial and shorten storage needs (Extended Data Fig. A9).

* CSP: Concentrated solar power; UHV: Ultra-High Voltage

205 Planning implications and outlook

Large-scale deployment to achieve energy systems with a very high share of variable renewable generation poses well-known challenges due to temporal and spatial variability [2, 3]. While existing energy system studies predominantly focus on Europe, the United States, and China [4], many developing countries with pressing energy development needs remain comparatively understudied. By unifying resource abundance, storage needs, and spatial balance into a single global renewable zone map, we show that the constraints on very-high-renewable systems are more widespread and more structural than climate analyses alone imply, namely, the scarcity of areas with both-abundant resources (14% of global land), the nearly worldwide requirement of long-duration storage (99.6% of land requires at least one-week storage), and the systematic misalignment in spatial distribution of resources and densely populated areas (44% of countries). Taken together, these findings highlight that globally, transmission for geographic diversification and storage for temporal balancing should be primary infrastructure priorities. VRE targets that focus on installed capacity alone should be complemented by balancing strategies. We anticipate that our framework will help shift renewable planning from capacity targets toward strategies that confront regional constraints from the outset, with better coordination for a more efficient deployment.

To facilitate knowledge transfer from frontrunners in renewable deployment, we cluster countries into four groups with shared constraints. With frontrunner countries generating up to 69% electricity by renewables (Denmark in 2024 [27]), the clusters offer valuable lessons and challenges to consider that low-share renewable systems have not yet encountered. Clearly, planning should also take into account other available resources in a given country. Equatorial countries in the ITCZ belt with low offshore wind potential ($0\text{--}5\text{ m s}^{-1}$) typically have high hydropower potential where the geography supports it. For example, Congo holds ~ 100 GW of potential ($<3\%$ exploited [41]); Peru, Ecuador, and Colombia derive 50–80% of generation from hydro [42], although reliance on hydropower in these regions still introduces the issue of ENSO-driven output reductions of 30–50% during El Niño years [43]. Other technology options, such as deep geothermal energy and offshore floating solar, an emerging technology with pilots in China and the Netherlands [44], could also partially fill the gaps. These renewable technologies could be integrated into an updated classification of our framework, along with land-use constraints (agriculture, conservation, urban expansion) to refine deployable resource estimates, resulting in a fully unified renewable geography framework.

Several caveats apply. Our classification is a broad planning framework, but economic viability depends on factors like prices, regulations, and financing conditions that global thresholds cannot capture. The built-up-area demand proxy does not fully reflect per-capita consumption or temporal demand patterns, nor does it accurately depict specific industrial centres such as in Germany or China. Geopolitics and pressures for energy independence can promote or impede VRE deployment, depending on a country’s existing (fossil) resources [45].

Climate change will also reshape the classification over time. Our 1995–2025 climatology provides a present-day baseline. Future changes to wind and solar resources will vary significantly across regions and depend on the emissions trajectory of the

250 next decades [46]. Two climate-change signals will most directly affect the two low-
favourable clusters above. First, projected ITCZ widening [47] could expand the
equatorial zone of suppressed offshore wind, worsening the tropical conditions in Clus-
ter IV. Second, intensified East Asian monsoon variability, with summer precipitation
255 projected to increase by up to 17% [48], would amplify the renewable–population mis-
match in Cluster III. Across all clusters, cloud and aerosol projections remain the
largest source of solar-resource uncertainty [23, 49].

By synthesising resource abundance, temporal variability, and demand proxim-
ity into a coherent renewable zone classification, our study fills a gap between broad
global resource assessments and detailed national or regional energy system models,
260 enabling a rapid, globally comparable assessment of renewable deployment strategies.
It should be understood as a living classification, to be updated as resource assess-
ments, demand distributions, and technologies evolve, in direct analogy to periodic
Köppen–Geiger updates [50]. Like the Köppen–Geiger for climate, our classification
provides a framework for analysis and communication that researchers, planners, pol-
265 icymakers, and investors can use, either through aggregated classification maps, such
as those we make available at <https://www.renewablezones.org/>, or through analysis
of the data underlying the classification, which we make freely available for others to
further build upon.

Methods

Data and grid

All analysis was performed on a 0.25° global latitude–longitude grid, matching the ERA5 reanalysis grid [51], and covering the latitudes 80°N – 60°S .

Solar photovoltaic capacity factors data were obtained from the Global Solar Atlas[6], using the PV Electricity Output (PVOUT) variable representing long-term average daily photovoltaic power output per unit peak capacity, with a temporal average 12 x 24 (month x hour) profile and unit kWh/kWp. Daily mean capacity factors were calculated by dividing daily total PVOUT by 24 h. The Global Solar Atlas involves three main models: solar radiation model, air temperature model, and PV power simulation model. Global data coverage is calculated for different periods for different geographical regions, available starting from 1994–2019 to 2024. The Global Solar Atlas data have been validated statistically against 228 public sites worldwide, resulting in good quality for both GHI (Global Horizontal Irradiance, within $\pm 4\%$) and DNI (Direct Normal Irradiance, within $\pm 9\%$) values. Higher uncertainty can be expected from high-latitude regions, regions in humid tropical climates, regions with high concentrations of aerosols, high mountains, and regions with limited ground measurements [6]. The Global Solar Atlas does not consider most regions north of 60°N as economically viable for solar technology [6], resulting in a visible cut with a low threshold of solar capacity factor around 0.1. We address this issue by interpolating the missing data using a 2D linear regression method, trained on available solar capacity factors with two predicting climate variables: solar shortwave radiation downward (ssrd) and 2 m temperature (t2m) from ERA5 for the period 1995–2025 (Extended Data Fig. A10).

Onshore wind capacity factors were obtained from the Global Wind Atlas version GWA 4.0 (June 2025)[5] for IEC Class II (variable name CAPACITY-FACTOR_IEC2) turbines at 100 m hub height, representing the most common standard wind turbines for medium wind, with average wind speed 8.5 m/s and extreme gust 42.5 m/s[52]. The Global Wind Atlas dataset downscales from large-scale climate wind reanalysis data ERA5 [51] for the period 2008–2017 to microscale climate wind data, accounting for orography, surface roughness, displacement height, and bathymetry. Ongoing extensive validation has been conducted to ensure the quality of the dataset, resulting in an average absolute bias of 11% for 52 mean wind speeds, with the largest biases occurring in sites with the lowest mean wind speeds (below 4 m/s) [5]. The land area for wind onshore and for countries (border, area) was masked using the Python package regionmask[53] using the “natural_earth_v5.0.0.countries.110” dataset version 0.13.0 (2024). Country boundaries, including their maritime areas, were generated using the Geoboundaries module from the Modelblocks project (https://github.com/modelblocks-org/module_geo_boundaries/). During this process, Contested Exclusive Economic Zones, such as Taiwan or the Falkland Islands, are removed. Geopolitical entities that have their own entry in the data but are either too small or not independent territories, such as Hong Kong, Macau, Gibraltar, Vatican City, Svalbard and Jan Mayen, were also removed.

Offshore wind capacity factors were estimated from ERA5 100 m wind speeds (1995–2025) to avoid known maritime artifacts in the Global Wind Atlas products[5]. Seasonal variability was quantified from ERA5 hourly 100 m wind speed and surface solar radiation downwards, aggregated to daily resolution for the period 1995–2025. ERA5 data were accessed in Zarr format from the ECMWF Climate Data Store via the Destination Earth Data Hub (<https://earthdatahub.destine.eu/>).

An electricity demand proxy was constructed from the Global Human Settlement Layer (GHSL) Built-Up Surface dataset[18], specifically the GHS-BUILT-S (2023 release), providing total built-up surface area (m^2) at 30 arcsec resolution (approximately 1 km at equator) for the year 2023. Built-up area serves as a spatial proxy for electricity consumption based on the established correlation between building stock and energy demand [54], though it does not capture variations in per-capita consumption across development levels or temporal demand patterns.

To keep consistency within dataset, elevation data were calculated from ERA5 geopotential height at the surface, converted to geometric height via division by standard gravity (9.80665 m s^{-2}). Global mean elevation over land grid cells (excluding ocean and offshore zones) was computed as 657 m. Note that this value is lower than some literature estimates (840 m [55]) due to grid resolution effects.

Precipitation data were derived from ERA5 total precipitation, summed to annual totals and averaged over 1995–2025. Global mean precipitation over land grid cells was 810 mm yr^{-1} (0.81 m yr^{-1}).

Köppen-Geiger climate classification data were obtained from Kottek et al.[13] for the reference period 1976–2000, providing climate class assignments (A: Tropical, B: Dry, C: Temperate, D: Continental, E: Polar, plus subclasses) in shapefile format. The shapefiles were rasterised to our 0.25° analysis grid using nearest interpolation to preserve discrete classification boundaries.

Resource abundance classification

Resource abundance quantifies the long-term climatological mean availability of wind or solar power. Each resource was classified into three levels: high, moderate, and low, using capacity factor thresholds selected based on: (1) capacity factor values commonly considered suitable for commercial deployment under current economic and technological conditions, and (2) empirical distributions from global atlas data, with thresholds approximately corresponding to the 33rd and 66th percentiles to create three roughly equal-sized bins. The selected thresholds also reflect the frequency distribution of their values globally (Extended Data Fig. A2).

For solar photovoltaics (PV), capacity factor thresholds were set at 0.15 (low-to-moderate boundary) and 0.20 (moderate-to-high boundary). These values reflect typical performance for utility-scale solar photovoltaics installations in marginal versus favourable climates under current technology, ranging from 15–30% [56]. We focus on utility-scale PV because it is more controllable and better integrated into system-level planning and regulation than distributed rooftop PV. Capacity factors below 0.15 can nonetheless remain economically viable behind-the-meter, as illustrated by PV rooftop in Germany [57]. Our interactive web application at <https://www.renewablezones.org/> allows users to experiment with different thresholds.

For onshore wind, thresholds were set at 0.25 (low-to-moderate) and 0.35 (moderate-to-high), reflecting the performance of typical wind onshore turbines ranging from 25–45% [58].

For offshore wind, thresholds of 7 and 8.5 m/s for wind speed at 100m were employed (based on the 33rd and 66th percentile of offshore wind climatology from ERA5 data 1995-2025 [51]). From the distribution of wind offshore from the Global Wind Atlas [5], this value is approximately equivalent to the global distribution of a capacity factor of 0.37 and 0.53 for wind offshore.

To test how these thresholds influence the results, we performed sensitivity tests with different thresholds for abundance criteria: (a) based on the 33rd and 66th percentile, equivalent to solar CF of 0.16 and 0.19, wind onshore CF of 0.20 and 0.33; (b) a lower low-to-moderate threshold for solar: 0.10 and 0.20, reflecting many countries still deploy solar power in regions with low solar resources; (c) higher moderate-to-high threshold for wind onshore power, reflecting the current wind turbines can achieve higher CF; (d) Abundance classification using climatological data from ERA5 for 1995-2025 instead of Global Atlases. Results show that the lower-to-moderate threshold of solar CF have the strongest influence on renewable zone classification, with up to 22.5% reduction in wind-dominant group (W) accompanied with 15.7% increase in solar dominant group (S) when lowering the threshold for solar power (Experiment b); and similarly a reduction of up to 7.2% in solar-dominant group (S) when lowering the threshold for wind onshore (Experiment a). Most importantly, group P (poor-both) is very sensitive to the low-to-moderate threshold of solar power, virtually decreased to none (0.1%) in Experiment b (Extended Data Table A1). Increasing the moderate-to-high threshold does not substantially change the distribution (up to 4.3% difference in Experiment c). Experiment d shows smoother zones, highlighting the benefits of using the Global Wind and Solar Atlases in our classification, incorporating information on orographically complex terrain and local microclimates, see Extended Data Fig. A1).

Storage duration and optimal wind-solar ratio

To estimate temporal balancing requirements, storage duration for each grid cell over 1995–2025 is computed using the energy deficit framework from Antonini et al. [17]. The energy-deficit metric characterises the amount of storage needed to keep a constant production over the year and is directly relevant for estimating storage and balancing requirements in renewable-dominated power systems. Same as Antonini et al. [17], the target generation we use are aimed to characterise the variability of wind and solar combination, not to represent an actual electricity demand. For each year, we obtain the maximum cumulative deficit between a constant generation target (normalised to unity) and an optimal mix from 100 m wind speed and surface solar radiation downwards (ssrd). This method captures both weather and seasonal variability from the method of Antonini et al. [17].

For each grid cell, a normalised generation profile was constructed as $P_{\text{generation}}(t)$ with a constant target $P_{\text{target}} = 1$. The instantaneous imbalance is

$$\Delta(t) = P_{\text{generation}}(t) - P_{\text{target}} \quad (1)$$

and the cumulative energy deficit for each year is

$$E_{\text{deficit}}(t) = \int_0^t [P_{\text{target}}(\tau) - P_{\text{generation}}(\tau)] d\tau, \quad t \in [0, T] \quad (2)$$

400 The generation year runs from 1 July to 30 June to capture winter Dunkelflaute events (prolonged low-wind, low-solar periods) commonly occur in winter in Northern hemisphere [29]. To avoid edge effects at year boundaries, each annual time series is repeated back-to-back before calculating cumulative minima [17]. Storage duration is defined as the mean of maximum deficit across all years.

405 To determine the optimal ratio mix that minimises storage requirements, we normalise both wind and solar time series to 0–1 and repeat the deficit calculation for wind capacity shares (α) from 0 to 1 in 0.1 increments. An optimal ratio of 0 would mean pure solar, while 1 means a pure wind system. The α yielding the lowest mean storage duration is retained to get the storage duration metric. Instead of minimising the average deficit, we can also plan for worst-case resilience by minimising the longest deficit: this yields higher storage requirements across all countries, with storage rising from 13 to 20 days average (range: 5–104 days, see Extended Data Fig. A11b). For comparison, an equal ratio of wind and solar (0.5) would yield much longer storage duration required of 3–110 days, averaging at 30 days (Extended Data Fig. A11c).

Electricity demand proxy

415 Potential electricity demand was approximated using proximity-weighted built-up surface area. For each grid cell i , the demand fraction is calculated by the built-up surface area in m^2 divided by its pixel area. Then a distance-weighted sum of this fraction in surrounding cells within radius $R = 2$ (200–220 km depending on latitude) was computed:

$$D_i = \sum_{j \in \mathcal{N}_i(R)} \frac{B_j}{d_{ij}} \quad (3)$$

420 where B_j is built-up surface area fraction (no unit) in cell j from GHSL data, d_{ij} is great-circle distance between cell centroids (assigned to 1 for the same grid cell), and $\mathcal{N}_i(R)$ denotes all cells within the specified radius. This formulation assumes demand at a potential generation site increases with proximity to built-up areas, reflecting transmission losses and infrastructure costs. The value for each grid cell was normalised
425 by its cell size to account for the size dependency on latitude. The result is a proxy of electricity demand intensity.

The demand proxy was normalised using its 95th percentile to $[0,1]$ to reduce heavy-tail effects from megacity regions (Extended Data Fig. A4). High-demand regions were defined as grid cells exceeding the 50th percentile of D_i^* . This method was chosen because the demand distribution is strongly right-skewed; lower thresholds would
430 classify most non-polar, non-desert land as high-demand, reducing the discriminatory power of the proxy.

Spatial correlation and transmission needs

To assess the spatial balancing needs for each country, we calculate the spatial correlation between resource availability and demand proximity. The Spearman correlation method was used to rank and assess how well resource and demand are co-located, putting less weight on megacities (see Extended Data Fig. A7).

Spatial correlation is calculated for each country and its maritime areas. The maritime areas are defined using the Geoboundaries module from the Modelblocks project (https://github.com/modelblocks-org/module_geo_boundaries/). Overseas territories disconnected from primary grids (Alaska, Hawaii, French Guiana, etc.) are excluded to avoid mis-assignment of the mainland grids. Furthermore, countries or territories with a size below 64 pixels, such as European micro-states and small island-countries (Maldives, most Pacific islands) are filtered out to calculate meaningful spatial correlation metric.

K-means clustering for renewable strategic groups

Countries and their maritime areas are combined, then categorised into four clusters representing different groups for renewable strategic planning, based on three criteria: (1) resource quality (the higher score between wind and solar for each grid cell, assuming technology with higher abundance would be deployed, Extended Data Fig. A6); (2) temporal balancing needs, shown by the average storage duration; (3) spatial balancing needs, shown by the Spearman spatial correlation between resource abundance and demand proximity (Extended Data Fig. A7). These three metrics were normalised in preparation for K-means clustering.

Note that K-means clustering prioritises the distance to the cluster centroid, and thus a country is classified based on its total distance in three criteria (resource, storage, resource-demand spatial correlation). For example, Namibia has a high resource abundance, leading it to be categorised into cluster I "Abundant resources, transmission-bound" even though it has positive resource-demand spatial correlation (Fig. 4a).

There are trade-offs when reducing complex multi-factors into discrete groups and zones with thresholds, with the former including nuances, while the latter helps understanding and communicating quickly to a wide audience. Our analysis is subject to the selected thresholds (see Methods and Extended Data Table A1), and the K-mean clustering method can result in slightly different groupings of countries depending on the seeding and the underlying thresholds. Therefore, the results should be considered with this dynamic rather than a rigid categorical thinking. The readers are encouraged to check out our interactive map (<https://www.renewablezones.org/>) to explore more.

LLM statement During the preparation of this work, the author(s) used AI Tool (Claude) to improve the code, the readability and flow of the language. After using this tool, the author(s) reviewed and edited the content thoroughly, and take(s) full responsibility for the content of the publication.

Declarations

- Funding: Not applicable
- 475 • Competing interests: There are no competing interests to declare.
- Ethics approval and consent to participate: Not applicable
- Consent for publication: Not applicable
- Data availability: Global capacity factor data for solar power are available at <https://globalsolaratlas.info/download/world>, for wind power at <https://globalwindatlas.info/en/download/gis-files>; ERA5 data are accessible in Zarr format at <https://earthdatahub.destine.eu/collections/era5/datasets/era5-single-levels-atmosphere>; Build-up surface data to proxy demand are available at <https://human-settlement.emergency.copernicus.eu/download.php?ds=bu>.
- Materials availability: No physical materials were generated in this work.
- 485 • Code availability: The code to process data, analyse data, and produce figures and tables are available at <https://github.com/LinhHo/koeppen-renewables>.
- Author contribution: L.H.: Conceptualization, Methodology, Software, Validation, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Review Editing, Visualization; S.P.: Conceptualization, Methodology, Software, Writing – Review Editing, Visualization, Supervision, Project Administration.
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Appendix A Extended Data

Table A1 Sensitivity tests of renewable zones by thresholds and datasets. Zone percentage shares under alternative resource-threshold definitions (change from baseline in parentheses). Baseline scenario uses the same thresholds as the main text and in Fig. 1 (Solar CF: 0.15 and 0.20, wind CF 0.25 and 0.35); Test (a) with 33rd and 66th percentiles result in thresholds for solar CF at 0.16 and 0.19, for wind CF at 0.20 and 0.3; Test (b) uses a lower low-to-moderate for solar CF at 0.10; Test (c) uses a higher moderate-to-high threshold for wind CF at 0.40; Test (d) uses ERA5 climatology-only for abundance calculation and 33rd and 66th percentile for thresholds. The greatest absolute changes in each test are shown in **bold**.

Zone	Baseline	(a) 33rd & 66th pctile	(b) Solar CF 0.10, 0.20	(c) Wind CF 0.25, 0.40	(d) ERA5 climatol- ogy
A	14.1	17.2 (+3.1)	23.5 (+9.4)	14.6 (+0.5)	19.6 (+5.5)
W	22.7	27.9 (+5.2)	0.2 (−22.5)	18.5 (−4.2)	28.2 (+5.5)
Ws	10.4	6.2 (−4.2)	19.6 (+9.2)	6.7 (−3.7)	8.8 (−1.6)
S	33.1	25.9 (−7.2)	48.8 (+15.7)	37.3 (+4.2)	26.4 (−6.7)
Sw	7.0	11.8 (+4.8)	7.7 (+0.7)	11.3 (+4.3)	10.5 (+3.5)
P	12.9	11.0 (−1.9)	0.1 (−12.8)	11.6 (+1.3)	6.6 (−6.3)

Table A2 Statistics of renewable zones by main group and subgroup. Percentage of land area of subgroups in the renewable zone classification

Zones	Subgroup	Percentage	Main group
A	A	3.8	14.1
	A_L	3.9	
	A_V	4.0	
	A_VL	2.4	
P	P	5.5	12.9
	P_L	7.4	
S	S	11.8	33.1
	S_L	3.3	
	S_V	15.3	
	S_VL	2.7	
Sw	Sw	1.2	7.0
	Sw_L	2.5	
	Sw_V	1.9	
	Sw_VL	1.4	
W	W	6.0	22.7
	W_L	6.4	
	W_V	1.7	
	W_VL	8.6	
Ws	Ws	3.5	10.4
	Ws_L	3.4	
	Ws_V	1.4	
	Ws_VL	2.1	

Table A3 Countries with poor-both and high demand areas. List of 78 countries with ‘Poor both high demand’ subgroup (% red area), sorted by decreasing percentage of this subgroup to the country’s size, and their average attributes (latitude, elevation, precipitation). Horizontal lines are shown for countries with a percentage higher than 50%, 25%, and 10%.

#	Country	Lat.	Elev. [m]	Precip. [m/yr]	Grid cells	% red area
1	Slovenia	46.12	519.92	1.26	36	88.89
2	Slovakia	48.83	525.42	0.89	91	81.32
3	Switzerland	46.90	1176.78	1.63	86	77.91
4	Bosnia and Herz.	44.40	628.12	1.11	91	74.73
5	Ecuador	-1.24	956.18	3.60	326	72.39
6	Austria	47.50	972.52	1.34	167	66.47
7	Croatia	45.54	222.90	0.95	106	65.09
8	Serbia	44.13	425.89	0.82	136	61.03
9	Romania	46.42	579.21	0.91	440	57.27
10	Czechia	49.74	428.23	0.79	166	57.23
11	Vietnam	20.34	486.10	2.12	455	54.29
12	Hungary	47.36	169.82	0.72	174	48.28
13	Japan	37.63	420.43	1.82	658	48.18
14	Taiwan	23.88	1013.62	3.40	51	45.10
15	Bhutan	27.18	1978.21	3.95	58	43.10
16	Georgia	42.59	1319.18	1.65	118	38.98
17	Gabon	-1.23	272.52	2.49	352	34.94
18	Montenegro	43.09	1230.47	1.24	24	33.33
19	Germany	49.08	454.83	1.00	726	29.61
20	Panama	8.78	455.92	3.42	99	23.23
21	China	29.01	626.31	1.52	15269	23.17
22	Solomon Is.	-9.29	287.69	4.47	33	21.21
23	Papua New Guinea	-6.61	1044.70	5.06	592	20.61
24	Costa Rica	10.02	919.61	3.20	73	20.55
25	Belarus	53.42	154.52	0.73	454	20.04
26	France	45.80	407.20	1.10	1164	19.76
27	Kosovo	42.81	934.64	0.95	21	19.05
28	Indonesia	-0.88	470.25	3.53	2380	18.32
29	Congo	-3.42	354.27	1.77	446	17.49
30	Laos	19.97	979.99	1.78	312	17.31
31	Colombia	4.11	1220.55	6.09	1504	16.22
32	Eq. Guinea	1.55	182.31	3.38	38	13.16
33	Italy	45.97	1255.38	1.63	559	11.81
34	Fiji	-18.00	348.41	2.48	26	11.54
35	Peru	-8.96	1691.78	3.17	1731	11.09
36	Malaysia	2.63	259.00	3.34	438	10.27
37	Sweden	62.75	301.83	0.77	1275	9.65
38	Philippines	11.24	473.09	3.52	393	9.41
39	New Zealand	-41.23	510.83	2.51	480	9.38
40	Norway	60.64	504.00	1.13	1392	8.84
41	Bulgaria	43.03	675.79	0.91	193	8.81
42	Ukraine	49.40	432.51	0.94	1133	8.47
43	Poland	50.44	348.08	0.91	655	8.09
44	Russia	56.97	298.74	0.71	46826	7.80
45	Myanmar	26.80	1402.39	4.27	939	6.50
46	Armenia	40.92	1351.52	0.83	49	6.12
47	Azerbaijan	40.69	548.55	0.82	156	5.77
48	Turkey	41.07	751.66	1.45	1331	4.96
49	Lithuania	54.18	137.04	0.74	146	4.79
50	India	27.90	1814.84	4.11	4452	3.19
51	New Caledonia	-22.00	365.40	1.80	33	3.03
52	United States	48.35	636.23	1.32	18000	3.00
53	Nigeria	4.93	18.32	2.98	1200	2.83
54	Finland	63.21	127.53	0.76	1025	2.83

Table A3 continued.

#	Country	Lat.	Elev. [m]	Precip. [m/yr]	Grid cells	% red area
55	Canada	51.52	997.83	1.18	26220	2.68
56	Spain	43.23	574.05	1.33	849	2.59
57	North Macedonia	41.75	780.22	0.83	42	2.38
58	Chile	-41.33	473.11	2.80	1386	2.24
59	Bolivia	-16.51	1747.35	3.40	1470	1.90
60	Albania	42.50	1386.87	1.98	53	1.89
61	Moldova	47.50	156.42	0.58	63	1.59
62	Iran	36.99	610.03	1.50	2489	1.49
63	Nepal	27.42	2557.72	4.67	223	1.35
64	Venezuela	8.36	1502.17	2.88	1185	1.18
65	Cameroon	4.38	247.17	4.08	599	1.00
66	Kazakhstan	49.99	897.80	0.99	5291	0.93
67	Dem. Rep. Congo	-5.15	336.10	1.51	3033	0.76
68	Brazil	-25.82	424.54	2.03	11370	0.71
69	Latvia	56.50	64.56	0.79	148	0.68
70	Uganda	0.38	1777.82	4.76	318	0.63
71	Nicaragua	11.00	139.22	3.47	173	0.58
72	Angola	-5.25	130.98	1.53	1658	0.42
73	Thailand	8.88	259.78	2.34	686	0.29
74	Côte d'Ivoire	5.50	47.79	1.91	432	0.23
75	Madagascar	-15.50	388.34	3.42	810	0.12
76	Australia	-40.12	392.76	1.32	11138	0.05
77	Mexico	17.25	172.40	3.24	2804	0.04
78	Argentina	-23.25	1694.60	3.11	4461	0.02

(a) Cluster statistics

Table A4 Cluster characteristics and country membership. Clusters defined in Fig. 4. (a) Average value of each component (normalised) per cluster. (b) Countries belonging to each cluster; those mentioned in the main text are in bold.

Average (normalised)	Cluster I: abundant resources, transmission-bound	Cluster II: moderate resources, mild mismatch	Cluster III: good resources, highly constrained	Cluster IV: co-located but low resources
Resource quality	0.81	0.38	0.66	0.26
Storage	0.28	0.28	0.68	0.35
Resource-demand correlation	-0.26	-0.03	-0.31	0.53

(b) Cluster membership

Cluster	Countries
Cluster I: abundant resources, transmission-bound	Algeria, Argentina, Australia, Botswana, Canada, Chad, Chile, Egypt, Ethiopia, Finland, Germany, Greenland, Iceland, Ireland, Kazakhstan, Libya, Mali, Mauritania, Namibia, New Zealand, Niger, Norway, Poland, Saudi Arabia, Somalia, South Africa, Sudan, Turkmenistan, United Kingdom, United States , Uruguay, Uzbekistan, Yemen, Zambia, Zimbabwe, Belgium, Denmark , Dominican Republic, Estonia, Latvia, Lithuania, Netherlands
Cluster II: moderate resources, mild mismatch	Angola, Bahamas, Belarus, Bolivia, Brazil, Cameroon, Central African Republic, Colombia, Democratic Republic of the Congo, Ecuador, Fiji, France, Gabon, Greece, Japan, Kenya, Madagascar, New Caledonia, Nicaragua, Nigeria, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Republic of the Congo, Romania, Russia, Solomon Islands, South Korea, South Sudan, Spain , Sweden, Tanzania, Ukraine, Vanuatu, Venezuela, Vietnam, Austria, Benin, Bhutan, Bosnia and Herzegovina, Bulgaria, Burkina Faso, Croatia, Czechia, Guyana, Haiti, Honduras, Hungary, Israel, Jamaica, Kyrgyzstan, Laos, Malawi, Moldova, North Korea, Puerto Rico, Samoa, Serbia, Slovakia, Suriname, Switzerland, Togo, Trinidad and Tobago, Uganda
Cluster III: good resources, highly constrained	Afghanistan, China , Iran, Iraq, Mongolia, Morocco, Oman, Pakistan, Tunisia, Belize, Nepal, Syria, Tajikistan, United Arab Emirates
Cluster IV: co-located but low resources	Cuba, Côte d'Ivoire, Ghana, Guinea, India , Indonesia, Italy , Malaysia, Mozambique, Myanmar, México, Panama, Senegal, Sri Lanka, Thailand, Turkey, Albania, Azerbaijan, Bangladesh, Brunei, Cambodia, Costa Rica, Cyprus, El Salvador, Equatorial Guinea, Eritrea, Georgia, Guatemala, Guinea-Bissau, Liberia, Malta, Qatar, Sierra Leone, Timor-Leste

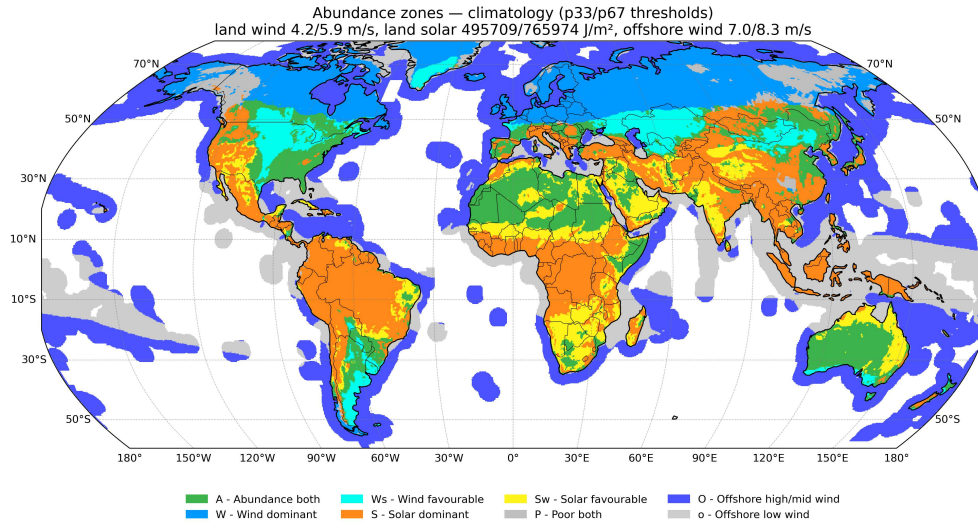


Fig. A1 Renewable zone abundance using ERA5-only climatology. Data variable for solar (surface shortwave downward radiation) and wind speed at 100m have thresholds of 33rd and 67th quantiles. Compared to using the Global Wind and Solar Atlases (Fig. 1 and Extended Data Fig. A3a), the result shows smoother renewable zones, e.g., in dry climate zones in the Sahara, Australia, in complex mountainous terrain, e.g., the Tibetan plateau; stronger abundance of solar resources in Eastern China, of wind resources, e.g., in Eastern South America, Southern Africa. Northern regions such as North Canada and Greenland show lower solar potential compared to Fig. 1, Extended Data Fig. A3a.

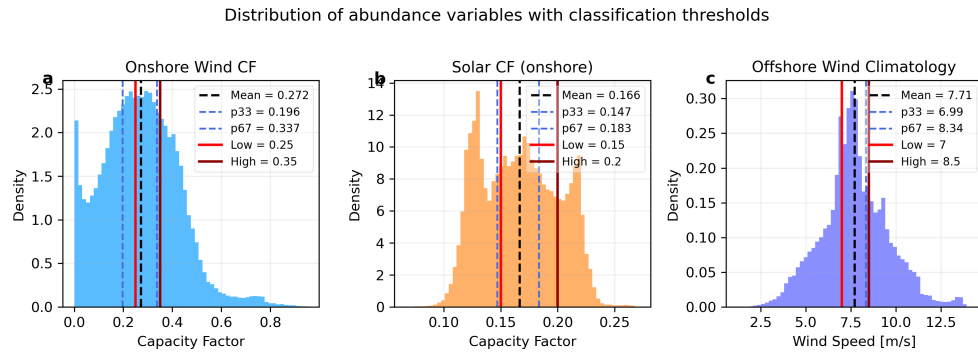


Fig. A2 Distribution of abundance values. Histograms frequency distribution of solar and wind (onshore and offshore) abundance globally for 1995-2025. The thresholds for renewable classifications (Table legend in Fig. 1) are selected partially to reflect the 33rd and 67th percentiles. One exception is wind power onshore, which has a higher threshold of 0.25 (low—mid) to reflect the industry's standard to be economically feasible.

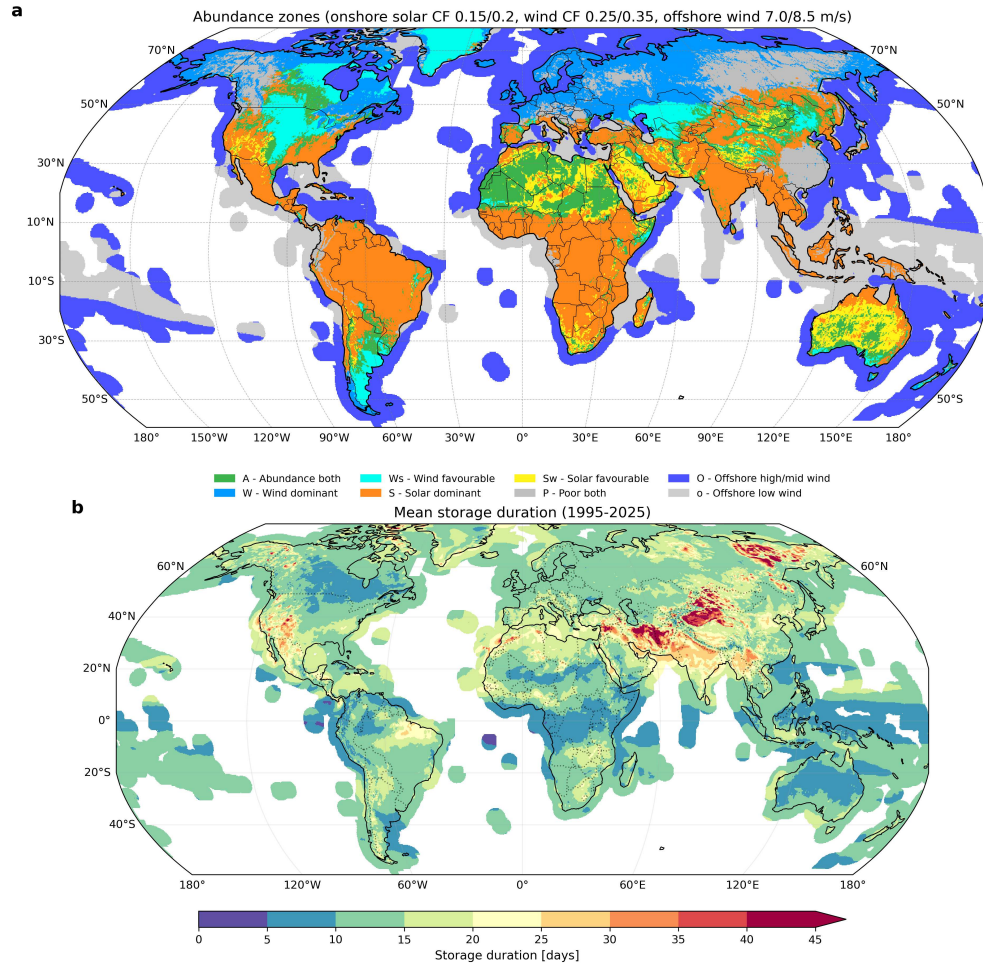


Fig. A3 Maps of abundance and storage components separately. Maps with two components in Köppen renewable zones. (a) Resource abundance (same thresholds as in Fig 1, see statistics in Extended Data Table A1,A2); (b) Storage duration required to keep a constant supply annually with an optimally mix wind/solar source, average 13 days with range 3—88 days. Colourbar shows an increment of five days up to 45 days for clearer differentiation for most areas. Long-duration storage (14 days or longer) accounts for 48% of the onshore area and 30% of the offshore area.

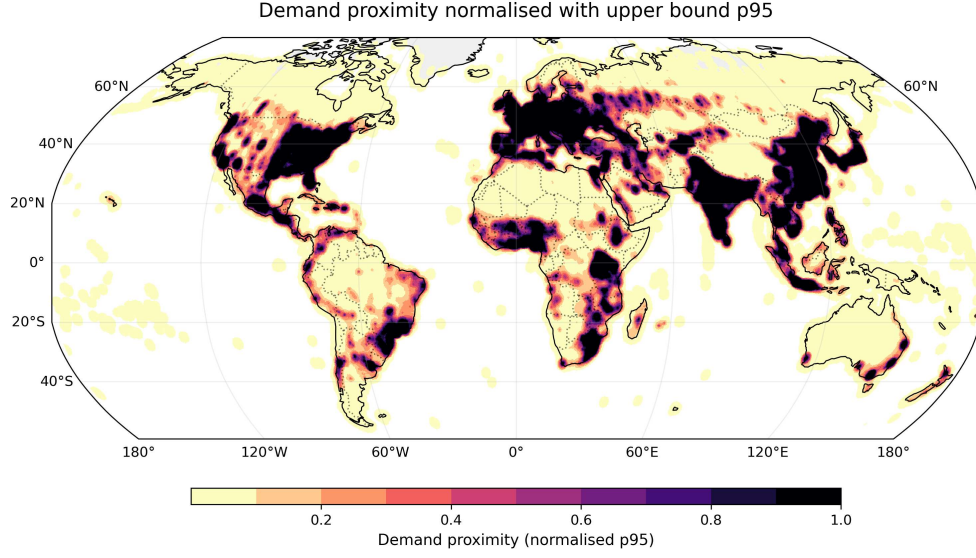


Fig. A4 Map of the demand component. Demand proximity normalised with 95th percentile to reduce the skewness.

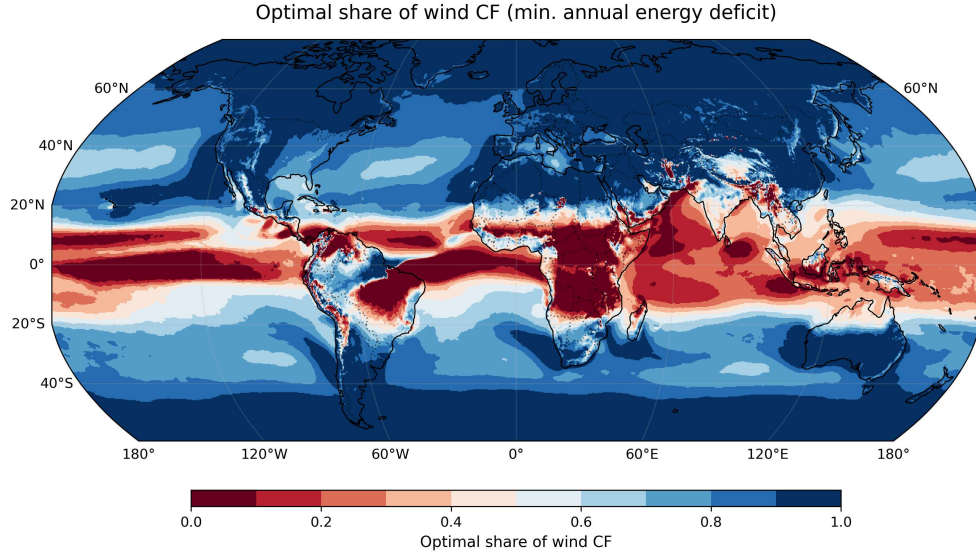


Fig. A5 Optimal share of wind power to minimise storage duration. Optimal share of wind in the mix wind + solar (normalised) to minimise the average annual energy deficit over the period 1995—2025. The optimal wind share reveals strong latitudinal gradients, with equatorial regions (20°N/S) favour solar-dominated systems (alpha < 0.2) due to ITCZ-suppressed winds; mid-latitudes (30–40°N/S) favour balanced mixtures (alpha 0.4–0.6), reflecting seasonal complementarity between summer solar and winter wind maxima; high latitudes (>40°N) favour wind-heavy systems (alpha > 0.8) where low solar elevation angles reduce photovoltaic output.

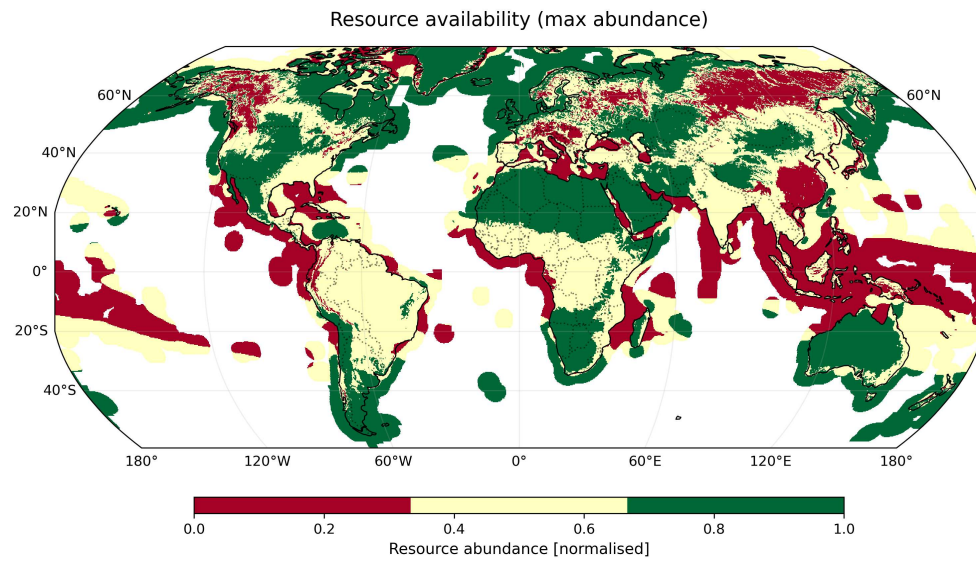


Fig. A6 Resource quality metric. Resource quality based on the higher value of abundance from wind or solar (high: 3, medium: 2, low: 1, from Fig. 1), then normalised to a range of 0 to 1.

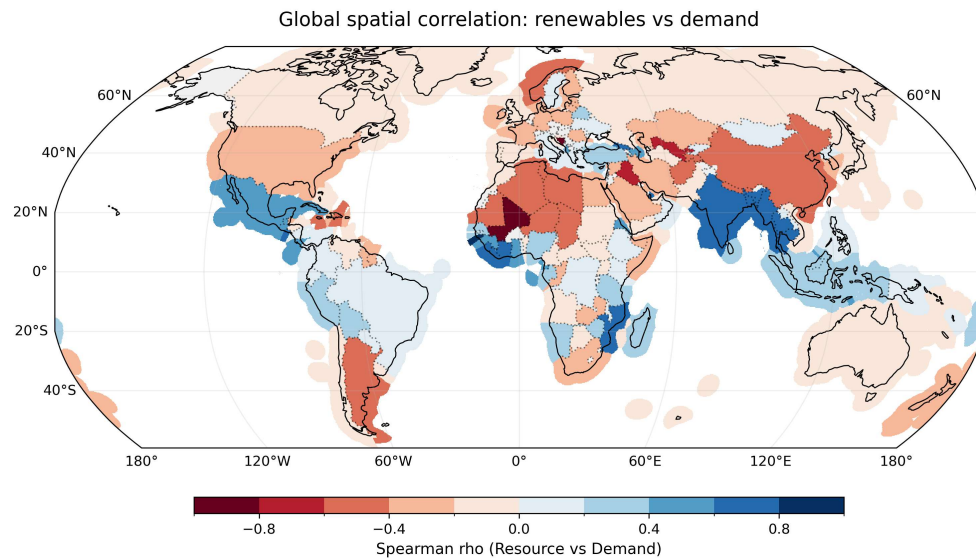


Fig. A7 Resource–demand spatial correlation by countries. Spearman ranking spatial correlation between resource availability and demand proximity by countries.

Renewable zone composition by cluster

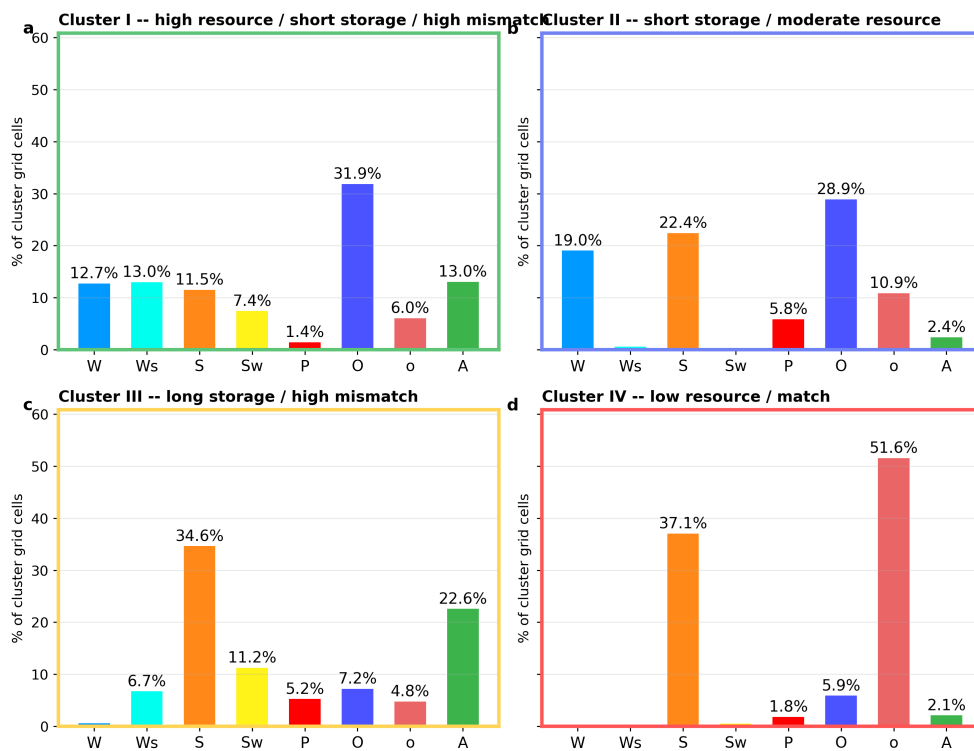


Fig. A8 Renewable zone distribution in four country clusters. Renewable zones in each cluster in Fig. 4 and Table 1. Renewable zones are shown with the same colour scheme as Fig. 1 main groups (A: abundant-both, W: wind-dominant, Ws: wind-favourable, S: solar-dominant, Sw: solar favourable, P: poor-both, O: high-mid offshore wind, o: low offshore wind).

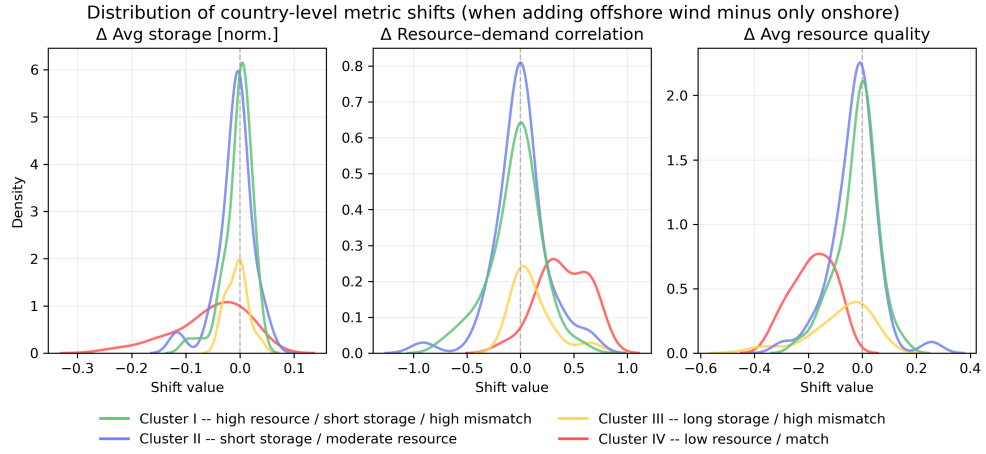


Fig. A9 Effect of adding wind offshore. Effects on three metrics of clustering countries when adding offshore wind, compared to considering only onshore resources.

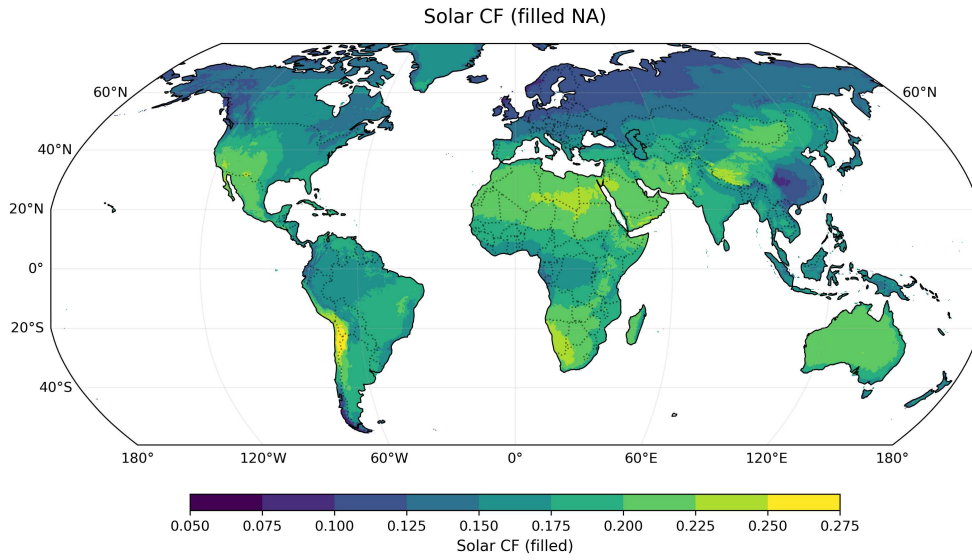


Fig. A10 Solar capacity factor after filling missing values. Global solar capacity factors after filling missing values from the Global Solar Atlas [6] above 60°N, using 2D linear regression with least-squares solution trained on two climate variables: solar radiation and temperature, see Methods.

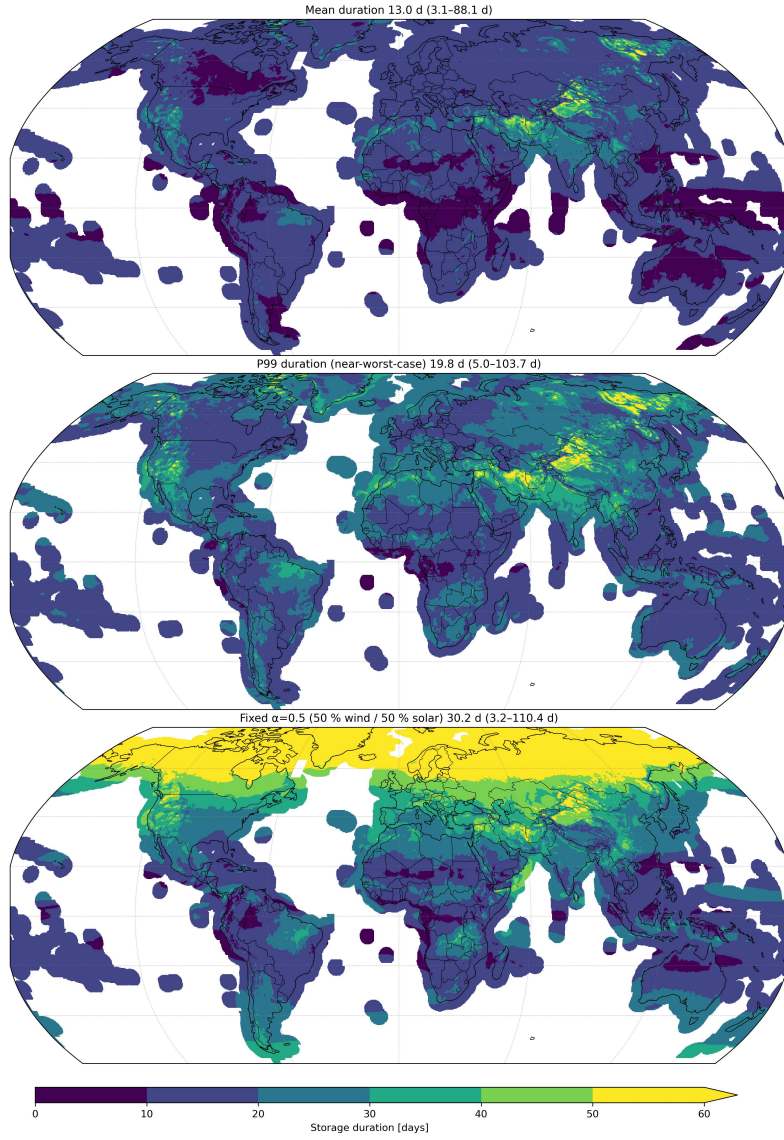


Fig. A11 Storage duration with different minimising criteria. Storage duration when minimising energy deficit considering the mean value (a), p99 duration (b) and a fixed ratio of 50% wind (c), with the mean value of storage duration (days) and their range in parentheses (minimum and maximum) for each experiment.

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