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Designing low-carbon power systems for Great Britain in 2050 that are robust to the spatiotemporal and inter-annual variability of weather

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The design of cost-effective power systems with high shares of variable renewable energy (VRE) technologies requires a modelling approach that simultaneously represents the whole energy system combined with the spatiotemporal and inter-annual variability of VRE. Here, we soft-link a long-term energy system model, which explores new energy system configurations from years to decades, with a high spatial and temporal resolution power system model that captures VRE variability from hours to years. Applying this methodology to Great Britain for 2050, we find that VRE-focused power system design is highly sensitive to the inter-annual variability of weather and that planning based on a single year can lead to operational inadequacy and failure to meet long-term decarbonization objectives. However, some insights do emerge that are relatively stable to weather-year. Reinforcement of the transmission system consistently leads to a decrease in system costs while electricity storage and flexible generation, needed to integrate VRE into the system, are generally deployed close to demand centres.

The Paris Agreement of the United Nations Framework Convention on Climate Change sets out the goal of limiting global average surface temperature rise to well below 2 °C and to pursue efforts to limit it to 1.5 °C above pre-industrial levels[1]. Consequently, the world is looking to clean, renewable energy solutions[2]: transforming the energy system[3] from being carbon-intensive and inefficient[4] to deeply decarbonized[5], highly efficient[4] and, to a large extent, renewable[5]. The power sector is leading the decarbonization charge[6] and by 2050 low- or zero-carbon electricity could expand to become the dominant form of energy supply[7]. Renewable energy systems are characterized by the spatial and temporal variability of supply and critics therefore point to the potentially high integration costs[2]. Important methods to manage renewable intermittency are to integrate different renewable technologies into the system (technological diversity) and to take advantage of the fact that contemporaneous weather conditions can differ from one location to the next by spreading VRE deployment over a large geographical area (spatial diversity). By combining VRE production from different sources at different locations, the variance in their output can be significantly reduced[8,9]. To facilitate such a system, the existing high-voltage transmission network has to be reinforced or expanded. Electricity storage[10,11], flexible generation[10] and demand-side measures[12] are other options to manage the intermittency of VRE.

To provide detailed insights into the transition to a power system with high shares of VRE, we need to combine long-term planning with a representation of the spatial and temporal variability of VRE, including the inter-annual characteristics of VRE production and their integration options. Energy system models (ESMs) allow us to: understand trade-offs between different sectors as well as the necessary mitigation burden placed on the power sector to reach a given carbon target; and consider investment pathways of technologies (that is, build rates of technologies, and technology choice in previous years)[13]. ESMs trade off spatial and temporal resolution to provide long-term pathways for the entire energy system but it has been shown that the level of spatial[14], temporal[15,16] and technical[15] detail affects results in systems with a considerable amount of VRE[17]. Broadly speaking, in the literature there are two main approaches taken to address the challenge of modelling long-term energy systems with significant shares of VRE. The first such approach is the improvement of the temporal[18–21] resolution or time-slice representation[13,22], spatial resolution[14], technical detail[23] or VRE representation via a stochastic approach[24] in ESMs. Second, other studies recognize that a combination of models can better represent the long-term integration of variable renewable energy sources into the power system: refs [25–27] soft-link an ESM to a temporally detailed power system model (PSM), ref. [28] hard-links a long-term model with a dispatch model (for a number of representative days per year), ref. [29] combines a deterministic planning optimization module with a Monte Carlo simulation of system operation, ref. [30] links a bottom-up accounting framework to a high-resolution PSM. It is worth noting that temporally and spatially explicit PSMs[31–38], which allow for a good representation of VRE, have been developed but do not provide whole energy system consistency. Further, by averaging multiple years or using a single weather-year most of these studies neglect the inter-annual variability of weather. Ref. [35] does study multiple years but only at a daily time step and ref. [39] captures the effect of inter-annual variability on VRE generation but not its optimal spatial deployment pattern. The most comprehensive approaches regarding time resolution and inter-annual variability are refs [38,40] in which the system is optimized over several weather-years individually but not over the contiguous time series.

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In this study, we combine the following key aspects that are important in understanding the design of future energy systems with high shares of VRE and ultimately achieve long-term decarbonization targets: a representation of the inter-annual variability of weather and its effect on system planning and VRE supply; the spatial and temporal detail necessary to account for differences in VRE output and timing of production, demand and infrastructure; modelling of the trade-offs and interaction of different VRE integration options; and a whole energy systems view to consider the electrification of other sectors and an internally consistent assessment of the mitigation burden placed on the electricity sector (see Supplementary Note 12 for a literature review). We demonstrate this by using a modelling approach that soft-links a long-term ESM (UKTM) to a high-spatial-resolution and high-temporal-resolution PSM (highRES) (see Methods). We apply our modelling approach to Great Britain, a country with limited interconnection (7% of peak demand) and where national energy security is a high public and political priority[41]. Our results show that the inter-annual variability of weather substantially affects the planning and operation of power systems with medium and, in some respects even more so, high shares of VRE but consistent patterns do emerge. If additional flexibility (for example, on the demand side) is unavailable, we find that systems planned on the basis of one weather-year can lead to operational inadequacy and failure to meet long-term carbon targets placed on the sector as part of the decarbonization of the whole energy system.

Soft-linking modelling approach

Our modelling approach soft-links a long-term ESM (UKTM) to a high-spatial-resolution and high-temporal-resolution PSM (highRES). For details, see Methods. Applying this approach to Great Britain, we use the ESM to develop internally consistent, whole energy system scenarios that both meet the UK's Climate Change Act 2008[42] (that is, a reduction of greenhouse gas (GHG) emissions of 80% relative to 1990 levels by 2050) and have high penetration of VRE. The ESM sets the boundaries on the electricity system (that is, total electricity demand, generation capacities and CO_2 grid intensity constraint) as an input to the PSM that uses ten years of weather data to capture and explore the inter-variability of weather conditions. In our methodology, we aim at a balanced approach between spatiotemporal resolution, temporal coverage (that is, how many weather-years we consider) and technical detail (that is, focusing on system adequacy and using a simplified grid representation). We give the PSM transmission grid extension, storage and flexible gas generation as VRE integration options. We choose not to include demand-side measures as the large-scale implementation in the domestic and non-domestic sector and further uptake for industry are uncertain[12,43,44] due to the inherent challenges around behaviour change facing non-cost barriers[33,45] and as a result studies and data on costs are limited[46], even more so from a spatial distribution perspective (see Supplementary Note 9). However, like the system operator National Grid in its modelling[47], we follow the recommendation[48] by the UK government (Office of Gas and Electricity Markets and the Department for Business, Energy and Industrial Strategy) and implement load-shedding at a cost set to the value of lost load of £6,000 MWh^{-1}. We use the PSM to study the sensitivity of system planning and operation due to inter-annual weather variability by using ten different weather-years to drive VRE production. We also compare these results to when our PSM considers a ten-year continuous time series.

LCOE, emissions and capacities of VRE integration options

Table 1 shows the power system designed by the ESM for 2050 for a scenario with 50% (50VRE) and 80% (80VRE) of generation from VRE sources.

Table 1 | Historic and 2050 modelled power system characteristics

Parameter	2015	2050 50VRE	2050 80VRE
Gas capacity (GW)	32[a]	Decided by highRES	Decided by highRES
Coal capacity (GW)	21[a]	0	0
Nuclear capacity (GW)	9[a]	34	12.4
Solar PV capacity (GW)	10[b]	44	50
Onshore wind capacity (GW)	9[b]	32	27
Offshore wind capacity (GW)	5[b]	39	68
Biomass capacity (GW)	5[b]	7	0.4
Interconnection capacity (GW)	5[c]	6	3.6
Storage capacity (GW)	3[c] (pump storage)	Decided by highRES	Decided by highRES
Hydropower capacity (GW)	2[b]	2	1.6
Other capacity (GW)	1[a,c]	0.5	0.5
Electricity demand (GWh)	358,363[d]	516,882	416,757
CO_2 grid intensity (gCO_2 kWh^{-1})	334[e]	4.4	4.9

[a]Ref. [68]; [b]ref. [69]; [c]ref. [70]; [d]ref. [71]; [e]ref. [72]. 50VRE and 80VRE scenarios are based on UKTM unless otherwise indicated.

For each scenario, we study two different cases in highRES: optimizing all three flexibility options (allflex); and optimizing only flexible generation and storage and we fix the transmission network to its 2015 capacities (flex + store). We differentiate between these two scenarios as, on the one hand, transmission line extension can take decades from conception to completion, with the planning system being a fundamental barrier[49], yet on the other hand it can unlock the benefits of greater spatial diversification. For each scenario and case, we allow the model to make investment and operational decisions based on 1 year of weather data at a time and 10 years simultaneously; that is, system capacities and dispatch are planned over snapshots of 8,760 hours (8,784 hours for leap years) in the former and 87,648 hours in the latter. This allows us to analyse the difference in optimal system configurations when planning for a single weather-year and when considering the full variability of 10 years.

In terms of generation it is worth noting that for our system nuclear power functions as the base load with VRE generation fluctuating on top of that base to meet demand. Excess production is either being used to permit the daily cycling of storage or curtailed. Periods of low VRE generation are covered by flexible natural gas generation (see Supplementary Figs. 12–16).

Figure 1 shows the distribution of the levelized cost of electricity (LCOE) and grid CO_2 intensity in our individual-year runs (that is, one year of weather data at a time), and the runs that consider all 10 weather-years simultaneously for both our VRE generation scenarios. These results demonstrate that inter-annual weather variability leads to a spread in system LCOE that is seen to increase at higher renewable penetration. That is, 'poor' weather-years lead to greater flexibility costs both in terms of capacity and utilization while the opposite is true for 'good' weather-years. This sensitivity increases with a greater share of VRE.

For both scenarios, the allflex case has significantly (Kolmogorov–Smirnov test, P value < 0.01; hereafter, this is our definition of a

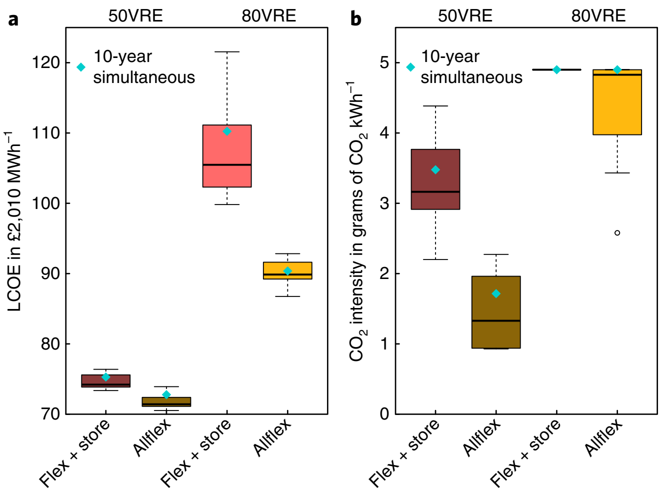

Fig. 1 | Distribution of LCOE and CO_2 emissions for both scenarios and cases using the ten different weathers-years. a, Boxplots showing the spread in LCOE over the ten weather-years. Dark/light red for the flex + store case 50VRE/80VRE scenarios, respectively; dark/light yellow for the allflex case 50VRE/80VRE scenarios, respectively. **b**, Boxplots showing the spread in CO_2 emissions over the ten weather-years. Dark/light red for the flex + store case 50VRE/80VRE scenarios, respectively; dark/light yellow for the allflex case 50VRE/80VRE scenarios, respectively. The back line in the middle of the box represents the median. The box spans the first quartile to the third quartile (the interquartile range). The whiskers extend up to 1.5 times the interquartile range from the top or bottom of the box to the furthest datum within that distance. Data beyond that distance are represented by circles (outliers). The cyan diamonds show the results from the runs that consider ten years simultaneously.

significant result) lower LCOE than the flex + store, indicating that this result is robust to the weather variability sampled here. In the former, greater spatial diversification allows sites with higher output and/or a favourable timing of production to be chosen, leading to lower overall costs. This reduction in LCOE is seen to be greater for higher shares of VRE, underscoring how cost-effective spatial diversification becomes as VRE penetration grows. Finally, the runs considering ten weather-years simultaneously are found to be costlier than the median of the individual years. This is because the system designed for the full ten years is suboptimal for each individual year, leading to higher investment and operation costs and, in the right panel, higher grid CO_2 intensity.

Figure 1 also shows that system CO_2 intensity changes on the basis of weather-year due to varying utilization of flexible fossil generation. At higher VRE penetration, this generation often reaches the CO_2 intensity limit required for the electricity system to be consistent with the 80% GHG reduction target applied to the whole energy system. Once more, in the vast majority of years, grid intensity is significantly lower (P value < 0.01) in the allflex 50VRE generation runs than that scenario's flex + store case. Here, we can infer that a spatially diversified VRE portfolio leads to a lower utilization of flexible generation.

The key point to take from Fig. 1 is that inter-annual weather variability is shown to drive a substantial spread in key system metrics and, in the case of LCOE, this sensitivity increases with higher VRE penetration.

Figure 2 shows the total national installed capacity of the three flexibility options considered here for both our scenarios in the allflex case (flex + store case in Supplementary Fig. 18). In 50VRE, flexible generation and storage vary by about ±40% while transmission capacities are considerably less sensitive to weather-year, varying by about ±15% and showing a 70% increase relative to 2015 levels. Figure 2 also shows that the capacity credit of VRE (that is, the amount of firm capacity replaced per unit installed) is highly dependent on weather-year (see Supplementary Table 8 for the calculation and capacity credit per scenario and year).

The 80VRE scenario has a greater spread of natural gas and storage capacities than 50VRE and, while the distributions are not statistically different between the scenarios, it is worth remembering that the total demand is lower in the former and so the installed capacity per unit demand is greater. In addition, transmission line capacities are significantly higher in 80VRE, indicating that reinforcement remains a consistent, cost-effective option across the weather-years as VRE shares increase.

In the ten weather simultaneous cases, we see that the capacity of flexible generation is higher than any of the individual years. This occurs for two reasons: its capacity is set by the hours at the peak in the decadal residual load time series combined with the fact that the ten-year system design is sub-optimal for each individual year. The capacities of storage and transmission do not see such a substantial increase. For storage, this is because it is more cost effective for it to be cycled daily to cover diurnal peak load and for low-capital-cost, high-marginal-cost gas to be used to cover all-time peaks in the demand time series and periods of low storage availability due to low VRE output. For transmission, the relatively minor increase is caused by the system design being sub optimal for each individual year.

Spatial deployment of VREs and VRE integration options

In this section, we show where the highRES model locates VRE capacities and VRE integration options. Figure 3 shows the locations of the zones in Figs. 4 and 5.

Figure 4 shows the locations of the VRE capacities for the 80VRE scenario in the allflex and flex + store cases (for the 50VRE scenario, see Supplementary Fig. 17). We find that in the 80VRE scenario, solar energy is mainly deployed in the south where the highest capacity factors are. Onshore wind is consistently located in Scotland, although without additional transmission capacity it is not deployed on Shetland or the Outer Hebrides, and west, south and southwest England. Offshore wind is placed around the North Sea, the south and southwest and in the allflex scenario it is additionally located in Scotland. In both scenarios, wind is spread around the country in sites that balance high average capacity factors with a system beneficial timing of production. However, in the flex + store case, the model is constrained by the current transmission line capacity and thus chooses locations further south, closer to demand.

While consistent deployment patterns emerge, the precise amount of capacity located in each zone is highly sensitive to the inter-annual variability of the weather data. Furthermore, for photovoltaics (PV) and, to a lesser extent, wind capacity deployment outliers are observed in some years. In the case of solar, this occurs because the transmission system is consistently reinforced to move wind-generated electricity down from Scotland and northern England (see Fig. 5) to demand centres in the south. Given this large transmission capacity and the relatively small annual capacity factor differences between southern England (~0.11–0.12) and Scotland (~0.09–0.1), for some years it becomes optimal to build solar further north than would be expected, hence the small number of solar outliers in the flex + store results.

While the installed capacity in a zone is certainly correlated with that zone's annual capacity factor, Supplementary Figs. 19–29 clearly show that the model balances high capacity factors with a system beneficial timing of production (that is, spatial diversification). When running all ten years at once, both cases follow similar deployment patterns to their respective individual-year runs, albeit without choosing any outlier locations. The key point here is that the deployment variability in the individual-year runs is seen to

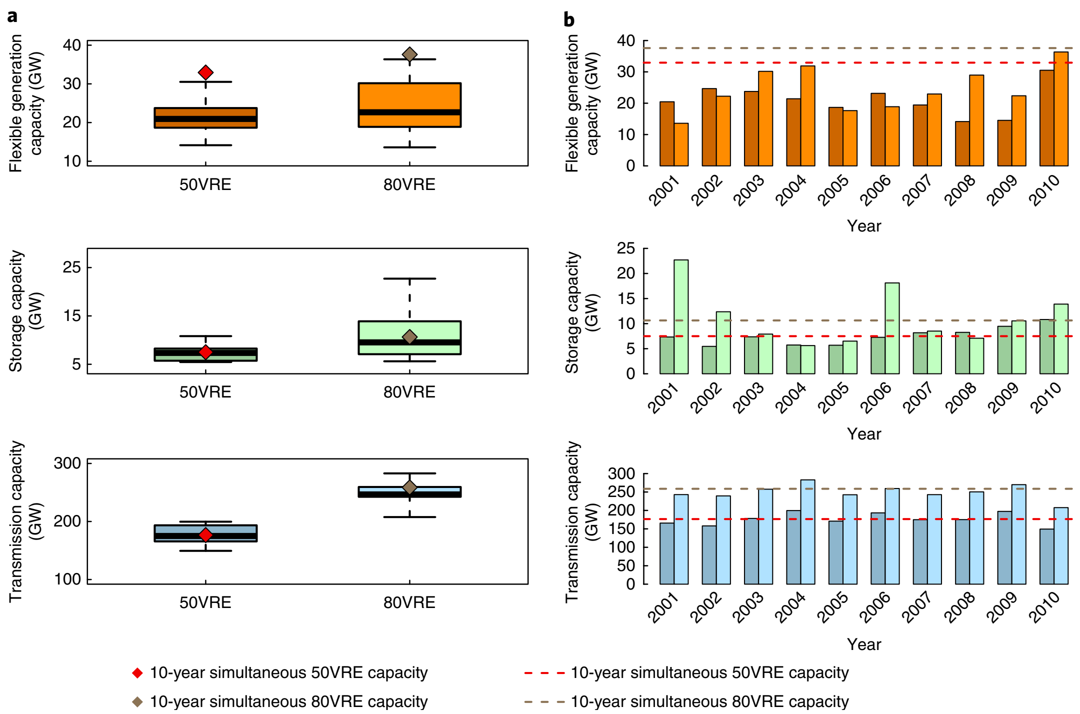

Fig. 2 | National installed capacities of the three VRE integration options for the 50VRE and 80 VRE scenarios allflex case. a, Orange/green/blue boxplots representing the flexible generation/storage/transmission capacity for the ten weather-years; dark orange/green/blue are for the 50VRE and light orange/green/blue are for the 80VRE scenario. **b**, Orange/green/blue bar charts representing the flexible generation/storage/transmission capacity per year; dark orange/green/blue are for the 50VRE and light orange/green/blue are for the 80VRE scenario. The red/brown diamonds and dashed lines show the results for the ten-year simultaneous run for the 50VRE and 80VRE scenario, respectively. For the boxplots, the back line in the middle of the box represents the median. The box spans the first quartile to the third quartile (the interquartile range). The whiskers extend up to 1.5 times the interquartile range from the top or bottom of the box to the furthest datum within that distance.

capture the locations and capacities chosen by the ten-year simultaneous run for both scenarios. However, we note that the capacities deployed in the full decadal runs often do not match the median levels from the box plots shown in Fig. 4.

Figure 5 compares the placement of VRE integration options in the two scenarios for the allflex case. We see that the model places storage mainly around demand centres (with the largest amount of storage typically located in London) and not close to installed VRE capacity (compare Fig. 4 and Fig. 5) in the north, but the exact location is dependent on the weather-year. As one would expect, flexible generation is installed close to demand. The transmission network undergoes a consistent, sizable reinforcement to bring electricity from Scotland to the south, southern England to London and Devon/Cornwall to South Wales. When combined with Fig. 2, this demonstrates that grid reinforcement at the national level is robust to inter-annual weather variability and, as such, is likely to be a low-risk investment option in systems with significant VRE shares. While the spatial pattern is very similar, the level of reinforcement tends to be consistently greater in the 80VRE scenario. Again, the variability of the ten individual years mostly captures the variability in the ten-year simultaneous run.

Basing system design on single weather-years

Given that we have demonstrated the sizable impact the inter-annual variability of weather has on power system design, next we test how planning for a single year affects system operation in other years. For each VRE generation scenario, we identify the most weather-sensitive allflex system configuration (see Methods; 2008 for 50VRE and 2005 for 80VRE) and run it with the remaining nine weather/demand-years. From Fig. 6, we see that both our scenarios have hours where supply does not match demand. The

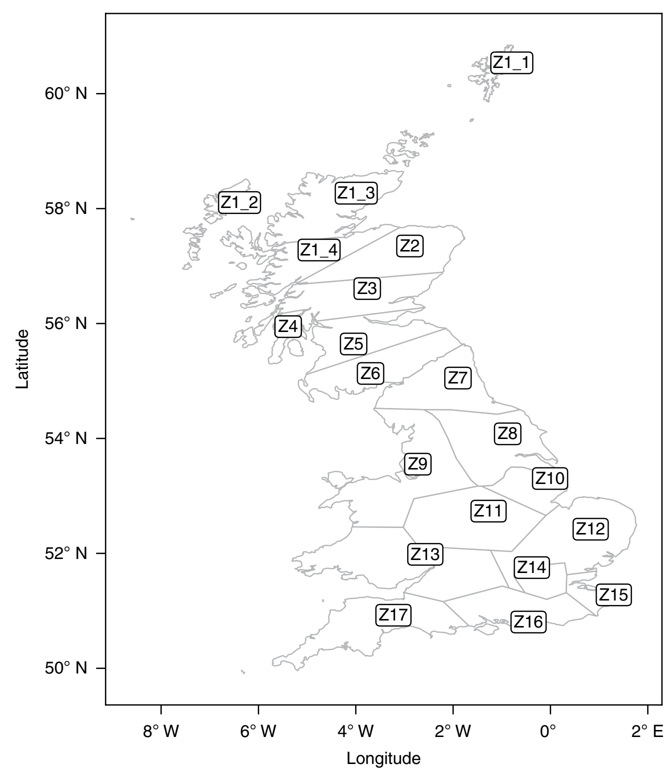

Fig. 3 | Location of zones Zones modelled in highRES based on those used in the National Grid's Seven Year Statements. Following ref. [33] and ref. [73], we split Z1 into four zones (Z1_1, Z1_2, Z1_3 and Z1_4).

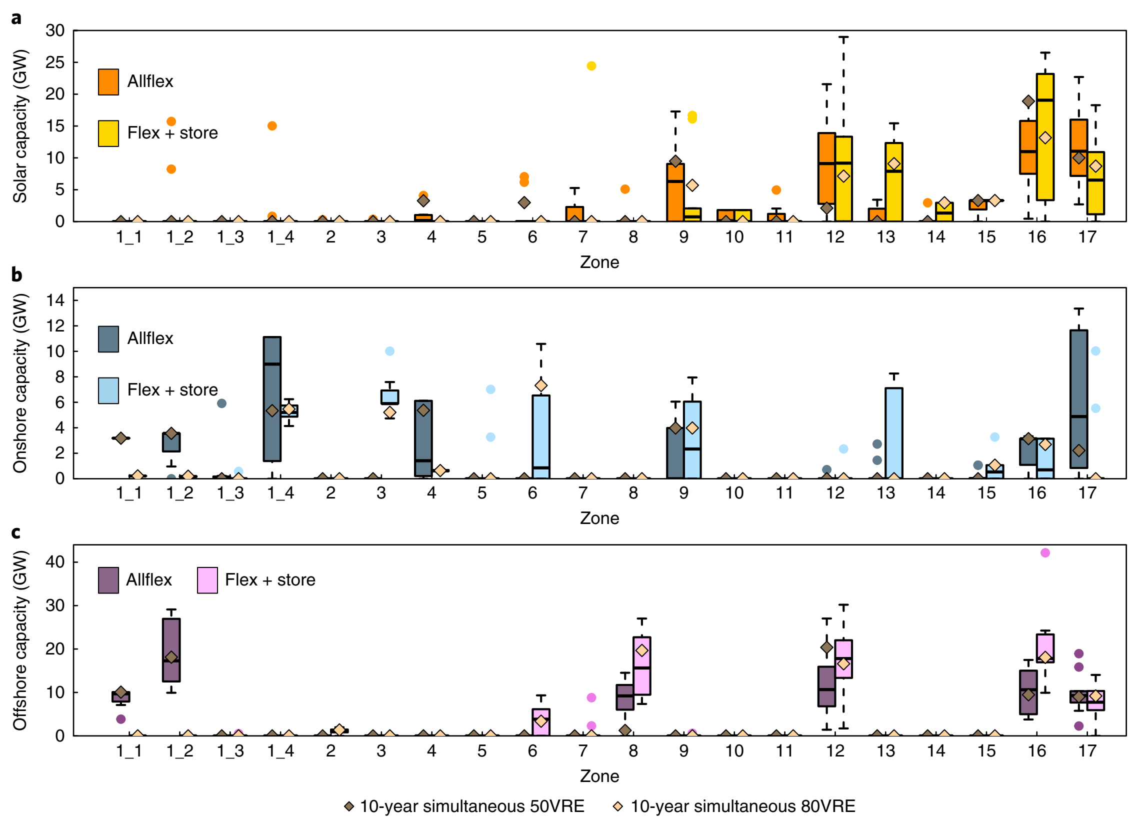

Fig. 4 | Location and capacities of VREs for the 80VRE scenario in the allflex and flex + store cases. a, Solar capacity per zone. The orange boxplots represent the ten-weather-year allflex case; the yellow boxplots represent the ten-weather-year flex + store case. **b**, Onshore wind capacity per zone. The dark blue boxplots represent the ten-weather-year allflex case; the light blue boxplots represent the ten-weather-year flex + store case. **c**, Offshore wind capacity per zone. The dark purple boxplots represent the ten-weather-year allflex case; the light purple boxplots represent the ten-weather-year flex + store case. The brown/beige diamonds represent the capacities resulting from the ten-year simultaneous run allflex and flex + store cases, respectively. See Fig. 3 for the definitions of the zones. The back line in the middle of the box represents the median. The box spans the first quartile to the third quartile (the interquartile range). The whiskers extend up to 1.5 times the interquartile range from the top or bottom of the box to the furthest datum within that distance. Data beyond that distance are represented by coloured circles (outliers).

most weather-sensitive 80VRE system has over 5% of hours with unmet demand ranging up to 33 GW, a substantially higher fraction than the 50VRE case. This is due both to the greater sensitivity of the former to weather and the interaction of that sensitivity with the grid CO_2 intensity limit applied to the system. Here we clearly see that planning VRE-focused systems based on a single weather-year can lead to operational inadequacy and failure to meet long-term carbon reduction targets (see Supplementary Fig. 30) unless further system flexibility is available (for example, on the demand side).

Discussion and insights for policymakers and planners

In this study we have used a methodology that soft-links a long-term whole ESM to a high-spatial-resolution and high-temporal-resolution PSM to understand how the planning and operation of future VRE-focused power systems in Great Britain are affected by inter-annual weather variability. A few caveats of our study need to be highlighted. Our study focuses on the supply side. Demand-side measures apart from load-shedding are not modelled but would be of value to investigate with a similar approach. The model has a simplified representation of system security (that is, system adequacy) and grid representation and not all costs such as start-up costs and distribution line upgrades are represented. To keep the model computationally tractable, we opt for a linear formulation (we do not represent unit commitment) that solves in a feasible time frame given the number of runs we perform: 400 with 8,760/8,784 (leap year) time steps and 4 decadal runs.

We demonstrate the importance of considering inter-annual variability, as it has significant impacts on the design and operation of systems with medium and, in some respects even more so, high shares of VRE. We show that inter-annual weather variability drives a spread in system LCOE, caused by both different optimal total investment and operational costs depending on weather-year, and CO_2 emissions that increase at higher renewable penetration. Furthermore, planning a system based on a decade's worth of variability at once leads to higher total costs and emissions in each individual year of that period than would be expected from the optimal system designs when those years are considered individually.

The key insight here for national policymakers attempting to understand how to achieve long-term economy-wide decarbonization targets, such as that mandated by the UK's Climate Change Act, by transitioning to a highly renewable electricity system is that modelling analyses that use single weather-years may give misleading results. We show that, because such studies neglect the extensive range of weather variability a real-world system would experience, they may design systems that are operationally inadequate and fail to meet carbon targets in line with the long-term decarbonization of the whole energy system. Furthermore, depending on the weather-year chosen, they may also underestimate the costs of meeting emissions targets with the potential extent of the underestimate growing at higher shares of renewables. While we have focused on the UK, the need for such analyses to consider multiple weather-years may

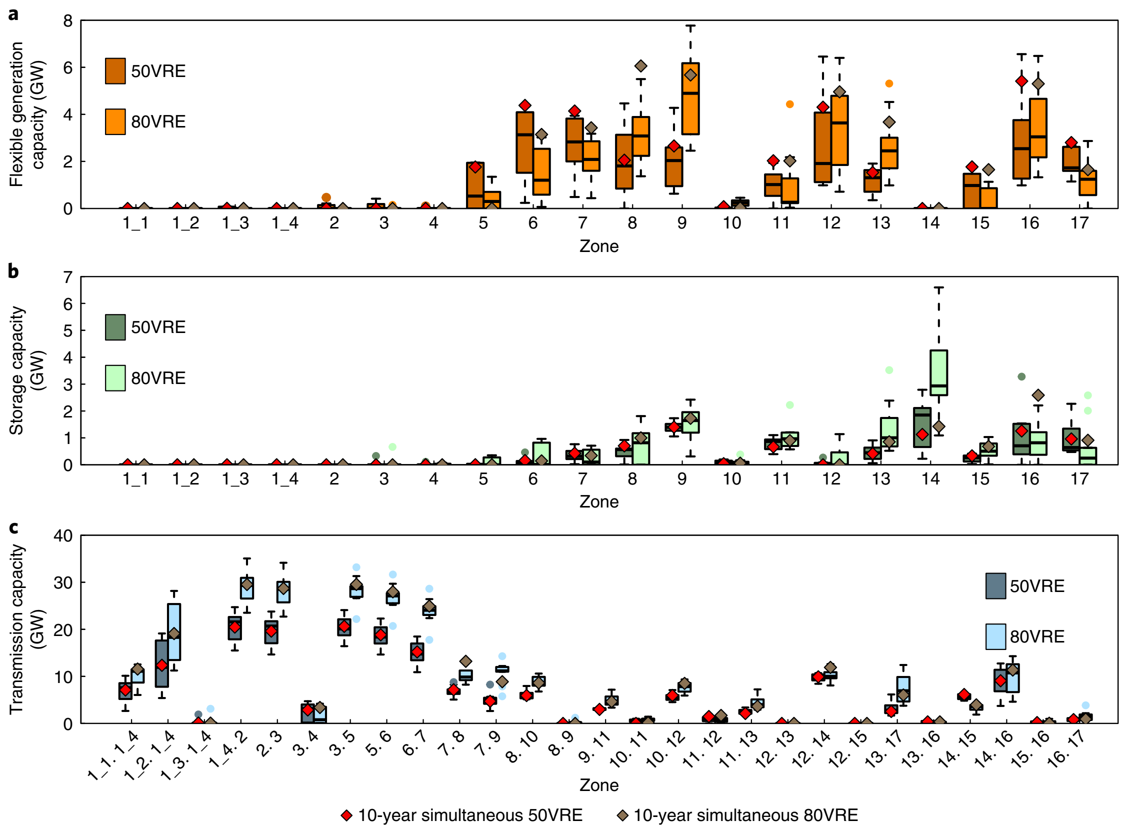

Fig. 5 | Location and capacities of VRE integration options for the 80VRE and 50VRE scenarios allflex case. a, Flexible generation capacity per zone. The dark orange boxplots represent the ten-weather-year 50VRE scenario; the light orange boxplots represent the ten-weather-year 80VRE scenario. **b**, Storage capacity per zone. The dark green boxplots represent the ten-weather-year 50VRE scenario; the light green boxplots represent the ten-weather-year 80VRE scenario. **c**, Transmission capacity per zone. The dark blue boxplots represent the ten-weather-year 50VRE scenario; the light purple boxplots represent the ten-weather-year 80VRE scenario. The red/brown diamonds represent the capacities resulting from the ten-year simultaneous run 50VRE and 80VRE, respectively. See Fig. 3 for the definitions of the zones. The back line in the middle of the box represents the median. The box spans the first quartile to the third quartile (the interquartile range). The whiskers extend up to 1.5 times the interquartile range from the top or bottom of the box to the furthest datum within that distance. Data beyond that distance are represented by coloured circles (outliers).

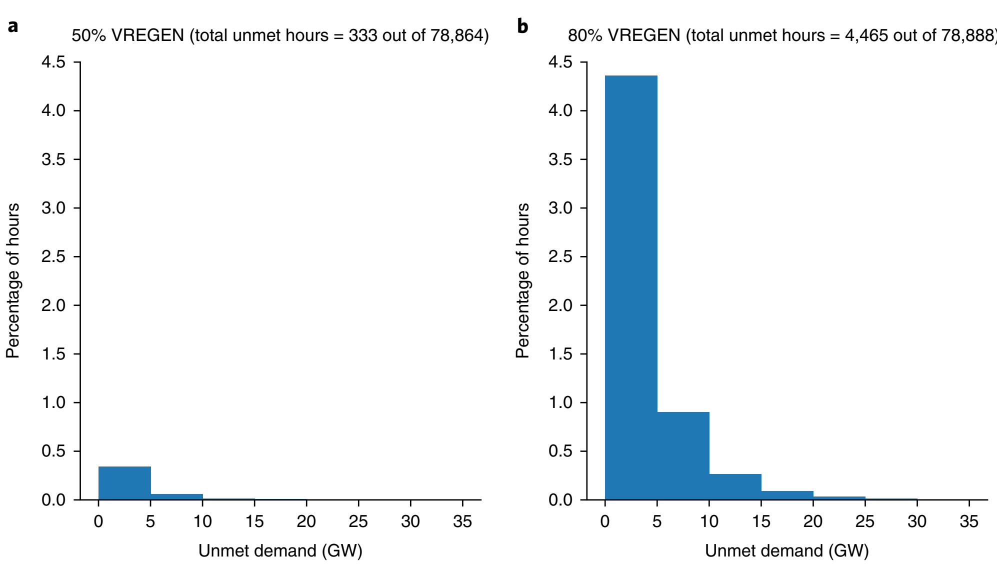

Fig. 6 | Unmet demand hours as a result of planning the power system based on a single weather-year. a,**b**, The percentage of hours where supply and demand do not match as a function of the amount of unmet demand during that hour when planning the power system based on the weather-year 2008 for 50VRE (**a**) and the weather-year 2005 for 80VRE (**b**) and then driving the system with the remaining nine years, one year at a time. In both panels, the entire system design is based on the planning year (for example, the location of generation assets and the location/capacity of integration options) and then fixed for the other years.

be extended to other VRE-reliant power systems that experience significant inter-annual weather variability and do not have access to additional, cost-effective flexibility (for example, on the demand side). This caveat is important to these insights and therefore future work should look to assess the impact of inter-annual weather variability on systems with additional flexibility. From a policy perspective, it is clear that if high shares of VRE are to be a considered an option for the long-term decarbonization of the whole energy system, the implications of inter-annual weather variability must be considered.

For energy planners, our results indicate which elements of a future power system with high shares of VRE are consistent, and so may be considered 'no-regret' investments, and which are sensitive to the variability of the weather from year to year. We observe consistent spatial patterns in the VRE deployment: most solar energy is deployed in the south and wind energy is located around the country to take advantage of high-capacity factors in combination with a diversity in timing of production. However, the precise amount of capacity located in a particular region is found to be highly sensitive to weather-year. While we notice a spread in profitability of the supply options over the weather-years, we observe a consistent revenue gap for most technologies (see Supplementary Figs. 31 and 32). Our study shows that the benefits of transmission line upgrades to move electricity from the north and south/southwest to demand centres are relatively insensitive to weather-year: grid reinforcement significantly reduces LCOE and emissions, capacities are significantly higher with larger shares of VRE and the extent and spatial pattern of reinforcement are all consistent across the weather-years. On the contrary, the capacities of flexible generation and storage required for VRE integration are sensitive to weather-year; however, their typical spatial deployment pattern is less so. It is important to note that in the ten-year continuous run the capacity of flexible generation is higher than in any of the individual years. Flexible generation, which has low capital and high marginal costs, is used to cover peaks in demand and its utilization is highly sensitive to the weather-year (as can be seen from the inter-annual variability in emissions).

To conclude, our findings show that, if power systems with high shares of VRE are to play a key role in the long-term, global decarbonization goal set out by the Paris Agreement, modellers and decision-makers alike must account for their particular system's sensitivity to inter-annual weather variability.

Methods

HighRES model description. The high-spatial-resolution and high-temporal-resolution electricity system model (highRES) minimizes power system costs to meet hourly demand subject to a number of technical constraints. HighRES optimizes the dispatch and locations of power plants as well as the investment and locations of VRE integration options. Other outputs from highRES are total annuitized power system costs, generation per source and emissions. Integration options represented in highRES are flexible generation (modelled as an open-cycle gas turbine), electricity storage (modelled as a NaS battery) and high-voltage transmission grid reinforcement. Constraints are that supply must match demand in every hour and technical constraints describing the ramping of power plants, storage operation, the flow of electricity via the transmission grid and safety margins. Here, we opt for a linear model with simplified technical complexity but with high spatial and temporal resolution and multiple weather-years at full hourly resolution that we feel is suitable for our objectives.

The strong point of highRES is the good representation of VRE. This consists of two parts: a resource assessment and hourly modelling of generation. First, we perform a literature review helping us to define technical, social and environmental exclusion zones (see Supplementary Note 4). For solar energy, we differentiate between rooftop- and ground-mounted plants. Using data on the building area, we calculate the rooftop area in each grid cell. For ground-mounted PV, we exclude nationally protected areas, good agricultural land, built-up areas and areas with a slope greater than 15 degrees. For onshore wind, we exclude nationally protected areas, areas with a slope greater than 15 degrees, cities and a buffer distance around cities of 800 m, 150 m around highways and 5 km around airports. For offshore wind energy, we include areas up to a water depth of 70 m. To capture the spatial and temporal variability of VRE production and simultaneously model its interaction with storage, the transmission system and conventional generation at large scales (that is, at the national or continental level), time series data with sufficiently high spatial and temporal detail and coverage are needed (see Supplementary Note 5). Like a number of recent studies[32,33,35,50–53], we opt to use state-of-the-art global climate reanalysis and satellite-based data, both of which provide a suitable balance between temporal and spatial resolution while simultaneously maintaining broad, homogeneous temporal and spatial coverage. To derive hourly capacity factors for onshore and offshore wind, we use data from the Climate Forecast System Reanalysis of the National Centers for Environmental Prediction[54]. Data are available both onshore and offshore on a uniform grid at $0.5° \times 0.5°$ ($35\,km \times 50\,km$) resolution. We adopt this as our reference grid for the model (see Supplementary Fig. 1). For rooftop- and ground-mounted PV, we use data from the Satellite Application Facility on Climate Monitoring[55]. We convert the data from 2001–2010 into hourly capacity factor. For this study, renewable capacity factors have been aggregated to the zonal level before model execution. As such, highRES decides how much capacity is built in a given zone and that capacity is multiplied by the hourly average zonal capacity factor to get generation.

Demand also varies in time and space. We have performed an analysis to see how weather and electricity demand correlate (see Supplementary Fig. 7). In general, we see no correlation between demand and wind speed or solar irradiance but a weak anti-correlation with temperature. As a result of this analysis, we run the model using the respective demand year to the weather-year. We therefore scale the hourly electricity demand profile from the National Grid for 2002–2010 (2001 is not available and we use the year 2002 for 2001) using the total electricity demand from UKTM for 2050. We have performed a literature review but could not find any studies suggesting a different spatial demand distribution for 2050 compared to today's. We thus disaggregate the demand profiles down to the 20 Seven Year Statement zones (see Fig. 3) used by the National Grid based on shares taken from the National Grid's 2005 GB Seven Year Statement. HighRES matches demand and supply at the zonal level. The zones are connected by a simplified representation of the high-voltage transmission grid. At present, following refs [56–58], who developed a similar model, highRES currently does not consider electricity demand to be price-elastic below the value of lost load of £6,000 MWh^{-1} (following refs [47,48]), at which point load is shed. This is justified from a short-run perspective by ref. [59] that finds the elasticity of electricity demand to be very low. From a long-run standpoint, refs [20–22] argue that this is justified if the average electricity prices between model runs do not vary dramatically. In our case, the average electricity price across 50VRE and 80VRE runs varies by about $\pm 20\%$. Furthermore, we would argue that while demand elasticity may affect the total installed capacity of the flexibility options we consider, it is unlikely to significantly impact the spatial sensitivity of VRE to weather-year that we observe.

A more detailed model description including the equations, data and assumptions can be found in Supplementary Notes 2–9.

UKTM model description. We use the long-time-horizon UK TIMES model (UKTM)[60–63] developed at the UCL Energy Institute as a successor to the UK MARKAL model[19]. In addition to its academic use, UKTM is the central long-term energy system pathway model used for policy analysis at the Department of Energy and Climate Change and the Committee on Climate Change[64,65]. UKTM is a linear, bottom-up, technology-rich cost-optimizing model instantiated within the TIMES framework[60–63]. It minimizes total energy system costs required to satisfy the exogenously set energy service demands subject to a number of additional constraints[66]. UKTM contains 16 time slices: 4 seasons and 4 intraday intervals (day, evening, late evening, night) and one region (UK). The model comprises a time period from 2010 (the base year) to 2050 with one model period covering five years (represented by one representative year). UKTM represents the entire UK energy system from imports and domestic production of fuel resources, through fuel processing and supply, explicit representation of infrastructure, conversion to secondary energy carriers (including electricity, heat and hydrogen), end-use technologies and energy service demands. Generally, it minimizes the total welfare costs (under perfect foresight) to meet the exogenously given, but price-elastic, sectoral energy demands under a range of input assumptions and additional constraints, thereby delivering a cost-optimal, system-wide solution for the energy transition for the coming decades. A key strength of UKTM is that it represents the whole UK energy system under a given decarbonization objective, which means that trade-offs between mitigation efforts in one sector versus another can be explored. The model is divided into three supply-side sectors (resources and trade, processing and infrastructure, and electricity generation) and five demand sectors (residential, services, industry, transport and agriculture). All sectors are calibrated to the base year 2010, for which the existing stock of energy technologies and their characteristics are known and taken into account. A large variety of future supply and demand technologies are represented by techno-economic parameters such as the capacity factor, energy efficiency, lifetime, capital costs, and operation and maintenance costs. Moreover, assumptions are also exogenously provided for attributes not directly connected to individual technologies, such as fuel import prices, resource availability and the potentials of renewable energy sources. UKTM tracks all energy flows as well as CO_2, CH_4, N_2O and hydrofluorocarbon emissions.

Study set-up. For this study we soft-link UKTM with highRES. Comparable studies[25–27,67] use a soft-linking approach with the exception of ref. [28], which hard-links a long-term model with a dispatch model (for a number of representative days per year).

We use UKTM to develop internally consistent, whole energy system scenarios that both meet the UK's Climate Change Act 2008[42] (that is, a reduction of GHG emissions of 80% relative to 1990 levels by 2050), and have high penetration of VRE. We run UKTM with an 80% GHG emission reduction target relative to 1990 levels by 2050 and assume that carbon capture and storage (CCS) is not available. We make this assumption for two reasons. The first reason is to ensure that UKTM designs a power system, and therefore energy system, with high shares of VRE. The second reason is because of the sizable uncertainty around whether CCS will ever feature at scale, particularly in light of the UK government recently cancelling its £1 billion CCS competition. We use this as our first scenario for an internally consistent exemplar of a power system with high shares of VRE for our analysis. As it produces 50% generation from VRE, we call it 50VRE. We then run a second scenario with the same characteristics as the first but also apply a constraint that UKTM must generate a minimum of 80% of electricity from VRE and name it 80VRE.

We use total electricity demand, fuel prices, generation capacities and the CO_2 grid intensity from UKTM as input into highRES. As UKTM is a whole ESM, it sets the boundaries on the electricity system (that is, it determines which sectors get electrified). We combine total annual electricity demand for 2050 from UKTM with historical from National Grid hourly load profiles. We use marginal commodity prices for 2050 from UKTM (that is, the shadow price) as fuel costs in highRES. We take power generation capacities from UKTM as input into highRES. UKTM decides on the grid CO_2 intensity for the power sector to reach an overall 80% GHG emission reduction. Within UKTM there is a parametrization of flexible generation used to integrate VRE into the system. However, here we discard the capacities of flexible generation suggested by UKTM and let highRES decide. HighRES finds the optimal location for generation capacities as well as the optimal capacities and locations of VRE integration options. Supplementary Fig. 10 shows how we soft-link UKTM to highRES.

For the first part of the study, we perform 44 different model runs: using the weather data from 2001–2010 each year at a time and for the whole ten years at once for the two scenarios (50VRE and 80VRE) and two different cases. In the allflex case, highRES can invest into all three integration options; in the flex+storage case, we fix transmission lines to their current capacities and allow the model to invest into only electricity storage and flexible generation. In all runs, highRES is restricted from installing any nuclear, biomass or open-cycle gas turbine capacity in Z14 (London). Nuclear is also prevented from being deployed in northern Scotland.

To test how planning for a single year affects system operation in other years, we need to identify the most weather-sensitive system. We therefore run every combination of planning weather-year and input weather-year for the allflex case of both our VRE generation scenarios (90 model runs per scenario). That is, in these runs all capacities (generation, storage and transmission) and their locations are fixed to the planning weather-year, for example 2001, while VRE generation and demand come from the remaining years 2002–2010, one year at a time. Here, we define system weather sensitivity on the basis of the cumulative number of hours with unmet demand over the remaining nine years. We find 2008 and 2005 to be the most sensitive systems for 50VRE and 80VRE, respectively. Furthermore, it is important to note that the much larger fraction of unmet demand hours in the latter scenario is strongly influenced by the interaction between its weather sensitivity and the grid CO_2 intensity limit applied to the system. This is because the system's sensitivity to weather leads to an increase in the utilization of flexible fossil generation up to a level permitted by the CO_2 intensity constraint and beyond which the demand becomes unmet. We also investigate the impact of reaching long-term emission targets when planning the system on the basis of only one year of weather data. We fix the power system design (capacities and spatial distribution) obtained from each weather-year for the allflex cases and run the model using the 9 remaining weather-years with the CO_2 constraint turned off (90 model runs per scenario) (see Supplementary Fig. 30).

Supplementary Fig. 11 illustrates the study set-up including the number of scenarios, cases, running modes, temporal coverage and number of model runs.

Data availability. The highRES model and UKTM results are available from the corresponding author upon request. The UKTM model will be made publicly available during 2018.

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Author contributions

M.Z. designed the study with J.P. M.Z. and J.P. developed the highRES model. B.F. co-built the UKTM model. M.Z. and J.P conducted the highRES model runs. B.F. and P.-H.L. conducted the UKTM model runs. M.Z. conducted the spatial analysis on the capacity potential per technology, E.S. generated the wind time series; J.P. generated the PV time series. B.F. wrote the text on UKTM; E.S. wrote the text on generating wind time series. M.Z. wrote the document with J.P. and they generated figures and tables.

Competing interests

The authors declare no competing interests.

Additional information

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