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Changes in European wind energy generation potential within
a 1.5°C warmer world

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Abstract

Global climate model simulations from the “*Half a degree Additional warming, Prognosis and Projected Impacts*” (HAPPI) project were used to assess how wind power generation over Europe would change in a future world where global temperatures reach 1.5°C above pre-industrial levels. Comparing recent historical (2006-2015) and future 1.5°C forcing experiments highlights that the climate models demonstrate a northward shift in the Atlantic jet, leading to a significant ($p < 0.01$) increase in surface winds over the UK and Northern Europe and a significant ($p < 0.05$) reduction over Southern Europe. The northward shift of the jet is in agreement with other studies. We use a wind turbine power model to transform daily near-surface (10 m) wind speeds into daily wind power output, accounting for sub-daily variability, the height of the turbine, and power losses due to transmission and distribution of electricity. To reduce regional model biases we use bias-corrected 10 m wind speeds. We see an increase in power generation potential over much of Europe, with the greatest increase in load factor over the UK of around four percentage points. Increases in variability are seen over much of central and northern Europe with the largest seasonal change in summer. Focusing on the UK, we find that wind energy production during spring and autumn under 1.5°C forcing would become as productive as it is currently during the peak winter season. Similarly, summer winds would increase driving up wind generation to resemble levels currently seen in spring and autumn. We conclude that the potential for wind energy in Northern Europe may be greater than has been previously assumed, with likely increases even in a 1.5°C warmer world. While there is the potential for Southern Europe to see a reduction in their wind resource, these decreases are likely to be negligible.

1. Introduction

In December 2015, the Conference of the Parties (COP) to the United Nations Framework Convention on Climate Change (UNFCCC) convened a meeting in Paris, France, and invited the Intergovernmental Panel on Climate Change (IPCC) to provide a Special Report “on the impacts of global warming of 1.5°C above pre-industrial levels and related greenhouse gas emission pathways.” The resulting IPCC report is due to be released in September 2018 (<http://www.ipcc.ch/report/sr15/>). The IPCC determined that current climate datasets (such as the Coupled Model Intercomparison Project Phase 5, CMIP5) are not wholly suited to the task of assessing regional impacts with a 1.5°C warming scenario (Mitchell et al., 2016),

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while CMIP6 was not going to be available in time to be used for this assessment. Therefore the “Half a degree Additional warming, Prognosis and Projected Impacts” (HAPPI) project was formed and called on the climate modelling groups around the world to undertake a series of experiments specifically designed to quantify the relative risks associated with 1.5°C and 2°C of warming (Mitchell et al., 2017; <http://www.happimip.org/>). In this study we specifically use the HAPPI dataset to address the question “*How would a future 1.5°C warmer world affect wind energy generation across Europe?*”

In a move to a low-carbon economy, wind power is a crucial component of electricity generation. Wind power now comprises a significant share of the world’s electricity supply, with total global installed capacity of 487 GW at the end of 2016, and around 154 GW installed in Europe (GWEC, 2017). Wind energy now accounts for 18% of the total installed power generation capacity in Europe (Wind Europe, 2017) and is set to increase further in line with the European Commission’s “2030 Energy Strategy” which currently includes a renewable energy target of at least 27%.

The output from wind turbines is related nonlinearly to the local, intermittent and highly variable nature of wind. This makes it challenging to match demand and supply. Therefore, near-term weather forecasts are routinely employed to help optimise this balance (Foley et al., 2012). Climate models may also provide potential utility on longer monthly and seasonal timescales, but this potential is currently underutilised and is an area of active research (Torralba et al 2017, MacLeod et al 2017, White et al 2017). Various studies have used post-processed output from climate models at their native resolutions, and applied dynamical and statistical downscaling to simulate possible changes in wind resource. Changes found in the annual-mean, for standard future forcing scenarios from the previous two CMIP exercises (CMIP3 and CMIP5), include increases in Northern Europe (Pryor and Barthelmie 2010, Hueging et al 2013), and decreases over Southern Europe (Carvalho et al 2017). However, the scope of these changes and seasonal details vary between climate models (Reyers et al 2016, Tobin et al 2015).

A key factor influencing future changes in wind energy generation is the change in the large-scale wind patterns. Climate models generally project a northward shift of the peak North Atlantic westerly winds, by about 1 degree latitude at the end of the 21st century under the “business as usual” representative concentration pathway 8.5 (RCP8.5) scenario (Christensen et al., 2013; Collins et al., 2013). However, this hides seasonal differences as the poleward shift of the Atlantic jet is less pronounced in winter (Barnes and Polvani 2013). Assessing the downstream extension of the westerly wind maximum has been shown to be a

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3 better description of the changes over mainland Europe (e.g. Haarsma et al 2013), although it
4 should be noted that there is considerable uncertainty about dynamical changes (Shepherd,
5 2014). It is important to note that projected changes in the frequency of phenomena affecting
6 variability of wind power generation, such as blocking and extratropical cyclones, are
7 generally small when averaged over different climate models (Ohba et al., 2016), and more
8 uncertain than changes in the mean state (Masato et al., 2013; Zappa et al., 2013). However,
9 there is agreement within the literature that climate models project a substantial decrease in
10 winter storm frequency in the Mediterranean (Christensen et al., 2013; Zappa et al., 2013).

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12 To make robust predictions about wind generation under a future 1.5°C warmer world
13 it is important that any regional model biases are corrected, and that we have large sample
14 sizes to enable extreme conditions to be represented. This makes the HAPPI dataset ideal for
15 this study. In this paper our primary aim is to identify regions across Europe which will likely
16 see increases and decreases in wind generation potential within a 1.5°C warming world.

27 **2. Methodology**

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29 This study uses output from atmosphere-only global climate models run as part of the “*Half a*
30 *degree Additional warming, Prognosis and Projected Impacts*” (HAPPI) project (Mitchell et
31 al., 2017, <http://www.happimip.org>). Ten different modelling centres took part in HAPPI,
32 each running the three ‘Tier 1’ experiments: (i) a climate run for a recent decade, 2006-2015;
33 (ii) 1.5°C warmer than pre-industrial (1861-1880 conditions) relevant for the 2106-2115
34 period; and (iii) similar to the previous experiment but for 2.0°C warmer than pre-industrial.
35 Each experiment required 50- to 100-member ensembles, each spanning 10 years. In this
36 paper we will only use the historical and future 1.5°C experiments (experiments (i) and (ii)
37 described above). More details on the design of the HAPPI experiments is covered in the
38 supplementary material and Mitchell et al., 2017.

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40 In this study we only use those models where daily mean 10 m wind speed has been
41 locally bias-corrected by using the “Inter-Sectoral Impact Model Intercomparison Project”
42 ISIMIP2b calibration methodology (Lange, 2016). The bias correction was performed on a
43 regular 0.5°×0.5° grid using a first-order conservative remapping scheme over all land-points
44 (see <https://www.isimip.org/gettingstarted/isimip2b-bias-correction/>). The transfer functions
45 for the bias-corrections were computed from longer runs of 25 years or more. The four
46 available bias-corrected models used are here referred to as: CAM4-2-degree (based on
47 CAM4, Neale et al. 2013), ECHAM6-3-LR (Stevens et al, 2013), MIROC5 (Watanabe et al.,
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2010), and NorESM1-HAPPI (based on NorESM1-M, Bentsen et al., 2013). Only the first 10 ensemble members for each of the four models were bias-corrected, providing us with 100 years of daily data for each model and each experiment. To ensure we only show multi-model mean changes between experiments where there is reasonable agreement between the four models, in this paper we only define a change (between 1.5°C and the historical experiment) for those regions where three or four models agree on the sign of that change. Then, for each model grid-point, the multi-model mean change is calculated by averaging only those values that are in agreement (e.g., Kaye et al., 2012). For example, if the change in load factor in a single grid-point between the historical and 1.5°C experiments for the four individual models is 2, -1, 3, and 4, then we only average the positive values (here giving a value of 3). The -1 is ignored as an outlier.

The wind turbine power curves are derived using the methodology in Macleod et al., 2017 which was validated from up to 11 years of data from 282 turbines located across varying terrain. Daily mean surface winds are transformed to a wind turbine load factor using a defined ‘power curve’ (see Figure S1 in supplementary material). Here we define the cut-in speed at 4 ms⁻¹ (where the wind turbine blades start to turn) and a cut-out speed of 25 ms⁻¹ (above which the blades are prevented from spinning for safety). The power generation is capped at the rated power (speed at which maximum load factor is reached), here 12.5 ms⁻¹. Load factor is measured as a percentage and is defined as the actual power generated relative to the maximum. This methodology accounts for the sub-daily temporal variability in wind speed using a Rayleigh distribution, the increase in wind speed from near-surface (10 m) to turbine height (here defined as 60 m), and power losses due to the transmission and distribution of electricity. After taking these corrections into account, the resulting power curve (shown by the orange line in Figure S1) is then used to transform daily 10 m wind speeds from the model simulations into daily load factor. It should be noted that Macleod et al (2017) found that the calculation of load factor is relatively insensitive to the atmospheric temperature (compared to wind speeds) and so it is appropriate to use a fixed temperature in the calculation of the power curve, which here was set at 10°C.

Our aim is to identify regions across Europe which will likely see increases and decreases in wind generation potential within a 1.5°C warming world. In order to constrain the problem, we use the same power curve throughout the study, thus making the assumption that any changes in surface roughness and sub-daily wind distribution, within the timeframe of reaching a 1.5°C warming world, will be small relative to the changes driven by large-scale winds. Predicting future efficiency gains from improvements in turbine technology and

optimisations in hub-height is also highly uncertain. Using the same power curve throughout this study therefore allows us to focus solely on the relative changes in wind energy generation driven by shifts in large-scale wind patterns. Due to these various uncertainties and the lack of sub-daily of climate model data output, the assumptions made here are reasonable for a climate scenario-based study and are in line with those found in other studies (e.g., Karneckas et al., 2017).

3. Results

Four atmosphere-only climate models are used to assess the change in wind energy generation between recent historical climate conditions (2006-2015) and a future where global mean surface temperatures reach 1.5°C above pre-industrial levels. We start by assessing how the models compare in their representation of large scale wind change. Figure 1 shows the change in the median zonal wind speeds at 850 hPa (u_{850}) between the future 1.5°C and historical experiments. The models all simulate a northward shift in the region of the Atlantic jet (Figure 1), resulting in a significant increase ($p < 0.01$) in wind speeds around 54°N (over the UK, Germany and Poland) and a significant ($p < 0.05$) decrease around 42°N (over north Africa and Spain) (see Figure S2).. The regional peak magnitudes of wind speed change agree well between the CAM2-2degree, ECHAM-3-LR and MIROC5 models at around 4 ms⁻¹, while the NorESM1-HAPPI model appears to be more sensitive to the additional global greenhouse gas forcing with changes exceeding 6 ms⁻¹ seen over Germany, and over and downwind of Scotland.

We now assess the seasonal impact these changes have on the generation of wind energy and variability (Figure 2). The seasonal mean wind load factor for each of the four models is calculated as described in section 2. As the 10 m wind speed fields are bias-corrected, the mean historical maps for each model are all very similar to one-another, therefore (after transformation using the power curve seen in Figure S1) it is appropriate to simply calculate and display the multi-model mean (Figure 2a-d, labelled as ' P '). However, the change in wind power generation (calculated in percentage points) under 1.5°C varies somewhat between the four models, as expected from Figure 1. From now on the multi-model mean changes (between 1.5°C and the historical experiment) are shown only for those regions where three or four models agree on the sign of the change (see section 2 for details).

The multi-model change under 1.5°C is shown in Figure 2e-h (labelled ΔP). Under the historical experiment, the largest load factor is generally seen in winter (Figure 2a,

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December-February ‘DJF’), with values exceeding 20% over the UK and similar values over the Portugal coastline, with slightly lower values seen across mainland Europe, especially over Poland and Belarus. These spatial patterns are similar across the four seasons, although with lower values in spring (2b, March-May ‘MAM’) and autumn (2d, September-November ‘SON’), with the lowest values found in summer (2c, June-August ‘JJA’) with values around 10% over the UK. This seasonality is in agreement with Heide et al (2010). The seasonal spatial changes (ΔP) across the four seasons are also very similar to one another, with the largest increases found over the UK, with an increase in load factor of up to four percentage points seen across the four seasons (Figure 2e-h). Changes over mainland Europe are less pronounced, with even a small reduction (around 1 percentage point) in load factor over parts of Spain. This again is in agreement with Figure 1.

We also assess the day-to-day standard deviation (σ) of load factor within the historical experiment in Figure 2i-l, and the change under a 1.5°C future in Figure 2m-p ($\Delta\sigma$). The regions and seasons with the largest σ values appear to be broadly similar to those with the largest values of P . However, the seasons with the largest change under a 1.5°C future ($\Delta\sigma$) are summer and autumn (JJA and SON), with the highest values across the UK and central and eastern Europe.

In Figure 3 we assess the change in potential viability of wind farms across Europe. Here we use a load factor threshold of 10%, which is suitable for the specific power curve used in this study (Figure S1), to more clearly highlight the spatial differences between Northern and Southern Europe. (Note that while this threshold of ‘viability’ might be higher if we calculated our load factors using a different power curve, the spatial distribution should be fairly robust). Over the UK, the coastal zone over Portugal and the northern parts of central Europe (France, Belgium, Netherlands, Germany, Denmark, Poland, and Belarus) the mean load factor exceeds 10% during both the historical and 1.5°C experiments (blue shading). Conversely, most of Southern Europe falls below this threshold in both experiments (white/unshaded). What is potentially more interesting though are those regions where we see a switch in the exceedance between experiments. Here we see large areas where wind farms could become more viable in the future; over Germany, Poland and Lithuania (purple shading). However, there are only a few regions where we see the opposite situation, where the historical load factor exceeds this threshold then drops below it within the 1.5°C future experiment (black shading). This is expected from Figure 2 as in general most regions see an increase in load factor, especially in Northern Europe, with few regions showing any decrease.

We now focus on Central England within the UK (3.5°W – 0°E , 51.5°N – 53.5°N) where we see the largest changes in load factor under a 1.5°C warming world (see Figure 2). In Figure 4 we show the distributions of the probability of exceedance in daily mean load factor to illustrate how the frequencies of larger values ($>20\%$) change between experiments and between seasons. Note that the maximum load factor is 45%, limited by the power curve used in this study as shown by Figure S1. In agreement with Figure 2, historical values of load factor (black lines) are generally larger in DJF and smaller in JJA, with MAM and SON sharing similar distributions to one another. The smallest shift between experiments is seen in DJF while the largest shift is in JJA. In these figure panels we see that the 1.5°C distributions in MAM and SON resemble those seen in the historical DJF, i.e. under 1.5°C forcing we could see 9 months of the year where wind resource resembles those seen in the current peak winter months. Similarly, the future 1.5°C distribution in JJA seems to match the historical distributions in MAM and SON.

4. Discussion

The results in this paper are in broad agreement with Pryor et al (2005) who find an increase in the annual wind energy resource over Northern Europe, though they found that a large fraction of their uncertainty (within the regional climate model simulations used) originate from the inter-model differences of the global climate model boundary conditions. Our findings also agree with the review of climate change impacts on wind energy of Pryor and Barthelmie (2010), who find that the potential for wind energy in Northern Europe is not at risk from climate change. Results here suggest that with 1.5°C warming, load factor potential in Northern Europe will only increase. Any decreases seen here in Southern Europe are small and unlikely to impact the potential for wind power generation. This is in agreement with Carvalho et al (2017).

Due to large inter-model uncertainties, many studies have emphasised the need to consider multiple climate models when assessing future changes in wind energy (e.g., Reyers et al 2016, Tobin et al 2015). Despite this, there are still notable disagreements between studies. For example, over the USA Johnson and Erhardt (2016) found the opposite sign of impact compared to Karnauskas et al (2017). Additionally: while we find a large change in future wind resource over the UK, Karnauskas et al (2017) showed little change; and while Carvalho et al (2017) finds the largest increases in generation around the Baltic sea, we find the largest increases over the west of Northern Europe. Also in contrast to our findings,

dynamically or statistically downscaled climate models have shown decreases in wind energy potential over Western Europe (southern UK, Germany and France) (Hueging et al, 2013 and Reyers et al, 2016). The lack of regional agreement between these climate modelling based studies demonstrates the sensitivity to the inter-model spread, thus requiring a large radiative forcing (e.g., RCP8.5) to produce a clear signal of change (Reyers et al., 2016). In response to this, the HAPPI project was designed to reduce inter-model spread and produce a clearer signal of change between experiments. This was achieved by: (i) fixing the levels of greenhouse gas forcing; (ii) using sea surface temperatures (SSTs) which are based on observations, thus reducing the occurrence of atmospheric artefacts driven by SST biases which are characteristic of atmosphere-ocean coupled models; and (iii) using relatively large number of ensemble runs for each model assessed. As a result, our analysis demonstrates that notable changes in wind power potential could occur even under this weaker forcing. However, we recognise that further investigation using larger number of models, and the addition of dynamical downscaling, would be important to better understand the likelihood of the changes presented in this paper.

Whilst our analysis focuses mainly on potential changes in the underlying wind resource, there are other factors which will influence load factor which have not been taken into account in this study, such as improvements in wind turbine technology and site placement. For example, the average load factor in the UK has increased from 26% to 32% between 2005 and 2015, whilst projections based on planned long-term installations suggest that the UK average load factor may approach 40% by 2025 (Drew et al 2015, Staffell and Pfenninger 2016). For Europe as a whole, planned developments of the wind fleet are estimated to have load factors one-third higher than today, and any increases in underlying wind speeds will increase this further.

The limited spatial resolution of climate models limits their ability to accurately simulate wind speeds, particularly in regions of complex topography. Here, models are unable to represent the detailed topography and thus they are likely to underestimate the potential load factor possible by missing speed-up and blockage effects. The true potential of wind power will be achieved in reality by optimised placement of turbines at points within a region reaching on average higher wind speeds than those around them. Indeed, Staffell and Pfenninger (2016) find that basing load factor estimates based on “reanalysis” data (which like climate models have limited spatial resolution) leads to errors across Europe, with underestimation in the mountainous regions of Southern Europe and Scandinavia relative to Northern Europe. They recommend that in order to obtain accurate values of load factor with

reanalysis data, results should be bias corrected according to actual load factor data. The suggestion would also likely apply to load factor calculated using climate models. Though the winds from the climate model are bias corrected, in this current study no bias correction of load factor has been attempted as the main focus of the paper is on relative changes; any calibration factor would be applied to present-day and future load factor estimates equally and so the relative change would be unaffected.

Limited spatial resolution also means that sub-grid scale processes and turbulent effects occurring below the grid scale will be unrepresented. Given this, we must deduce that any sub-grid scale nonlinear changes in the wind speed under a 1.5°C scenario are not represented in the models. The results then are valid under the assumption that these are small relative to changes in the large scale. Of course, this a limitation is faced by all results derived from climate model projections.

5. Conclusion

As of February 2018, 195 UNFCCC members have signed the agreement to keep global mean temperature rise this century well below 2°C above pre-industrial levels, and to pursue efforts to limit the temperature increase even further to 1.5°C. To this end, an Intergovernmental Panel on Climate Change (IPCC) “Special Report on Global Warming of 1.5°C” will be published in autumn 2018 with the aim to help strengthen the global response to the threat of climate change, produce sustainable development strategies and outline efforts to eliminate poverty.

In this particular study, we focused on how the potential for future wind generation of electricity over Europe would change within a 1.5°C warming world, relative to current climate conditions. We used large ensembles from atmosphere-only global climate models from the “*Half a degree Additional warming, Prognosis and Projected Impacts*” (HAPPI). We derived daily wind power output by adopting the methodology from MacLeod et al (2017) using the output of the four models where near-surface (10 m) wind speeds had been bias-corrected. This method takes into account the distributions of sub-daily variability, the height of the turbine, and power losses due to transmission and distribution of electricity.

We found an increase in load factor over much of Europe, with the UK seeing the greatest increase by around four percentage points. However, we also found that the UK would experience the greatest increase in variability, especially during the summer months

(June-August). Germany and Poland could also see regions with notable increases in variability.

Lastly, we assessed the change in distribution of daily load factor between current climate conditions and a future 1.5°C warmer world, and difference between seasons, for Central England, UK. We found that wind energy resources during spring and autumn could become as productive as they are currently during the peak winter season, i.e., under 1.5°C forcing 9 months of the year could see wind speeds that resemble those currently seen in the peak winter seasons. Similarly, during the summer months where wind speeds are generally low, wind under a 1.5°C warming world could increase to resemble those currently seen in spring and autumn. While this study only assessed the changes in wind resources over land (where the data was bias corrected, see section 2), there is no indication (Figure 1) that the regional changes would be significantly different offshore. It should be noted that we only assessed broad-scale changes in winds highlighting regions with the potential for increases and decreases in future wind generation. As an area of further work one could consider localised changes in surface roughness, e.g., through changes in vegetation.

We conclude that the potential for wind energy in Northern Europe may be greater than has been previously assumed (TCEP, 2017), with likely increases even in a 1.5°C warmer world presenting an opportunity for climate mitigation. While there is the potential for Southern Europe to see a reduction in their wind resource, any changes are likely to be negligible.

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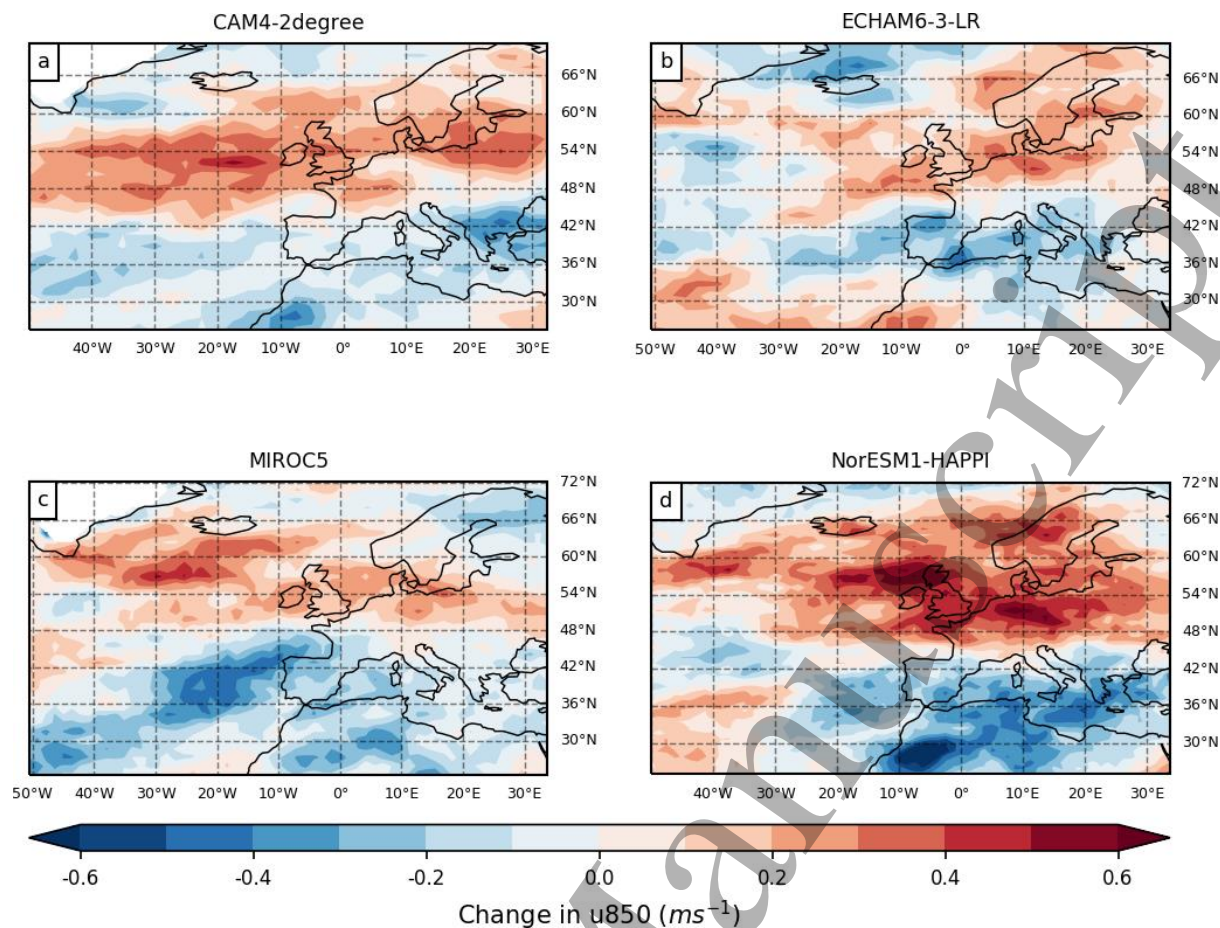


Figure 1. Change in median annual zonal wind speed at 850 hPa (u_{850}) between the historical and 1.5°C experiments within the four global climate models assessed within this study (as labelled atop each panel).

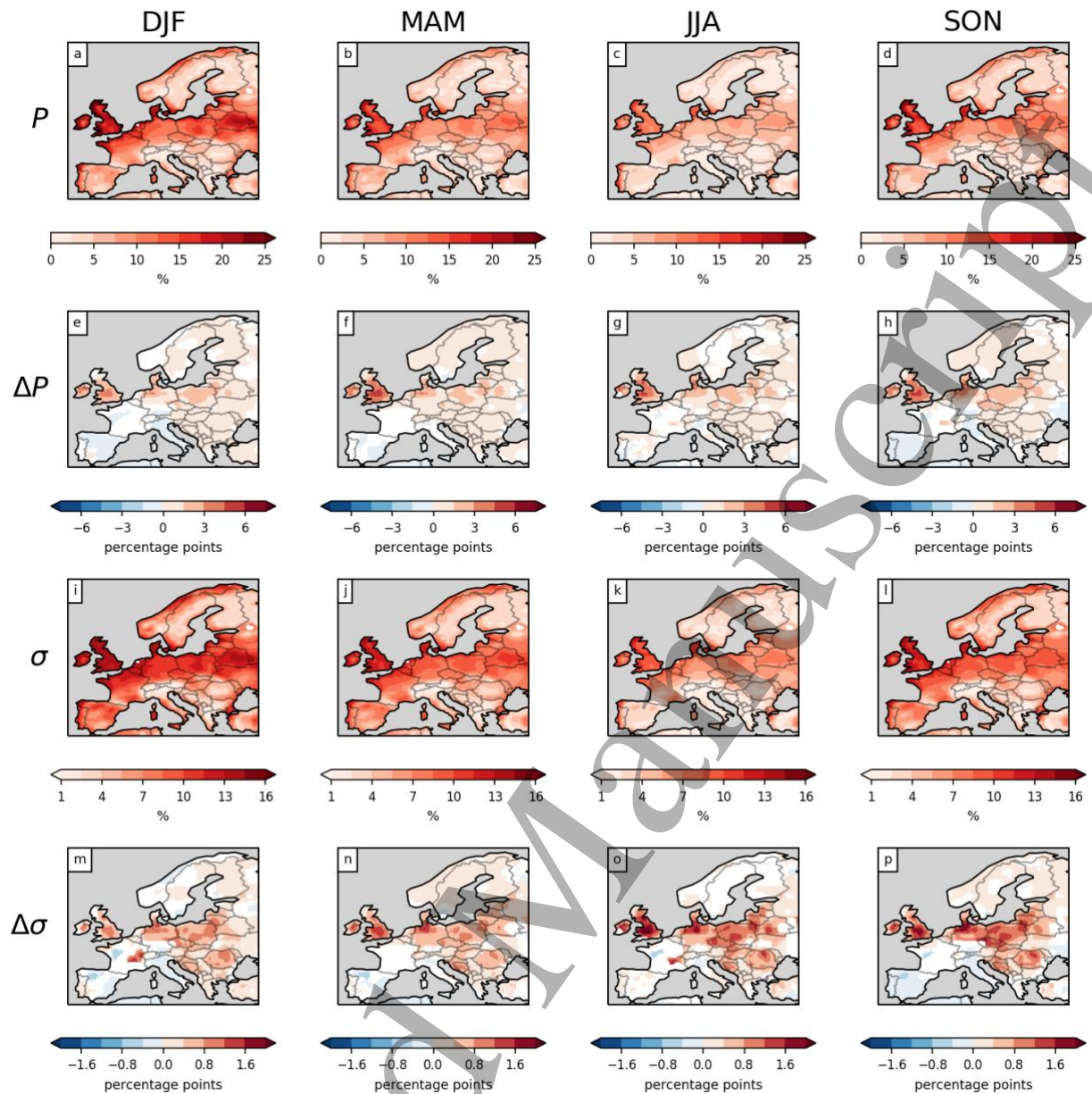


Figure 2. Multi-model mean values of wind generation load factor (P) derived from the historical experiment near-surface (10 m) wind data are shown in the first row (panels a-d), while the second row (e-h) shows the change between the historical and 1.5°C experiments (ΔP). The third row (i-l) shows the historical standard deviation (σ) in daily wind generation, while the bottom row (m-p) shows the change under 1.5°C ($\Delta\sigma$). The columns represent the four seasons: winter (December-January, DJF), spring (March-May, MAM), summer (June-August, JJA) and autumn (September-November, SON).

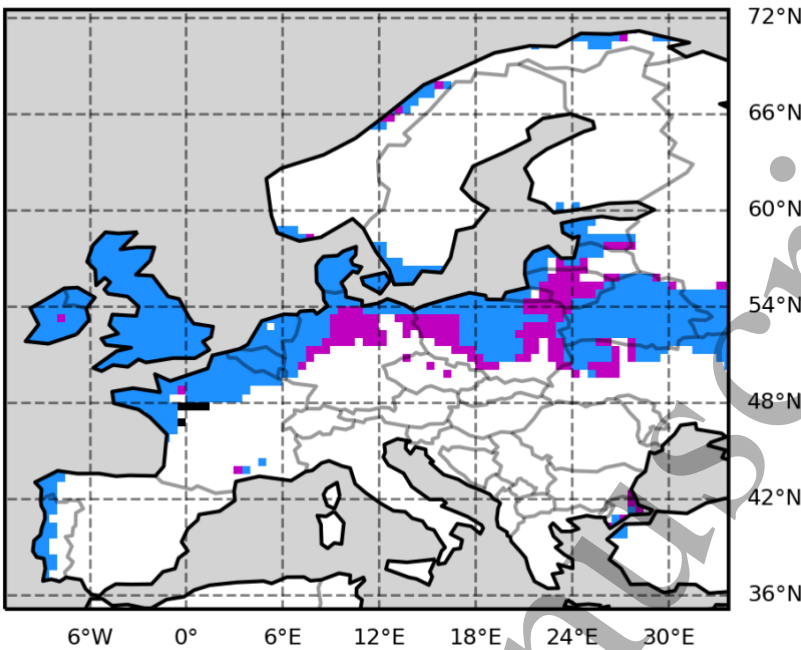


Figure 3. Demonstrating potential spatial changes in the viability of wind farms under a future forcing of 1.5°C. Here we adopt a threshold of 10% which is suitable for the power curve used in this study. The shading over land represents the four possible combinations of exceedance of the 10% threshold for the historical and 1.5°C experiment. Blue shading represents those regions where the annual mean load factor exceeds the threshold in the historical and future experiments. Conversely, the white/unshaded regions are those where the load factors lie below the threshold in both experiments. The purple coloured regions are those where load factor lies below 10% in the historical experiment but then exceeds this level in the 1.5°C experiment; while the black regions (for which there are only a few points, over France) highlights regions which are currently viable but becomes unviable in a 1.5°C warming world. Note that ocean points are masked as those points were not bias-corrected (grey shading).

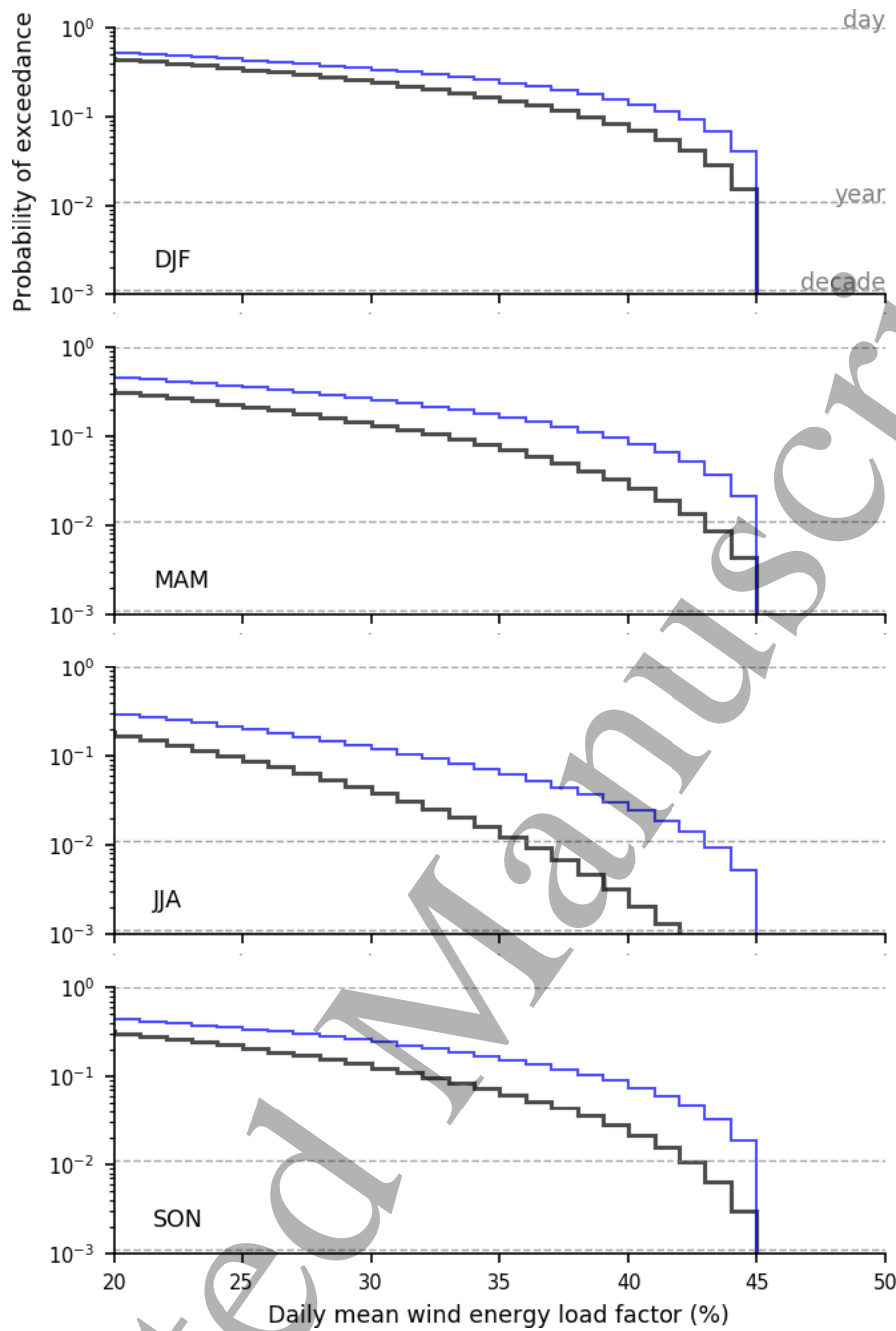


Figure 4. Probability of exceedance of daily load factor over Central England, UK, where we consistently see a notable increase under a 1.5°C forcing across all seasons (as seen in Figure 2). The black lines represent the frequency distribution for the historical experiment, while the blue lines represents the future 1.5°C experiment. The daily load factor data are computed from daily mean 10 m wind data from four climate models, each run for 100 years.