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# Identifying and characterising large ramps in power output of offshore wind farms

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## Abstract

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Recently there has been a significant change in the distribution of wind farms in Great Britain with the construction of clusters of large offshore wind farms. These clusters can produce large ramping events (i.e. changes in power output) on temporal scales which are critical for managing the power system (30 minute, 60 minute and 4 hours). This study analyses generation data from the Thames Estuary cluster in conjunction with meteorological observations to determine the magnitude and frequency of ramping events and the meteorological mechanism.

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Over a 4 hour time window, the extreme ramping events of the Thames Estuary cluster were caused by the passage of a cyclone and associated weather fronts. On shorter time scales, the largest ramping events over 30 minute and 60 minute time windows are not associated with the passage of fronts. They are caused by three main meteorological mechanisms; (1) very high wind speeds associated with a cyclone causing turbine cut-out (2) gusts associated with thunderstorms and (3) organised band of convection following a front. Despite clustering offshore capacity, the addition of offshore wind farms has increased the mean separation between capacity and therefore reduced the variability in nationally aggregated generation on high frequency time scales.

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Keywords: wind; offshore; variability; ramping; extremes

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## 1.0 Introduction

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To meet ambitious carbon reduction targets, global renewable energy deployment has expanded dramatically. In the UK, the capacity of wind power has grown steadily from 2.9 GW in 2008 to 17.9 GW by June 2017 [1]. Due to the increasing penetration of wind power, extreme wind power generation events are of growing concern. In particular, ramps in generation provide challenges for the transmission system operator who schedule reserve holding in advance and require long term strategies for system balancing [2]. Consequently, a number of studies have focused on understanding and improving the predictability of wind power ramping events [3, 4, 5, 6].

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For the UK, Cannon et al. [7] used wind speed data derived from the MERRA reanalysis dataset to quantify the magnitude and frequency of nationally-aggregated wind generation ramping on time scales of 6 hours and greater based on the 2012 wind farm distribution. However, in recent years there has been a significant change in the distribution of wind farms in the Great Britain [8]. Since 2012, the capacity of offshore wind farms has increased from 2.4 GW to 5.0 GW with much of this capacity spread over a small number of very large wind farms located in clusters. For example, in the Thames Estuary alone there is approximately 1.7 GW of capacity. Drew et al. [3] showed this has led to large

40    regional ramps in generation on time scales of minutes to hours as local meteorological phenomena
41    simultaneously impacts production in several large farms. Given the large capacity of the farms, these
42    ramps can present a challenge in maintaining the balance between supply and demand on a national
43    scale, particularly if they are not accurately forecasted.

44    The problem posed by local ramping events is expected to be exacerbated in the coming years, given
45    the trend for clustering capacity in large offshore wind farms looks set to continue. The latest phase of
46    offshore wind development in the UK, launched in 2009, identified 9 zones within which a number of
47    individual wind farms could be located with a total capacity of over 30 GW [9, 10]. Consequently,
48    following the construction of the round 3 wind farms the majority of GB wind capacity would be
49    located offshore in clusters of very large wind farms [11, 12].

50    To improve the performance of operational wind power forecasts there is an increasing need for a
51    clear understanding of the meteorological features responsible for the extreme local ramping events
52    [13]. For example, Trombe et al. [14] showed that high frequency ramping of large Danish offshore
53    wind farms can be associated with heavy rainfall and therefore considered the scope for using data
54    from the rainfall radar to adjust the forecast in real-time if necessary. This study investigates whether
55    such an approach could be applied to ramping events in the Thames Estuary wind farms.

56    In addition to the problems posed by local ramping events, there are concerns that clustering capacity
57    could lead to an increase in the variability of the nationally aggregated wind generation (i.e. a reversal
58    of some of the smoothing benefits gained by the spatial dispersion of turbines). A number of studies
59    have investigated the reduction in wind power variability due to geographical dispersion of turbines
60    for single European countries. For example, Kubik et al. for Northern Ireland [15], Hurley and
61    Watson for Ireland [16], Hasche for Germany and Ireland [17] and Giebel [18], Landberg [19],
62    Buttler [20] and Huber et al. [21] considered the whole of Europe.

63    For the UK, Sinden [22] and Earl et al. [23] used wind speed data measured at Met Office surface
64    stations to quantify the inter-annual, seasonal and diurnal variability of UK aggregated wind
65    generation. However, these studies did not consider offshore sites and assumed the distribution of
66    wind capacity matched the distribution of weather stations which can lead to large errors [24]. To
67    address this problem, Cannon et al. [7] used wind speed data derived from the MERRA reanalysis
68    dataset to determine the characteristics of wind power in Great Britain over a 33 year period. The
69    study provides a detailed climatology of ramping on time scales of 6 hours and greater.

70    Using the approach outlined in Cannon et al. [7], Drew et al. [12] showed that the increased
71    penetration of offshore wind farms has little impact on the ramping of GB-aggregated wind
72    generation on time scales of greater than 6 hours. However, due to the resolution of the model,
73    MERRA reanalysis data cannot be used to determine the high frequency GB-aggregated power
74    swings (minutes to hours) or quantify the magnitude of wind power ramps at high spatial resolutions
75    (below 300 km), both of which are important considerations for managing the power system.

76    In the UK, the electricity market is managed in 30 minute windows, known as settlement periods. For
77    each period, suppliers and generators contract electricity up to 1 hour prior to the delivery time, a cut-
78    off time known as "gate closure". It is then the responsibility of the system operator (National Grid) to
79    take any necessary actions in order to balance the grid within each settlement period. The electricity
80    network in the UK is largely isolated with relatively few interconnectors to neighbouring countries
81    and therefore there is a reliance on large conventional power plants to manage the system. However,
82    these plants generally require a period of notice prior to generation to ramp up, generally assumed to

83 be at least 4 hours. To manage the power system, it is therefore important to understand the possible
84 ramps in power that could occur on time scales shorter than the ramp up time of a conventional power
85 plant (4 hours), between gate closure and settlement period (1 hour) and from one settlement period to
86 the next (30 minutes).

87 The aim of this study is to use a 30-minute averaged time series of wind power generation from a
88 number of regions across Great Britain (GB) in 2014 to investigate how the increased penetration of
89 clustered offshore wind capacity has affected the characteristics of generation at high spatial and
90 temporal resolutions. The first section considers the impact on high frequency variability of wind
91 generation on both a national and regional scale, particularly the magnitude of ramping in generation
92 on time scales of less than 4 hours. The second section determines the meteorological causes of
93 extreme regional ramping events using the Thames Estuary as a case study.

## 94 2.0 Datasets and analysis methods

95 One of the main challenges when investigating the variability of wind generation in the UK at high
96 spatiotemporal resolutions is the limited availability of suitable data. Actual metered data from the
97 individual wind farms is protected by commercial interests; therefore there is a reliance on nationally
98 aggregated data. However, analysis using this data is unable to quantify the regional power swings or
99 indicate how the variability has been affected by the change in wind farm distribution. Cradden et al.
100 [24] used an hourly 11 year hindcast derived using the Weather Research and Forecasting model
101 (WRF) at 3 km resolution to assess the variability of generation from 13 different regions in the UK.

102 This study introduces a new dataset which details the aggregated power output from four offshore
103 clusters (Anglia, Cumbria, N.Wales and Thames) and five onshore regions; Argyll, Ayrshire, Central,
104 Lothian and SSENW (see Figure 1) at 30 min resolution from 1st January 2014 to 31st December 2014
105 (see Table 1 and Figure 1). The total capacity across the 9 regions is 6.5 GW, which is approximately
106 70% of the total installed wind capacity of Great Britain.

107 A number of wind farms have been excluded from the analysis for two reasons (1) they the sole wind
108 farm in a region therefore it was not possible to produce anonymous, aggregated generation data or
109 (2) the data was not of sufficient quality. Despite the reduced number of wind farms, the dataset
110 provides a good representation of the wind resource. For example, the GB-aggregated capacity factor
111 for 2014 was calculated to be 31%, which compares well to the figure of 30.2% for the full wind farm
112 distribution [25].

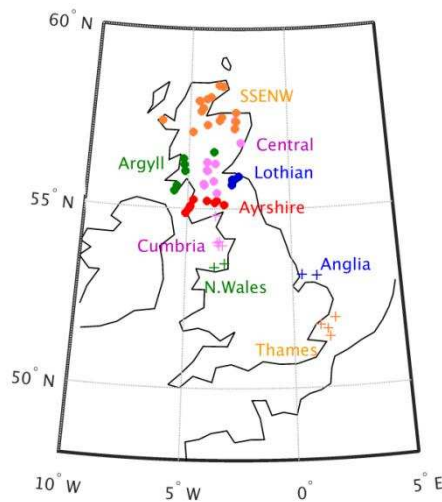|          | Mean separation (km) | Number of farms | Capacity (GW) |
|----------|----------------------|-----------------|---------------|
| Lothian  | 17.3                 | 5               | 0.44          |
| **N.Wales**  | **26.9**         | **3**           | **0.18**      |
| **Cumbria**  | **30.7**         | **5**           | **1.17**      |
| **Thames**   | **34.5**         | **4**           | **1.54**      |
| **Anglia**   | **38.1**         | **3**           | **0.33**      |
| Central  | 60.7                 | 11              | 1.22          |
| Ayrshire | 79.3                 | 8               | 0.52          |
| Argyll   | 89.1                 | 6               | 0.30          |
| SSENW    | 115.2                | 16              | 0.80          |

113 **Table 1 Details of the 4 offshore clusters (bold) and the 5 onshore regions. The mean separation is derived using**
114 **equation 1 based on the wind farms within each region.**

115 2.1 Spatial separation of capacity

116 The addition of offshore wind farms has changed the distribution of capacity in two distinct ways.
117 Firstly, there is an increased concentration of capacity in clusters. For each region the spatial
118 dispersion of the capacity has been quantified in terms of the mean separation per unit MW of
119 capacity, S, as calculated in [12] as:

$$s = \sum_{i=1}^{N} \frac{c_i}{C_T} \left( \sum_{j=1}^{N} \frac{c_j d_{ij}}{C_T} \right) \tag{1}$$

120 where $c_j$ is the wind farm capacity, $d_{ij}$ is the distance between wind farms, $N$ is the number of wind
121 farms in the region and $C_T$ is the total installed capacity of the region. The offshore regions are
122 generally made up of large wind farms clustered together in a relatively small area and consequently
123 have a low separation between units of capacity (26.9 km to 38.1 km). In comparison, onshore regions
124 generally consist of spatially dispersed small wind farms therefore the separation of the capacity is
125 larger (60.7 km to 115.2 km), with the exception of Lothian (17.3 km). Secondly, the addition of the
126 offshore regions has changed the geographical location of the generation. Figure 1 shows that all of
127 the onshore zones are located relatively close to each other in Scotland; therefore the mean separation
128 between the onshore capacity is only 168 km. In contrast, all of the offshore clusters are connected to
129 England, and are more geographically dispersed (mean separation of 327.6 km between the offshore
130 capacity), therefore by combining the onshore and offshore capacity the mean separation between
131 capacity for the GB wind farm distribution increases to 399 km.



132

133 **Figure 1 Map of the wind farm distribution used in this study. The onshore and offshore farms are represented by**
134 **the circles and crosses respectively.**

135 2.2 Impact of spatial separation on generation characteristics

136 To investigate the impact of spatial separation of capacity on wind power variability in Great Britain,
137 the 30-minute averaged time series of aggregated generation for each of the 9 regions have been
138 combined to derive a time series of power output for every possible combination of regions. This
139 ranges from a combination of two regions (36 possibilities) to the single combination of all nine

140     regions (GB-aggregate) and therefore amounts to a total of 515 possible wind farm distribution
141     scenarios each with a different number of wind farms and mean separation between capacity. The data
142     are then used to determine the impact of clustering capacity on the high frequency variability of the
143     wind generation.

144     A range of different metrics have been used to quantify the variability of wind generation. For the
145     purposes of this study a ramp, R, at time, t, is defined as the difference in the power output over a
146     period of time, Δt, given by:

$$R(t) = P(t + \Delta t) - P(t) \tag{2}$$

147     where P(t) is the power output at time, t. Using the 30-minute averaged dataset, a time series of ramps
148     for Δt=30 minutes, 60 minutes and 4 hours, has been calculated for each wind farm distribution
149     scenario. The standard deviation, σ, of each time series is then calculated to quantify the distribution
150     of the ramps for each scenario.

151     2.3 Thames Estuary analysis

152     Section 3.3 investigates the most extreme ramping events over three time scales (30 minutes, 60
153     minutes and 4 hours) of a single offshore cluster in order to determine the meteorological
154     mechanisms. The analysis focuses on the offshore wind farms in the Thames Estuary, located
155     approximately 100-200 km east of London, UK. This is the largest of the offshore clusters consisting
156     of 5 individual farms with a total capacity of 1.7 GW. Drew et al. [3] presents a detailed analysis of a
157     high frequency ramping event of this cluster which had significant implications on the management of
158     the power system. This study investigates the full range of extreme ramps to determine the
159     meteorological cause.

160     To determine extreme ramping events the 30 minute averaged time series of the capacity factor of the
161     Thames region (as outlined in section 2.2) has been used. The extreme ramping events for each time
162     window have been defined following a similar method to that outlined in Cutler et al. [6].
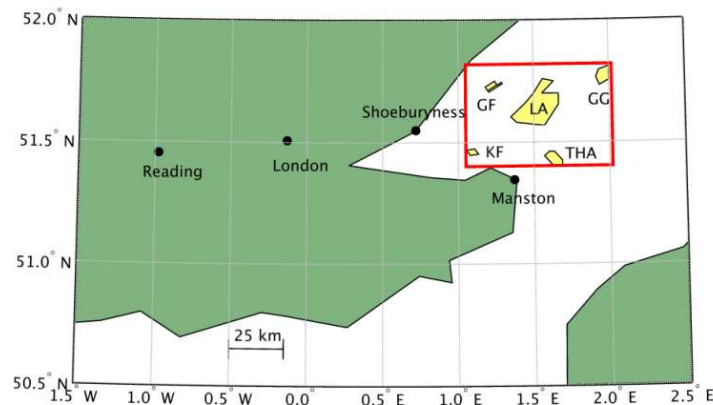
163     •   4 hour ramps: Find all instances where the 30 minute averaged capacity factor changes by
164         more than 40% within a 4 hour window. Two individual ramps occurring within a 6 hour
165         window of each other are considered the same event.
166     •   60 minute ramps: After removing the periods of time during which a 4 hour ramp occurs, find
167         the occasions where the 30 minute averaged capacity factor changes by more than 25% in a
168         60 minute time window. Two ramps are considered the same event if they occur within 1 hour
169         of each other.
170     •   30 minute ramps: After removing the periods where either a 4 hour or 60 minute ramp occurs,
171         find the occasions where the 30 minute averaged capacity factor changes by more than 15%
172         in a 30 minute time window.

173     To determine the meteorological mechanisms behind extreme ramping events, a number of datasets
174     have been used (Table 2). Firstly, the meteorological conditions in the Thames Estuary region have
175     been determined using 1-minute averaged observations of temperature, wind speed and surface
176     pressure from two nearby Met Office weather stations (shown in Figure 2) and rainfall rate data
177     derived from radar observations for an area of 4884 m$^2$ covering all of the wind farms on a 1km$^2$
178     spatial resolution and a 5 minute temporal resolution [26, 27]. On the larger scale, the synoptic scale
179     conditions have been determined using hourly wind fields and surface pressure from Modern-Era
180     Retrospective Analysis for Research and Applications (MERRA) data [28].

181     In addition to determining the meteorological conditions associated with ramps, hourly surface wind
182     field data from MERRA has been used to estimate the aggregated power generation of the wind farms
183     in the region, following the method of Cannon et al. [7]. Firstly, the horizontally gridded surface
184     hourly winds were bi-linearly interpolated to the location of each wind farm. The derived winds were
185     then vertically interpolated to the hub height of the turbines. Finally, the hub-height wind speeds were
186     converted to power output using a transfer function derived from empirical comparisons between the
187     derived wind speeds and recorded wind farm output. The power output was summed over all wind
188     farms to produce an hourly time series of generation of the Thames Estuary cluster.

189

| Dataset | Variables | Temporal resolution | Location |
|---|---|---|---|
| UK Met Office weather station observations | Air temperature (C) at 1.25 m above the ground. Mean wind speed and maximum gust at 10 m above the ground ($ms^{-1}$). Atmospheric pressure (hPa). | 1-minute | Manston (51.346°N, 1.337°E).and Shoeburyness (51.536°N, 0.809°E). |
| Met Office rainfall radar | Rainfall rate (mm $hr^{-1}$) | 5-minute | Thames Estuary region (see Figure 2) on 1 $km^2$ resolution. |
| MERRA: Modern-Era Retrospective Analysis for Research and Applications | Mean wind speed ($ms^{-1}$) at heights of 2 m, 10 m and 50 m. Surface pressure (hPa). | Hourly | 0.5° x 0.667° global grid. |

190     **Table 1 Details of the meteorological datasets used in this study.**



191

192     **Figure 2 Map showing the location of the 5 wind farms in the Thames Estuary: Greater Gabbard (GG), London**
193     **Array (LA), Gunfleet Sands (GF), Kentish Flats (KF) and Thanet (THA). The red box indicates the region for which**
194     **radar rainfall data was obtained. The map also shows the locations of the surface meteorological stations: Manston**
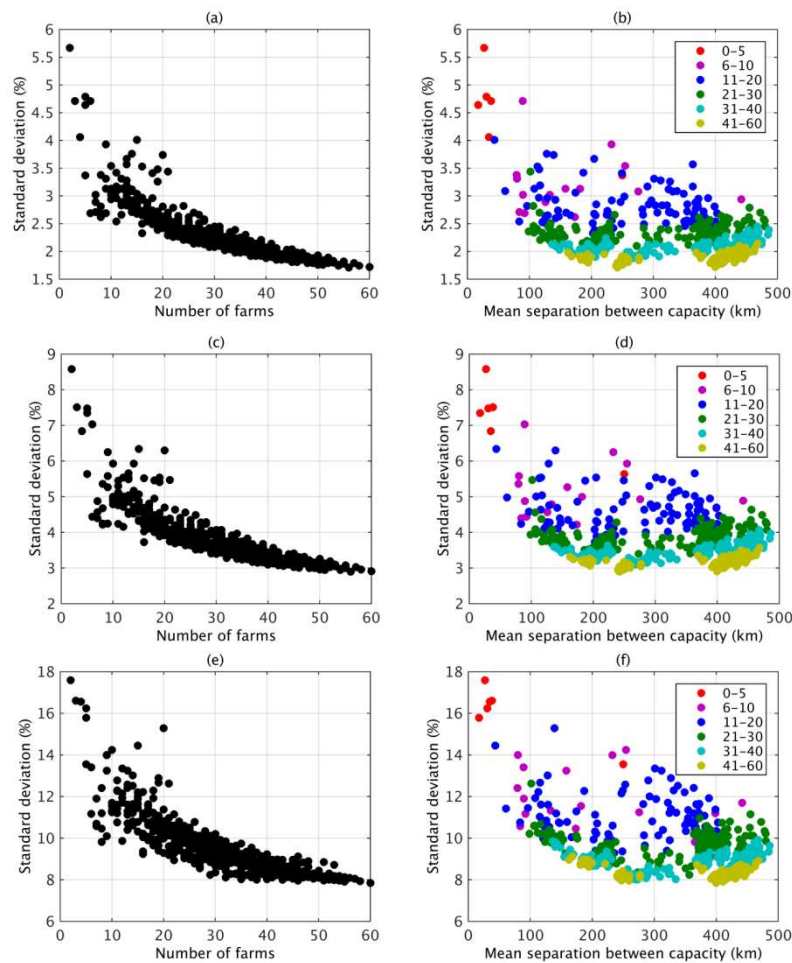195     **and Shoeburyness.**

196 3.0 Results

197     The dataset outlined in Section 2 has been used to address a series of questions related to wind power
198     variability. Section 3.1 investigates the impact of the offshore wind farms on the GB-aggregated wind
199     generation characteristics, with a particular emphasis on the impact of changing the separation
200     between capacity and the number of wind farms on the magnitude on the high frequency ramps.
201     Section 3.2 determines the magnitude of regional high frequency power swings for the offshore

202 clusters and compares the results to that of the more spatially-dispersed onshore regions. Finally,
203 Section 3.3 quantifies the high frequency ramping of wind farms in the Thames Estuary, the largest
204 offshore cluster and identifies the meteorological mechanism.

205 3.1 Impact of clustering capacity on generation variability

206 This section determines how the magnitude of the ramps in regional wind power varies with two
207 metrics used to define the level of clustering (1) the number of wind farms aggregated and (2) the
208 mean separation between capacity. For all 515 possible wind farm distributions, the time series of
209 power ramps over three time periods (30 minutes, 60 minutes and 4 hours) have been determine. The
210 standard deviation of the resulting time series was calculated and is used as a measure of the
211 magnitude of the ramps.



212

**Figure 3 Standard deviation of the power ramps of each of the 515 different wind farm distributions as a function of**
**the number of farms in the distribution and the mean separation between the capacity for three time windows (a)-(b)**
**30 minutes, (c)-(d) 60 minutes and (e)-(f) 4 hours.**

216 For all three time scales, the magnitude of the ramps decreases as the number of wind farms in the
217 distribution increases (see Figures 3(a)-(f)). A large reduction in the standard deviation is shown
218 between 5 and 30 wind farms before levelling off as the number of farms increases further. For
219 example, for the 30 minute ramps the standard deviation decreases from approximately 4.8% to 2.1%
220 as the number of wind farms increases from 5 to 25, but decreases to only 1.9% as the number of
221 wind farms increases further to 50. However, for all time scales the lowest standard deviation is
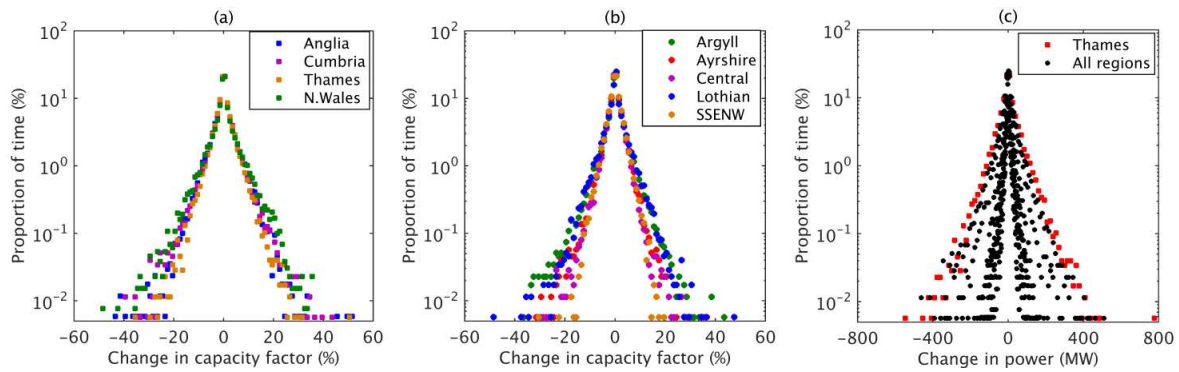222 shown for the largest number of wind farms (i.e. the full GB wind farm distribution).

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223  This analysis indicates that the number of wind farms aggregated is a useful parameter for estimating
224  the distribution of power swings on time scales of 30 minutes to 4 hours. In comparison, the
225  separation between capacity is not a good indicator of the size of the ramps. For all time scales,
226  increasing the separation (but keeping the number of wind farms the same) has little impact on the
227  size of the ramps (see Figures 3(b), 3(d) and 3(f). For example, for a wind farm distribution which
228  contains 41-60 farms, if the separation between the units of capacity is 200 km the standard deviation
229  of the 30 minute ramps is between 1.8% and 2.0%. If the separation were to increase to 400 km the
230  standard deviation is very similar (1.7% - 2.0%). These results suggest that on the time scales
231  considered, the power ramps of the regions are not well correlated, therefore the magnitude of the
232  aggregated ramps decrease as more and more regions (number of farms) are added, irrespective of any
233  potential change in the separation between capacity.

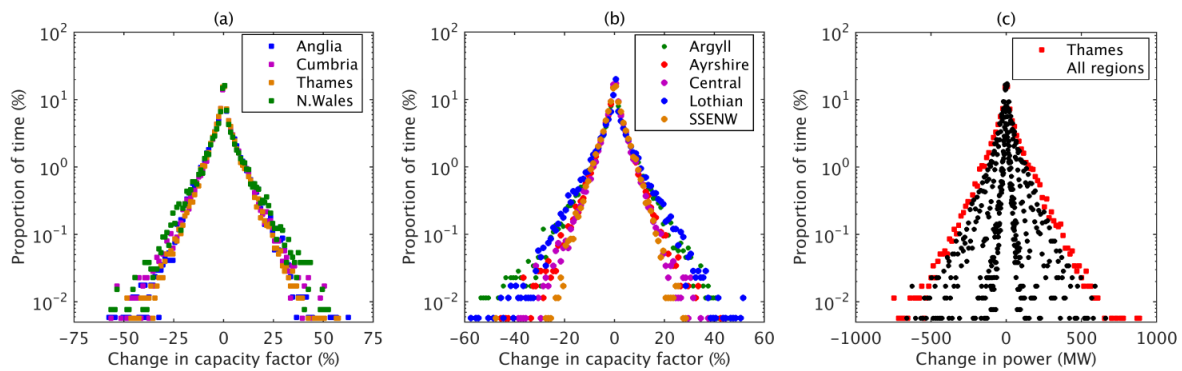234  ## 3.2 Regional power ramps

235  The analysis in section 3.2 has shown that the magnitude of the power ramps of a wind farm
236  distribution is highly dependent on the number of wind farms. The recent trend of concentrating a
237  small number of very large wind farms therefore results in an increase in the magnitude of the local
238  power ramps. Figures 4 to 6 show the distribution of the power ramps for each region in Great Britain
239  in 2014. For all time intervals, the distribution is approximately symmetric with median values close
240  to zero for both the onshore and offshore regions, indicating that positive and negative ramps have a
241  similar distribution.

242  In general, when considered in terms of a change in capacity factor, the magnitude of the ramps is
243  larger for the offshore clusters for all time scales. Consequently, if the system operator were to hold
244  reserve to protect against a 90th percentile swing, for the onshore regions it would equate to on
245  average 3.8%, 6.0% and 14.5% of capacity for 30 minutes, 60 minutes and 4 hours respectively. In
246  comparison a similar holding for the offshore regions would equate to an average of 4.8%, 7.9% and
247  18.9% of capacity. This is due to the offshore clusters containing a lower number of farms than the
248  onshore zones. As the 4 offshore regions have a similar number of farms, the magnitude of ramps is
249  very similar for all offshore regions- with slight differences in the extreme values. For the onshore
250  regions, there is generally a larger spread in the distributions reflecting the variability in the number of
251  farms across the regions. For example, for Lothian there are a similar number of wind farms to the
252  offshore regions and the standard deviation of the ramps is 4.7%, 7.6% and 17.9% for 30 minutes, 60
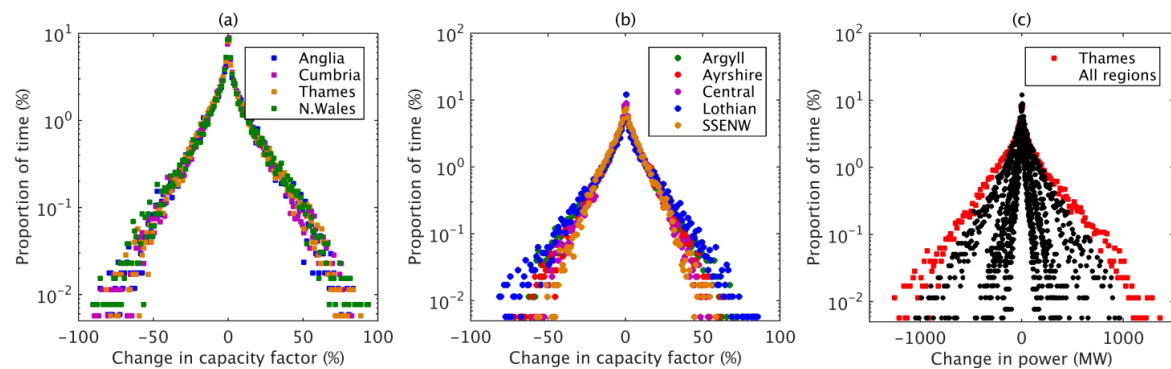253  minutes and 4 hours respectively.

254  When considered in terms of change in power (MW), due to large capacity in Thames Estuary, the
255  ramps of the cluster are larger than all other regions for all time scales (as shown in Figures 4-6 (c)).
256  For example, for the 30 minutes, 60 minutes and 4 hour time window, the maximum ramp in the
257  Thames Estuary is 777 MW, 886 MW and 1363 MW. Power ramps of this magnitude could
258  potentially pose a challenge to those responsible for maintaining a balance between supply and
259  demand on the power system. Accurate meteorological forecasting is critical to decisions made on
260  holding reserve, but can be difficult on such short timescales. Here follows a detailed investigation
261  into the meteorological conditions causing ramps in the Thames Estuary, to inform development of
262  accurate forecasts.

**Figure 4 Distribution of the change in capacity factor within a 30 minute time window in 2014 for (a) offshore clusters (b) onshore regions. (c) The ramps expressed in terms of power (MW).**



**Figure 5 Distribution of the change in capacity factor within a 60 minute time window in 2014 for (a) offshore clusters (b) onshore regions. (c) The ramps expressed in terms of power (MW).**



**Figure 6 Distribution of the change in capacity factor within a 4 hour time window in 2014 for (a) offshore clusters (b) onshore regions. (c) The ramps expressed in terms of power (MW).**

## 3.3 Thames Estuary ramping

In Section 3.2 it was shown that the clusters of offshore wind farms can lead to large high frequency regional power ramps. This section analyses the generation data from the Thames Estuary cluster (the largest of the offshore clusters in terms of capacity) in more detail, to identify the extreme ramping events and determine the meteorological drivers. As with the previous sections, the analysis has been completed on three time scales (30 minutes, 60 minutes and 4 hours).
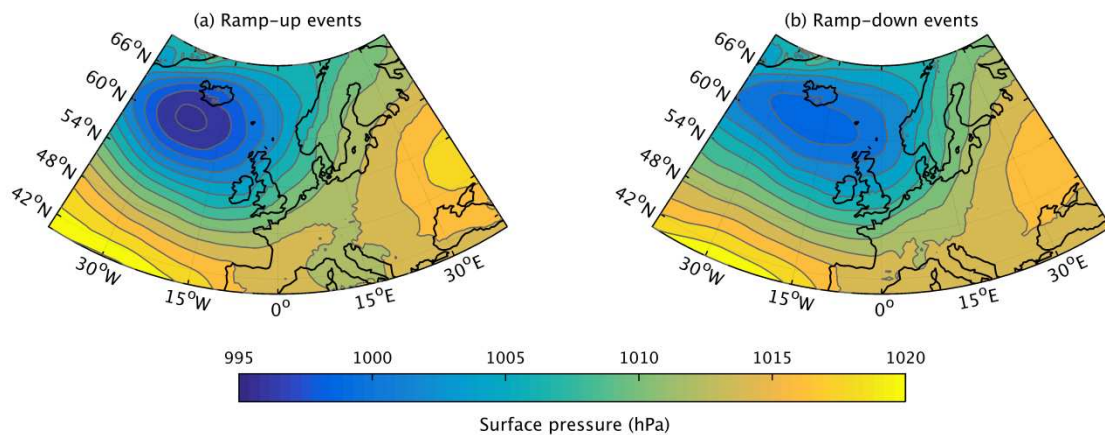
### 3.3.1 Extreme ramps over a 4-hour time window

Following the method outlined in section 2.3 (the hourly capacity factor changes by more than 40% over a 4 hour time window), 74 ramp-up events and 69 ramp-down events were identified. Events occurred throughout the year, however a larger proportion occurred in winter (39% in DJF) than any

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282    of the other seasons (22% in MAM, 24% in JJA and 15% in SON). The most extreme ramp-up event
283    was 86.2% which equates to a change in power of 1.3 GW and the most extreme ramp-down was
284    76.7% which equates to a change in power of 1.2 GW.

285    For each event, the synoptic meteorological conditions have been investigated using the surface
286    pressure data from MERRA (see figure 7). All of the extreme ramping events on this time scale can
287    be linked to the passage of an extra-tropical cyclone (low pressure system) and the associated weather
288    fronts. For all of the 74 ramp-up events, there is a clear pattern in the surface pressure field. A low
289    pressure system is centred over Iceland and the frontal features stretch south-east across the UK.
290    There is a similar pattern for the ramp-down events however the centre of the low pressure has moved
291    eastwards and the gradient in surface pressure over the UK has weakened. Additionally, the frontal
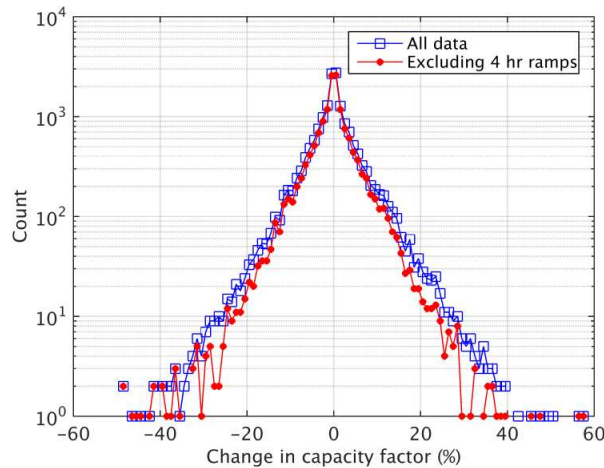292    features are now located east of the cluster.

293    By applying the method developed in Cannon et al. [7], the hourly generation of the Thames Estuary
294    cluster in 2014 has been estimated based on the surface wind field given by MERRA. The derived
295    data have been analysed to determine whether extreme ramping events are captured.  MERRA is
296    defined to have captured a ramp if it is at least 75% of the size of the measured ramp within a ±3 hour
297    time window of when it occurred. Based on this criterion, the MERRA derived data captures all 74
298    ramp-up events and 69 ramp-down events which occurred in the Thames Estuary offshore cluster
299    during 2014. This confirms that the extreme ramping on this time scale is the result of synoptic scale
300    meteorological features which are well reproduced by the reanalysis product.



301

302    **Figure 7 Mean sea level pressure averaged across all (a) 74 ramp-up events and (b) 69 ramp-down events.**

303    3.3.2 Extreme ramps over a 1-hour time window

304    For the full year of measured data, power ramps over a one hour time window have been calculated
305    and the frequency distribution of the ramps is shown in Figure 8 (this is the same data as the Thames
306    curve in Figure 5(a)). The data have then been filtered to remove the periods which contain a 4 hour
307    ramp (identified in section 3.3.1) and the distribution of the filtered ramps is also shown in Figure 8.
308    A comparison of the probability density functions shows the most extreme 60 minute ramping events
309    are the same in both distributions. For the both the filtered and unfiltered datasets the largest ramp-
310    down is -48.8% and the largest ramp-up event is 57.9%. This indicates that the most extreme 1 hour
311    ramps are not part of a larger scale ramp and are therefore not caused by the passage of low pressure
312    system but by smaller scale meteorological features.

Using the criteria outlined in section 2.3, 24 x 1 hour extreme ramping events have been identified. Further analysis shows, on 10 occasions an extreme ramp-up and ramp-down occurred within 3 hours of each other (as shown in Table 3). These ramps were combined to produce 14 independent events. For each event, the meteorological conditions have been investigated using surface pressure fields from MERRA, observations of surface temperature and wind speed from Met Office weather stations close to the cluster (Manston and Shoeburyness) and rainfall radar data. Based on the meteorological data, 3 main drivers of the extreme ramping on this time scale have been identified; (1) turbine cut-out due to high wind speed conditions (2) outflow or gust fronts from thunderstorms and (3) organised band of convection following a frontal system.
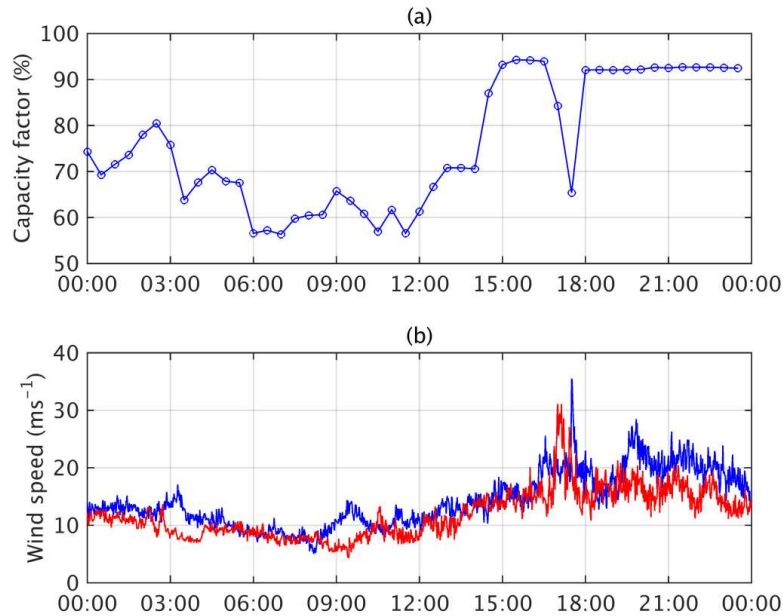
3.3.3 High wind speed cut-out

There were 5 ramping events associated with the high wind speed shutdown of turbines. The largest of which occurred on 14th February 2014, when the output of the farms reduced by 44.3% (i.e. a reduction in power output of 680 MW in 1 hour). All 5 of the cut-out ramping events occurred in winter and are associated with a low pressure system located over the UK. The strong pressure gradient leads to very high wind speeds in the Thames Estuary region. For all of the events, the 1 minute mean wind speed at both Manston and Shoeburyness exceeds 25 ms$^{-1}$ during the period when generation is reduced.
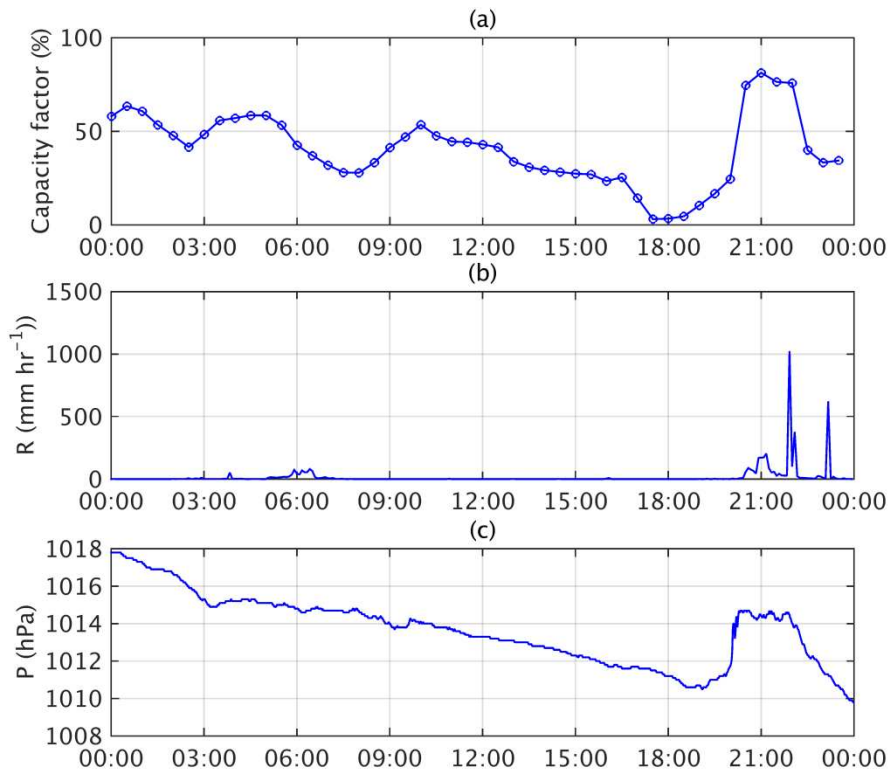
Three of the five events are characterised by a large reduction in the output as the turbines cut-out followed by a similar sized ramp-up. For example, on 25th January 2014 at 16:00 there was a reduction in capacity factor of the cluster by 28.6% (see Figure 9) which corresponds to a spike in wind speeds observed in the region (at Manston, the mean wind speed peaked at 35.5 ms$^{-1}$ at 17:30). Following this, there is a reduction in wind speeds and therefore the turbines start to generate again and therefore there is a ramp-up of 26.7% at 17:00.

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| No. | Date | Ramp-up (%) and time | Ramp-down (%) and time | Maximum rainfall rate (mm hr$^{-1}$) | Type |
|---|---|---|---|---|---|
| 1 | 25/01 | 26.7 (17:00) | -28.6 (16:00) | 91 | Cut-out |
| 2 | 12/02 | 38.3 (16:30) | -29.0 (14:00) | 15 | Cut-out |
| 3 | 14/02 | | -44.3 (22:00) | 26 | Cut-out |
| 4 | 07/03 | 27.6 (20:00) | | 150 | Post-frontal |
| 5 | 23/03 | 32.6 (16:30) | -28.4 (17:30) | 71 | Thunderstorms |
| 6 | 24/05 | 26.3 (16:30) | | 97 | Post-frontal |
| 7 | 07/06 | 45.4 (08:30) | -48.8 (10:00) | 12 | Thunderstorms |
| 8 | 18/07 | 57.9 (19:30) | -42.5 (22:00) | 1023 | Thunderstorms |
| 9 | 19/07 | 39.1 (04:30) | -25.4 (07:00) | 64 | Thunderstorms |
| 10 | 19/07 | 28.6 (19:30) | -28.4 (20:30) | 115 | Thunderstorms |
| 11 | 14/08 | 26.8 (14:30) | -45.9 (15:30) | 396 | Thunderstorms |
| 12 | 03/11 | 31.1 (13:30) | -48.8 (15:30) | 147 | Post-frontal |
| 13 | 19/12 | 36.9 (09:30) | -39.8 (07:00) | 622 | Cut-out |
| 14 | 26/12 | | -36.3 (23:30) | 77 | Cut-out |

**Table 3 Meteorological conditions for the 60 minute ramping events which occurred in the Thames Estuary in 2014 identified using the method outlined in section 2.3.**



349

**Figure 9 Meteorological conditions on 25th January 2014. (a) 30 minute averaged wind power generation of the Thames Estuary cluster (expressed in terms of capacity factor) (b) 1-minute averaged wind speed observations from Manston (blue) and Shoeburyness (red).**

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**Figure 10 Meteorological conditions for the wind power ramping event on 18th July 2014. (a) 30 minute averaged wind power generation of the Thames Estuary cluster (expressed in terms of capacity factor) (b) the maximum rainfall rate of any gridbox in the Thames Estuary on a 5 minute resolution and (c) 1-minute surface pressure observations from Manston.**
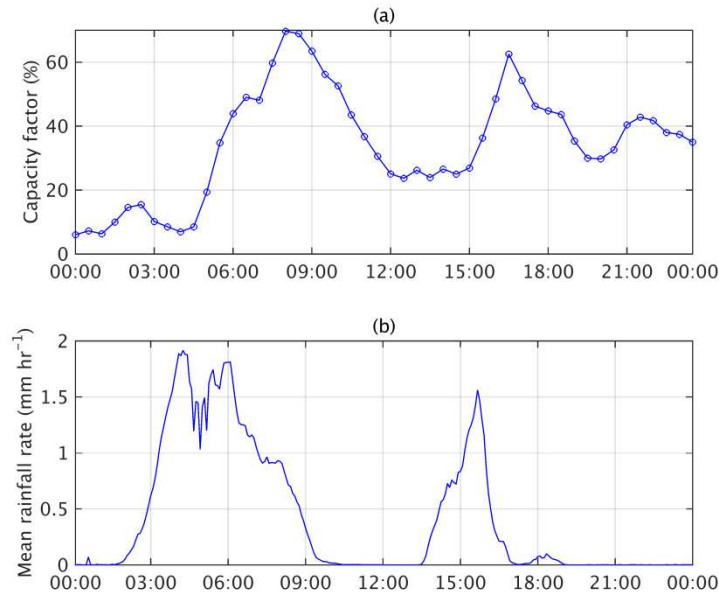
### 3.3.4 Thunderstorms

There were 6 ramping events caused by the wind speed gusts associated with a thunderstorm (2 on 19th July 2014), all of which occurred between March and August. For these events the atmospheric conditions are dominated by a high pressure system (anticyclonic) located over the UK and a low pressure system to the south west. Analysis of the meteorological conditions in the Thames Estuary shows that all ramps coincide with other meteorological conditions which are a signature of the thunderstorm, such as a period of heavy rainfall in the region and large fluctuations in temperature. For example, the maximum rainfall rate during the ramp for any 1 km radar gridbox in the Thames Estuary exceeds 64 mm hr$^{-1}$- for all but one of the ramping events. Furthermore, observations at Manston and Shoeburyness show there is generally sharp drop in temperature during the ramping event.

The largest ramping event associated with a thunderstorm occurred on the 18th July 2014. At 19:30 the capacity factor of the cluster increased by 57.9% (890 MW in 1 hr). Figure 10 shows this ramp coincided with very heavy rainfall across the region. The maximum rainfall rate derived from the radar observations was 1023 mm hr$^{-1}$ at 22:00. In addition, the surface pressure observed at Manston increased by 4 hPa in a 25 minute period (Figure 10(c)).

### 3.3.5 Post-frontal convection

Three events are caused by a band of increased wind speeds which occur after a front. The elevated wind speeds lead to an increase in power output from the cluster for a short period of time before the

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379  <span style="color:red">feature moves away from the region. As with the thunderstorms, there is also a signature of these</span>
380  <span style="color:red">features in the rainfall data.</span> Figure 11 shows the capacity factor of the Thames Estuary wind farms on
381  24th May 2014 and the mean rainfall rate across the region. During the morning a weather front
382  moved across the South East of England which led to high wind speeds and heavy rainfall. After the
383  front moved eastwards away from the cluster of farms, their wind generation reduced dramatically,
384  falling from 69.7% of capacity at 08:00 to only 23.7% at 13:00. In the mid-afternoon there was an
385  increase in wind power generation and by 17:00 the output was back up to 62.6%, however this ramp
386  had a short duration and by 20:00 the output had reduced to only 30.0%. Figure 11(b) shows a
387  corresponding ramp in the rainfall in the region.



388

**Figure 11 Meteorological conditions for the wind power ramping event and the meteorological conditions on 24th May 2014. (a) The 30 minute averaged wind power generation of the Thames Estuary cluster (expressed in terms of capacity factor) and (b) the mean rainfall rate across the Thames Estuary on a 5 minute resolution.**
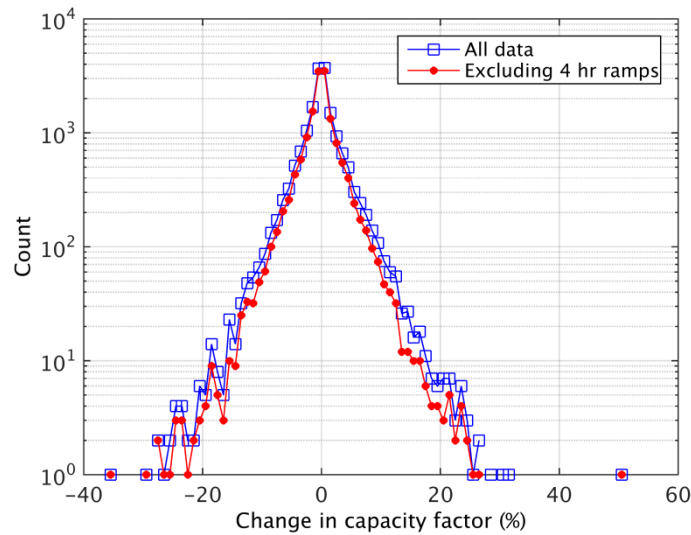
392  3.4 Extreme ramps over 30 time windows

393  For the full year of the data the power ramps over a 30 minute time window have been calculated
394  using the method outlined in Section 2.3. The data have then been filtered to remove the periods
395  which correspond to a 4 hour ramp (derived in section 3.3.1). As with the 60 minute ramps, Figure 12
396  shows that the most extreme 30 minute ramping events are not associated with a larger scale ramp and
397  therefore are not caused by the passage of low pressure system but by a smaller scale meteorological
398  feature.

399  Using the method outlined in section 2.3, only 6 30-minute ramping events have been identified (see
400  Table 4). For each event, the meteorological mechanism has been determined using a range of
401  datasets. Based on the analysis, 4 of the ramps were shown to be associated with the high wind speed
402  cut-out of turbines and two are associated with thunderstorms.

403

| No. | Date | Ramp-up (%) and time | Ramp-down (%) and time | Maximum rainfall rate (mm hr$^{-1}$) | Type |
|---|---|---|---|---|---|
| 1 | 03/01 | | -18.3 (15:30) | 9 | Cut-out |
| 2 | 26/01 | | -16.0 (18:00) | 8 | Cut-out |
| 3 | 28/01 | | -17.4 (04:00) | 37 | Cut-out |
| 4 | 01/02 | 15.2 (07:30) | | 14 | Cut-in |
| 5 | 19/07 | 21.3 (08:30) | | 19 | Thunderstorm |
| 6 | 19/07 | 16.7 (12:00) | | 20 | Thunderstorm |

**Table 4 Details of the 30 minute ramping events which occurred in the Thames Estuary in 2014 identified using the method outlined in section 2.3.**



**Figure 12 The 30 minute ramps for the Thames Estuary cluster during 2014 using the whole dataset (blue) and then excluding the periods during which a 4 hour ramp occurs.**

## 4.0 Conclusions

In recent years there has been a significant change in the distribution of wind capacity in the UK, with the construction of several clusters of very large offshore wind farms. This paper investigates how this change has affected the magnitude of the nationally aggregated and regionalised ramps on temporal scales which are critical for the management of the power system (30 minute, 60 minute and 4 hours). In addition, the extreme high frequency ramps of the largest cluster of offshore wind farms (Thames Estuary) have been investigated in detail to determine the meteorological drivers.

Despite the clustering of capacity in relatively small areas, the addition of the offshore wind farms reduces the high frequency variability of nationally aggregated generation. This study has used two key parameters to quantify the level of clustering; (1) number of wind farms in the region (2) mean separation between capacity. The level of the variability has been considered in terms of the magnitude of the power ramps on the three timescales which are of importance for system management (30 minutes, 60 minutes and 4 hours). For this metric, the magnitude of the variability was highly correlated to the number of wind farms aggregated. As the number of wind farms in the distribution increases, the magnitude of the ramps decreases. This reduction is particularly large between 5 and 25 wind farms before levelling off as the number of farms increases further. In contrast, the mean separation between capacity had little impact on the magnitude of the power swings. In fact, keeping the number of wind farms fixed but changing the separation has a negligible impact on the standard deviation of the distribution of the power swings. These results show that the ramps on these time scales in the different regions are not correlated; therefore aggregating the regions leads to a smoothing effect.

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As the magnitude of the high frequency power swings are highly dependent on the number of wind farms, the recent trend in Great Britain for clustering capacity in a small number of very large wind farms results in an increase in the local power swings. For example, if the system operator were to hold reserve to protect against a $90^{th}$ percentile swing, for the onshore regions in 2014 it would equate to on average 3.8%, 6.0% and 14.5% of capacity for 30 minutes, 60 minutes and 4 hours respectively. In comparison, a similar holding for the offshore regions would equate to an average of 4.8%, 7.9% and 18.9% of capacity. Consequently, for clusters with high levels of capacity this could lead to very large ramps in power. For example, for the Thames Estuary, an 18.9% ramp equates to a change in power of 290 MW. This effect would be exacerbated in the future with the development of even larger clusters (e.g. Dogger Bank which could have a capacity in excess of 4 GW).

The meteorological conditions leading to extreme high frequency ramping of an offshore cluster have been investigated in more detail using the Thames Estuary as a case study. Over a 4 hour time window, the largest ramp in capacity factor was 86.2% (which equates to a power swing of 1.3 GW). This, along with the other extreme 4 hour ramping events was caused by the passage of a cyclone and the associated weather fronts. On shorter time scales, the largest ramping events over 30 minute and 60 minute time windows are not associated with the passage of fronts. They are caused by three main meteorological mechanisms; (1) very high wind speeds associated with a cyclone causing turbine cut-out (2) gusts associated with thunderstorms and (3) organised band of convection following a front.

To minimise the balancing costs associated with the extreme high frequency ramping events the meteorological features need to be captured by the wind power forecast. Drew et al. [3] has shown that high resolution ensemble models are able to capture the elevated wind speed associated with post-frontal convection. However, the timing and location of the feature may not be exactly correct. This study has shown that this problem could potentially be addressed by considering the use of real time meteorological observations, such as data from the rainfall radar to adjust the forecast in real-time if necessary.

## Acknowledgements

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# 1  Identifying and characterising large ramps in power output of
# 2  offshore wind farms

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8

9  ## Abstract

10  Recently there has been a significant change in the distribution of wind farms in Great Britain with the
11  construction of clusters of large offshore wind farms. These clusters can produce large ramping events
12  (i.e. changes in power output) on temporal scales which are critical for managing the power system
13  (30 minute, 60 minute and 4 hours). This study analyses generation data from the Thames Estuary
14  cluster in conjunction with meteorological observations to determine the magnitude and frequency of
15  ramping events and the meteorological mechanism.

16  Over a 4 hour time window, the extreme ramping events of the Thames Estuary cluster were caused
17  by the passage of a cyclone and associated weather fronts. On shorter time scales, the largest ramping
18  events over 30 minute and 60 minute time windows are not associated with the passage of fronts.
19  They are caused by three main meteorological mechanisms; (1) very high wind speeds associated with
20  a cyclone causing turbine cut-out (2) gusts associated with thunderstorms and (3) organised band of
21  convection following a front. Despite clustering offshore capacity, the addition of offshore wind farms
22  has increased the mean separation between capacity and therefore reduced the variability in nationally
23  aggregated generation on high frequency time scales.

24  Keywords: wind; offshore; variability; ramping; extremes

25  ## 1.0 Introduction

26  To meet ambitious carbon reduction targets, global renewable energy deployment has expanded
27  dramatically. In the UK, the capacity of wind power has grown steadily from 2.9 GW in 2008 to 17.9
28  GW by June 2017 [1]. Due to the increasing penetration of wind power, extreme wind power
29  generation events are of growing concern. In particular, ramps in generation provide challenges for
30  the transmission system operator who schedule reserve holding in advance and require long term
31  strategies for system balancing [2]. Consequently, a number of studies have focused on understanding
32  and improving the predictability of wind power ramping events [3, 4, 5, 6].

33  For the UK, Cannon et al. [7] used wind speed data derived from the MERRA reanalysis dataset to
34  quantify the magnitude and frequency of nationally-aggregated wind generation ramping on time
35  scales of 6 hours and greater based on the 2012 wind farm distribution. However, in recent years there
36  has been a significant change in the distribution of wind farms in the Great Britain [8]. Since 2012,
37  the capacity of offshore wind farms has increased from 2.4 GW to 5.0 GW with much of this capacity
38  spread over a small number of very large wind farms located in clusters. For example, in the Thames
39  Estuary alone there is approximately 1.7 GW of capacity. Drew et al. [3] showed this has led to large

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40    regional ramps in generation on time scales of minutes to hours as local meteorological phenomena
41    simultaneously impacts production in several large farms. Given the large capacity of the farms, these
42    ramps can present a challenge in maintaining the balance between supply and demand on a national
43    scale, particularly if they are not accurately forecasted.

44    The problem posed by local ramping events is expected to be exacerbated in the coming years, given
45    the trend for clustering capacity in large offshore wind farms looks set to continue. The latest phase of
46    offshore wind development in the UK, launched in 2009, identified 9 zones within which a number of
47    individual wind farms could be located with a total capacity of over 30 GW [9, 10]. Consequently,
48    following the construction of the round 3 wind farms the majority of GB wind capacity would be
49    located offshore in clusters of very large wind farms [11, 12].

50    To improve the performance of operational wind power forecasts there is an increasing need for a
51    clear understanding of the meteorological features responsible for the extreme local ramping events
52    [13]. For example, Trombe et al. [14] showed that high frequency ramping of large Danish offshore
53    wind farms can be associated with heavy rainfall and therefore considered the scope for using data
54    from the rainfall radar to adjust the forecast in real-time if necessary. This study investigates whether
55    such an approach could be applied to ramping events in the Thames Estuary wind farms.

56    In addition to the problems posed by local ramping events, there are concerns that clustering capacity
57    could lead to an increase in the variability of the nationally aggregated wind generation (i.e. a reversal
58    of some of the smoothing benefits gained by the spatial dispersion of turbines). A number of studies
59    have investigated the reduction in wind power variability due to geographical dispersion of turbines
60    for single European countries. For example, Kubik et al. for Northern Ireland [15], Hurley and
61    Watson for Ireland [16], Hasche for Germany and Ireland [17] and Giebel [18], Landberg [19],
62    Buttler [20] and Huber et al. [21] considered the whole of Europe.

63    For the UK, Sinden [22] and Earl et al. [23] used wind speed data measured at Met Office surface
64    stations to quantify the inter-annual, seasonal and diurnal variability of UK aggregated wind
65    generation. However, these studies did not consider offshore sites and assumed the distribution of
66    wind capacity matched the distribution of weather stations which can lead to large errors [24]. To
67    address this problem, Cannon et al. [7] used wind speed data derived from the MERRA reanalysis
68    dataset to determine the characteristics of wind power in Great Britain over a 33 year period. The
69    study provides a detailed climatology of ramping on time scales of 6 hours and greater.

70    Using the approach outlined in Cannon et al. [7], Drew et al. [12] showed that the increased
71    penetration of offshore wind farms has little impact on the ramping of GB-aggregated wind
72    generation on time scales of greater than 6 hours. However, due to the resolution of the model,
73    MERRA reanalysis data cannot be used to determine the high frequency GB-aggregated power
74    swings (minutes to hours) or quantify the magnitude of wind power ramps at high spatial resolutions
75    (below 300 km), both of which are important considerations for managing the power system.

76    In the UK, the electricity market is managed in 30 minute windows, known as settlement periods. For
77    each period, suppliers and generators contract electricity up to 1 hour prior to the delivery time, a cut-
78    off time known as "gate closure". It is then the responsibility of the system operator (National Grid) to
79    take any necessary actions in order to balance the grid within each settlement period. The electricity
80    network in the UK is largely isolated with relatively few interconnectors to neighbouring countries
81    and therefore there is a reliance on large conventional power plants to manage the system. However,
82    these plants generally require a period of notice prior to generation to ramp up, generally assumed to

be at least 4 hours. To manage the power system, it is therefore important to understand the possible ramps in power that could occur on time scales shorter than the ramp up time of a conventional power plant (4 hours), between gate closure and settlement period (1 hour) and from one settlement period to the next (30 minutes).

The aim of this study is to use a 30-minute averaged time series of wind power generation from a number of regions across Great Britain (GB) in 2014 to investigate how the increased penetration of clustered offshore wind capacity has affected the characteristics of generation at high spatial and temporal resolutions. The first section considers the impact on high frequency variability of wind generation on both a national and regional scale, particularly the magnitude of ramping in generation on time scales of less than 4 hours. The second section determines the meteorological causes of extreme regional ramping events using the Thames Estuary as a case study.

## 2.0 Datasets and analysis methods

One of the main challenges when investigating the variability of wind generation in the UK at high spatiotemporal resolutions is the limited availability of suitable data. Actual metered data from the individual wind farms is protected by commercial interests; therefore there is a reliance on nationally aggregated data. However, analysis using this data is unable to quantify the regional power swings or indicate how the variability has been affected by the change in wind farm distribution. Cradden et al. [24] used an hourly 11 year hindcast derived using the Weather Research and Forecasting model (WRF) at 3 km resolution to assess the variability of generation from 13 different regions in the UK.

This study introduces a new dataset which details the aggregated power output from four offshore clusters (Anglia, Cumbria, N.Wales and Thames) and five onshore regions; Argyll, Ayrshire, Central, Lothian and SSENW (see Figure 1) at 30 min resolution from 1st January 2014 to 31st December 2014 (see Table 1 and Figure 1). The total capacity across the 9 regions is 6.5 GW, which is approximately 70% of the total installed wind capacity of Great Britain.

A number of wind farms have been excluded from the analysis for two reasons (1) they the sole wind farm in a region therefore it was not possible to produce anonymous, aggregated generation data or (2) the data was not of sufficient quality. Despite the reduced number of wind farms, the dataset provides a good representation of the wind resource. For example, the GB-aggregated capacity factor for 2014 was calculated to be 31%, which compares well to the figure of 30.2% for the full wind farm distribution [25].

| | Mean separation (km) | Number of farms | Capacity (GW) |
|---|---|---|---|
| Lothian | 17.3 | 5 | 0.44 |
| **N.Wales** | **26.9** | **3** | **0.18** |
| **Cumbria** | **30.7** | **5** | **1.17** |
| **Thames** | **34.5** | **4** | **1.54** |
| **Anglia** | **38.1** | **3** | **0.33** |
| Central | 60.7 | 11 | 1.22 |
| Ayrshire | 79.3 | 8 | 0.52 |
| Argyll | 89.1 | 6 | 0.30 |
| SSENW | 115.2 | 16 | 0.80 |

115 2.1 Spatial separation of capacity

116 The addition of offshore wind farms has changed the distribution of capacity in two distinct ways.
117 Firstly, there is an increased concentration of capacity in clusters. For each region the spatial
118 dispersion of the capacity has been quantified in terms of the mean separation per unit MW of
119 capacity, S, as calculated in [12] as:

$$s = \sum_{i=1}^{N} \frac{c_i}{C_T} \left( \sum_{j=1}^{N} \frac{c_j d_{ij}}{C_T} \right) \tag{1}$$

120 where $c_j$ is the wind farm capacity, $d_{ij}$ is the distance between wind farms, $N$ is the number of wind
121 farms in the region and $C_T$ is the total installed capacity of the region. The offshore regions are
122 generally made up of large wind farms clustered together in a relatively small area and consequently
123 have a low separation between units of capacity (26.9 km to 38.1 km). In comparison, onshore regions
124 generally consist of spatially dispersed small wind farms therefore the separation of the capacity is
125 larger (60.7 km to 115.2 km), with the exception of Lothian (17.3 km). Secondly, the addition of the
126 offshore regions has changed the geographical location of the generation. Figure 1 shows that all of
127 the onshore zones are located relatively close to each other in Scotland; therefore the mean separation
128 between the onshore capacity is only 168 km. In contrast, all of the offshore clusters are connected to
129 England, and are more geographically dispersed (mean separation of 327.6 km between the offshore
130 capacity), therefore by combining the onshore and offshore capacity the mean separation between
131 capacity for the GB wind farm distribution increases to 399 km.



132

133 **Figure 1 Map of the wind farm distribution used in this study. The onshore and offshore farms are represented by**
134 **the circles and crosses respectively.**

135 2.2 Impact of spatial separation on generation characteristics

136 To investigate the impact of spatial separation of capacity on wind power variability in Great Britain,
137 the 30-minute averaged time series of aggregated generation for each of the 9 regions have been
138 combined to derive a time series of power output for every possible combination of regions. This
139 ranges from a combination of two regions (36 possibilities) to the single combination of all nine

140 regions (GB-aggregate) and therefore amounts to a total of 515 possible wind farm distribution
141 scenarios each with a different number of wind farms and mean separation between capacity. The data
142 are then used to determine the impact of clustering capacity on the high frequency variability of the
143 wind generation.

144 A range of different metrics have been used to quantify the variability of wind generation. For the
145 purposes of this study a ramp, R, at time, t, is defined as the difference in the power output over a
146 period of time, Δt, given by:

$$R(t) = P(t + \Delta t) - P(t) \tag{2}$$

147 where P(t) is the power output at time, t. Using the 30-minute averaged dataset, a time series of ramps
148 for Δt=30 minutes, 60 minutes and 4 hours, has been calculated for each wind farm distribution
149 scenario. The standard deviation, σ, of each time series is then calculated to quantify the distribution
150 of the ramps for each scenario.

151 2.3 Thames Estuary analysis

152 Section 3.3 investigates the most extreme ramping events over three time scales (30 minutes, 60
153 minutes and 4 hours) of a single offshore cluster in order to determine the meteorological
154 mechanisms. The analysis focuses on the offshore wind farms in the Thames Estuary, located
155 approximately 100-200 km east of London, UK. This is the largest of the offshore clusters consisting
156 of 5 individual farms with a total capacity of 1.7 GW. Drew et al. [3] presents a detailed analysis of a
157 high frequency ramping event of this cluster which had significant implications on the management of
158 the power system. This study investigates the full range of extreme ramps to determine the
159 meteorological cause.

160 To determine extreme ramping events the 30 minute averaged time series of the capacity factor of the
161 Thames region (as outlined in section 2.2) has been used. The extreme ramping events for each time
162 window have been defined following a similar method to that outlined in Cutler et al. [6].

- 4 hour ramps: Find all instances where the 30 minute averaged capacity factor changes by
more than 40% within a 4 hour window. Two individual ramps occurring within a 6 hour
window of each other are considered the same event.
- 60 minute ramps: After removing the periods of time during which a 4 hour ramp occurs, find
the occasions where the 30 minute averaged capacity factor changes by more than 25% in a
60 minute time window. Two ramps are considered the same event if they occur within 1 hour
of each other.
- 30 minute ramps: After removing the periods where either a 4 hour or 60 minute ramp occurs,
find the occasions where the 30 minute averaged capacity factor changes by more than 15%
in a 30 minute time window.

173 To determine the meteorological mechanisms behind extreme ramping events, a number of datasets
174 have been used (Table 2). Firstly, the meteorological conditions in the Thames Estuary region have
175 been determined using 1-minute averaged observations of temperature, wind speed and surface
176 pressure from two nearby Met Office weather stations (shown in Figure 2) and rainfall rate data
177 derived from radar observations for an area of 4884 m$^2$ covering all of the wind farms on a 1km$^2$
178 spatial resolution and a 5 minute temporal resolution [26, 27]. On the larger scale, the synoptic scale
179 conditions have been determined using hourly wind fields and surface pressure from Modern-Era
180 Retrospective Analysis for Research and Applications (MERRA) data [28].

181  In addition to determining the meteorological conditions associated with ramps, hourly surface wind
182  field data from MERRA has been used to estimate the aggregated power generation of the wind farms
183  in the region, following the method of Cannon et al. [7]. Firstly, the horizontally gridded surface
184  hourly winds were bi-linearly interpolated to the location of each wind farm. The derived winds were
185  then vertically interpolated to the hub height of the turbines. Finally, the hub-height wind speeds were
186  converted to power output using a transfer function derived from empirical comparisons between the
187  derived wind speeds and recorded wind farm output. The power output was summed over all wind
188  farms to produce an hourly time series of generation of the Thames Estuary cluster.

189

| Dataset | Variables | Temporal resolution | Location |
|---|---|---|---|
| UK Met Office weather station observations | Air temperature (C) at 1.25 m above the ground. Mean wind speed and maximum gust at 10 m above the ground ($ms^{-1}$). Atmospheric pressure (hPa). | 1-minute | Manston (51.346°N, 1.337°E).and Shoeburyness (51.536°N, 0.809°E). |
| Met Office rainfall radar | Rainfall rate (mm $hr^{-1}$) | 5-minute | Thames Estuary region (see Figure 2) on 1 $km^2$ resolution. |
| MERRA: Modern-Era Retrospective Analysis for Research and Applications | Mean wind speed ($ms^{-1}$) at heights of 2 m, 10 m and 50 m. Surface pressure (hPa). | Hourly | 0.5° x 0.667° global grid. |

190  **Table 1 Details of the meteorological datasets used in this study.**

191



192  **Figure 2 Map showing the location of the 5 wind farms in the Thames Estuary: Greater Gabbard (GG), London**
193  **Array (LA), Gunfleet Sands (GF), Kentish Flats (KF) and Thanet (THA). The red box indicates the region for which**
194  **radar rainfall data was obtained. The map also shows the locations of the surface meteorological stations: Manston**
195  **and Shoeburyness.**

196  ## 3.0 Results

197  The dataset outlined in Section 2 has been used to address a series of questions related to wind power
198  variability. Section 3.1 investigates the impact of the offshore wind farms on the GB-aggregated wind
199  generation characteristics, with a particular emphasis on the impact of changing the separation
200  between capacity and the number of wind farms on the magnitude on the high frequency ramps.
201  Section 3.2 determines the magnitude of regional high frequency power swings for the offshore

202 clusters and compares the results to that of the more spatially-dispersed onshore regions. Finally,
203 Section 3.3 quantifies the high frequency ramping of wind farms in the Thames Estuary, the largest
204 offshore cluster and identifies the meteorological mechanism.

205 3.1 Impact of clustering capacity on generation variability

206 This section determines how the magnitude of the ramps in regional wind power varies with two
207 metrics used to define the level of clustering (1) the number of wind farms aggregated and (2) the
208 mean separation between capacity. For all 515 possible wind farm distributions, the time series of
209 power ramps over three time periods (30 minutes, 60 minutes and 4 hours) have been determine. The
210 standard deviation of the resulting time series was calculated and is used as a measure of the
211 magnitude of the ramps.



212

**Figure 3 Standard deviation of the power ramps of each of the 515 different wind farm distributions as a function of**
**the number of farms in the distribution and the mean separation between the capacity for three time windows (a)-(b)**
**30 minutes, (c)-(d) 60 minutes and (e)-(f) 4 hours.**

216 For all three time scales, the magnitude of the ramps decreases as the number of wind farms in the
217 distribution increases (see Figures 3(a)-(f)). A large reduction in the standard deviation is shown
218 between 5 and 30 wind farms before levelling off as the number of farms increases further. For
219 example, for the 30 minute ramps the standard deviation decreases from approximately 4.8% to 2.1%
220 as the number of wind farms increases from 5 to 25, but decreases to only 1.9% as the number of
221 wind farms increases further to 50. However, for all time scales the lowest standard deviation is
222 shown for the largest number of wind farms (i.e. the full GB wind farm distribution).

7

223    This analysis indicates that the number of wind farms aggregated is a useful parameter for estimating
224    the distribution of power swings on time scales of 30 minutes to 4 hours. In comparison, the
225    separation between capacity is not a good indicator of the size of the ramps. For all time scales,
226    increasing the separation (but keeping the number of wind farms the same) has little impact on the
227    size of the ramps (see Figures 3(b), 3(d) and 3(f). For example, for a wind farm distribution which
228    contains 41-60 farms, if the separation between the units of capacity is 200 km the standard deviation
229    of the 30 minute ramps is between 1.8% and 2.0%. If the separation were to increase to 400 km the
230    standard deviation is very similar (1.7% - 2.0%). These results suggest that on the time scales
231    considered, the power ramps of the regions are not well correlated, therefore the magnitude of the
232    aggregated ramps decrease as more and more regions (number of farms) are added, irrespective of any
233    potential change in the separation between capacity.

234    3.2 Regional power ramps

235    The analysis in section 3.2 has shown that the magnitude of the power ramps of a wind farm
236    distribution is highly dependent on the number of wind farms. The recent trend of concentrating a
237    small number of very large wind farms therefore results in an increase in the magnitude of the local
238    power ramps. Figures 4 to 6 show the distribution of the power ramps for each region in Great Britain
239    in 2014. For all time intervals, the distribution is approximately symmetric with median values close
240    to zero for both the onshore and offshore regions, indicating that positive and negative ramps have a
241    similar distribution.

242    In general, when considered in terms of a change in capacity factor, the magnitude of the ramps is
243    larger for the offshore clusters for all time scales. Consequently, if the system operator were to hold
244    reserve to protect against a 90th percentile swing, for the onshore regions it would equate to on
245    average 3.8%, 6.0% and 14.5% of capacity for 30 minutes, 60 minutes and 4 hours respectively. In
246    comparison a similar holding for the offshore regions would equate to an average of 4.8%, 7.9% and
247    18.9% of capacity. This is due to the offshore clusters containing a lower number of farms than the
248    onshore zones. As the 4 offshore regions have a similar number of farms, the magnitude of ramps is
249    very similar for all offshore regions- with slight differences in the extreme values. For the onshore
250    regions, there is generally a larger spread in the distributions reflecting the variability in the number of
251    farms across the regions. For example, for Lothian there are a similar number of wind farms to the
252    offshore regions and the standard deviation of the ramps is 4.7%, 7.6% and 17.9% for 30 minutes, 60
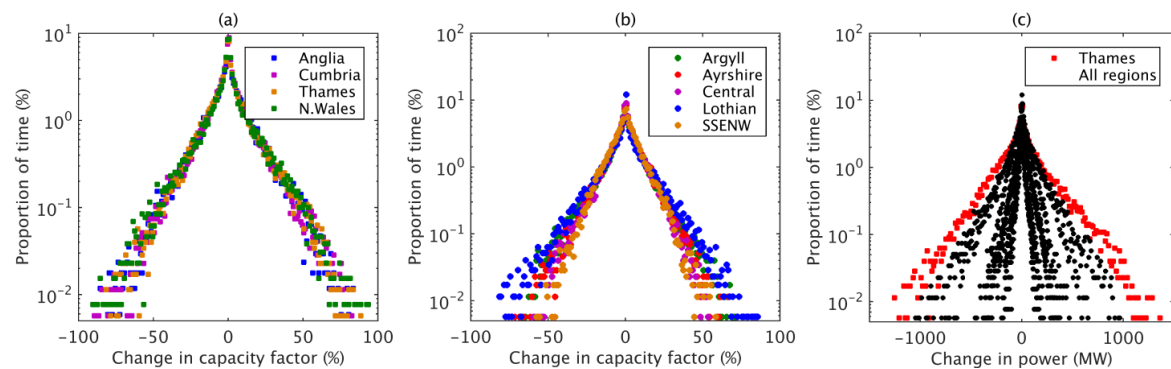253    minutes and 4 hours respectively.

254    When considered in terms of change in power (MW), due to large capacity in Thames Estuary, the
255    ramps of the cluster are larger than all other regions for all time scales (as shown in Figures 4-6 (c)).
256    For example, for the 30 minutes, 60 minutes and 4 hour time window, the maximum ramp in the
257    Thames Estuary is 777 MW, 886 MW and 1363 MW. Power ramps of this magnitude could
258    potentially pose a challenge to those responsible for maintaining a balance between supply and
259    demand on the power system. Accurate meteorological forecasting is critical to decisions made on
260    holding reserve, but can be difficult on such short timescales. Here follows a detailed investigation
261    into the meteorological conditions causing ramps in the Thames Estuary, to inform development of
262    accurate forecasts.

**Figure 4 Distribution of the change in capacity factor within a 30 minute time window in 2014 for (a) offshore clusters (b) onshore regions. (c) The ramps expressed in terms of power (MW).**



**Figure 5 Distribution of the change in capacity factor within a 60 minute time window in 2014 for (a) offshore clusters (b) onshore regions. (c) The ramps expressed in terms of power (MW).**



**Figure 6 Distribution of the change in capacity factor within a 4 hour time window in 2014 for (a) offshore clusters (b) onshore regions. (c) The ramps expressed in terms of power (MW).**

## 3.3 Thames Estuary ramping

In Section 3.2 it was shown that the clusters of offshore wind farms can lead to large high frequency regional power ramps. This section analyses the generation data from the Thames Estuary cluster (the largest of the offshore clusters in terms of capacity) in more detail, to identify the extreme ramping events and determine the meteorological drivers. As with the previous sections, the analysis has been completed on three time scales (30 minutes, 60 minutes and 4 hours).

### 3.3.1 Extreme ramps over a 4-hour time window

Following the method outlined in section 2.3 (the hourly capacity factor changes by more than 40% over a 4 hour time window), 74 ramp-up events and 69 ramp-down events were identified. Events occurred throughout the year, however a larger proportion occurred in winter (39% in DJF) than any

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282   of the other seasons (22% in MAM, 24% in JJA and 15% in SON). The most extreme ramp-up event
283   was 86.2% which equates to a change in power of 1.3 GW and the most extreme ramp-down was
284   76.7% which equates to a change in power of 1.2 GW.

285   For each event, the synoptic meteorological conditions have been investigated using the surface
286   pressure data from MERRA (see figure 7). All of the extreme ramping events on this time scale can
287   be linked to the passage of an extra-tropical cyclone (low pressure system) and the associated weather
288   fronts. For all of the 74 ramp-up events, there is a clear pattern in the surface pressure field. A low
289   pressure system is centred over Iceland and the frontal features stretch south-east across the UK.
290   There is a similar pattern for the ramp-down events however the centre of the low pressure has moved
291   eastwards and the gradient in surface pressure over the UK has weakened. Additionally, the frontal
292   features are now located east of the cluster.

293   By applying the method developed in Cannon et al. [7], the hourly generation of the Thames Estuary
294   cluster in 2014 has been estimated based on the surface wind field given by MERRA. The derived
295   data have been analysed to determine whether extreme ramping events are captured.  MERRA is
296   defined to have captured a ramp if it is at least 75% of the size of the measured ramp within a ±3 hour
297   time window of when it occurred. Based on this criterion, the MERRA derived data captures all 74
298   ramp-up events and 69 ramp-down events which occurred in the Thames Estuary offshore cluster
299   during 2014. This confirms that the extreme ramping on this time scale is the result of synoptic scale
300   meteorological features which are well reproduced by the reanalysis product.



301

302   **Figure 7 Mean sea level pressure averaged across all (a) 74 ramp-up events and (b) 69 ramp-down events.**

303   3.3.2 Extreme ramps over a 1-hour time window

304   For the full year of measured data, power ramps over a one hour time window have been calculated
305   and the frequency distribution of the ramps is shown in Figure 8 (this is the same data as the Thames
306   curve in Figure 5(a)). The data have then been filtered to remove the periods which contain a 4 hour
307   ramp (identified in section 3.3.1) and the distribution of the filtered ramps is also shown in Figure 8.
308   A comparison of the probability density functions shows the most extreme 60 minute ramping events
309   are the same in both distributions. For the both the filtered and unfiltered datasets the largest ramp-
310   down is -48.8% and the largest ramp-up event is 57.9%. This indicates that the most extreme 1 hour
311   ramps are not part of a larger scale ramp and are therefore not caused by the passage of low pressure
312   system but by smaller scale meteorological features.

Using the criteria outlined in section 2.3, 24 x 1 hour extreme ramping events have been identified. Further analysis shows, on 10 occasions an extreme ramp-up and ramp-down occurred within 3 hours of each other (as shown in Table 3). These ramps were combined to produce 14 independent events. For each event, the meteorological conditions have been investigated using surface pressure fields from MERRA, observations of surface temperature and wind speed from Met Office weather stations close to the cluster (Manston and Shoeburyness) and rainfall radar data. Based on the meteorological data, 3 main drivers of the extreme ramping on this time scale have been identified; (1) turbine cut-out due to high wind speed conditions (2) outflow or gust fronts from thunderstorms and (3) organised band of convection following a frontal system.

3.3.3 High wind speed cut-out

There were 5 ramping events associated with the high wind speed shutdown of turbines. The largest of which occurred on 14th February 2014, when the output of the farms reduced by 44.3% (i.e. a reduction in power output of 680 MW in 1 hour). All 5 of the cut-out ramping events occurred in winter and are associated with a low pressure system located over the UK. The strong pressure gradient leads to very high wind speeds in the Thames Estuary region. For all of the events, the 1 minute mean wind speed at both Manston and Shoeburyness exceeds 25 ms$^{-1}$ during the period when generation is reduced.

Three of the five events are characterised by a large reduction in the output as the turbines cut-out followed by a similar sized ramp-up. For example, on 25th January 2014 at 16:00 there was a reduction in capacity factor of the cluster by 28.6% (see Figure 9) which corresponds to a spike in wind speeds observed in the region (at Manston, the mean wind speed peaked at 35.5 ms$^{-1}$ at 17:30). Following this, there is a reduction in wind speeds and therefore the turbines start to generate again and therefore there is a ramp-up of 26.7% at 17:00.

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| No. | Date | Ramp-up (%) and time | Ramp-down (%) and time | Maximum rainfall rate (mm hr$^{-1}$) | Type |
|---|---|---|---|---|---|
| 1 | 25/01 | 26.7 (17:00) | -28.6 (16:00) | 91 | Cut-out |
| 2 | 12/02 | 38.3 (16:30) | -29.0 (14:00) | 15 | Cut-out |
| 3 | 14/02 | | -44.3 (22:00) | 26 | Cut-out |
| 4 | 07/03 | 27.6 (20:00) | | 150 | Post-frontal |
| 5 | 23/03 | 32.6 (16:30) | -28.4 (17:30) | 71 | Thunderstorms |
| 6 | 24/05 | 26.3 (16:30) | | 97 | Post-frontal |
| 7 | 07/06 | 45.4 (08:30) | -48.8 (10:00) | 12 | Thunderstorms |
| 8 | 18/07 | 57.9 (19:30) | -42.5 (22:00) | 1023 | Thunderstorms |
| 9 | 19/07 | 39.1 (04:30) | -25.4 (07:00) | 64 | Thunderstorms |
| 10 | 19/07 | 28.6 (19:30) | -28.4 (20:30) | 115 | Thunderstorms |
| 11 | 14/08 | 26.8 (14:30) | -45.9 (15:30) | 396 | Thunderstorms |
| 12 | 03/11 | 31.1 (13:30) | -48.8 (15:30) | 147 | Post-frontal |
| 13 | 19/12 | 36.9 (09:30) | -39.8 (07:00) | 622 | Cut-out |
| 14 | 26/12 | | -36.3 (23:30) | 77 | Cut-out |

**Table 3 Meteorological conditions for the 60 minute ramping events which occurred in the Thames Estuary in 2014 identified using the method outlined in section 2.3.**



349

350 **Figure 9 Meteorological conditions on 25th January 2014. (a) 30 minute averaged wind power generation of the**
351 **Thames Estuary cluster (expressed in terms of capacity factor) (b) 1-minute averaged wind speed observations from**
352 **Manston (blue) and Shoeburyness (red).**

353

Figure 10 Meteorological conditions for the wind power ramping event on 18th July 2014. (a) 30 minute averaged wind power generation of the Thames Estuary cluster (expressed in terms of capacity factor) (b) the maximum rainfall ra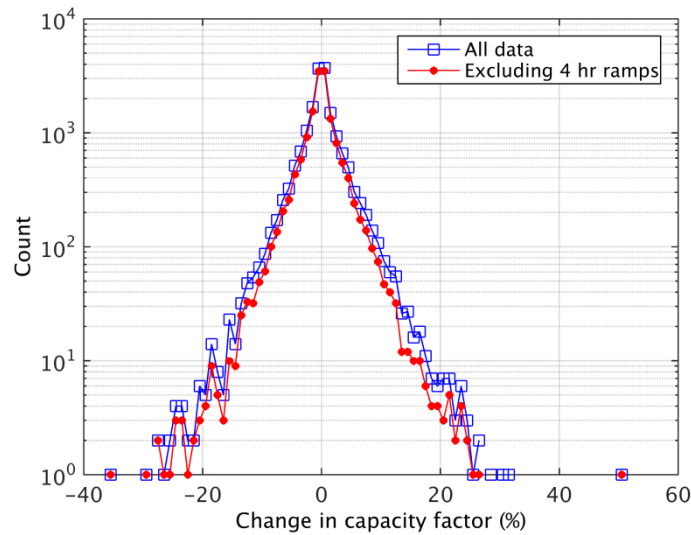te of any gridbox in the Thames Estuary on a 5 minute resolution and (c) 1-minute surface pressure observations from Manston.

3.3.4 Thunderstorms

There were 6 ramping events caused by the wind speed gusts associated with a thunderstorm (2 on 19th July 2014), all of which occurred between March and August. For these events the atmospheric conditions are dominated by a high pressure system (anticyclonic) located over the UK and a low pressure system to the south west. Analysis of the meteorological conditions in the Thames Estuary shows that all ramps coincide with other meteorological conditions which are a signature of the thunderstorm, such as a period of heavy rainfall in the region and large fluctuations in temperature. For example, the maximum rainfall rate during the ramp for any 1 km radar gridbox in the Thames Estuary exceeds 64 mm hr$^{-1}$- for all but one of the ramping events. Furthermore, observations at Manston and Shoeburyness show there is generally sharp drop in temperature during the ramping event.

The largest ramping event associated with a thunderstorm occurred on the 18th July 2014. At 19:30 the capacity factor of the cluster increased by 57.9% (890 MW in 1 hr). Figure 10 shows this ramp coincided with very heavy rainfall across the region. The maximum rainfall rate derived from the radar observations was 1023 mm hr$^{-1}$ at 22:00. In addition, the surface pressure observed at Manston increased by 4 hPa in a 25 minute period (Figure 10(c)).

3.3.5 Post-frontal convection

Three events are caused by a band of increased wind speeds which occur after a front. The elevated wind speeds lead to an increase in power output from the cluster for a short period of time before the

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379 feature moves away from the region. As with the thunderstorms, there is also a signature of these
380 features in the rainfall data. Figure 11 shows the capacity factor of the Thames Estuary wind farms on
381 24th May 2014 and the mean rainfall rate across the region. During the morning a weather front
382 moved across the South East of England which led to high wind speeds and heavy rainfall. After the
383 front moved eastwards away from the cluster of farms, their wind generation reduced dramatically,
384 falling from 69.7% of capacity at 08:00 to only 23.7% at 13:00. In the mid-afternoon there was an
385 increase in wind power generation and by 17:00 the output was back up to 62.6%, however this ramp
386 had a short duration and by 20:00 the output had reduced to only 30.0%. Figure 11(b) shows a
387 corresponding ramp in the rainfall in the region.



388

389 **Figure 11 Meteorological conditions for the wind power ramping event and the meteorological conditions on 24th May**
390 **2014. (a) The 30 minute averaged wind power generation of the Thames Estuary cluster (expressed in terms of**
391 **capacity factor) and (b) the mean rainfall rate across the Thames Estuary on a 5 minute resolution.**

392 3.4 Extreme ramps over 30 time windows

393 For the full year of the data the power ramps over a 30 minute time window have been calculated
394 using the method outlined in Section 2.3. The data have then been filtered to remove the periods
395 which correspond to a 4 hour ramp (derived in section 3.3.1). As with the 60 minute ramps, Figure 12
396 shows that the most extreme 30 minute ramping events are not associated with a larger scale ramp and
397 therefore are not caused by the passage of low pressure system but by a smaller scale meteorological
398 feature.

399 Using the method outlined in section 2.3, only 6 30-minute ramping events have been identified (see
400 Table 4). For each event, the meteorological mechanism has been determined using a range of
401 datasets. Based on the analysis, 4 of the ramps were shown to be associated with the high wind speed
402 cut-out of turbines and two are associated with thunderstorms.

403

| No. | Date | Ramp-up (%) and time | Ramp-down (%) and time | Maximum rainfall rate (mm hr$^{-1}$) | Type |
|---|---|---|---|---|---|
| 1 | 03/01 | | -18.3 (15:30) | 9 | Cut-out |
| 2 | 26/01 | | -16.0 (18:00) | 8 | Cut-out |
| 3 | 28/01 | | -17.4 (04:00) | 37 | Cut-out |
| 4 | 01/02 | 15.2 (07:30) | | 14 | Cut-in |
| 5 | 19/07 | 21.3 (08:30) | | 19 | Thunderstorm |
| 6 | 19/07 | 16.7 (12:00) | | 20 | Thunderstorm |

**Table 4 Details of the 30 minute ramping events which occurred in the Thames Estuary in 2014 identified using the method outlined in section 2.3.**



**Figure 12 The 30 minute ramps for the Thames Estuary cluster during 2014 using the whole dataset (blue) and then excluding the periods during which a 4 hour ramp occurs.**

## 4.0 Conclusions

In recent years there has been a significant change in the distribution of wind capacity in the UK, with the construction of several clusters of very large offshore wind farms. This paper investigates how this change has affected the magnitude of the nationally aggregated and regionalised ramps on temporal scales which are critical for the management of the power system (30 minute, 60 minute and 4 hours). In addition, the extreme high frequency ramps of the largest cluster of offshore wind farms (Thames Estuary) have been investigated in detail to determine the meteorological drivers.

Despite the clustering of capacity in relatively small areas, the addition of the offshore wind farms reduces the high frequency variability of nationally aggregated generation. This study has used two key parameters to quantify the level of clustering; (1) number of wind farms in the region (2) mean separation between capacity. The level of the variability has been considered in terms of the magnitude of the power ramps on the three timescales which are of importance for system management (30 minutes, 60 minutes and 4 hours). For this metric, the magnitude of the variability was highly correlated to the number of wind farms aggregated. As the number of wind farms in the distribution increases, the magnitude of the ramps decreases. This reduction is particularly large between 5 and 25 wind farms before levelling off as the number of farms increases further. In contrast, the mean separation between capacity had little impact on the magnitude of the power swings. In fact, keeping the number of wind farms fixed but changing the separation has a negligible impact on the standard deviation of the distribution of the power swings. These results show that the ramps on these time scales in the different regions are not correlated; therefore aggregating the regions leads to a smoothing effect.

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As the magnitude of the high frequency power swings are highly dependent on the number of wind farms, the recent trend in Great Britain for clustering capacity in a small number of very large wind farms results in an increase in the local power swings. For example, if the system operator were to hold reserve to protect against a 90$^{th}$ percentile swing, for the onshore regions in 2014 it would equate to on average 3.8%, 6.0% and 14.5% of capacity for 30 minutes, 60 minutes and 4 hours respectively. In comparison, a similar holding for the offshore regions would equate to an average of 4.8%, 7.9% and 18.9% of capacity. Consequently, for clusters with high levels of capacity this could lead to very large ramps in power. For example, for the Thames Estuary, an 18.9% ramp equates to a change in power of 290 MW. This effect would be exacerbated in the future with the development of even larger clusters (e.g. Dogger Bank which could have a capacity in excess of 4 GW).

The meteorological conditions leading to extreme high frequency ramping of an offshore cluster have been investigated in more detail using the Thames Estuary as a case study. Over a 4 hour time window, the largest ramp in capacity factor was 86.2% (which equates to a power swing of 1.3 GW). This, along with the other extreme 4 hour ramping events was caused by the passage of a cyclone and the associated weather fronts. On shorter time scales, the largest ramping events over 30 minute and 60 minute time windows are not associated with the passage of fronts. They are caused by three main meteorological mechanisms; (1) very high wind speeds associated with a cyclone causing turbine cut-out (2) gusts associated with thunderstorms and (3) organised band of convection following a front.

To minimise the balancing costs associated with the extreme high frequency ramping events the meteorological features need to be captured by the wind power forecast. Drew et al. [3] has shown that high resolution ensemble models are able to capture the elevated wind speed associated with post-frontal convection. However, the timing and location of the feature may not be exactly correct. This study has shown that this problem could potentially be addressed by considering the use of real time meteorological observations, such as data from the rainfall radar to adjust the forecast in real-time if necessary.

## Acknowledgements

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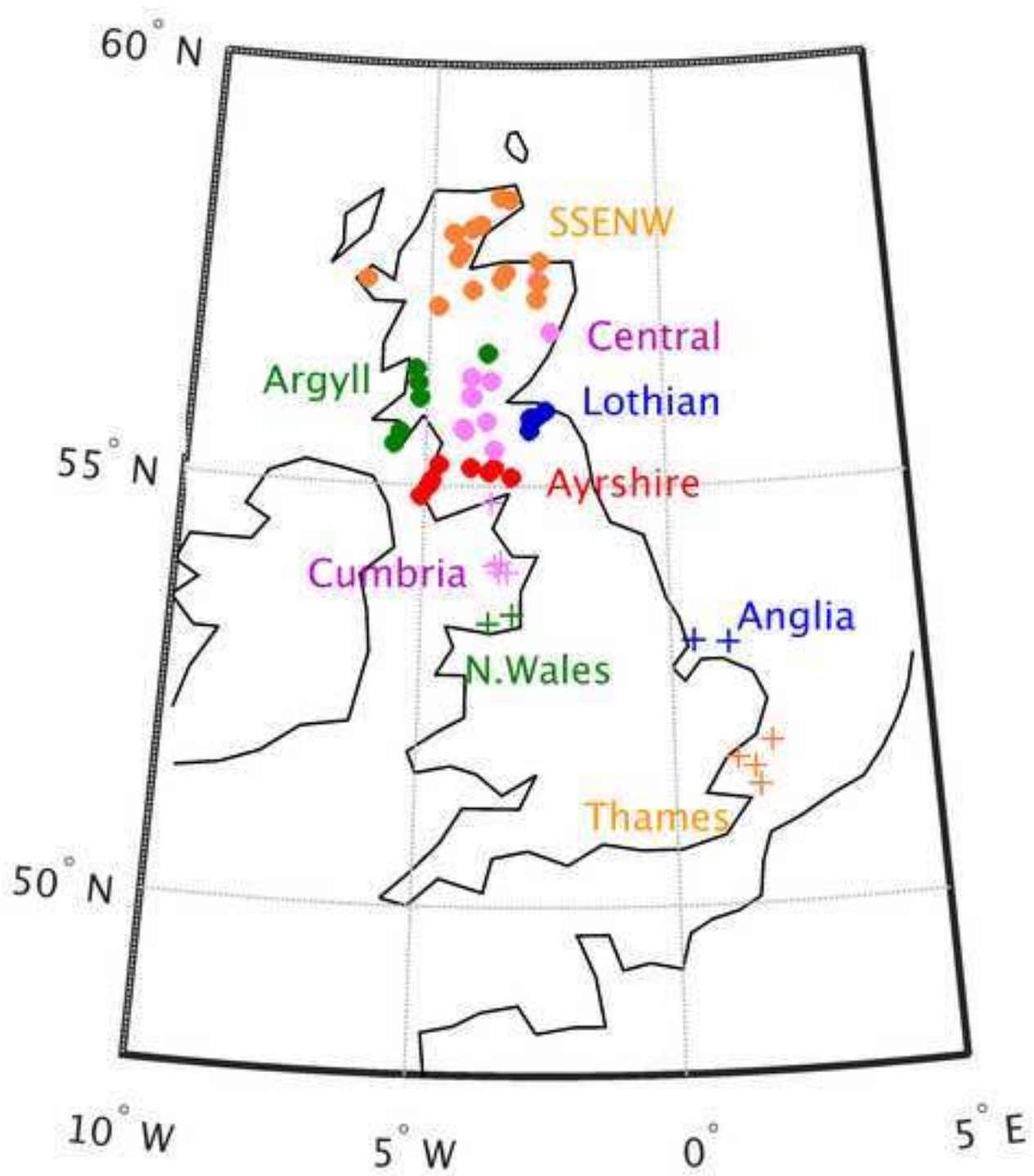**Figure 1**
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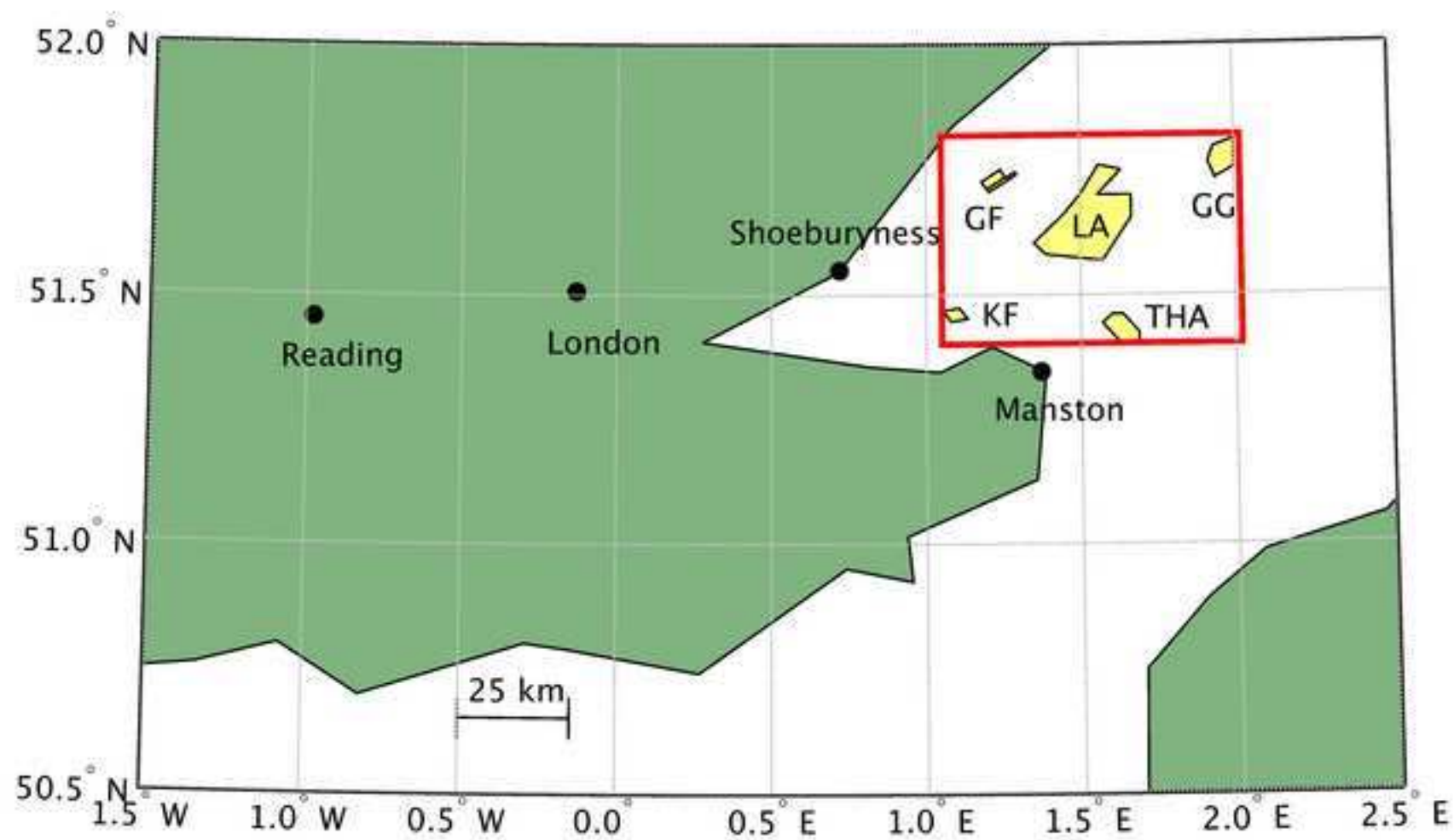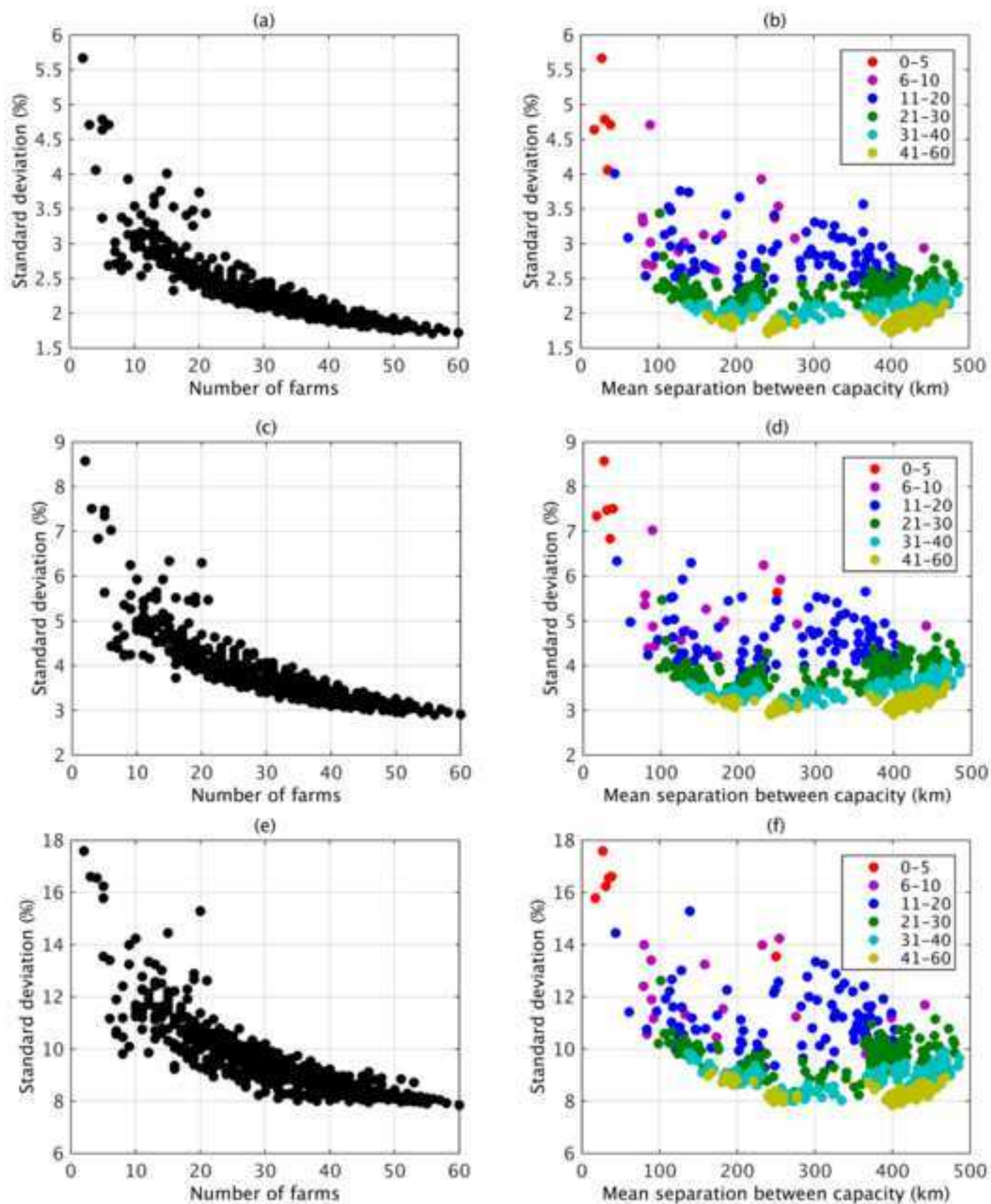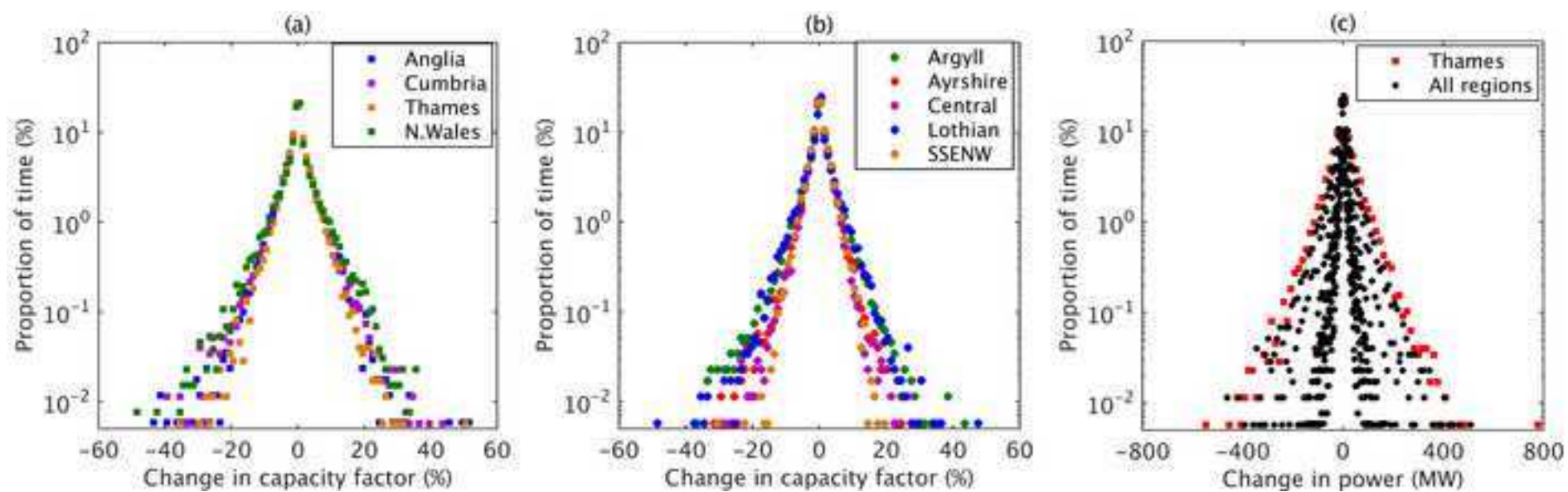**Click here to download high resolution image**



Figure 2

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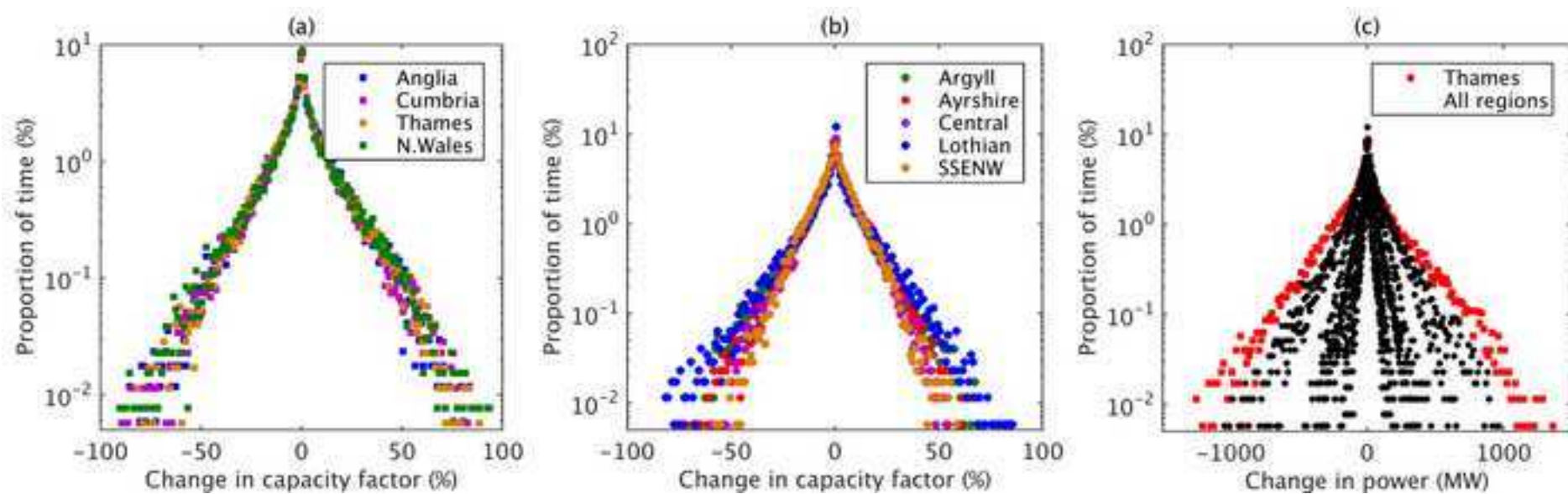**Figure 5**
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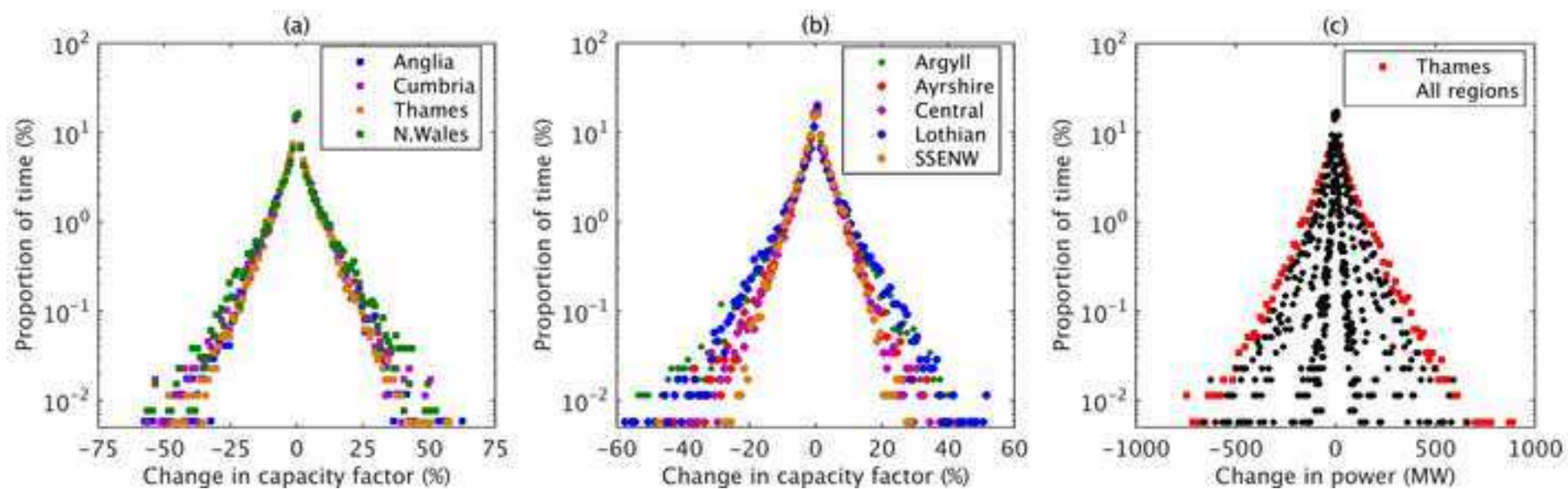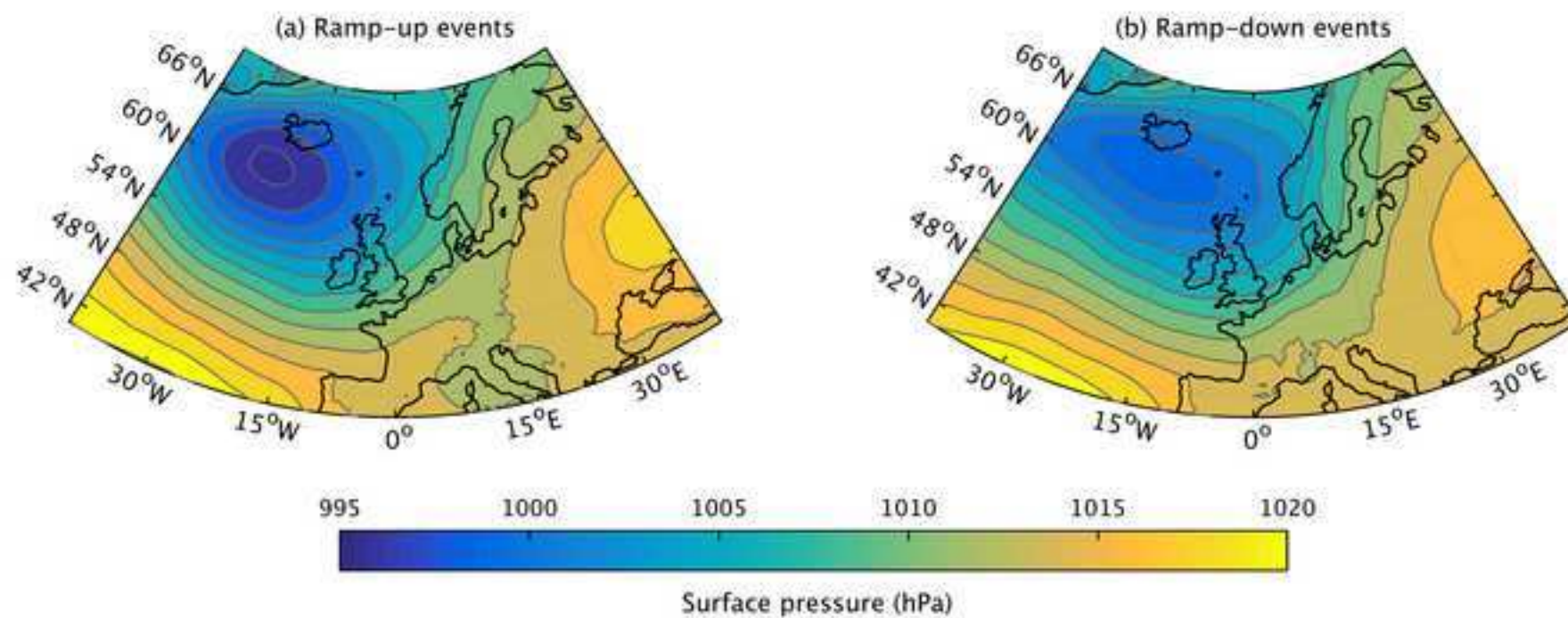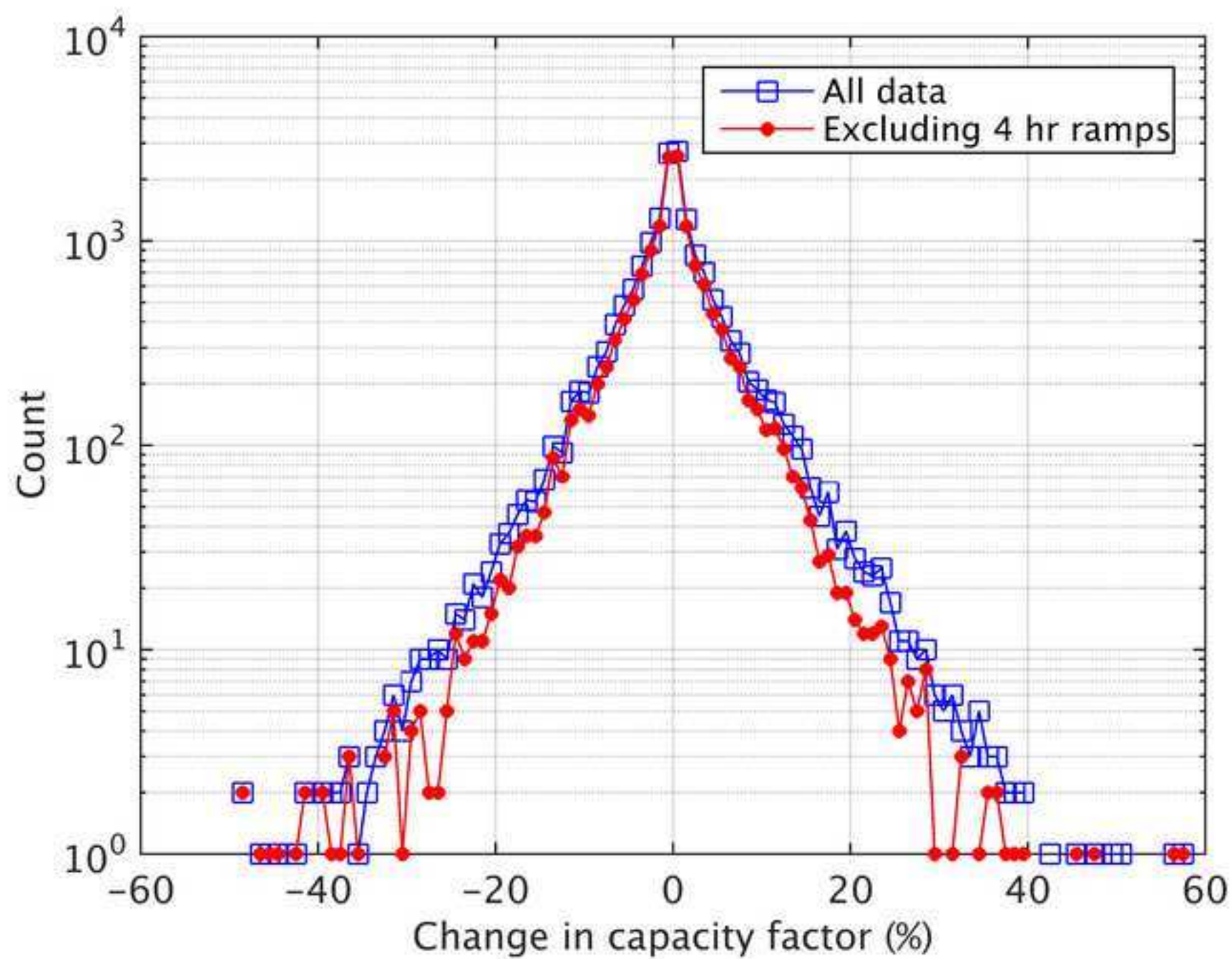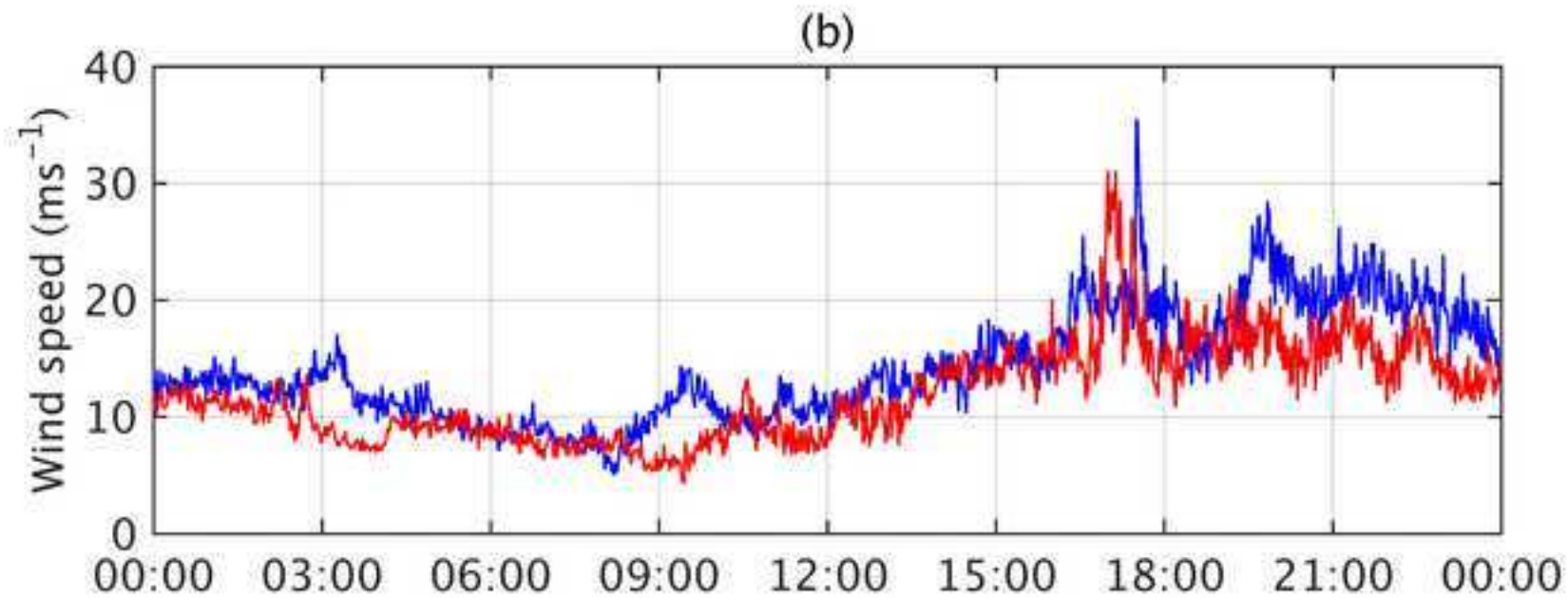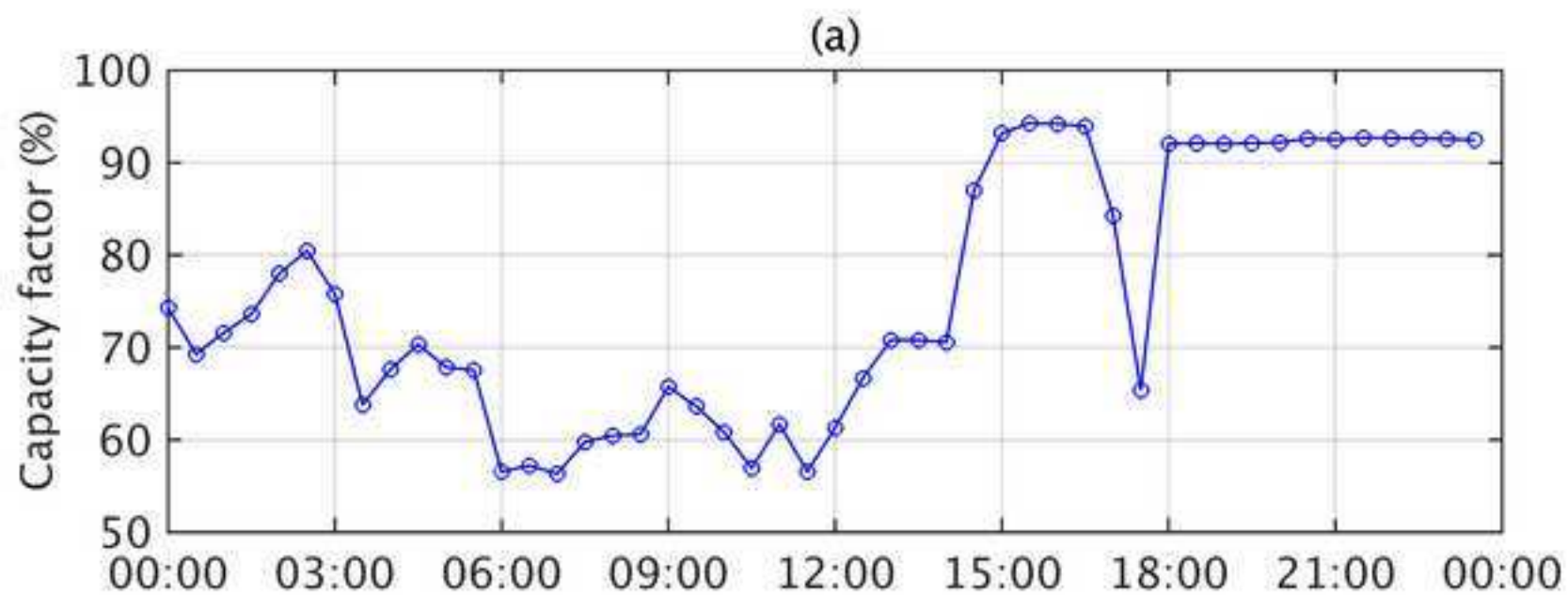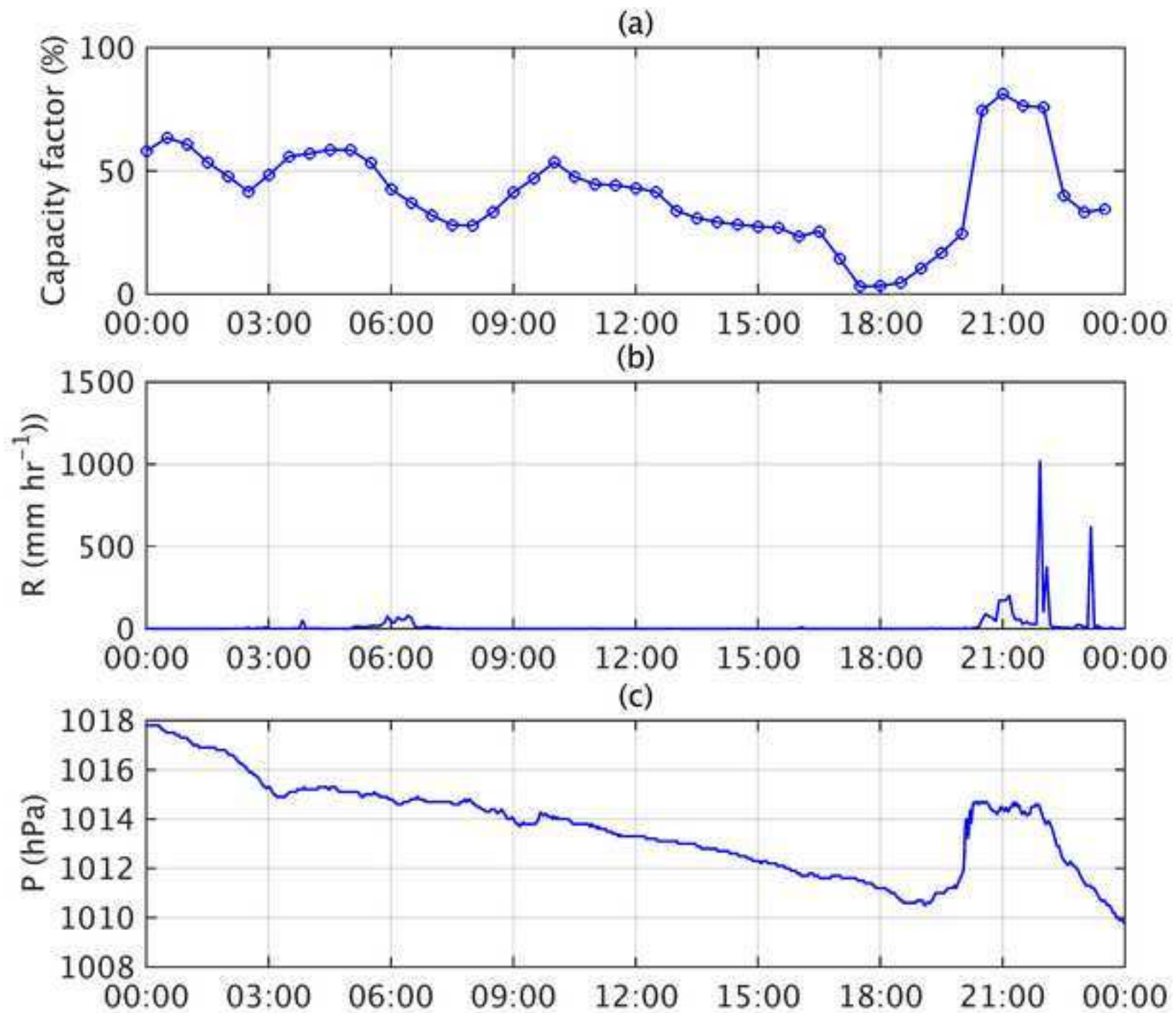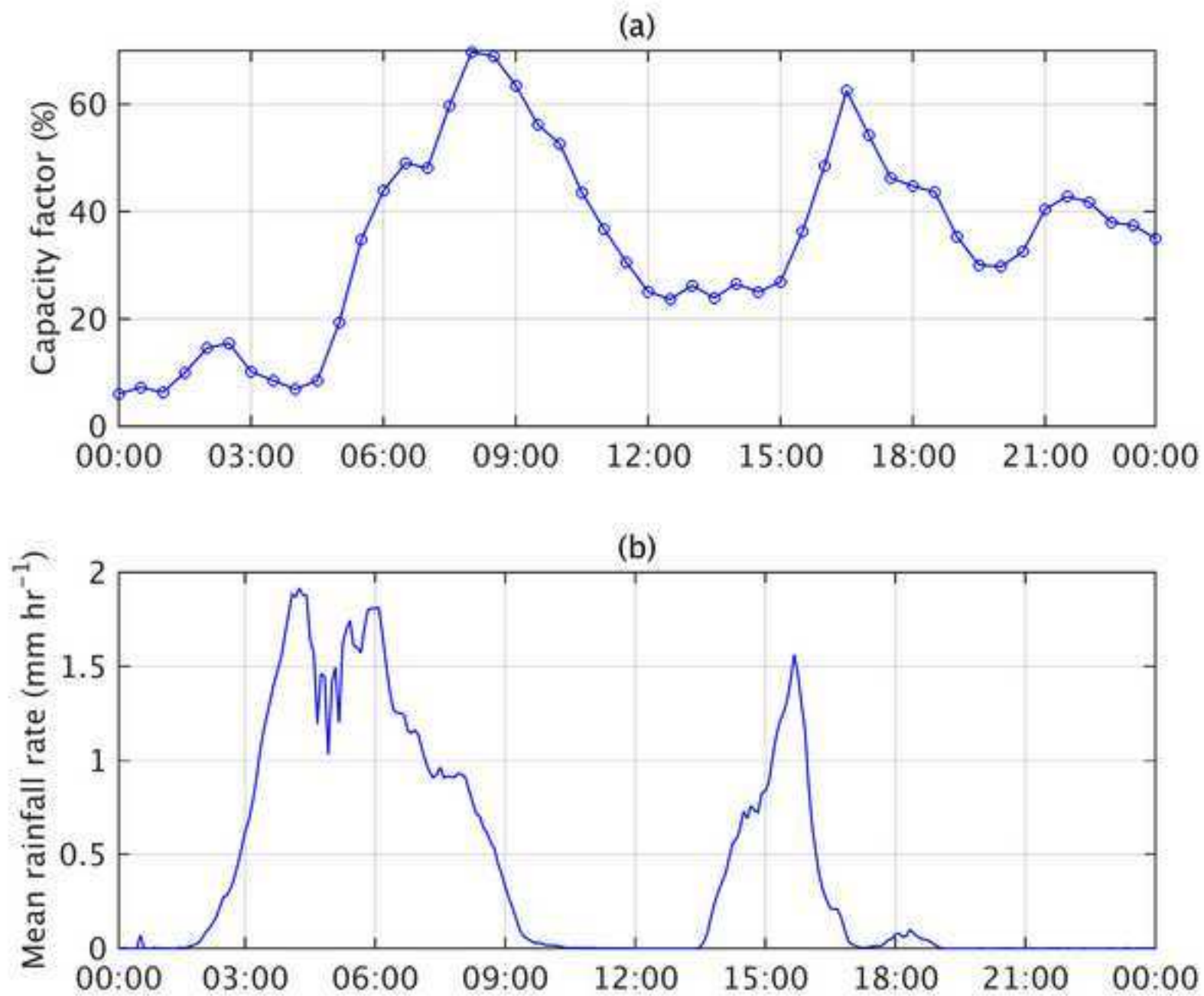**Figure 6**
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**Figure 7**
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(a)

(b)