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Abstract: This study investigates how the number and geographical distribution of solar installations may reduce aggregate irradiance variability and therefore lessen the overall impact of photovoltaic (PV) on grid distribution. The current distribution of UK solar farms is analysed. It is found that variability is linked to site clustering. Other factors may include distance and direction between sites, proximity to coast, local topography and weather patterns (i.e. wind, cloud etc.). These factors do not operate in isolation but form a complex and unpredictable system. The UK solar farm fleet currently comprises a range of system sizes which, when viewed en masse, reduces temporal variation in PV generation. The predominant southwest–northeast direction of solar farm groups is also beneficial in reducing output variability within grid supply point areas.

1 Introduction

The installed solar energy base in the UK has increased rapidly in recent years. A total capacity of 10.8 GWp of photovoltaic (PV) power was recorded in July 2016 [1], with installation being expected up to 13 GWp by 2020. This results in the perception that increasing PV deployment could place an overall stress on the power system. National Grid has warned that incorporating more than 10 GWp of solar electricity would adversely affect the transmission system [2]. Concern about operational security and possible power outages has already caused one distribution network operator (DNO) to refuse grid connection to new large-scale renewable projects in the southwest (SW) for at least 3–6 years [3]. These decisions are largely based on worst-case assumptions that all systems' instantaneous power output will follow the same trend. However, studies in the USA, Germany and Australia suggest that the impact of PV on national electricity distribution systems is related to the number and geographic distribution of installations, rather than the capacity of individual systems. Spatial dispersion of solar systems reduces the variability of energy generation, which arises primarily from smoothing cloud movements.

This paper analyses how size, number and spatial distribution of solar farms mitigate the effects of irradiance variation on the grid in a maritime climate such as the UK. A demonstration of smoothing due to the geographic distribution of PV sites is presented. Having shown the impact of site location on generation output, the current pattern of UK site dispersion is investigated. A 5 year trend in solar farm location is studied, together with possible drivers of this trend, with a view to predict the long-term impact on the transmission network.

2 Current knowledge of influence of PV system distribution

Several studies have demonstrated that high irradiance variability at a single site will be reduced when the surrounding group of sites is included. Torpey [4] reports a substantial reduction (61%) in standard deviation over a short distance for 1 min data between one site and six sites 1–10 km apart in California. He establishes that many small systems in a distribution system are unlikely to be problematic, because no single generator can significantly impact system voltage. On the other hand, in the case of single large systems, or groups of relatively large systems, output variability can be an issue.

Similar findings were reported for large areas. International Energy Agency photovoltaic power systems (IEA PVPS) 14 [5] describes smoothing by aggregate PV systems in six regions around the world at various time scales. Variability reduction (VR, i.e. variance in irradiance over time at one site divided by the variance of the average of several sites) ranged from 1.0 to 3.9.

It maybe seen from these studies that much more capacity can be installed without harmful consequences for the grid if the fleet is considered in aggregate. Previous authors [4–14] have verified that increasing spatial dispersion and number of sites reduces variability in incident irradiation and PV generation. Yet the same number of sites covering the same geographical area may form different patterns, e.g. linear, circular etc.; and this feature may exert a considerable effect on variability smoothing. To date, accurate point pattern or cluster analysis for the PV fleet has not been considered and the basis of their effect is given here.

Categorisation of cluster shapes is useful in many disciplines (e.g. epidemiology [15], criminology [16] and disaster analysis [17]). It helps to explain the relationship between data records and suggest reasons for their geographic position. Nonetheless, very little research has been done generally in the field of cluster shape analysis. There is neither agreed terminology for patterns or shapes, nor are there any classification algorithms.

3 Effect of size, number and cluster shape on irradiance smoothing for selected groups of PV sites

3.1 Sourcing and calculating PV site data

The solar installations information utilised in this analysis are from the Department of Energy and Climate Change Renewable Energy Planning database, renewable energy planning database (REPD) 2015 (575 × 1−50 MW installations at September 2015). Average hourly global horizontal irradiance for 10 years (2005–2014) was interpolated [18] from UK Met. Office ground station readings [19] for each system.

3.2 Experiment with existing solar farm locations

The literature indicates that the irradiance variability of one large site maybe ameliorated when included with readings from surrounding smaller installations. It was decided to test this finding with real solar farm locations in the UK. Six large solar farms were identified (Fig. 1). A number of systems around each large farm,

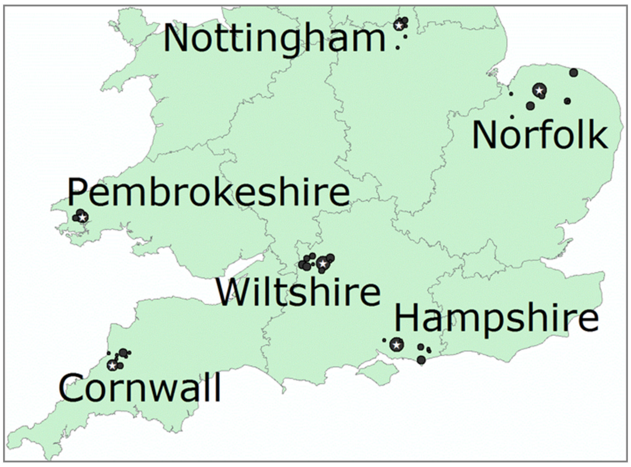


Fig. 1 *Groups of UK solar farms for smoothing analysis. Largest of each group marked with white star*

equivalent in net capacity to the major installation, were selected to test the impact of variability. These solar farm groups have various numbers of members and cluster shapes [Table 1 (see Fig. 2)].

The average hourly irradiance for 2014 (5019 daylight hours recorded across all UK Met. Office ground stations) was analysed for each major site and averaged for the systems comprising the group. About 5019 h is the total number of hours all UK Met Office ground stations recorded an irradiance of at least 0.278 Wh/m^2 (1 kJ/m^2). That is, Lerwick in Scotland might record a value at 4 am on 2 June 2014 but not Camborne in Cornwall. Another day, the opposite might occur. All ground stations are used in the irradiance interpolation algorithm. No inverter cut-off is used in PV output calculations but low values contribute very little. Standard deviation and variance for each major site and group were calculated.

Three of the groups exhibit the anticipated decrease in variability (as compared with the larger single site). That is, the percentage reduction in standard deviation between the main single site of the group and the average of the group is positive [(1)]. VR is >1 [(2)], meaning that irradiance variability is less. The VR range of 0.997–1.005 compares well with IEA PVPS 14 [5] results. These authors obtained a VR of 1.3 for 2013 hourly data acquired from 18 weather stations throughout the UK with an overall radius of 600 km. The cases explored here are distributed over much smaller areas, as detailed in Table 1 (Fig. 2). Relatively low variability is expected for the UK (compared with other less windy worldwide locations) and for longer time intervals [5], owing to cloud speed

$$\%\,\sigma\,\text{reduction} = \frac{\left(\sigma_{\text{Main}} - \sigma_{\text{Group}}\right)}{\sigma_{\text{Main}}} \times 100 \qquad (1)$$

$$\text{VR} = \frac{\sigma_{\text{Main}}}{\sigma_{\text{Group}}} \qquad (2)$$

Radius covered by the sites and number of sites does not appear to influence variability, since these differ between groups with high and low VRs. This is in contrast to findings from other researchers in Australia [4], whose site groups had similar radii.

On the other hand, it is notable that the three groups with VR > 1 have low mean distances between group members. The small mean distance values are caused by the spatial layout of the groups. They are multipart with two or three sets of points. The points in each set are close together and the other set or sets in the overall group are at two or three times the intra-set distance. Thus, incoming weather systems pass over first one, and then consecutive sets in each group.

Since weather fronts generally approach the UK from the SW, it was expected that the long, linear SW–northeast (NE) Norfolk site would show most smoothing. On the other hand, the irradiance is already fairly constant across this flat, low-lying region. Irradiance changes less on an hourly basis in Norfolk than in the SW (Fig. 3*a*). Standard deviation of hour-to-hour irradiance change for 2014 daylight hours is 89 Wh/m^2 for the main group site in Cornwall and 84 Wh/m^2 for the main site in Norfolk. The Cornish Peninsula is more subject to cloud formation due to the proximity of the sea.

The relationship between irradiance changes and wind direction differs in Norfolk and Cornwall (Fig. 3*b*). In Norfolk, the majority of all types of hourly irradiance change occur when the wind is from the SW. In Cornwall, large irradiance rise is associated with a southerly wind direction. This often brings warm, dry weather in the UK. Large hour-to-hour irradiance falls happen when the wind is northwesterly. This direction is equated with showery conditions. Lesser changes are linked to the SW wind.

The three VR > 1 sites are closer to the coast where weather is more changeable. From the findings so far, it is surmised that irradiance variability is affected by either: (a) a pattern of site layout and intra-site distance or (b) proximity to coast.

3.3 Experiment with potential solar farm locations

The results obtained using actual current solar farm locations differed to those of other researchers and it was therefore decided to further examine the concept of grouping sites to reduce irradiance variability. More tests changing the radius, number and pattern of sites were considered necessary. This was achieved by studying hourly global horizontal irradiance calculated for potential future (simulated) solar farms, rather than existing installations as reported above. Realistic positions for the potential sites were identified as described in the next section. Section 3.2.2 details how representational cluster shapes and distributions were simulated. Two scenarios were envisaged. Both consist of one large solar farm surrounded by varying numbers and patterns of smaller farms. However, in the first scenario, all the sites are positioned in the SW, because this area is coastal and exhibited the greatest decrease in group variability for existing solar farms. In the second scenario, the cluster of sites is placed near Oxford, because this locality is relatively far from the sea and receives fairly high solar irradiation (by UK standards).

3.3.1 Identification of potential solar farm location: Potential locations for future solar farms were selected by excluding unsuitable areas and examining the remainder. The checklist of criteria to be filtered out was drawn up from several solar consultancy websites. The following electronic maps were combined using a geographical information system: national parks, urban regions and woodland regions from ordnance survey (OS) Strategi 1 : 250,000 scale vector [20]; less favoured areas (mountainous areas) from Defra [21]; moorland line from Rural Payments Agency [21]; and larger areas from the Environment Agency Flood Zone 2 Map [22]. The countryside left was judged appropriate for large-scale solar installation. Fig. 4 illustrates this process applied to the SW of the UK. Dartmoor (in the centre of the map) and Exmoor National Parks (peninsula N coast) are clearly visible, as is the Somerset Levels flood plain to the NE.

3.3.2 Numbers and cluster patterns for groups of potential solar farms: To simulate authentic impact on the grid, the decision was taken to locate each potential solar farm group within a single grid supply point (GSP) (400 kV) area. GSP positions were obtained from National Grid. Since the area feeding into each GSP is unknown, supply point areas were devised by creating Thiessen polygons. This involves constructing a triangle for each supply point by drawing straight lines as follows. First, two lines are drawn between the GSP at point A and each of the two GSPs nearest to it, B and C. Second, the triangle is closed by a third line from B to C. Next, the perpendicular bisector of all three edges of the triangle is drawn. Finally, a set of polygons is formed from the connection of bisectors (Fig. 5*a*).

The number and distribution of existing solar farms within each GSP area were examined. There were found to be between zero and 53 solar farms in each GSP area (Fig. 5*b*). Ignoring zero

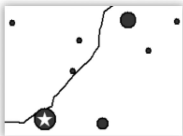
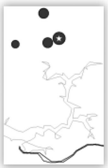
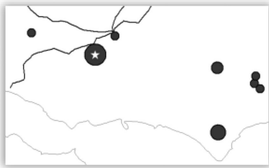
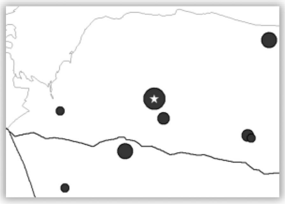
Location	Capacity MW	No. Sites	Image of Cluster with high voltage lines and coastlines	Mean Distance km	Radius of Cluster (km)	% Reduction in Std Dev	VR
Cornwall	40	8		0.75	9	0.48	1.005
Pembrokeshire	32	4		3	4	0.26	1.003
Hampshire	48	7		0.7	20	0.25	1.002
Norfolk	50	7		11	33	-0.07	0.999
Wiltshire	70	9		4.6	12	-0.09	0.999
Nottinghamshire	27	6		3.1	12	-0.34	0.997

Fig. 2 *Details of UK solar farm groups and results of smoothing analysis*

occurrences and counts of <3 (too low for analysis of group effects), 4–9 was the most frequent interval (Fig. 5*c*).

Having ascertained feasible numbers, the patterns of solar farms in each GSP area were classified. As already noted, there is no agreed standard methodology for this process. Modern computer algorithms offer a number of classification possibilities including neural networks or self-organising maps (SOMs) and several other machine learning techniques (decision trees, *K*-means and hierarchical clustering). For instance, SOMs have been applied in the identification of clusters in spatial data [23, 24], whilst evolutionary algorithms have been used to select monitoring locations [25]. Land use change analysis has been carried out with cellular automata models and decision tree machine learning [26]. Also relevant to the current research is trajectory prediction with a machine algorithm [27]. However, some of these techniques only offer a choice of pre-defined patterns. Others define their cluster by a centre-point, leading to a tendency for circular or elliptical clusters. Owing to these reasons and because a comparatively small amount of data was involved (only 145 GSP areas have more than one solar farm), solar farm patterns in each area were categorised manually by direct cartographic analysis. It is recognised that this is subjective, depending on both the author's interpretation and level of map resolution (1 : 500,000 was used). Notwithstanding, this is the first known attempt at classifying site cluster patterns.

Of the 28 GSP areas containing more than 7 solar farms, 17 exhibited a linear pattern and 7 had wedge-shaped clusters. Half of the linear patterns pointed from SW to NE, just one ran NW–SE and the rest had an E–W direction. There were single occurrences of a circle, ellipse, lower and upper semi-circle pattern. It maybe surmised that the most frequently occurring linear SW–NE pattern is dictated by the shape of the SW Peninsula (and its power lines) where most existing solar farms are located.

With a view to realism, sets of numbers and patterns were chosen for potential solar farms in the SW scenario as listed in Table 1. Four sets are illustrated in Fig. 6. The linear SW–NE pattern was then tested in the Oxford scenario to ascertain whether

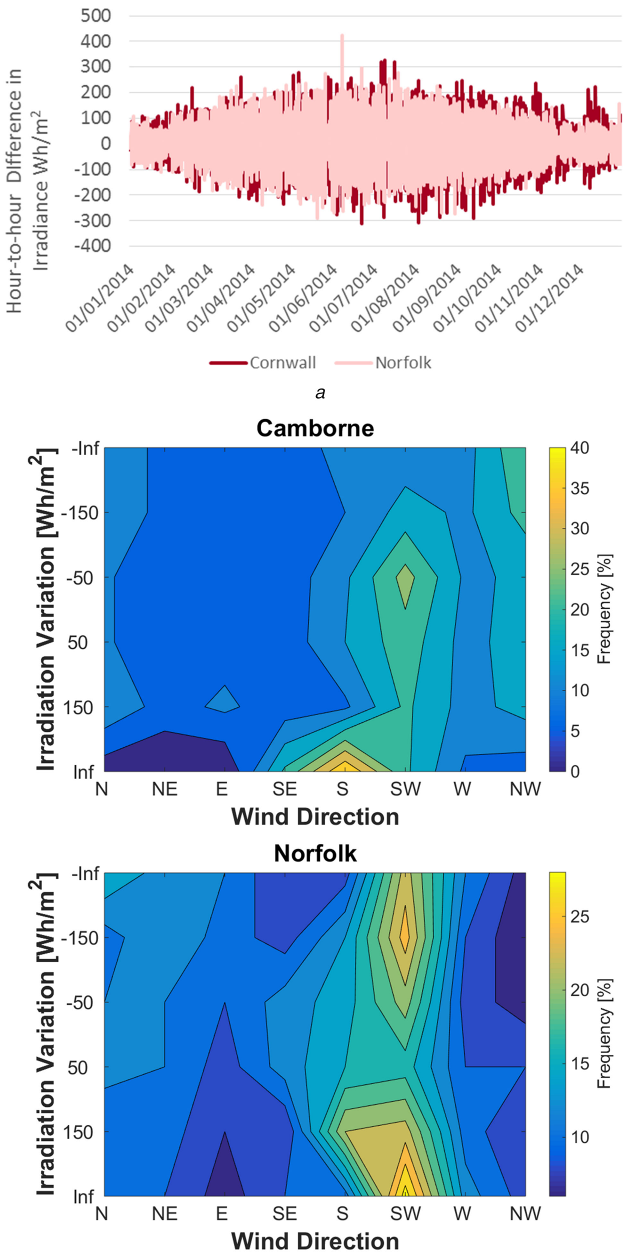


Fig. 3 *Changes in irradiance in Cornwall and Norfolk*
(a) Hourly irradiance change in Cornwall and Norfolk, ***(b)*** Wind direction frequencies for hourly irradiation variation bins (2014) (from [19]) in Norfolk and Cornwall

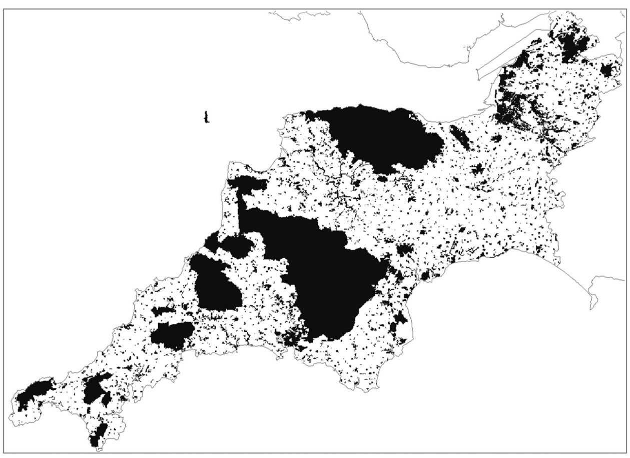


Fig. 4 *Potential solar farm locations in the SW produced by elimination of unsuitable areas. Exclusion zones – black. Potential locations – white*

variability decreases as a result of proximity to coast rather than the spatial relationship between sites.

3.3.3 Irradiance smoothing results for potential solar farm locations: The smoothing analysis for the SW and Oxford scenarios is summarised in Table 1.

As in the case of the existing solar farms, the findings for potential large-scale solar installations suggest that there is no relationship between irradiance variability and number of sites or radius of cluster (inconsistent results between groups with higher and lower VRs).

Variability was found to be linked to low mean distance for existing sites. Due to the fact that potential sites are being investigated here, it is possible to vary attributes and study the effect. The Oxford location has fewer constraints for location of solar farms and allowed greater flexibility in positioning. So, the low mean distance/variability relationship was not always observed with potential locations. There is a greater reduction in standard deviation between the main site group and the average of the group for group Ox-5A as compared with Ox-5B. Yet, the converse is observed between Ox-5A and Ox-5C. The mean distance measure hides the fact that some potential groups have an even distribution (e.g. all sites 2.5 km apart) whilst others have an uneven distribution (e.g. all sites an average of 2.5 km apart). It was found that an even distribution reduced variability (Ox-5B has an even distribution). Also, closer proximity of the majority of group sites to the main site is advantageous (Ox-4A has two sites 2.5 and 5 km from the main site; Ox-4B has all sites more than 10 km from the main site).

Moving on to look at cluster patterns, the V-23 potential group is similar in layout to the actual Cornwall group (despite having more members), being a wedge comprising three diagonal lines SW–NE. They are both in the Alverdiscott substation area. Nevertheless, variability was found to be decreased for Cornwall but not for V-23. Therefore, though the site layout pattern is having an effect, this is not consistent. The same phenomenon is noted with the most common linear SW–NE pattern. This has a smoothing effect in the fictitious SW and Oxford scenarios but not for the actual Norfolk example. Like Norfolk, the Oxfordshire countryside is flat, though, in general, the fields are smaller. The landscape in the SW is gently rolling. One explanation is that local topography is having an influence. The open landscape of Norfolk has adverse consequences for variability.

Direction of site grouping is also causing some effect. For the potential sites, an E–W direction had a lower VR than SW–NE direction. For the actual sites, the Cornwall SW–NE group had a higher VR than the Hampshire E–W group. As noted above, this is not the case with the Norfolk group. Proximity to coast with more variable weather was found to be an important factor for 'real' solar farms, whereas for the potential scenarios, the inland Oxford sites have greater variability.

Overall quantity of irradiation received is not indicative of variability. The SW groups received an hourly maximum of 932 Wh/m^2 at the main (largest) site in 2014 and have a lower variability than the Oxford groups which received an hourly maximum of 901 Wh/m^2 at the main site in 2014. When evaluated on a daily basis, variability was found to be greatest in spring and autumn. This is likely due to more dynamic weather.

Thus, the inference is that irradiance variability is caused by a complex combination of locational, topographical, seasonal and weather elements, summarised in Table 2. Not all of these come into play at any one time. The radii of site clusters are small enough for latitudinal effects to be ignored. All sites within each cluster are also situated on the same type of terrain, i.e. flat or slightly undulating countryside. There is no sudden change to mountains, sand dunes etc. within groups.

Finally, it must be noted that all effects are subtle. If the VR is presented as an integer, all the groups studied exhibit an increase in variability in comparison with a single site.

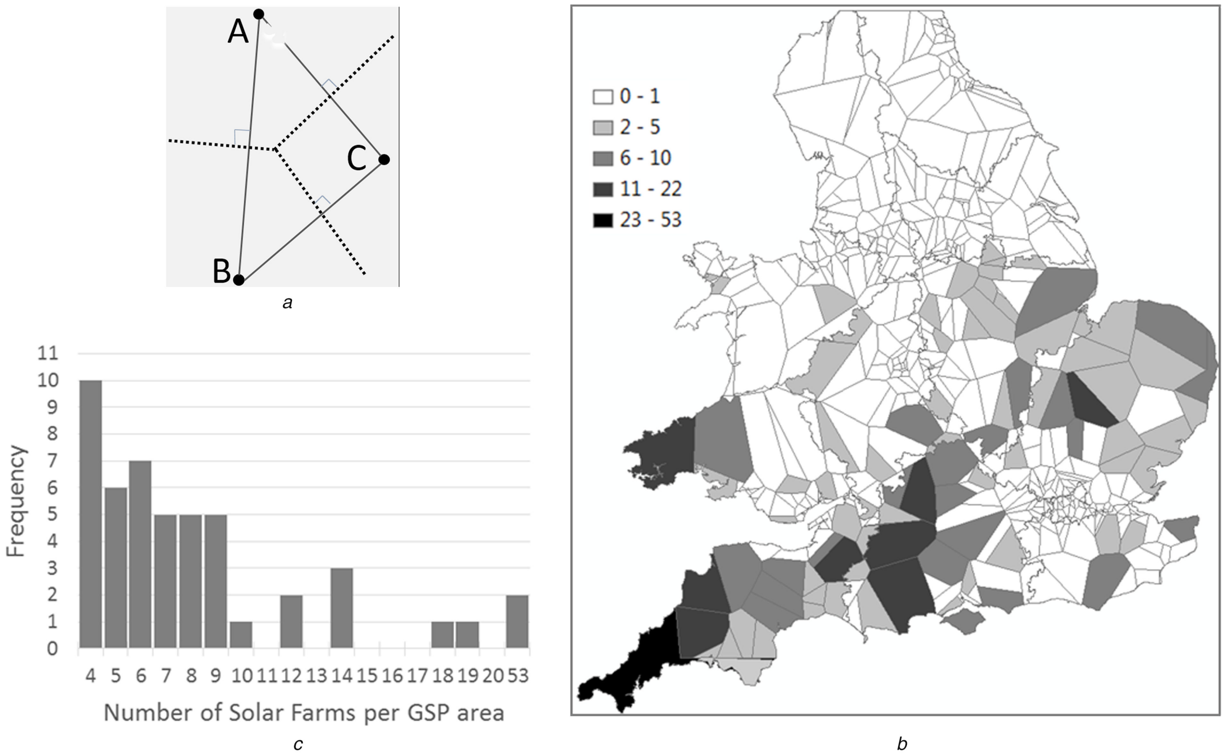


Fig. 5 *Number and distribution of existing solar farms within GSP areas*
(a) Construction of GSP areas using Thiessen polygons, ***(b)*** Number of solar farms per GSP area, ***(c)*** Frequency solar farms per GSP area

Fig. 6 *Potential solar farm clusters in SW: one large and one small linear SE–NW; one linear E–W; one wedge. Constrained areas unsuitable for large-scale PV shown in grey*

4 Current pattern of UK solar farm dispersal and associated grid stresses

This investigation, as well as others, has concluded that stress on the grid as a whole is mitigated where there are many small sites or a single large site surrounded by smaller sites (rather than clusters of large sites) (Microgrid analysis is not within the scope of this paper.). Fig. 7 summarises the current installations of solar farms in the UK, showing a large variance in size and distribution.

It maybe seen that Cornwall has only one major (over 30 MW) but many smaller installations. This suggests that the grid in Cornwall may not be as affected by power fluctuations as elsewhere. The output will be smoothed by the mix of system sizes. However, following an imaginary line in Fig. 7 from the Bristol Channel to the NE, two clusters of high-capacity systems are identified. The substations and high-voltage lines they feed into are listed in Table 3 (Note: Fig. 7 is presented in simple point form for brevity. The clusters have been proven to be significant with two geostatistical tools: Anselin Local Moran's I [28] and Getis-Ord Gi* [29, 30]. These algorithms have previously been used to analyse weather data [31] and site distribution [32].).

On the whole, the distribution of solar farms in the UK currently displays a combination of adjacent small systems or alternatively large and small adjoining. The few exceptions are given in Table 3. This bodes fairly well as far as impact on the grid is concerned. The next section explores the likelihood of future change.

5 Trends in solar farm location

Analysis of the 5 years data of the REPD reveals that total number of solar farms is increasing in all areas. The rest of England and Wales is beginning to encroach on the huge lead of the SW in terms of percentage.

Mean size of solar farm has increased exponentially throughout the country (Fig. 8*a*), by an average of 23% per year. In 2014, there was a 43% increase in mean installation size.

While sizes are increasing in all areas, the SW has one of lowest mean sizes (Fig. 8*b*). The largest installations are found in Oxfordshire and Norfolk.

6 Trend drivers

It has been shown that the trend is for bigger farms and that the largest installations are located in the southern and eastern DNOs. Fig. 9*a* reveals that the solar resource, administrative regime and land rents play a role in deciding installation size.

The greater the solar resource, the larger the size (Fig. 9*b*). Similarly, the lower the land rent, the larger the size (Fig. 9*c*).

7 Conclusion and future work

An alternative method of investigating grid stresses, based on mix of sizes of installations and geographical diversity, rather than number or capacity has been presented. It was observed that irradiance variability at a given location maybe alleviated by taking the aggregate of neighbouring installations. Ignoring the smoothing effect of groups of systems could lead to unnecessary grid restrictions. Reduction in variability results from a complex

Table 1 Details of potential solar farm groups and results of smoothing analysis

	Abbreviation	Symbol on map		Number of sites	Pattern	Direction	Mean distance, Km	Radius of cluster, km	Percentage reduction in standard deviation	VR
SW	L-SWNE-9	big circle	¡	9	linear	SW–NE	5.25	21	−0.053	0.999
	L-SWNE-5A	small circle	•	5	linear	SW–NE	5.25	14	−0.022	1.000
	L-SWNE-5B			5	linear	SW–NE	10.5	21	−0.074	0.999
	L-EW	X	×	8	linear	EW	4.5	11.5	−0.295	0.997
	V	triangle	▴	8	wedge	SW–NE	5.29	23	−0.076	0.999
	V-23			23	wedge	SW–NE	5.25	21	−0.093	0.999
Oxfordshire	Ox-8			8	linear	SW–NE	2.5	8.75	0.746	1.008
	Ox-5A			5	linear	SW–NE	5.25	8.75	0.746	1.008
	Ox-5B			5	linear	SW–NE	2.5	8.75	0.947	1.010
	Ox-5C			5	linear	SW–NE	3.75	8.75	0.696	1.007
	Ox-4A			4	linear – near	SW–NE	6	8.75	0.676	1.007
	Ox-4B			4	linear – far	SW–NE	6	8.75	0.306	1.003

Table 2 Factors examined for influence on irradiance variability

Factor	Impact on variability	Consistent
number of sites	no	yes
radius of site cluster	no	yes
quantity of irradiation	no	yes
mean distance	yes	no
linear SWNE shape	yes	no
direction SWNE	yes	no
coastal location	yes	no
local weather patterns, e.g. wind	yes	no
evenness of distribution	yes	yes
proximity to main site	yes	yes
local topography	yes	yes
season	yes	yes

Fig. 7 *Location of UK solar farms (2015) and proximity to high-voltage lines (the larger and hotter the circle, the higher the capacity of the solar farm)*

relationship between pattern of site clustering, proximity to coast, terrain and weather fronts. The complete set of factors may or may not appear to exert an influence simultaneously. The precise effect of each component and how it is triggered by the others requires further investigation. Impacts can be very small and further investigation with sub-hourly irradiance data will be carried out in future work.

Current size distribution of UK solar farms maybe described as predominantly small adjacent to small in the SW and mostly large next to small in the rest of the country. This indicates an

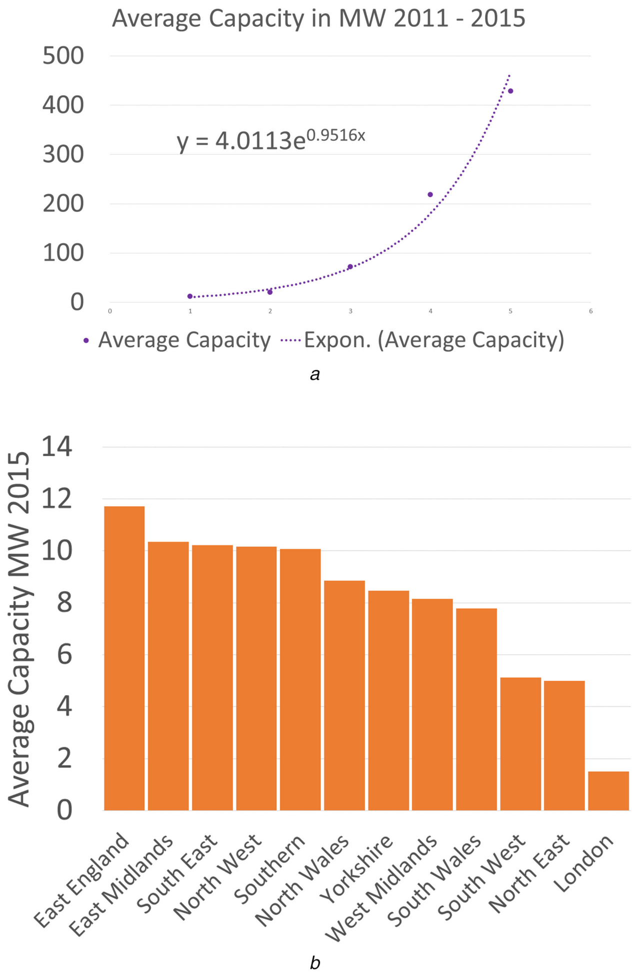


Fig. 8 *Average capacity of solar farms in MW 2011–2015*
(a) Growth of mean size of solar farms 2011–2015, ***(b)*** Average capacity of solar farms in each DNO 2015

Table 3 Parts of UK national grid subject to greatest stresses from solar farm output

Substation name	County	Route number	Route name
Minety	Wiltshire	ZF	Cowley–Minety
Didcot	Wiltshire	4YG	Bramley–Didcote
Pelham	Hertfordshire	4ZM	Burwell Main–Pelham
Burwell	Cambridgeshire	4ZM	Burwell Main–Pelham

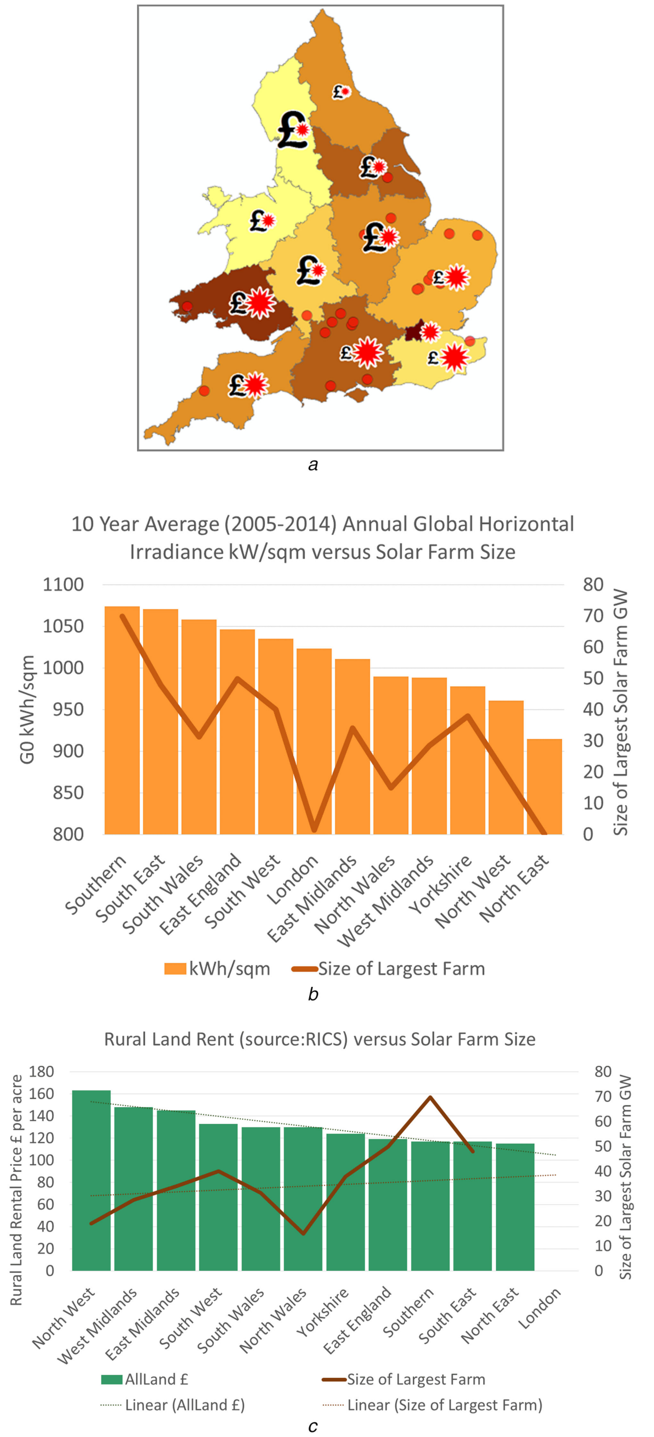


Fig. 9 *Trend drivers for size of UK solar farms*
(a) Influence of the solar resource (sun symbols), rural land rents (£, source: Royal Institution of Chartered Surveyors (RICS)), percentage planning permission granted (background: pale least, dark most) on location of largest UK solar farms (farms over 30 MW depicted as red circles), ***(b)*** Influence of the solar resource on size of UK solar farms, ***(c)*** Influence of rural land rent (average of arable and pasture) on size of UK solar farms

attenuation of PV impact on the transmission grid. Additionally, when solar farms are grouped by GSP, more than half of the groups tend toward a SW–NE direction. Owing to the prevailing wind and weather patterns, this is also an advantage in terms of balancing grid load from PV.

In general, the PV deployment trend is skewed toward big farms which is unhelpful as regards grid stresses. However, larger solar installations are being positioned outside of the SW, which is the most overloaded DNO. Size of system is being driven mainly by land rental price.

Thus, present solar farm distribution is beneficial for reducing PV impact by smoothing variability in the output. This is unlikely to change in the DNO which has the highest input from renewables.

8 Acknowledgments

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