A boundary layer scaling technique for estimating near-surface wind energy using numerical weather prediction and wind map data

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HIGHLIGHTS

- Improved accuracy of wind speed predictions from a boundary layer scaling technique.
- Highly accurate power density predictions from numerical weather prediction data.
- Boundary layer scaling more suitable for wind speed prediction than mandated method.
- Robust wind resource assessment techniques for near-surface wind speeds.

ARTICLE INFO

ABSTRACT

A boundary layer scaling (BLS) method for predicting long-term average near-surface wind speeds and power densities was developed in this work. The method was based on the scaling of reference climatological data either from long-term average wind maps or from hourly wind speeds obtained from high-resolution Numerical Weather Prediction (NWP) models, with case study applications from Great Britain. It incorporated a more detailed parameterisation of surface aerodynamics than previous studies and the predicted wind speeds and power densities were validated against observational wind speeds from 124 sites across Great Britain. The BLS model could offer long-term average wind speed predictions using wind map data derived from long-term observational data, with a mean percentage error of 1.5% which provided an improvement on the commonly used NOABL (Numerical Objective Analysis of Boundary Layer) wind map. The boundary layer scaling of NWP data was not, however, able to improve upon the use of raw NWP data for near surface wind speed predictions. However, the use of NWP data scaled by the BLS model could offer improved power density predictions compared to the use of the reference data sets. Using a vertical scaling of the shape factor of a Weibull distribution fitted to the BLS NWP data, power density predictions with a 1% mean percentage error were achieved. This provided a significant improvement on the use of a fixed shape factor which must be utilised when only long-term average wind speeds are available from reference wind maps. The work therefore highlights the advantages that use of a BLS model for wind speed and NWP data for power density predictions can offer for small to medium scale wind energy resource assessments, potentially facilitating more robust annual energy production and financial assessments of prospective small and medium scale wind turbine installations.

1. Introduction

National governments across the world are attempting to decarbonise their electricity supplies as part of their efforts to meet CO_2 emission reduction targets and mitigate the risks of climate change [1]. As part of this action, national governments have committed to ambitious renewable energy generation targets. The European Union (EU) has set a target of providing 50% of total electricity supply from renewable energy generating sources by 2030, while China and Australia have committed to 35% and 23.5% of total electricity being supplied by renewable energy generation by 2020 respectively [1]. As part of the EU's renewable energy generation commitment, the UK government committed to a legally binding target to provide 15% of its total energy from renewable sources by 2020 [2]. Meeting these targets requires a

transition of energy systems across the world from fossil-fuel based to low-carbon electricity sources. Microgeneration technologies such as small scale wind turbines, which are installed to provide energy for a single home or a community [3], can play a key role in energy systems transition [4]. The UK has one of the highest wind resource potentials in Europe [5] and therefore wind power, including small and medium wind energy, will be a key component in the UK's energy system transition.

Microgeneration technologies are costly to install and therefore to promote microgeneration uptake, a financial subsidy is typically required to stimulate deployment [4]. In some countries, a Feed-in Tariff (FIT) has been introduced to provide this financial subsidy to micro-generation installers [6–10]. For example, in the UK, a FIT was introduced in 2010 to provided financial incentives for each kilowatt-hour of electricity generated by microgeneration technologies, including wind turbines, installed in England, Wales or Scotland [11]. Similar schemes have been deployed in other countries with particular success in terms of uptake achieved in Germany [9]. However, even with financial subsidies, and indeed to optimise the returns from these, microgeneration technologies must be sited in locations where there is sufficient resource to ensure that each installation is financially viable. This is particularly relevant for small and medium wind turbines as wind resource is highly variable, both spatially and temporally [12,13]. Small and medium wind turbines utilise near-surface winds, defined as wind at the lowest level of the boundary layer, close to the surface of the Earth [13], to generate electricity. Near-surface winds are typically monitored at 10 m above ground level [14], although turbine hub heights could be higher than this for medium scale wind turbines. Therefore, any wind resource assessment for small and medium wind turbines must estimate near-surface winds. In this study, the accuracy of wind resource estimation methodologies for near-surface wind speeds were investigated, using sites in Great Britain as a case study.

For small and medium wind turbines, where the overall investment potentially is much lower than for large wind farms, a wind resource assessment method is required at the initial project stage which is quick to deploy and economically viable [15]. It must, however, still be rigorous enough to ensure that the estimated annual energy production is accurate, providing the turbine installer with sufficient confidence to either move forward with the installation, or to justify further project costs for a more in-depth wind resource characterisation. For such turbines, on-site anemometry conducted over a number of years to capture all temporal variability in a site's wind resource is not practicable due to the timescales and costs associated [15]. In the absence of on-site measurements, alternative methodologies to assess wind resource availability at initial project stages are required. A desk study is usually undertaken at this stage [16] and at a minimum, should provide an accurate prediction of average hub height wind speed and power density in the wind flow, from which the annual energy production of the wind turbine can be estimated [15]. Power density describes the energy per unit area in the wind flow and is calculated based upon the estimated wind speed frequency distribution at a particular site [15].

An initial assessment of near-surface wind resource can be conducted using numerous methods [7,17–20]. Near-surface wind speed estimations can be produced through the vertical and horizontal scaling of available reference wind data which will vary in terms of spatial and temporal resolution, depending on location. A commonly available source of reference data is reanalysis wind data, including the Modern Era Retrospective-Analysis for Research and Applications (MERRA) data set [7,20]. Weather forecasting data however, tends to be higher resolution and could be available from national meteorological centres or from the Weather Research and Forecasting (WRF) model [19]. Typical methods for using such data sets include the application of a Kalman filter to a time-series of Numerical Weather Prediction (NWP) wind data [18] or through scaling methods. Examples of each of these approaches have been used to estimate near-surface wind speeds for grid squares, sized at around 1 km using NWP data, up to 30 km for

studies utilising WRF data [19]. For small and medium wind turbines, which require accurate estimation of the spatially variable wind resource, coarser spatial resolutions may be insufficient to provide an accurate wind resource estimation at a specific location. A previous study has analysed the coupling of a meso-scale model using WRF and the Wind Atlas Analysis and Application Program (WAsP) micro-scale model to estimated wind speed at 60 m on a higher spatial resolution [17]. However, the cost of the WAsP micro-scale modelling technique, typically the purchasing of the license [21], is likely to be prohibitive at the initial stages of a small and medium wind turbine project, due to lower project budgets. While these wind resource assessment techniques predict hourly wind speeds, it is argued here that for small and medium wind turbines, at the initial scoping stage of the project, only a demonstration of technical viability using a long-term average wind speed is required. Once a site's viability has been established using this long-term average wind speed, wind resource assessment techniques which forecast hourly wind speeds, can be implemented to fully characterise a site's wind resource at later project stages.

A quick, lost cost yet effective assessment of the long-term average wind speed of a proposed site for a small and medium wind turbine is therefore required. For all wind turbines under 50 kW to receive payments under the British FIT, a wind resource estimation technique prescribed within the FIT accreditation process must also be completed [22]. The Microgeneration Certification Scheme (MCS) methodology is described as a "*method using freely available wind speed data (NOABL) and simple tabulated correction factors for the local terrain, obstructions and turbine height*" [22]. The results of this methodology must be presented to potential wind turbine adopters with equal prominence compared to other more detailed wind resource assessment techniques conducted during the initial stages of the project [22]. Given its use of "simply tabulated correction factors", the suitability of the MCS method to provide an accurate long-term average wind speed prediction for reliable annual energy production estimates should be questioned.

A boundary layer scaling technique (BLS) for near-surface wind speed prediction has been developed by the Met Office [23] and refined by Weekes [15]. A BLS model applies a number of correction factors to a reference wind climatology, based on the surface characteristics of a site such as vegetation, buildings and surface morphology. Surface characteristics are parameterised into surface roughness values, describing the frictional effects of obstacles at the surface on wind flow momentum [23]. The role of surface roughness parameterisation in wind resource assessments is particularly important for near-surface wind predictions, which are more affected by surface drag than winds higher in the atmosphere [13]. The BLS and MCS models can be utilised to provide quick and cheap estimations of long-term average near-surface hub height wind speed.

Within Great Britain, two reference wind climatologies, in the form of wind maps, which provide long-term average wind speeds are available; the Numerical Objective Analysis of Boundary Layer (NOABL) [24] and the National Climatic Information Centre (NCIC) data sets [25]. From these average wind speeds, power density cannot be directly estimated since a frequency distribution is not provided. However, the use of a fixed Weibull shape factor to represent a wind speed distribution from which power density can be estimated has been suggested [23]. However, both power density and average wind speed can also be estimated from the hourly time-series of wind speeds available from NWP data, where available. NWP wind speed data was provided for this study by the Met Office from their UK4 and UKV NWP models [26]. The availability of these different reference wind climatologies allowed the accuracy of both wind speed and power density predictions to be analysed in this study. To provide wind speed predictions appropriate for the chosen wind turbine installation, reference wind climatologies must be scaled to the hub height of the proposed wind turbine. Wind map data was only available at the heights of 10 m, 25 m and 45 m [24,25]. Raw NWP data was available at several heights from the forecast model output, but must be scaled to provide near-
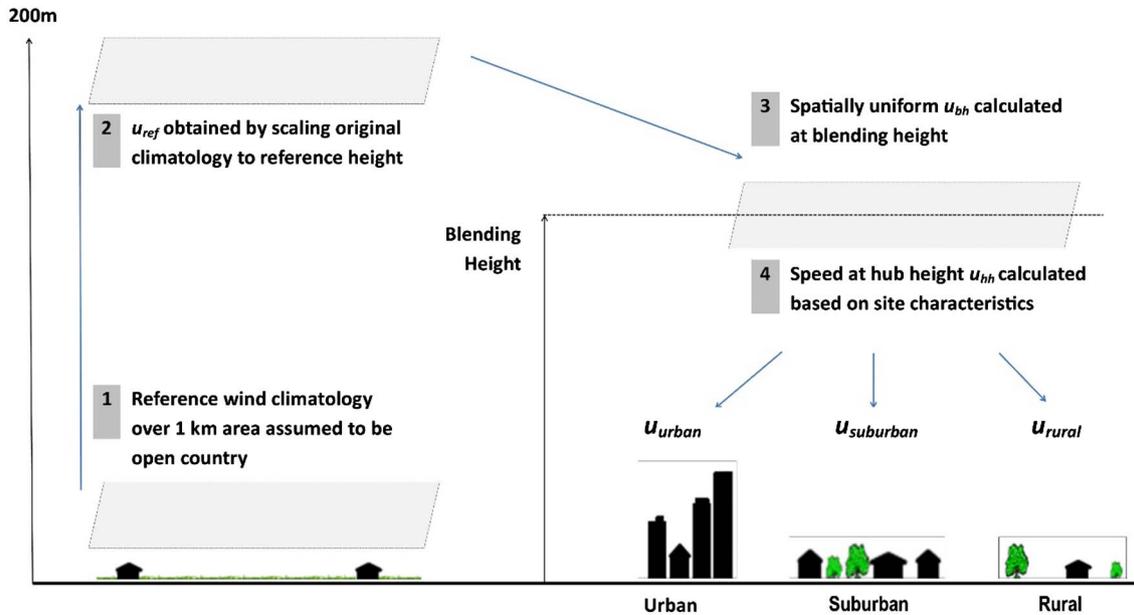
Fig. 1. Each stage of the boundary layer scaling model. Modified from [15].

surface wind speeds [27].

While scaling methodologies typically estimate average wind speeds, a method for estimating power density in the wind was also required. Power density can be estimated from the wind speed distribution of a site which is typically described using a Weibull distribution [28]. The Weibull shape factor, k, characterises diurnal variations in wind speed which influences the power density of near-surface wind flow [29]. Previous work by Weekes and Tomlin demonstrated, in a global sensitivity analysis study of a BLS method, that the Weibull shape factor was the most important parameter affecting predictions of wind power density for selected UK sites [30]. Several methods for estimating Weibull shape factors and their impact on power density predictions are therefore tested in this work. The shape factor has been shown to reach a maximum over land at a height known as the reversal height of the diurnal cycle [29]. When estimating power density, a vertical scaling technique of any fitted shape factors to account for the presence of a reversal height was included for analysis [29].

The aim of the analysis presented in this paper was to determine whether a BLS model can provide an accurate prediction of long-term average near-surface wind speeds using either wind map or NWP data. Additionally, this analysis investigated whether the BLS model could provide more accurate long-term near-surface wind speed predictions than the MCS methodology, used in the accreditation process of the FIT policy in Great Britain. In addition, power density predictions from BLS NWP, with and without a vertical scaling of shape factor, were also compared with those achieved using a fixed shape factor of 1.8, suggested for predicting power density when using long term average wind map data [23]. The analysis therefore allowed the most appropriate modelling technique for wind resource assessment at the initial stages of a small and medium wind turbine projected to be suggested. The inclusion of NWP data as a reference wind climatology for a BLS model is a novel aspect of this work and offered an insight as to whether it provides advantages as a reference wind climatology over the use of more commonly available long-term average wind maps.

2. Methodology

2.1. Wind flow in the boundary layer

Wind flow in the Earth's atmospheric boundary layer experiences frictional forces from surface morphology and roughness elements such as buildings and trees [13]. The magnitude of the frictional effect on wind speed varies with height from the surface and is dependent on the spatial distribution, size and shape of surface roughness elements. The spatially averaged effects of individual roughness elements on wind flow momentum are characterised by surface aerodynamic properties [13]. Surface roughness length z_0, is a parameterisation of the drag force that frictional elements exert on wind flow [13], while displacement height d, is the effective height at which wind speed is zero due to the presence of multiple frictional elements [15]. As such, displacement height in most rural areas where the spatial distribution of frictional elements is low, is classified as zero and only becomes influential when modelling wind flow through forest canopies or in suburban and urban areas [15].

Based on similarity theory and assuming neutral atmospheric stability, the vertical profile of average wind speeds is assumed to be logarithmic [13] and the average wind speed $\overline{u_z}$ at height z, is determined as;

$$\overline{u_z} = \frac{u_*}{\kappa}\ln\left(\frac{z-d}{z_0}\right)$$

(1)

where u_* is the friction velocity and κ is the von Kármán constant. The values of z_0 were estimated in this work through a parameterisation of land use data [31] while d was approximated from estimated values of z_0 [32]. Parameterisation of land use data for surface aerodynamic properties developed in this work is described in Section 2.2.

2.2. Boundary layer scaling model

Using the principles of boundary layer wind flow, a BLS model can be implemented to scale a reference wind climatology to provide long-term average near-surface wind speed predictions. Based on an approach developed by the Met Office [23], a reference wind climatology is scaled through a number of steps, as shown in Fig. 1, to the desired hub height of a prospective wind turbine. Initially, the reference wind speed from the climatology is scaled vertically to a reference height of 200 m to remove any frictional effects modelled in the raw climatology. From the reference height, the wind speed is scaled down to the desired hub height using a two-step process. Firstly, the wind speed at the reference height is scaled to a blending height, where the frictional effects of individual surface elements are homogenised across the upwind fetch

of the site. From the blending height, wind speed is then scaled to the hub height using the surface aerodynamics of a specific site. In this work, a hub height of 10 m was selected to allow for the validation of near-surface wind speed predictions using observational data at 10 m [14]. The validation data used in this work is discussed further in Section 2.6.

Surface roughness values can be calculated from experimental data [32]. However, such experimental data was not available for the numerous sites across Great Britain that were examined in this work. The parameterisation of surface roughness is however, a vital part of a BLS model [30]. Regional aerodynamic parameters are vital for the first stage of downscaling from the blending height, and site-specific surface roughness for the further scaling of the wind speed to the selected hub height. Weekes and Tomlin showed that uncertainties in local roughness values could contribute over 25% of the uncertainties in predicted power densities for a BLS model applied using long term wind reference maps for the UK. Their study however, used a limited number of land use classes for the estimation of surface roughness. Here, z_0 was parameterised based on the detailed Land Cover Map (LCM 2007) from the Centre of Ecology and Hydrology which covers all of Great Britain [31]. Thirteen different surface roughness classifications were developed using previous literature [23,32–36] with surface roughness values ranging from 2×10^{-4} m for open water [35] to 1.1 m for densely urban areas [33]. All 23 land use categories in the LCM were associated with one of the 13 surface roughness values, based on the surface characteristics represented in each land use category. Raw LCM data on a 25 m raster was parameterised to a surface roughness value at a 25 m scale, and then blended to a 100 m resolution, by averaging of all of the 25 m surface roughness values in the 100 m grid square. As part of the model development, the use of modal z_0 values rather than mean z_0 values was investigated in order to establish the sensitivity of the predictions to the chosen method. It was found that the wind speeds estimated using the modal z_0 values were marginally less accurate than those estimated using mean z_0 values. Therefore, whilst the sensitivity to the choice was small, the mean z_0 values were utilised in the BLS model presented here. The choice of a 0.01 km^2 grid square was dictated by available computational resources but is finer than previous studies, which used a 1 km^2 grid square [15,23]. The finer spatial resolution of surface roughness in this research offered a better characterisation of the frictional effects of the surface. Wind turbines with lower hub heights capture near-surface winds for energy generation and therefore better characterisation of surface roughness at a finer spatial resolution was designed to improve the accuracy of near-surface wind speed prediction. While this study utilised a land cover map for Great Britain [31], other land cover maps could be utilised to parameterise surface roughness in other locations.

Displacement height, d, was approximated from each grid square of surface roughness in this study. The approximation of displacement height from surface roughness values, z_0, is based on the empirical relationship between canopy height, z_h, and displacement height, d, suggested by Garratt [37] and discussed in Grimmond and Oke [32] with respect to morphometric data from 7 different cities;

$$z_h = 10z_0; \quad d = \frac{2}{3}z_h$$
$$\therefore \; d = \frac{20}{3}z_0 \tag{2}$$

The approximation of displacement height was implemented since detailed calculations of displacement height require the frontal and plan area of all frictional elements in the domain [15,38]. As with calculation of surface roughness, such detailed calculations were impractical in this work which examined numerous sites across Great Britain. The impact of the approximation will be greater in suburban areas where the height variability in surface roughness elements has been shown to exhibit a larger influence on surface drag [38].

The blending height and the regional roughness length which represents the spatially averaged surface roughness of the upwind fetch,

must both be calculated within the BLS model to model the frictional effect exerted on wind flow in the upwind fetch. The blending height was calculated over a site's 16 km^2 fetch, by tracking the growth of the boundary layer over the whole upwind fetch for the chosen wind direction sector [39]. A variability scale of the fetch, L_p, was estimated based upon the turbulent velocity fluctuations caused by differing patches of upwind surface roughness [39]. The variability scale, L_p, and each individual surface roughness patch in the upwind fetch, $z_{0,i}$, were utilised to calculate the blending height, B_h [39];

$$\left(\frac{B_h}{1.7\kappa L_p B_h} \right)^2 = \sum_{i=1}^{N} \left(\frac{f_i}{\left(\ln \frac{B_h}{z_{0,i}} \right)^2} \right) \tag{3}$$

where κ is the von Kármán constant, f_i is the fraction of each surface roughness value and N is the number of surface roughness patches in the fetch. The blending height and regional surface roughness were calculated for twelve 30° wind direction sectors of the fetch at each site, an increase in wind direction sectors compared to previous studies [15]. On average, the calculated blending height of the sites examined in this work was 140 m. The blending height differed for each site and in each of the twelve wind direction sectors for a single site. The average blending height for coastal locations was around 133 m, in contrast to higher blending heights of 145 m for sites in suburban locations. These higher blending heights resulted from a greater degree of surface roughness variability in the fetches of suburban sites, whilst for coastal sites, water formed the surface of the upwind fetch for several of the wind direction sectors, resulting in the lower average blending height. The average wind speed at the desired hub height was then calculated in each sector using the relevant regional aerodynamic parameters for the first down scaling step, followed by use of the local parameters for the second downscaling step. The long-term average wind speed of the site at the hub height was calculated from a frequency weighted sum of the predicted wind speeds in each of the twelve sectors.

The BLS model has been developed to provide a long-term average near-surface wind speed prediction for every 0.01 km^2 of Great Britain rather than just for sites with observational data as presented in this work. Monitoring stations from which the observational data was extracted, capture the wind conditions at an exact location and these conditions can vary greatly only short distances from the station [23]. Although a hub height of 10 m was selected in this work to allow validation of wind speed predictions using available observational data, the BLS model can estimate mean wind speeds at any desired hub height of a prospective small and medium wind turbine.

The breadth of surface roughness classifications presented in this paper is an extension of previous work, where eight instead of thirteen z_0 classifications were utilised [15]. The increased number of z_0 classifications influences the calculation of blending height, which has been implemented in other wind resource assessment models using fewer classifications [36,40,41]. The increased number of wind direction sectors allowed a greater degree of variability in the upwind conditions to be captured in this work's BLS model. The impact of these improvements on the accuracy of wind speed predictions have been tested against available observational data alongside the mandated MCS methodology.

2.3. Microgeneration Certification Scheme model

The Microgeneration Certification Scheme (MCS) methodology is the mandated minimum wind resource assessment required for all wind turbines up to 50 kW to qualify for FIT generation payments [22]. The MCS methodology is a site-specific methodology where average wind speed is determined by scaling NOABL wind speed data [22]. The scaling factor, C_f, corrects raw NOABL data at 10 m, $\bar{U}_{NOABL}$, to achieve a wind speed prediction, $\bar{U}_{MCS}$;
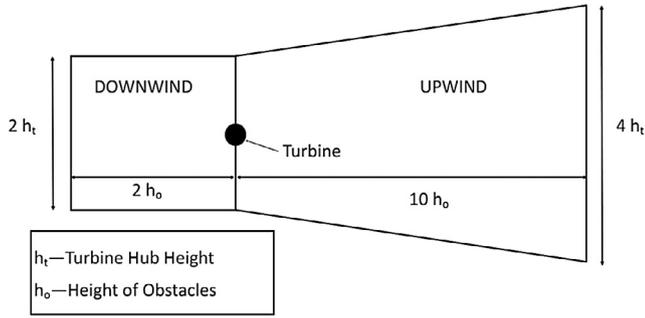
Fig. 2. Representation of the area surrounding a turbine site when considering the size of local obstacles in the MCS methodology. Modified from [22].

$$\overline{U}_{MCS} = C_f\, \overline{U}_{NOABL} \tag{4}$$

The scaling factor, C_f, is tabulated from the ratio between the hub height of the wind turbine and the height of the highest local obstacle and is dependent on the terrain classification of a site [22]. A representation of the area surrounding the turbine considered when assessing the height of local obstacles is given in Fig. 2.

An approximation of terrain classification and local obstacle height was developed in this work to allow for a comparison of the MCS methodology with the BLS model, since an analytical comparison of the MCS methodology has not previously been published. A site's terrain classification was estimated from the surface roughness values used in the BLS model. Surface roughness values were banded into five categories, corresponding to the terrain classes presented in the MCS method [22], as seen in Table 1.

In lieu of observational data regarding local obstacle heights, the height of the highest local obstacle was approximated as $10z_0$, which is equivalent to the canopy height, or the estimated mean building height at a site [32].

A schematic showing the comparison between the BLS and MCS modelling approaches is given in Fig. 3 highlighting the differences.

2.4. Reference wind climatology data

The BLS and MCS methodologies both require a reference wind climatology from which a wind speed prediction can be produced. Both the Numerical Objective Analysis of Boundary Layer (NOABL) and National Climatic Information Centre (NCIC) wind map data were used in this work. The NOABL and NCIC wind maps were created using different methodologies and observational data, as summarised in Table 2. NOABL and NCIC wind maps provided a long-term average wind speed for each 1 km^2 grid square of Great Britain, at heights of 10 m, 25 m and 45 m [24,25].

The NOABL data was used in both the BLS and MCS models, while NCIC data was only used in the BLS model since the MCS methodology was specifically designed to correct NOABL wind speeds at 10 m [22]. In this work, the NOABL and NCIC long-term average wind speeds at 10 m were scaled using the BLS model to estimate a new long-term average height dependent wind speed. Wind map data at 10 m was selected to maintain fidelity with the approaches in previous research

[15,23] on which this work's BLS model was based.

The unscaled wind map data at 10 m were also compared to its scaled counterpart to assess whether any improvements in wind speed accuracy were achieved with either the BLS or MCS models.

In addition to these observational based wind maps, Numerical Weather Prediction (NWP) wind speed data from the UK Met Office's UK4 and UKV models was utilised as a reference wind climatology for the BLS model [26]. The UK4 model provided hourly forecasts on a 4.4 km grid resolution from the initial 51 hours of the model run, while the UKV model provided hourly forecasts on a 1.5 km grid resolution from the first 30 hours of the model run [26]. Hourly time-series of wind speeds were provided from 2002 to 2012 for the UK4 model and from 2010 to 2014 for the UKV model. Wind speeds from both NWP models, available at 7 heights from 10 m to 200 m above ground level, were scaled to a hub height of 10 m in the BLS model. To facilitate a comparison of the wind speed accuracy available from each forecasting height, the BLS model scaled each hourly wind speed in the raw NWP dataset from its forecasting height to the reference height, before scaling down to the blending and hub heights. This process created a BLS NWP wind speed time-series from which long-term average wind speeds at each site were estimated. In addition to wind speed predictions, a Weibull distribution was fitted to the hourly BLS NWP data from which wind speed distributions and power densities were predicted. The reference wind climatologies used within this study only provided wind speeds for sites in Great Britain. The BLS model, however, could be implemented in any global location, provided that a reference wind climatology and land cover data with sufficient detail are available as inputs to the model.

2.5. Power density and shape factor

Power density in a wind regime can be estimated using a Weibull probability distribution with reasonable accuracy [42,43]. Weibull shape and scale factors were estimated from an hourly time-series of wind speed data in this work using a maximum likelihood method to fit the distribution [43]. The shape factor has been shown to reach a maximum over land at a height known as the reversal height of the diurnal cycle [29]. The reversal height is the average height at which the diurnal wind cycle of each site changes phase, from its night time minimum near the surface, to the night time maximum higher in the boundary layer. Fig. 4 illustrates the reversal height phenomena with Weibull shape factors recorded at various heights from two onshore sites in the US, published in a study by Wieringa [29].

The shape factor, k, at hub height, z, can be scaled vertically to account for the estimated reversal height, z_r, of a site;

$$k = k_s - c_k (z - z_s) e^{\left(-\frac{Z - Z_s}{Z_r - Z_s}\right)} \tag{5}$$

where, k_s is the initial shape factor at the height, z_s and c_k is an empirical coefficient determined as the gradient of a linear regression line of observed shape factors on a log-scale against observation height, [29]. Reversal height can be determined experimentally using observations of a site's vertical wind profile. However, for the sites in this work, vertical observations were not available and in practice are likely to not be available for an initial wind resource prediction and therefore
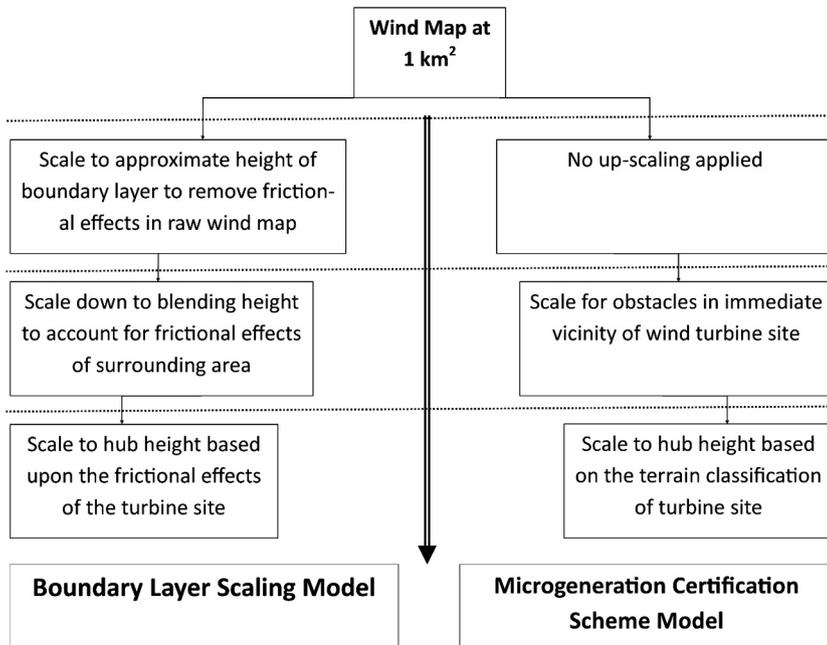
Table 1
Surface roughness value ranges used to determine MCS terrain classification.

Range of surface roughness values, z_0 (m)	MCS terrain classification and description [22]
< 0.041	Category 1 – Flat grassland, parkland or bare soil without hedges and only a few isolated obstructions
> = 0.041 and < 0.104	Category 2 – Gently undulating countryside, fields with crops, fences or low boundary hedges and few trees
> = 0.104 and < 0.54	Category 3 – Farmland with boundary hedges, occasional small farm structures, houses and trees, etc.
> = 0.54 and < 1.1	Category 4 – Woodland or low rise urban/suburban areas (e.g. domestic housing) with a plan area density of up to about 20%
> 1.1	Category 5 – Dense urban areas and city centres (e.g. buildings of four-stories or higher) with a plan area density greater than about 20%

Fig. 3. Diagrammatic representation of differences in the BLS and MCS wind resource assessment models.

Table 2
Comparison of NOABL and NCIC wind map data.

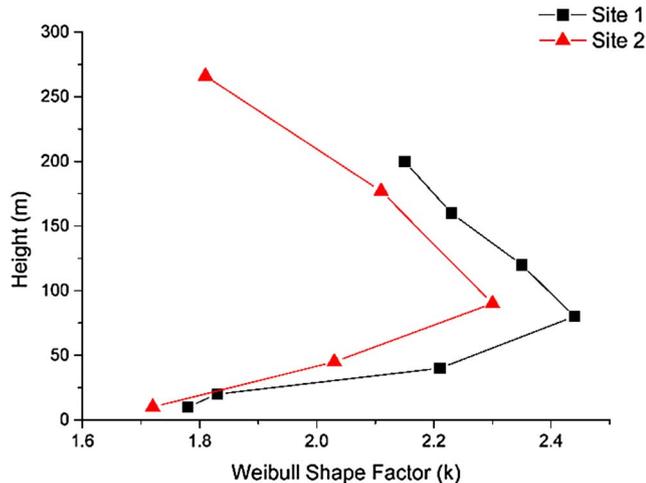| Variable	Numerical Objective Analysis of Boundary Layer (NOABL) [24]	National Climatic Information Centre (NCIC) [25].
Modelling approach	Linear flow model	Regression and interpolation
Number of observational sites Used	56	220
Time period of observational data	10 year (1975–1984)	30 year (1981–2010)

Fig. 4. Weibull shape factors at various heights of two US sites. Reproduced here using data taken from [29].

the reversal height must be estimated based on previous literature studies. On average, reversal heights of onshore sites are observed between 60 m and 80 m [29] and hence here, reversal heights of 60 m, 70 m and 80 m were selected in order to perform a sensitivity analysis.

In this work, a Weibull distribution was fitted to hourly BLS NWP data at 10 m from any forecasting height, with the shape factor of the fitted distribution utilised to estimate a site's power density. A fixed Weibull shape factor of 1.8 has previously been suggested as a suitable
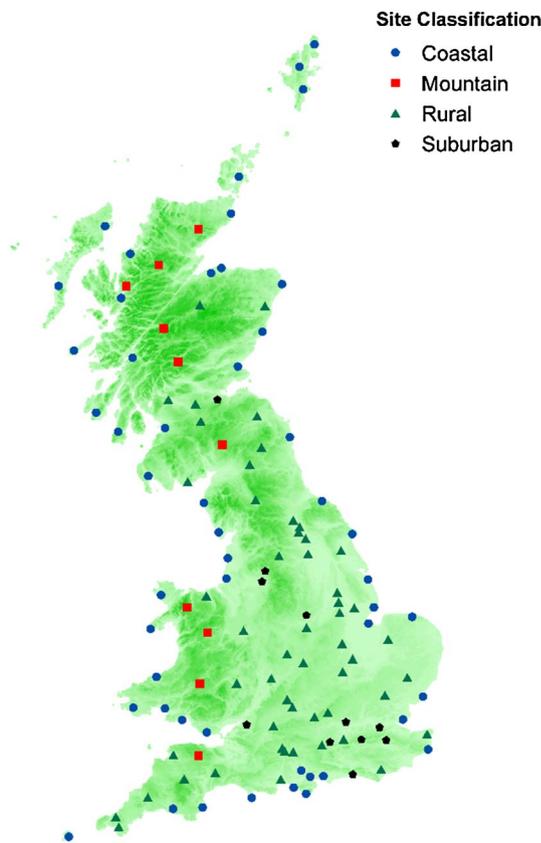
UK average value to predict power density when using wind map data [23]. Power density predictions using this fixed shape factor were compared with power densities using both unscaled and vertically scaled shape factors of the Weibull distributions fitted to hourly BLS NWP data.

2.6. Validation data and error metrics

All predictions in this work were validated using observational wind speeds from 124 sites across Great Britain, as shown in Fig. 5. Each site is a monitoring station in the Met Office's Integrated Data Archive System (MIDAS) [14] where wind speed data is collected at 10 m. The wind speed data is collected as a 10-min average to represent an hourly average wind speed of the site. The 124 sites were selected from a larger sample of MIDAS sites using two criteria: sites that were operational between 2002 and 2012; and sites that provided an hourly data coverage during this period of 90% or above.

For each site, a long-term average wind speed was calculated to validate the wind speed predictions, and a Weibull distribution was fitted to the hourly wind speed time series to derive the shape factor of the distribution to validate the power density predictions. UK4 data was available for all 124 sites in the validation sample, while 121 sites were available in the UKV data as 3 sites were outside the UKV domain.

Each of the 124 sites were classified visually from Ordnance Survey maps to determine their surrounding terrain and likely roughness elements [15]. This process classified the sites into one of four categories; coastal; mountain; rural and suburban. Site classifications allowed the effects of the physical characteristics of different terrains on the accuracy of wind speed predictions to be investigated [15]. The number of sites in each classification is provided in Table 3.

To determine the accuracy of wind speed predictions, error metrics to allow for a consistent comparison of the errors in each prediction across the sample were required. Two metrics; mean absolute error (MAE) and mean percentage error (MPE) were selected to assess the accuracy of wind speed predictions [15]. Mean absolute error is defined as;

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |\overline{u}_{obs,i} - \overline{u}_{pred,i}| \tag{6}$$

where, $\overline{u}_{pred,i}$ is the predicted mean wind speed at site, i, while, $\overline{u}_{obs,i}$ is the observed mean wind speed at site i, and n is the validation sample

Fig. 5. Location of each of the 124 sites selected in this work for validation of wind speeds using observational data.

Table 3
Number of sites in each site classification sample.

Site classification	Number of sites in sample
Coastal	50
Mountain	10
Rural	53
Suburban	11

size. Mean percentage error is defined as;

$$\text{MPE} = \frac{100\%}{n} \sum_{i=1}^{n} \frac{(\overline{u}_{obs,i} - \overline{u}_{pred,i})}{\overline{u}_{obs,i}} \tag{7}$$

By using the MPE metric to assess the accuracy of wind speed predictions, it was possible to determine whether the methodologies under or over-predicted the wind speed. A negative MPE indicated that the majority of sites were under-predicted by a methodology. Choice of the MPE metric also allowed for the error in a wind speed prediction to be analysed as a proportion of the observed wind speed. A wind speed error of 0.3 ms^{-1} has half the percentage error for an observational wind speed of 6.0 ms^{-1} compared to an observational wind speed of 3.0 ms^{-1}. This context was important to allow for an effective analysis of the relative error in the wind speed predictions of each methodology.

Power density predictions were normalised to, $P_{d,norm}$, by the observed power density [15] using the gamma function, Γ, to determine the accuracy of the prediction;

$$P_{d,norm} = \left[\frac{\Gamma(1 + 1/k_{pred})}{\Gamma(1 + 1/k_{obs})} \right]^3 \frac{\Gamma(1 + 3/k_{obs})}{\Gamma(1 + 3/k_{pred})} \tag{8}$$

where, k_{pred}, is the predicted shape factor from either BLS NWP or fixed at 1.8 and, k_{obs}, is the observed shape factor from each validation site.

All of the data processing and modelling work in this paper was conducted in the commercial software package, MATLAB R2013b [44] under an academic license.

3. Results and analysis

The work presented in this paper was developed to analyse the accuracy of wind speed and power density predictions available from both the MCS methodology and the BLS model using the reference wind climatologies of NOABL, NCIC and NWP data. To achieve this, the results and analysis in this paper are split into three sections;

1) Comparison of wind speed predictions from the BLS model and the MCS methodology each at a hub height of 10 m.
2) Analysis of wind speed predictions from the BLS model at a hub height of 10 m using NWP data from various forecasting heights as the reference wind climatology.
3) Comparison of power density predictions from Weibull distributions fitted to BLS NWP data with those using a fixed shape factor of 1.8.

3.1. Use of BLS method using observational based climatology data vs. MCS methodology

Wind speed predictions from five different models using different reference climatologies were compared; unscaled or raw NOABL data, unscaled or raw NCIC data, a BLS model using NOABL, a BLS model using NCIC and the MCS methodology. Use of the different wind maps as reference wind climatologies for the BLS allowed for the identification of the most appropriate reference wind climatology for wind speed predictions. Comparison with the raw wind map data at 10 m allowed for the determination of the improvement in wind speed prediction accuracy offered by the BLS model at this height although it should be noted that the models are capable of predicting height variability. Each prediction of wind speed was estimated at a hub height of 10 m and was initially analysed across the whole sample of validation sites.

The results presented in Fig. 6 and Table 4 show that the BLS model can offer more accurate wind speed predictions than the MCS methodology. The most accurate wind speed predictions were achieved from the BLS model when using the NCIC wind map data as the reference climatology. BLS NCIC wind speeds had a lower percentage and absolute error than the MCS wind speeds. The interquartile range of the BLS NCIC was also lower than the MCS, as are the 5th/95th and 1st/99th percentile ranges, demonstrating that BLS NCIC can offer more robust wind speed predictions than the MCS methodology. The differences in MAE for each of the scaled methodologies appear small, showing a 0.2 ms^{-1} difference between BLS NOABL and MCS wind speeds and a 0.5 ms^{-1} difference between BLS NCIC and MCS wind speeds. However, these errors have an impact on the annual energy production (AEP) estimates for a proposed wind turbine. Assuming a mean wind speed of 5 ms^{-1}, equivalent to the average wind speed across all sites sampled in this study, with a shape factor of 1.8, a 5 kW turbine[1] produces 9498 kW h annually. At a 0.2 ms^{-1} difference in error, this AEP estimate increases by 853 kW h or 9%, while for a 0.5 ms^{-1} difference, the AEP increases by 2,125 kW h which equates to a 22% increase in the AEP estimate. These differences in AEP estimates could be significant in an individual's decision to install a wind turbine, and therefore it is important to estimate the long-term average wind speed and the resulting AEP using a scaling methodology with the lowest absolute error.

The errors in the BLS NCIC wind speeds were also lower than that in the BLS NOABL wind speeds. The mean of both error metrics for the BLS NCIC were below that for the BLS NOABL. These results show that to

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[1] The 5 kW turbine used in this example was a Britwind R9000 5 kW wind turbine. The power curve can be found via a third party here - https://tinyurl.com/y8nn2aaj.
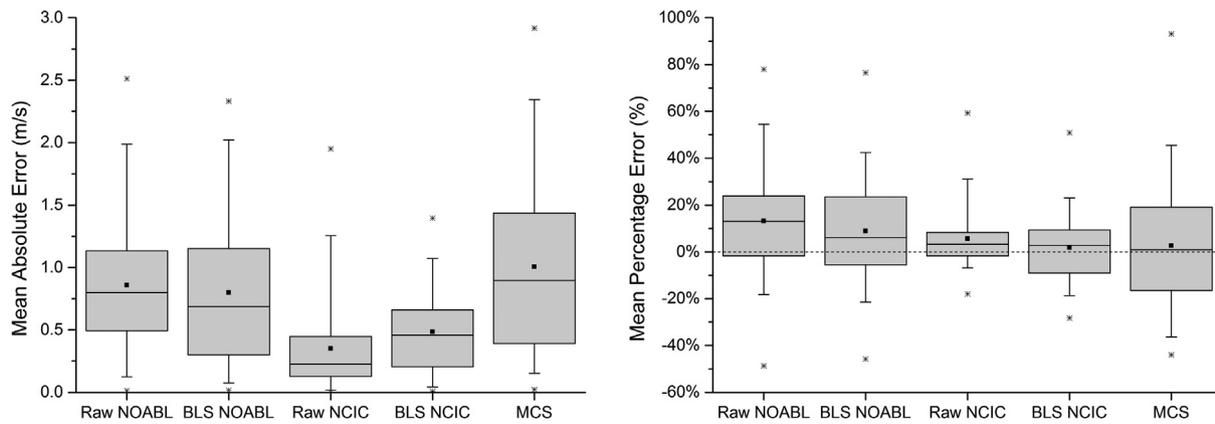
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Fig. 6. Error in wind speed prediction of each prediction methodology and raw wind map data, validated by observational wind speeds. Left: Mean absolute error. Right: Mean percentage error. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample.

Table 4
Summary of mean error in each prediction methodology and raw wind map data from MAE and MPE metrics.

Error metric (mean error)	Raw NOABL	BLS NOABL	Raw NCIC	BLS NCIC	MCS
MAE (ms^{-1})	0.86	0.80	0.35	0.49	1.01
MPE (%)	13.36	8.71	5.50	1.43	2.36

offer the most accurate wind speed predictions, the BLS model should be used with NCIC data as the reference wind climatology. However, the BLS NCIC wind speed predictions had a larger mean absolute error and interquartile range at 10 m than the raw NCIC wind speeds. This might raise questions about the suitability of using NCIC data in the BLS model. However, it is worth considering the methodology utilised to create the NCIC wind map. 220 MIDAS stations at 10 m provided observational data for the interpolation and regression which created the NCIC data [25]. It is therefore highly likely that the 124 MIDAS validation sites in this work were used within this process. Raw NCIC data at the MIDAS sites will be very close to the observational wind speeds as little or no interpolation is required at these sites. It is therefore exceptionally difficult for the BLS model to improve upon the accuracy of raw NCIC wind speeds at the validation sites selected in this work. An additional sample of validation sites, outside those 220 stations in the original NCIC sample, would be required to fully validate the performance of the BLS NCIC against the raw NCIC. However, such a validation data set was not available for this study.

Despite this uncertainty, the BLS model has certain advantages over the use of observational based wind maps. It can provide long-term average wind speeds at variable hub heights whereas raw data is only available at selected heights above ground level [25]. The BLS model presented here can also provide wind speed predictions on a 0.01 km^2 grid square whereas the raw data is only available only on a 1 km^2 grid square. These advantages offer considerable value over raw climatology data when assessing the viability of a prospective wind turbine site. The fact that the BLS NCIC data was close to the raw NCIC dataset at 10 m is encouraging and suggests that significant errors have not been introduced by the BLS process.

Fig. 7 shows both error metrics of the differing wind speed predictions split across the site classifications. At the coastal, rural and suburban sites, the results mirrored those observed when assessing the whole sample. BLS NCIC wind speeds had a lower error than the MCS in both metrics and the MPE of BLS NCIC was lower than that of the raw NCIC but exhibited a greater MAE.

However, at mountain sites, the MPE results differed from this trend. The MPE of the BLS model with either reference wind

climatology exhibited a larger over-prediction in wind speed than the raw wind map data at the mountain sites. The greater over-prediction in BLS wind speeds was likely due the lack of orographic correction in the BLS model. At these mountain sites, the scaling of wind speeds was based solely on the surface roughness value of each site. The surface roughness alone was insufficient to accurately scale the wind speeds, resulting in the over-prediction in wind speeds at mountain sites from the BLS model. For other terrain types, the scaled NCIC data improved the MPE over the raw data in all cases, indicating that an improved representation of orography would significantly improve the overall performance of the boundary layer scaling method.

As typified by the results in Fig. 7, in the majority of site classifications, MCS wind speeds had the highest MAE of all of the scaled wind climatologies. At the coastal sites, MCS had a MAE of 0.97 ms^{-1}, compared to 0.46 ms^{-1} for BLS NCIC and 0.59 ms^{-1} for BLS NOABL wind speeds. This was replicated in the MPE results at coastal sites, where MCS wind speeds had an MPE of −10.51% while BLS wind speeds had MPEs of −0.74% and −1.67% using NCIC and NOABL respectively. For 73% of coastal sites, the MCS under-predicted the wind speed. A similar trend was observed in the MAE results for rural and suburban areas, with MCS wind speeds exhibiting the greatest absolute error of the scaled wind climatologies. Only in the suburban sites did the MCS methodology achieve a significant improvement in MPE over the BLS NOABL, a 6.19% error compared to 16.51%. However, in this sample of sites, BLS NCIC wind speeds achieved an MPE of 0.70%. These results further highlight the differences between the BLS and MCS methodologies and the greater accuracy of estimated wind speeds available using the BLS methodology. The results in each site classification also highlighted that the scaling of wind speeds in the MCS methodology is insensitive to terrain type. In comparison to the BLS model, where the scaled wind speed may be over-predicted compared to the raw wind map data, MCS consistently reduced the wind speed in all areas.

These limitations of the MCS method highlight its inappropriateness as a wind resource assessment for small and medium turbines to provide accurate estimates of long-term average wind speeds. By comparison, the BLS method offers a more appropriate scaling of the wind map data based upon a site's surface roughness which resulted in wind speed predictions with greater accuracy. This improvement in the accuracy of wind speed predictions emphasises the BLS model as a more robust methodology than the MCS methodology which should be considered as a replacement to the MCS methodology in the FIT accreditation process. While the results may differ with an alternative reference wind climatology, the analysis demonstrates that the BLS model was able to effectively improve upon wind map data. The success of applying such scaling techniques in other regions would depend upon
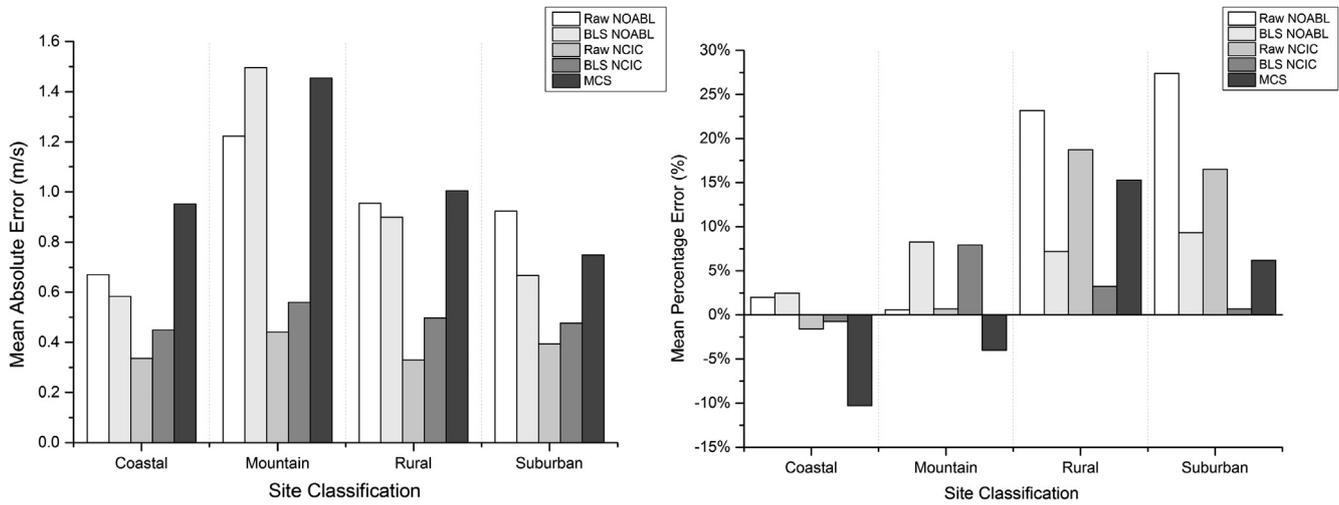
Fig. 7. Error in wind speed prediction of each methodology and raw wind map in each of the four site classifications, validated by observational wind speeds. Left: Mean absolute error. Right: Mean percentage error.

several factors, including the availability of high resolution land use data in order to develop suitable aerodynamic parameters for the scaling, as well as the resolution of the available climatology data.

3.2. Numerical weather prediction data as input climatology

Hourly NWP wind speed data from the Met Office's UK4 and UKV models were both analysed for their suitability as a reference wind climatology to the BLS model. Initially, wind speeds from the BLS of NWP data forecast at 10 m were compared to the wind speeds from raw NWP data at 10 m, as presented in Figs. 8 and 9. For both NWP data sets and in both error metrics, the raw NWP forecast at 10 m out-performed the BLS NWP forecast at 10 m. The performance of raw NWP data, offering more accurate wind speed predictions than the BLS NWP is likely to be a result of the treatment of atmospheric stability in the NWP models. While the BLS model assumed neutral atmospheric stability and a simple logarithmic vertical wind profile, both NWP models modelled atmospheric stability effects from surface heat exchange and turbulence and therefore offered a more realistic vertical wind profile for non-neutral conditions. This outweighed the effect of more realistic surface roughness representation in the BLS model that resulted in raw NWP outperforming BLS NWP data at 10 m.

NWP data from all forecasting heights scaled to 10 m in the BLS model were then analysed to determine which offered the most

accurate wind speeds. Figs. 8 and 9 show that the lowest MPE in the BLS NWP data was achieved from differing forecasting heights, either 150 m for UK4 and 100 m for UKV, whereas the lowest MAE in BLS NWP data was observed when scaling from 200 m for both NWP datasets. These results demonstrate that scaling NWP data forecast higher in the atmosphere can offer the most accurate near-surface wind speed predictions from the BLS model with NWP data. The accuracy of these wind speed predictions are a result of coupling a description of large-scale flow higher in the atmosphere from the NWP data, with a description of the surface roughness effects on near-surface wind from the BLS model. For UKV reference data, overall the BLS method offered wind speed predictions that were not significantly more accurate than the raw NWP data. Small improvements in wind speed predictions using BLS were seen however, when using the coarser UK4 data, indicating that the method may have a great utility for regions outside of the UK where high resolution reference data is not available. For the UK however, improvements to BLS methods must be made to improve their suitability for scaling high resolution NWP data for near-surface long-term average wind speeds. The results suggest that even for long term average predictions, the influence of atmospheric stability is important. Despite the challenges of accurately estimating near-surface long-term average wind speeds from the BLS model, use of hourly NWP data offered the ability to predict power densities which have relied on highly averaged parameterisations of Weibull shape factors when using wind
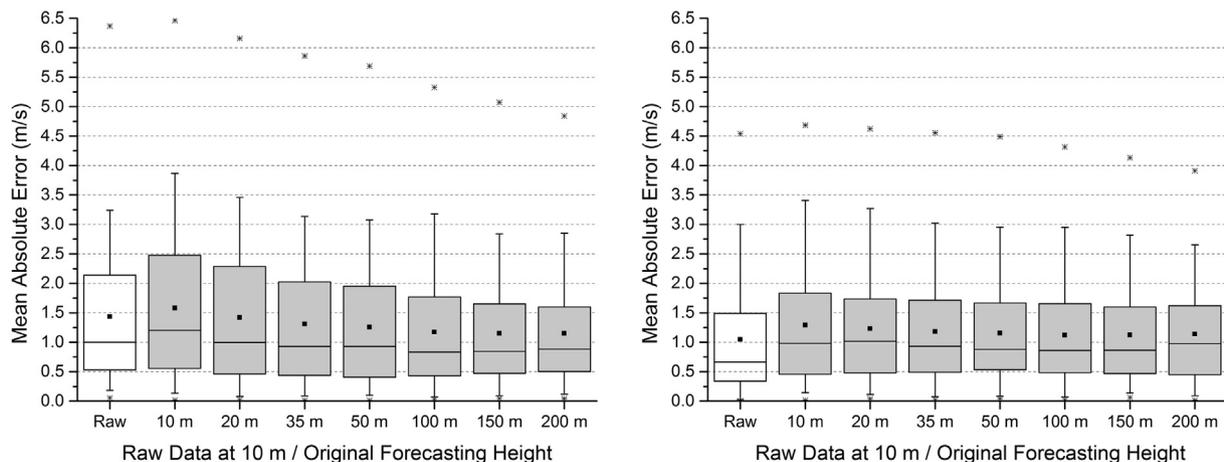

Fig. 8. Mean absolute error of BLS NWP from all forecasting height and raw NWP at 10 m, validated by observational wind speeds. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample.
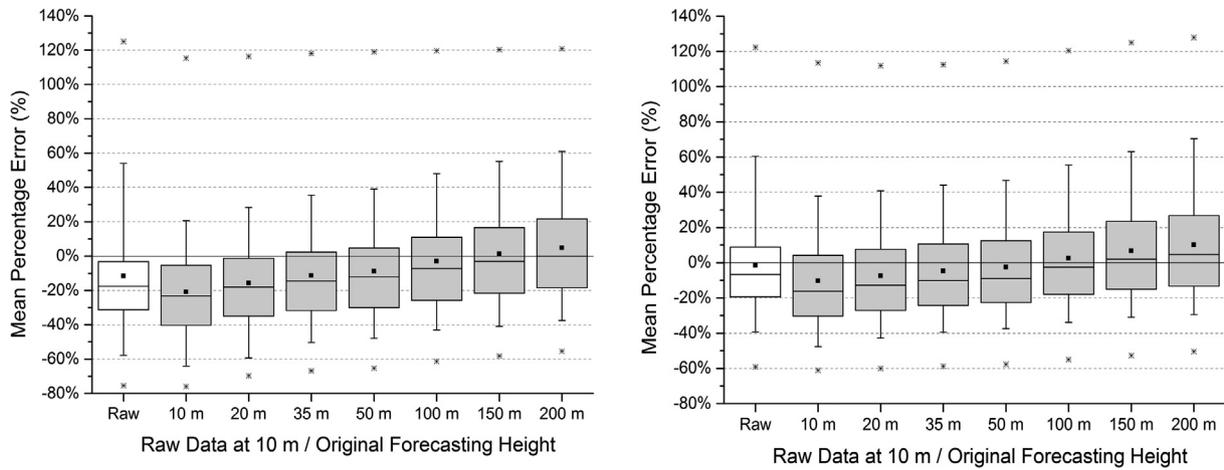
Fig. 9. Mean percentage error of BLS NWP from all forecasting heights and raw NWP at 10 m, validated by observational wind speeds. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample.

map data.

3.3. Shape factor and power density predictions

Weibull distributions were fitted to each BLS NWP dataset scaled to a hub height of 10 m and the shape factor of each distribution used to predict power density.

The normalised power density predictions from the fitted shape factors were initially compared to the normalised power density achieved using a fixed shape factor of 1.8, as shown in Fig. 10. The fixed shape factor of 1.8 provided the mean normalised power density closest to the observed power density, whereas power densities predicted from the BLS NWP data over predicted by an average of around 10%.

The over-prediction in power density from BLS NWP data was caused by the lack of extreme wind speeds in the raw NWP data. This resulted in the Weibull distribution fitted to the BLS NWP data being narrower, with a higher shape factor, than the Weibull distribution which described the observational wind speeds, which caused an over-prediction in power density. As discussed in Section 2.5, the Weibull shape factor can be scaled vertically to account for the reversal height of the diurnal cycle of a site, where the shape factor is at a maximum [29]. This vertical scaling of the shape factors was undertaken in this work with reversal heights of 60 m, 70 m and 80 m.

Fig. 11 shows the normalised power density calculated using a

vertical scaling of shape factors fitted to BLS UK4 and BLS UKV from 20 m using each reversal height. NWP data at 20 m was selected as it provided a more accurate description of diurnal variation of near-surface wind speeds. Vertical scaling of shape factors fitted to BLS NWP data offered significant improvements in power density predictions over BLS NWP without any scaling. Scaling the shape factor offered mean power density predictions within 1% of observed power densities while mean power density predictions using a fixed shape factor of 1.8 were within 3% of observed power densities. The results were not sensitive to the chosen reversal heights, presumed to be the result of the reversal heights being of a similar magnitude.

Scaling of the shape factor from BLS NWP data forecast at 20 m provided the most accurate power density predictions. However, scaling of NWP data forecast between 100 m or 200 m provided the most accurate wind speed predictions. This highlights that different facets of the raw NWP data affect the accuracy of wind speed and power density predictions. For the most accurate mean wind speed predictions from the BLS model, a description of large-scale atmospheric flow available in the NWP forecast between 100 m or 200 m is most suitable. However, the description of diurnal variation of wind speeds available in NWP data at 20 m can be scaled to provide the most accurate power density predictions. These different descriptions of wind flow variations available at the different forecasting heights of raw NWP data accounts for the selection of different heights of NWP data for wind speed or
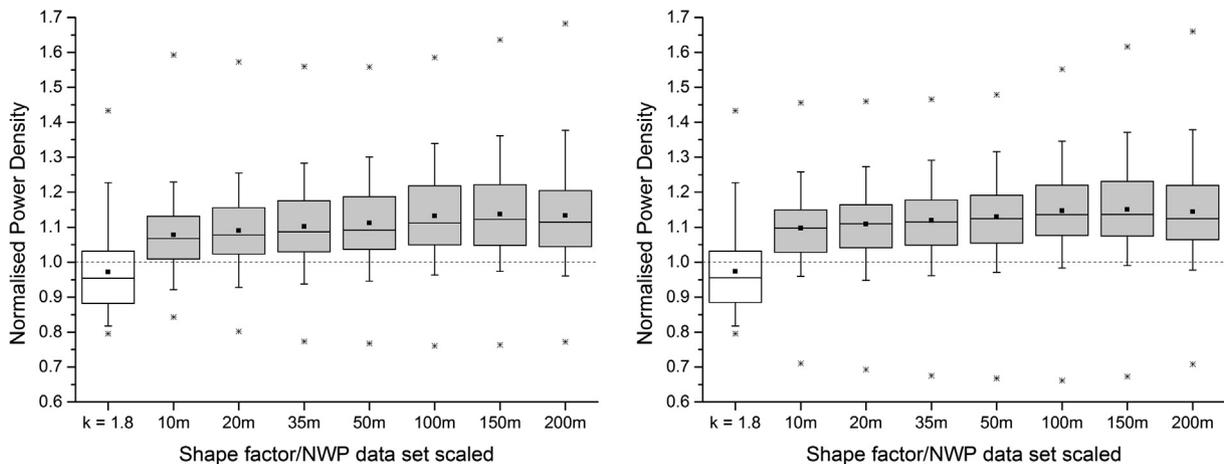

Fig. 10. Normalised power density from BLS NWP from all forecasting heights and the use of a fixed shape factor of 1.8. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample.
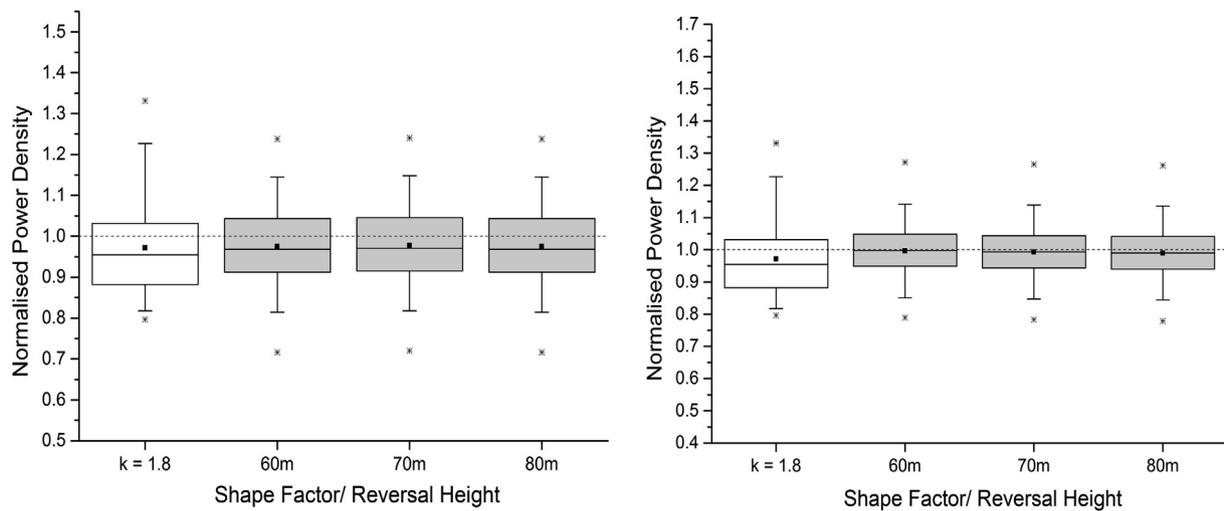
Fig. 11. Normalised power density from BLS NWP from 20 m scaled from reversal heights of 60 m, 70 m and 80 m and fixed shape factor of 1.8 without a vertical scaling. Left: UK4 data. Right: UKV data. Large boxes are the interquartile range showing the 25th, 50th and 75th percentile values, small squares are the mean error, whiskers are the 5th and 95th percentile values and crosses are the 1st and 99th percentile values of each sample.

power density predictions.

Vertical scaling of shape factors fitted to both BLS NWP datasets has improved the accuracy of the mean power density predictions, with BLS UK4 under-predicting and BLS UKV over-predicting by 1%. Additionally, the interquartile and 5th to 95th percentile ranges are reduced with the vertical scaling of the shape factor from the unscaled shape factors of BLS NWP data. Vertical scaling of shape factors fitted to BLS NWP can therefore provide accurate power density predictions to prospective small and medium wind turbine adopters. However, where such data is unavailable use of a fixed shape factor of 1.8 has been shown here to be a suitable alternative. While this finding was observed in power density predictions for sites in Great Britain, it is envisaged that a vertical scaling of BLS NWP data, which exhibits an over-prediction in the power density prediction, would be applicable in any location.

4. Conclusions

A boundary layer scaling model using NOABL, NCIC and NWP data as input climatologies was investigated to determine the accuracy of wind speed and power density predictions at a hub height of 10 m. This analysis was undertaken to understand if the BLS model could offer accurate wind speed predictions using wind map data or NWP data and whether the BLS model could provide wind speed predictions with greater accuracy than the MCS methodology, which is currently required for all wind turbines under 50 kW to gain accreditation to qualify for the FIT payments in Great Britain. In addition to this, the suitability of NWP data for wind speed predictions from the BLS model and power density predictions was analysed.

The most accurate wind speed predictions from the BLS model were achieved with NCIC data as the reference wind climatology. BLS NCIC wind speeds had significantly lower errors than the MCS predicted wind speeds over the validation sample. However, the BLS NCIC was outperformed by raw NCIC data for wind speed predictions at 10 m. This was a result of the validation sites in this work being included in the original observational dataset used in the creation of the NCIC database. Nevertheless, the BLS method can provide a vertical profile of mean wind speeds which is unavailable from the raw NCIC data and would be necessary when selecting the appropriate hub height of a prospective wind turbine. To provide a more realistic evaluation of BLS NCIC wind speeds, an alternative validation sample could be utilised. A validation sample of observational wind speeds from sites not included in the original sample of sites used for the development of the NCIC

database and from existing wind turbine sites at hub heights other than 10 m would be most suitable. However, such data is difficult to obtain due to its commercial sensitivity.

The BLS model utilising NWP data as a reference wind climatology was unable to improve the accuracy of long-term average near-surface wind speed estimates when compared to raw NWP data alone. The high-resolution NWP data offered a realistic vertical wind profile by modelling stability effects as opposed to the assumption of neutral atmospheric stability in the BLS model. Parameterisation of stability effects based on outputs from the NWP model would be required to improve upon the current BLS methodology to address this issue. The results are also likely to be related to the already high resolution of the UK's forecasting model. However, in other regions where such high-resolution modelling is not available, or there is a reliance on reanalysis data, there may be further scope for the scaling methodology to improve upon the raw data. The availability of high resolution land use data would be an important factor in determining the success of the scaling method.

Power density predictions achieved using a vertical scaling of shape factors fitted to BLS NWP were however encouraging. Power density predictions using this vertical scaling approach improved upon those using a fixed Weibull shape factor which is the only possible method of power density prediction when using long term average wind map data. The high-resolution time-series data available from NWP data therefore has clear advantages over the use of a fixed shape factor for power density predictions for small and medium wind turbines. However, where NWP data is unavailable from which to predict power density, use of a fixed shape factor of 1.8 has been shown to provide power density predictions which would be suitable for feasibility assessments.

The BLS model developed in this work was able to offer accurate long-term average near-surface wind speed predictions. This demonstrates that, at the initial scoping stage of a small or medium wind turbine project, the BLS model can be utilised by potential domestic adopters and commercial developers to determine a site's technical viability, quickly and cheaply. The BLS model also offered predictions of wind speed with significantly greater accuracy than the MCS methodology. These results have policy implications for the operation of the FIT policy in Great Britain. Implementation of a BLS model as the methodology required to gain accreditation for FIT payments could offer more accurate resource assessments to small and medium wind energy developers compared to use of the MCS method. While this research focussed on a case study in Great Britain, the findings are relevant to other locations, as they demonstrate the ability of the scaling

techniques to improve upon reference climatology data, provided that sufficiently detailed land use data is available for a particular region. The methodology may be particularly useful for regions where very high resolution (~ 1 km) reference wind data cannot be obtained, but where a more detailed land use data set can be developed for use within the BLS method. A more accurate resource assessment for both wind speed and power density predictions can support further deployment in the small and medium wind turbine market, both in Great Britain and globally, by offering a scoping method that can determine the viability of prospective wind turbine sites efficiently and with increased confidence.

Acknowledgements

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