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
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**A PROPOSED METHOD FOR GENERATING HIGH RESOLUTION CURRENT
AND FUTURE CLIMATE DATA FOR PASSIVHAUS DESIGN**

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ABSTRACT

The sensitivity of low energy and passive solar buildings to their climatic context creates a requirement for accurate local climate data. This situation takes on increasing importance in the context of modelling Passivhaus buildings where the absence of conventional oversized heating and cooling systems implies a greater reliance upon fabric and system optimisation. Conversely, future climatic changes may also pose serious implications for super insulated buildings with inadequate solar shading. Currently, many widely used building performance simulation (BPS) tools still rely on very limited sources of climate data.

The following research examines the need for regional and, in some cases, micro-regional climatic data when designing ultra-low energy Passivhaus buildings in the UK. The paper proposes a new methodology for generating this data in PHPP format. The data generated is compared to alternative sources, and the implications discussed in the context of three case studies examining a certified Passivhaus dwelling in a mountainous region of Wales as well as two locations, in close proximity, within London. If correctly implemented the use of such data should provide a more robust basis for future cost and performance optimisation in low energy and passive building design.

Keywords: climate change scenarios; climate data; Passivhaus; PHPP; urban heat islands

1.0 INTRODUCTION

Passivhaus Planning Package (PHPP12) is a simplified steady state building simulation tool that is primarily targeted at assisting architects and mechanical engineers in designing Passivhaus buildings [1]. According to the Passivhaus Institute (PHI) the verification of a Passivhaus design must be carried using the Passivhaus Planning Package (PHPP). As a result, this quasi-steady state software is the de facto software used for both the design and compliance predictions of Passivhaus buildings in the UK and around the world. PHPP has been validated using both dynamic thermal simulations using Dynbil [2] and empirical data from a large number of completed Passivhaus projects [3]. Dynamic simulation results predicted by Dynbil, have also been extensively compared to measured data for both dwellings and office buildings [4,5,6]. PHPP validation studies have generally shown good agreement between measured and predicted results including those derived from dynamic simulation [3]. The PHPP thermal model conforms to the calculation methods set out in EN ISO 13790 for determining heating

demand according to annual or monthly methods, and contains additional algorithms to calculate peak heating and cooling loads and assess overheating risks.

In addition to delivering design energy and peak load predictions a validated PHPP worksheet is primarily used to demonstrate compliance with the Passivhaus certification criteria. The key criteria for Passivhaus certification are that the building must have a Specific Annual Heat Demand (q_H) ≤ 15 kWh/m².yr or a Specific Peak Load (p_H) ≤ 10 W/m², together with a Specific Primary Energy Demand (q_p) ≤ 120 kWh/m².yr relative to the Treated Floor Area (TFA). Where a cooling energy requirement exists this must also be (q_c) ≤ 15 kWh/m².yr.

Like all building physics models the outputs from the PHPP model are predicated upon the use of appropriate boundary conditions. In the case of PHPP where, for certification purposes, the internal gains (residential, 2.1 W/m²) and operative temperature (20°C) are assumed to remain constant; the key boundary conditions used to determine the annual heating demand, cooling demand and peak loads depend almost entirely on the external climate.

In the context of a Passivhaus, where all of the supplementary heating may be provided solely via a small post-air heater, the risk associated with uncertainty in the peak heating load calculations could have real consequences. Conversely, overheating risks are likely to increase with climate change and a better understanding of cooling loads and future overheating risk predictions is needed [7]. Hence, there is a need to understand the uncertainty associated with the climate files used in order to determine the sensitivity and reliability of any design or certification predictions. Typical Meteorological Year (TMY) data sets in the USA, and Test Reference Year (TRY) data in Europe are some of the most commonly used formats of hourly weather data for Building Performance Simulation (BPS). The principles behind the generation of these datasets are similar in that a typical weather year is compiled by selecting the mean monthly data from long-term historic data typically spanning a 20-year+ period. As such these data sets represent typical (historic) conditions and the U.S. National Renewable Energy Laboratory (NREL) states that ‘they are not suited for designing systems and their components to meet the worst-case conditions occurring at a location’ [8].

In the original PHPP models, (PHPP04 and PHPP07) climate data for the UK was derived from TRY datasets for half a dozen locations. In most cases, this data was thought to be adequate for Passivhaus verification based on calculation of the mean annual heating demand. However, since it is possible to obtain Passivhaus certification

based on peak loads, questions were raised about the appropriateness of using only a single UK climate data set (Manchester) as a proxy for calculations across the entire UK [9]. This situation has recently evolved with the production of 22 UK regional datasets developed using Meteonorm (MN) interpolation, which have been cross-checked against EPW climate files and ratified by PHI [9].

This paper examines the limitations of the current system and presents a new method of obtaining much higher resolution climatic data for current and future probabilistic scenario modelling generated using the UKCP09 Weather Generator [10]. The results are compared to both site specific and regional proxy data [11] based on Meteonorm software interpolation methods and existing TRY data (where available).

2.0 METHODOLOGY

2.1 Generating Climate Data in PHPP format

The original climate data provided by the Passivhaus Institute (PHI) for design and certification in the UK was derived from TRY data [12]. Since many of the original PHPP data sets lacked the data necessary to carry out peak load evaluations, a reverse engineering process (involving multi-stage dynamic simulations) was developed by the PHI for the determination of peak load data [13]. Due to the lengthy processing time involved, complete PHPP datasets were only available for a limited number of locations

More recently, interpolation software, such as Meteonorm 6, has made it possible to generate complete climate data sets for virtually any geographic location in the world. Schneiders [14], however, cautions against the use of such software to derive peak load data since the reliability of the algorithms used to derive daily climate data from monthly data is not well established. Furthermore, Rawlins [15] proposed that site-specific daily irradiation is more accurately estimated from local sunshine observations than by interpolation from nearby radiometric stations, particularly where weather stations are located more than 20km away. For the interpolation of monthly average irradiation Rawlins states that the critical distance becomes slightly greater, at approximately 30km. By contrast the use of daily sunshine hour recordings from a location 50km away would generate RMSEs typically in the range of 14% - 22% [15].

2.1.1 Monthly climate data variables

The primary inputs required by PHPP to calculate the annual specific heating demand (SHD) are based on monthly mean climatic variables, namely: mean ambient temperature, global horizontal irradiation and the vertical slope irradiation for the cardinal aspects. Additional values such as sky temperature and ground temperature are subsequently derived from these values. Unlike the weather file formats used in most dynamic simulation programmes PHPP requires that the monthly irradiation data is broken down into its cardinal slope irradiance components in the weather file (Figure 1).

Month	1	2	3	4	5	6
Days	31	28	31	30	31	30
Wales - Ebbw Vale	Lat °N	51.7	Long °E	-3.1	Alt m	277
Ambient Temp (°C)	2.2	2.8	4.4	9.5	13.0	14.6
North	6	10	18	32	47	54
East	12	14	29	81	102	123
South	33	28	45	105	107	102
West	12	17	32	81	108	102
Global	18	26	51	127	172	187
Dew Point	2.3	2.6	3.7	4.5	7.4	9.8
Sky Temp	-5.8	-5.3	-3.7	-2.6	1.5	4.8
Ground Temp	7.4	6.2	6.2	7.5	9.7	12.2
Global horizontal irradiation (kWh/m ² .month)						
Monthly mean slope irradiation (kWh/m ² .month)						
Mean monthly ambient temperature (°C)						

Figure 1 PHPP sample climate data (partial set/ left hand side) showing 6 months of heating demand data

In addition to the monthly heating demand data (Figure 1

Month	1	2	3	4	5	6
Days	31	28	31	30	31	30
Wales - Ebbw Vale	Lat °N	51.7	Long °E	-3.1	Alt m	277
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Ground Temp	7.4	6.2	6.2	7.5	9.7	12.2
Global horizontal irradiation (kWh/m ² .month)						
Monthly mean slope irradiation (kWh/m ² .month)						
Mean monthly ambient temperature (°C)						

Figure 1) the PHPP climate file also contains data for determining the peak loads at a daily time step.

2.1.2 Peak load data and variables

By definition the peak heating and cooling loads require design temperatures and irradiation calculations to be conducted at a much smaller time step than the monthly data allows. Typically, these calculations are carried out at an hourly or sub hourly interval using a dynamic simulation. Historically the peak load slope irradiance data used by PHPP was derived using a process which involved changing the aperture area in a dynamic simulation reference model and recording the resultant impact upon monthly heating loads for each of the cardinal points [13, 16]. Such a method is robust in one sense since it begins by isolating the peak load and works backwards to derive the corresponding irradiation data. However, this approach is time consuming and necessitates a second (fully dynamic) model. The approach also entails a number of modelling uncertainties that are difficult to quantify, including the representivity of the TRY itself. Until recently, a significant further limitation of this approach has been the limited availability of regional and micro-regional TRY files, which have only been available for a limited number of locations in the UK.

In the case of Passivhaus buildings, which are characterised by high thermal inertia, it has been demonstrated that the peak load analysis can be carried out using data which is averaged over a longer time period than for

conventional buildings [12, 17, 18]. Further discussion of this time constant follows in the Methodology section. Figure 2 illustrates the two periods Weather1 (W1) and Weather2 (W2) for which the peak heating load is assessed. W1 corresponds to the coldest clear period, with relatively high daily irradiation but low ambient temperatures. W2 represents a prolonged cloudy winter period with very little irradiation but slightly milder temperatures [18]. These two discrete periods are entered in to the PHPP peak load calculation where the maximum load derived from either scenario becomes the peak load. Historically the peak load climate data was isolated from a TRY data set, and this is still considered by the PHI as the preferred method [14]. Since a TRY is effectively a mean weather year designers need to be acutely aware of the limitations inherent in this approach with respect to peak load plant sizing.

Heating Load		Cooling Load
Weather 1	Weather 2	Radiation
Radiation: W/m ²		W/m ²
-3.3	1.4	21.9
8	2	43
18	2	58
56	1	74
20	2	73
25	4	113
3d	3d	3d
		11.2
6.2	6.2	15.8

Peak ambient design temperature (°C)
Mean peak slope irradiance (W/m ²)
Mean peak global horizontal irradiance
Peak load time constant (days)

Figure 2 Peak load weather data showing key variables for the calculation of W1 and W2

2.2 Generating regional climate data files for PHPP heating demand

Obtaining mean monthly climatic data suitable for use in predicting the PHPP specific heating and cooling demand is relatively straightforward as there are now a number of possibilities for obtaining this data on a regional scale. Designers working with hourly or sub-hourly dynamic simulation tools in the UK can access high-resolution data via the PROMETHEUS web portal [19] which provides hourly EPW formatted climate files derived from the UKCP09 Weather Generator (WG). Worldwide it is possible for designers to generate future predictive data in a limited number of formats by using various tools such as the Meteonorm software. Various

data ‘morphing’ procedures have been elaborated by Belcher et al [20], Crawley [21] and Jentsch et al [22] who set out details for a series of shift and stretch functions which provide the underlying methods used to ‘morph’ existing TRY or baseline data sets in line with any given future climate change scenario. Crawley [21] provides further specific procedures for shifting the ambient temperature in Urban Heat Islands. Such methods are limited by the spatial distribution of the baseline TRY datasets and knowledge of the amplitude of the climate change input signals which were typically derived from 50km (or coarser) grid models. In addition to using a much higher spatial resolution the more recent PROMETHEUS files include probabilistic prediction of the future wind speed and direction which was absent from many earlier climate generator models [23].

2.3 Spatial resolution

For individual design based predictions the finest spatial resolution data attainable is typically the most relevant, since this should include micro climatic influences. In the case of Passivhaus and ultra-low energy design concepts, this requirement is amplified by the fact that useful solar gains may be compensating up to one third of the total losses [24]. In a study comparing long term in-situ measured data on a Passivhaus project near Cork, Ireland with proxy regional TRY data (Dublin) and interpolated data Morehead [25] concluded that a variation in the predicted space heating demand exceeding 30% was possible contingent upon the source data chosen. With implications for build costs, running costs, plant sizing and thermal comfort predicated upon these calculations the need for more accurate climate data and an understanding of limitations and associated risk becomes apparent.

Counter to this in the context of broader meta-studies, or for the purposes of standardised building certification, the use of a coarser resolution or even regional climate data may be warranted. Currently Passivhaus certification in the UK is based upon a newly adopted system that uses 22 regional data sets (Figure 3) generated by the BRE [10] using Meteonorm interpolation methods cross-checked against ASHRAE EPW files. Whilst the regional boundaries chosen reflect, in some cases, the administrative boundaries previously defined in the UK Standard Assessment Procedure (SAP) for overheating analysis there is no precise climatic basis for the boundaries used.

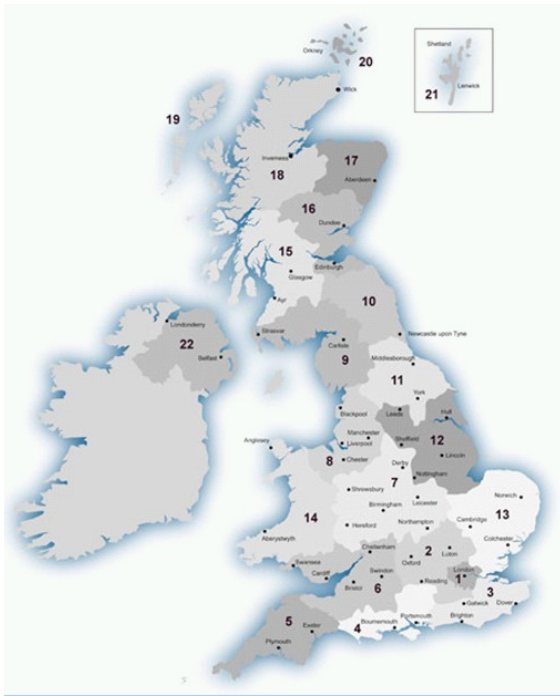


Figure 3 22 UK climatic regions currently used for Passivhaus certification (BRE, 2011)

An alternative source of regional data has been compiled by the Met Office Hadley Centre using 25km grid squares which reflect the Regional Climate Model (RCM) grid. This data is generated by averaging the 5km data sets that fall within these larger plots. Regional data for 14 administrative regions and 23 river basins has also been produced based on long-term (1961-1990) averages for all of the key monthly climatic variables. Such methods of producing representative regional data, which has been composited from finer grid resolutions, appears to offer a more robust basis for developing future regional datasets for Passivhaus certification. The raw data produced by the UKCP09 WG is not directly available in PHPP format however.

2.4 UKCP09 probabilistic data and Weather Generator

The HadRM3 RCM was developed by the Met Office Hadley Centre in order to downscale the simulations provided by the Global Climate Model (GCM). The RCM operates at a 25km resolution, providing outputs on a scale that is useful for impact assessment in the built environment. This model creates 434 unique land based grid squares containing probabilistic climate projections for most of the UK. For each 25km grid location 10,000 realisations (samples of the probability density function) have been generated for each decade and emissions scenario based on equi-probable changes in the underlying climatic variables.

The Weather Generator (WG) is a climate model downscaling tool which was developed by the Hadley Centre in order to provide outputs at a higher resolution than the regional climate model. By mapping the unique climate signal contained within each 25km grid square on to a much finer 5km grid baseline (Figure 4) approximately 11,000 viable grid data locations are produced covering the entire UK landmass. Each 5km grid square thus contains a 30 year baseline dataset for the reference period 1961-1990, coupled with the possibility to sample future probabilistic scenarios at 10-year intervals from 2020 to 2080 [26].



Figure 4 Showing UKCP09 5km and 25km grid resolutions for South Wales/ Severn region

Three climate change scenario outputs are available from the Weather Generator based on the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) climate principal scenarios: Low (A1F1), Medium (A1B) and High (B1). Further information on the global economic scenarios defining the SRES scenarios can be found in IPCC [27]. Each WG run randomly samples from the 10,000 change factors available to create a continuous thirty year time series based on the underlying baseline profile. A minimum of 100 randomly chosen samples of the WG climate data are needed to compile a single statistically representative climate file. Each WG run therefore results in a minimum of 3000 equi-probable future weather years of data. The WG operates at a daily temporal scale from which hourly variables are subsequently extrapolated based on existing relationship patterns in the observed baseline data.

Rainfall is the primary variable in the WG, and is estimated using the Neyman-Scott Rectangular Pulses (NSRP) model [28]. All of the other output variables are dependent upon the rainfall data. Inter variable relationships based on regression models developed from the measured daily station data are then used to predict mean daily temperatures, temperature range, vapour pressure and sunshine hours [27]. Further variables are subsequently calculated from the core variables using appropriate formulae. Hourly global solar irradiation, for example, is

only recorded at approximately 90 Met-office sites around the UK using predominately CM11 pyranometers [29]. Additional algorithms based on the work of Cowley [30] and Muneer [31] were therefore used to derive the global direct and diffuse irradiation components from the observed daily sunshine duration.

Validation work carried out by the WG team, analysed later in this paper, shows good agreement between the modelled direct and diffuse irradiation predictions and measured data from selected reference sites [32]. This validation check of the WG meta-model data is important in the context of understanding the overall uncertainties in this research, where further downstream models are used to derive monthly and daily slope irradiation data for each scenario.

2.4.1 Validation of UKCP Weather Generator source data

Of particular relevance to the key climate data inputs required by PHPP is the method used by the WG to estimate direct and diffuse irradiation at daily and hourly levels. The use of algorithms based upon the daily hours of sunshine and day length at a given location has allowed the WG to estimate the diffuse and direct beam components of the Global Irradiation at grid locations which do not directly record solar radiation measurements.

2.4.1.1 Daily irradiation

For global irradiation an algorithm developed by Cowley [30] based on sunshine duration has been implemented in the WG.

Cowley's equation is given as:

$$G = E \left[a \left\{ \left(\frac{n}{N} \right) + \left(\frac{b}{N} \right) \left(\frac{n}{N} \right)^2 \right\} + (1 - a) a' \right] \quad (1)$$

where G and E are the daily terrestrial and extra-terrestrial irradiation on a horizontal surface, n is the daily hours of sunshine and N is the day length.

$d = 0$ if $n = 0$, otherwise $d = 1$ if $n > 0$, and a' = average ratio of G/E for overcast days. The seasonal means for the coefficients a , a' and b were taken from Appendix B1 in Muneer [31].

To estimate diffuse irradiation (D) Muneer recommends the following global model, which was established using regression curves to fit the relationship between the daily diffuse ratio (D/G) and the clearness index (H_T).

The regression fit characterised by this model was based upon a number of global studies, including research carried out in the UK by Saluja and Muneer [32]

$$D/G = 0.962 + 0.779K_T - 4.375K_T^2 + 2.716K_T^3, \text{ for } K_T \geq 0.2 \quad (2)$$

$$D/G = 0.98, \text{ for } K_T < 0.2 \quad (3)$$

$$K_T = a + bS \quad (4)$$

where S is the sunshine hours. Muneer [31] demonstrates the validity of a global estimate for the relationship between D/G and K_T .

2.4.1.2 Hourly irradiance

The hourly irradiance models in the WG use Muneer's Meteorological Radiation Model (MRM) algorithm. MRM estimates the diffuse and direct components from ground based measurements: air temperature, wet bulb temperature and sunshine duration. The advantage of this approach is that such data is widely available worldwide and does not require sophisticated instrumentation [33].

The diffuse irradiance model is given by:

$$I_D = I_B \tau_{atm} \tau_g \tau_a \tau_w \left[\frac{0.55(1-\tau_a)}{1-\tau_a+m^{1.02}} + \frac{0.55(1-\tau_a)}{1-\tau_a+m^{1.02}} \right] \quad (5)$$

$$\tau_{atm} = 1 - 0.1(1 - \tau_a)(1 - m + m^{1.02}) \quad (6)$$

$$\tau_{atm} = 10^{-0.0042m^{1.7}} \quad (7)$$

where τ_{g} , τ_{a} , τ_{r} , τ_{o} and τ_{s} are atmospheric transmittances estimated by a set of equations using coefficients given in Muneer [30] deemed suitable for UK/northern Europe, m is the relative air mass (m' is adjusted for atmospheric pressure) obtained by Kasten's [34] formula.

The global irradiance is given by:

$$I_g = (I_B + I_D) \left(\frac{1}{1 - r_s r'_a} \right) \quad (8)$$

where r_s is the ground albedo, and $r'_a = 0.0083 + 0.17(1 - \tau'_a)$, τ'_a is the Rayleigh scattering computed at $m = 1.66$ and I_D is the attenuation of light through a medium calculated according to Beer's law.

A more detailed treatment of the above, including a detailed evaluation of the MRM algorithm for clear and over cast skies is provided in Muneer [31].

2.4.2. Validation results

In order to test the accuracy of these algorithms, the Met Office WG team compiled daily and hourly radiation data recorded at three UK weather stations. Hemsby (Norfolk), Finningley (South Yorkshire) and Stornoway (Western Isles) were the only UK stations at the time that recoded both daily and hourly irradiation plus the additional input variables needed for a weather generator run. A weather generator control run is a baseline (i.e. unperturbed) simulation run consisting of 100*30 year time periods, calibrated on the specific station data record. The half monthly means were calculated for the observed data (typically based on a 14-15 years of record data) and compared with those produced by the simulations. For hourly simulation of data, the method described above is employed, and the hourly figure is adjusted to equal to the daily total for consistency. Sample validation results for Hemsby (1982-1995) Finningley (1983-1995) and Stornoway (1982-1995) daily diffuse and direct irradiation are given in Figures 5- 7. The standard deviations for the 100 runs are shown to indicate the variability inherent within a stochastic model.

Hemsby - Direct and diffuse irradiation

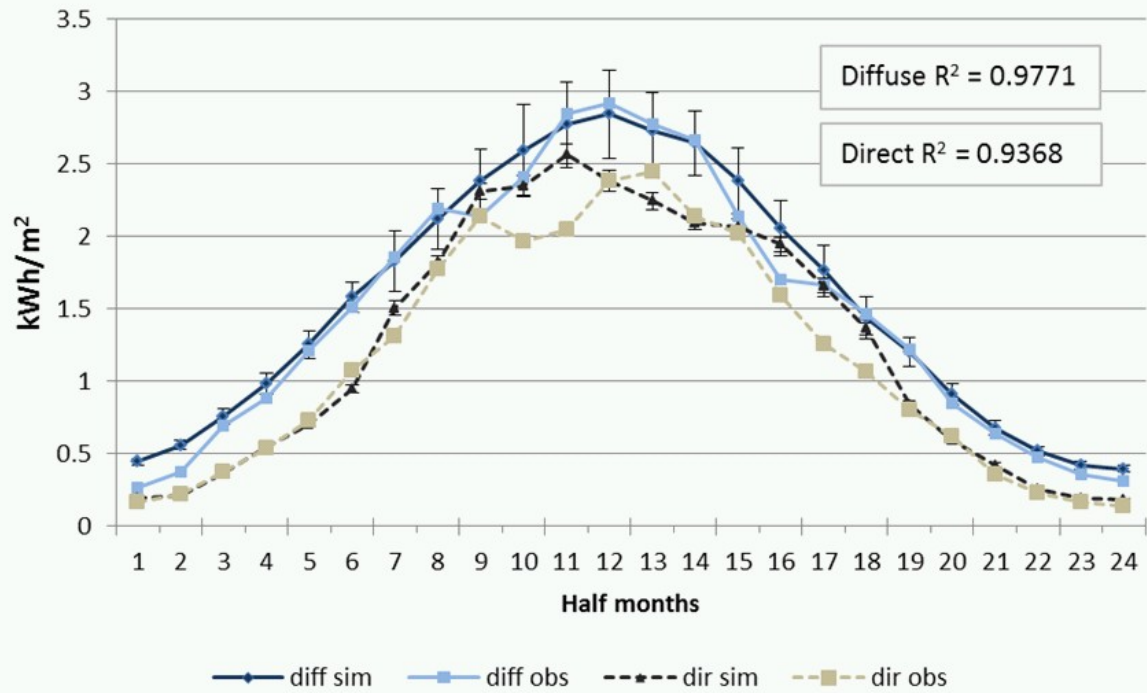


Figure 5. Compares the WG simulated diffuse and direct outputs with observed data for Hemsby (1982-1995). Error bars indicate variability over 100 WG runs at +/- 2 Standard deviations. (Data courtesy WG Team, Met Office)

Finningley - Direct and diffuse irradiation

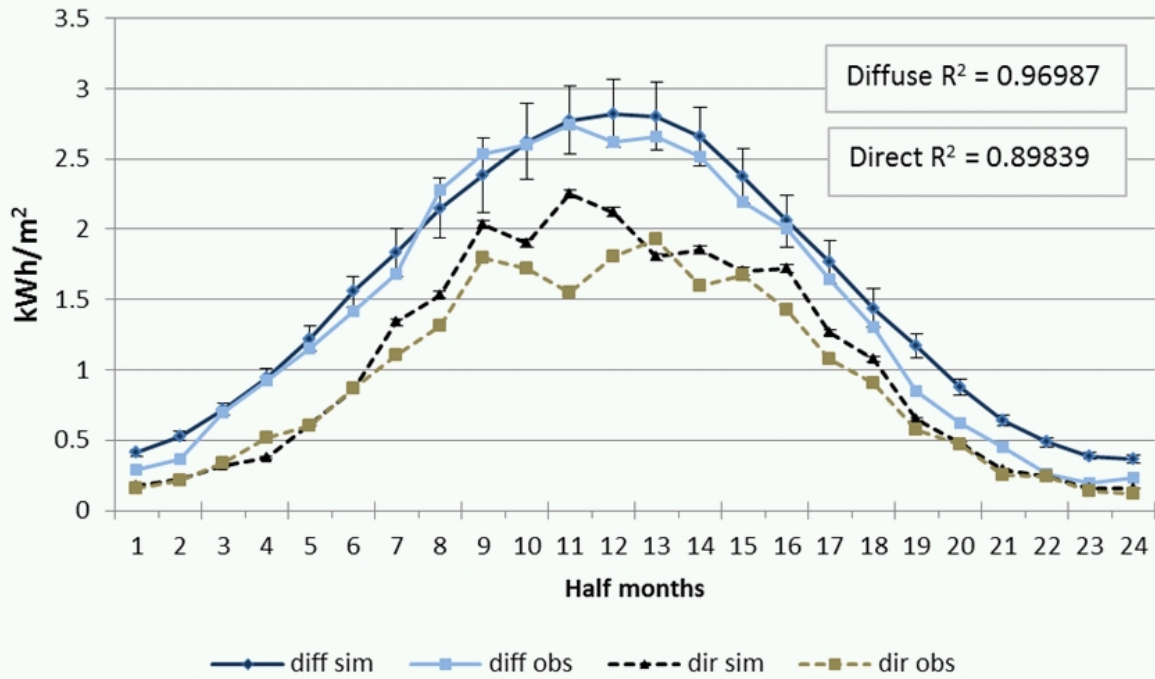


Figure 6. Compares the WG diffuse/direct output with observed data for Finningley, Doncaster (1983-1995). Error bars indicate the variability over the 100 WG runs at +/- 2 standard deviations. (Data courtesy WG Team, Met Office)

Stornoway - Direct and diffuse irradiation

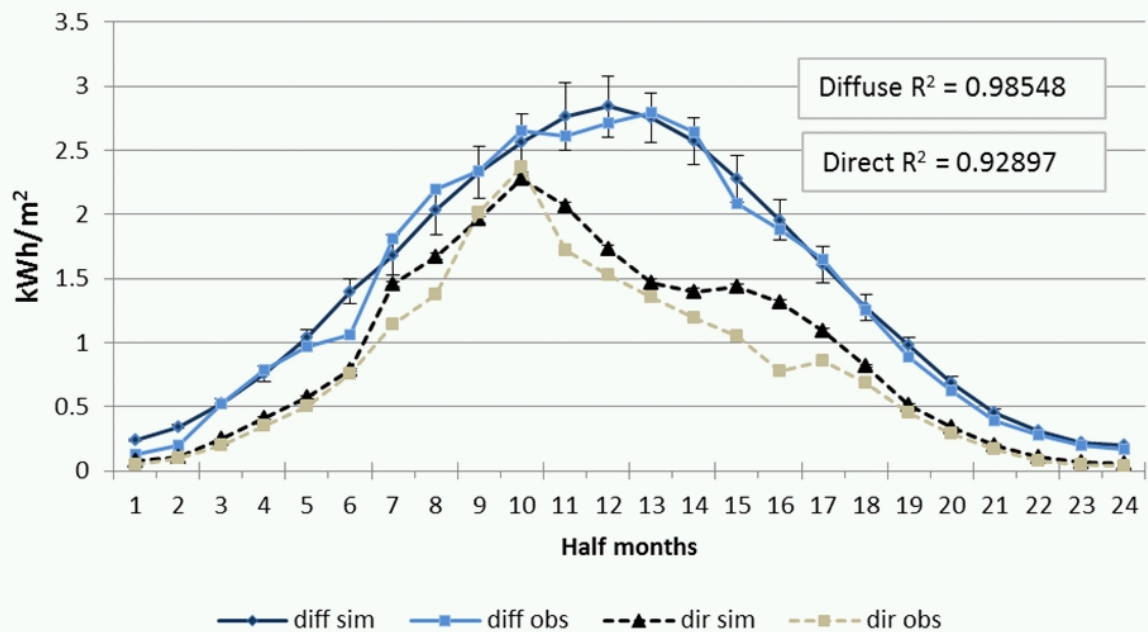


Figure 7. Compares the WG diffuse/direct output with observed data for Stornoway (1982-1995). Error bars indicate the variability over the 100 WG runs at +/- 2 standard deviations. (Data courtesy WG Team, Met Office)

The validation results suggest good agreement between the simulated and recorded data for 3 different sites across the UK. For the diffuse radiation the mean coefficient of determination (R^2) across the 3 sites was 0.9774, whilst for the direct radiation the mean value was 0.9214.

One of the strengths of using the WG model for generating the primary data for use in building simulation models is that the source model algorithms are independently validated. The current WG has undergone extensive field testing and further revisions have been made to the model as errors are reported or more accurate modelling procedures have become available [35].

2.5 Preparing the WG output data for building simulation models

Processing 3000 years of equally probable data sets per scenario for each location and time sequence is unwieldy from a building simulation perspective. In order to achieve representative building simulation weather files the WG data needs to be processed and additional variables added. In the UK the Chartered Institute of Building Services Engineers (CIBSE) has established a Test Reference Year (TRY) and Design Summer Year (DSY) formats for investigating both typical weather years and hotter than average summer years. TRYs are typically compiled from 20+ years of historical measured data (typically 1983 to 2004) which are then sorted by weighting key variables in order to create a composite year from the most typical individual months. The mathematical basis for this procedure can be found in Levermore and Parkinson [36]. When TRY weather files are produced they are compiled from representative months and the Finkelstein-Schafer (FS) statistic is commonly used to select the most average months. This method is considered superior to using the mean month since it selects the months that have less extreme daily values and are closer to the long term daily mean [37]. The FS statistic works by summing the absolute difference between the cumulative distribution function (CDF) values recorded for a particular variable on each day in a given month and the overall cumulative distribution function for each month considered, using the following equation.

$$FS_{m,y} = \sum_{i=1}^{N_m} |CDF_{i,m,y} - CDF_{i,m,N_y}| \quad (9)$$

The month in a given year with the lowest FS distribution is considered the most representative of all of the years for a given variable. In order to consider the most typical month where multiple variables are concerned a weighted index may be applied to each key variable. Typically dry bulb temperature, global irradiation and wind speed are selected as the key variables in a TRY and are given an equal weighting [23]. By multiplying the weighting by the FS statistic for each variable and then summing the products the overall ‘typical’ month may be selected as the one with the lowest weighted FS, using the following equation.

$$FS_{sum,t} = w_1 FS_t(Temp) + w_2 FS_t(G_{Irrad,t}) + w_3 FS_t(Ws) \quad (10)$$

Use of the Finkelstein-Schafer statistic method effectively reduces the risk of extreme individual daily or monthly variability occurring in the creation of a TRY. In the case of the data used by PHPP however this daily homogeneity is not a prerequisite since the model primarily relies on mean monthly inputs. In the case of the PHPP peak load (W1 and W2) and cooling load data which are based on daily temperature and irradiation data homogeneity is perhaps helpful in establishing ‘representative’ peak loads for a given CDF. However, peak loads by definition occur under extreme conditions and it is important to realise that in reality a one in ten year season is likely to contain brief periods of far more extreme data. It is also worthwhile considering the relevance of using historical baseline TRY data in the context of predicting the mean present day performance of a building. Whilst useful for illustrating the impacts of climate change the 1961-1990 (and even the 1983-2004) baseline periods are unlikely to accurately reflect the typical performance of buildings being designed today due to the rapid evolution of climate change.

2.6 Methodology– preparing WG data for PHPP

For the purpose of this study, in order to create statistically representative months keeping a consistent relationship between the mean dry bulb temperature and the global irradiation a CDF of these two even weighted variables was prepared from the 3000 years of source data. By sorting the data into a CDF and selecting the actual month with the closest fit to a given percentile a range of statistically significant climate files may be prepared for a sample location.

Whilst data from the 50th percentile can be seen as representative of the mean situation, (whereby it is as likely that the weighted temperature and irradiation will be greater as it will be lower for any given scenario); the entire

range of probabilistic values can be interrogated at any given percentile. This allows for example consideration of a one-in-ten year weather event by selecting either the 10th or 90th percentile, as appropriate. Transposing this data into a format suitable for use in the PHPP model requires several additional steps.

Monthly irradiation data (kWh/m².month) is needed for both the horizontal global mean values and for each of the cardinal compass directions in PHPP in order to correctly assign direct beam and diffuse irradiation to the model. Once the daily outputs from the UKCP09 generator data had been sorted and compiled into monthly percentiles, the diffuse and global irradiation was entered into a monthly radiation slope model for the appropriate latitude in order to derive the mean global slope irradiation values for 90-degree surfaces in each percentile month. The model used here was the Isotropic model developed by Muneer [31] as this model seemed to give the most reliable results when compared to outputs from the widely used Perez model (from files simulated using Meteonorm). In theory, an anisotropic slope model would improve the accuracy of the slope irradiation results in future refinements of this methodology as isotropic models are known to overestimate the irradiation on shaded surfaces [31].

2.7 Methodology– preparing additional variables for PHPP

Since ground temperatures are generated from formulae within the PHPP model itself, so to complete the monthly inputs the only additional values required are dew point and sky temperatures. Sky temperature values are needed to calculate the long wave radiative heat transfer and external surface temperatures. A range of single variable and more complex three variable methods are available for computing sky temperature; the choice of appropriate model depends on the meteorological data available and also upon the limits of accuracy required. More detailed discussion of uncertainty in long wave flux and sky temperature models can be found in Aubinet [38] and Remund [39]. Since PHPP requires only monthly mean data a relatively straightforward three variable approach was applied here, using a combination of data available from the 5km and 25km grid models: ambient air temperature (T_a), relative humidity (RH) and cloud cover (C).

The Swinbank formula [40] was used to calculate the downward long wave radiative flux (W/m²):

$$\varphi_d = (1 + KC^2) \cdot 0.7C \cdot 10^{-18} \cdot T_a^{2.182} \cdot RH^{0.07188} \quad (11)$$

A variation of the Stefan–Boltzmann law was then used to calculate the effective sky temperature (T_{sky}) based on the longwave radiation emitted from a grey body.

$$T_{sky} = \left(\frac{e_s}{\epsilon_g \sigma}\right)^{0.25} \quad (12)$$

Dew Point temperature (T_d) was calculated by rearranging Magnus-Tetens formula for vapour pressure [41] to provide the following expression, which is valid for the range $0^\circ\text{C} < T < 60^\circ\text{C}$, $0.01 < RH < 1.00$, $0^\circ\text{C} < T_d < 50^\circ\text{C}$

$$T_d = \frac{b \alpha(T, RH)}{\alpha - \alpha(T_d, RH)} \quad (13)$$

where:

$$\alpha = 17.27, b = 237.7 \text{ (}^\circ\text{C)}$$

and:

$$\alpha(T, RH) = \frac{aT}{b+T} + \ln(RH) \quad (14)$$

Peak load data for periods W1 and W2 represent the mean data across the peak load period, the length of which is dependent upon the time constant of the building. The time constant in a Passivhaus is typically much longer than conventional dwellings due to the thermal inertia created by high thermal resistance of the envelope and low rate of energetically effective air changes. A simple equation is currently used to determine the approximate time constant used to isolate the appropriate peak loads used in the PHPP calculation:

$$t_{peak} = \frac{K}{\bar{U}} \quad (15)$$

Where K is the total thermal capacity per unit treated floor area (Wh/K.m^2) and \bar{U} is the average area weighted U value of the thermal elements ($\text{W/m}^2\text{K}$)

Typical peak load time constants for Passivhaus dwellings are in the order of 3-7 days [12]. Use of a shorter peak load time constant inevitably results in more extreme design conditions being selected. In the study W1 was determined by creating a macro which isolated the lowest consecutive three day mean temperature and the corresponding irradiation from the appropriate percentile year. In the case of W2 a macro was created to select the lowest consecutive three day mean daily irradiation readings and the corresponding temperature from the appropriate percentile.

The three daily mean global horizontal irradiation levels for both W1 and W2 are entered in to an anisotropic daily slope irradiation model [31] and broken down into the principle cardinal aspects (N,E,S,W) for a 90 degree slope angle. Since the approach used here operates from daily global horizontal data the mean irradiation for E and W facing surfaces will be the same. A more accurate refinement, leading to slightly different aspect values for East and West facing surfaces would be to use an hourly slope model and then averaging the values over the duration of the peak load time constant.

3.0 CASE STUDY

The building chosen for the case study is the Larch House a 3bdm (87m² TFA) detached Passivhaus dwelling in Ebbw Vale, Wales. Completed in July 2010, this is one of the first social Passivhaus projects in the UK and the first Code for Sustainable Homes (CSH) Level 6 'zero carbon' Passivhaus in the UK [42]. The high surface area/volume (SA/V) characteristic of a small detached dwelling make this one of the most challenging typologies with which to achieve the Passivhaus standard. In addition to typical Passivhaus components, the building has exceptionally low U- values (walls 0.095 W/m²K, roof 0.074 W/m²K and floor 0.076 W/m²K) as well as an exceptional airtightness of 0.197 ac/h @n50. It should be noted that the building uses external roller blinds to help prevent summer overheating and these have been assumed to be operational during the overheating analysis.

Ebbw Vale is situated in a location where the affects of a maritime proximity combined with a mountain valley situation dominate the climate. This situation is common to many of the old mining towns situated in the 'Valleys' region north of Cardiff. Much of this area suffers from severe social and economic deprivation and is receiving significant regeneration funding from the Welsh Government. In 2008 as many as 43% of Blaenau

Gwent households were reported to be experiencing fuel poverty¹ and it is likely this figure will have increased in recent years [43]. As a result, this area has become a focal point for the construction of social housing in the Passivhaus format.

In total, three different sites are examined in order to demonstrate the initial findings of this research in 3 distinct climatic contexts. Case Study 1 examines the building's original location, the Ebbw Vale site in a mountainous valley in Wales. Case study 2 and 3 examine the predicted variations existing between two 5km² grid cell data sets in an urban context in central London. All three locations share this common building model, based on the certified Welsh 'Larch' Passivhaus (Figure 8) for comparative purposes throughout. It is noteworthy that these three locations all lie within 0.24 of a degree of latitude of one another with case study 1 (Ebbw Vale) 51.76 North, case study 2 (London CBD) 51.525 North and case study 3 (London Docklands) 51.523 North.

For consistency, we assume in all three case studies that climate change progresses broadly in line with a 'Medium' SRES scenario. The same approach may be used to examine any of the three principal (Low, Medium, High) IPCC SRES scenarios as well as to compare the historical baseline data for the 1961 -1990 period.

¹ Households are considered by the UK Government to be in 'fuel poverty' if they would have to spend more than 10% of their household income on fuel to keep their home in a 'satisfactory' condition. This is usually defined as 21 degrees for the main living area, and 18 degrees for other occupied rooms [43]



Figure 8 The 'Larch' Passivhaus Ebbw Vale (Jefferson Smith)

3.1 Case study 1 – Detached Passivhaus at Ebbw Vale, Wales (UKCP grid cell ref 3200210)

In order to compare the influence of the climate data sets in context, the datasets were entered into the PHPP model of a certified Passivhaus at Ebbw Vale. Figure 12 shows the resultant annual space heating demands normalised to the TFA of the dwelling. A clear progression is seen from the historic baseline to future probabilistic levels for the 50th percentile year. The current baseline appears to correspond well to the mean performance predicted by the Meteonorm software. In contrast, use of the BRE Severn region data (even when corrected for altitude) would lead to a significant under estimation of the space heating demand, to a level that falls below even the 2080M 50th percentile prediction for this location.

Consideration of the annual (space heating) energy demand and peak load are of considerable importance in the design of Passivhaus dwellings particularly where post air heating is used as the primary source of supplementary heat input.

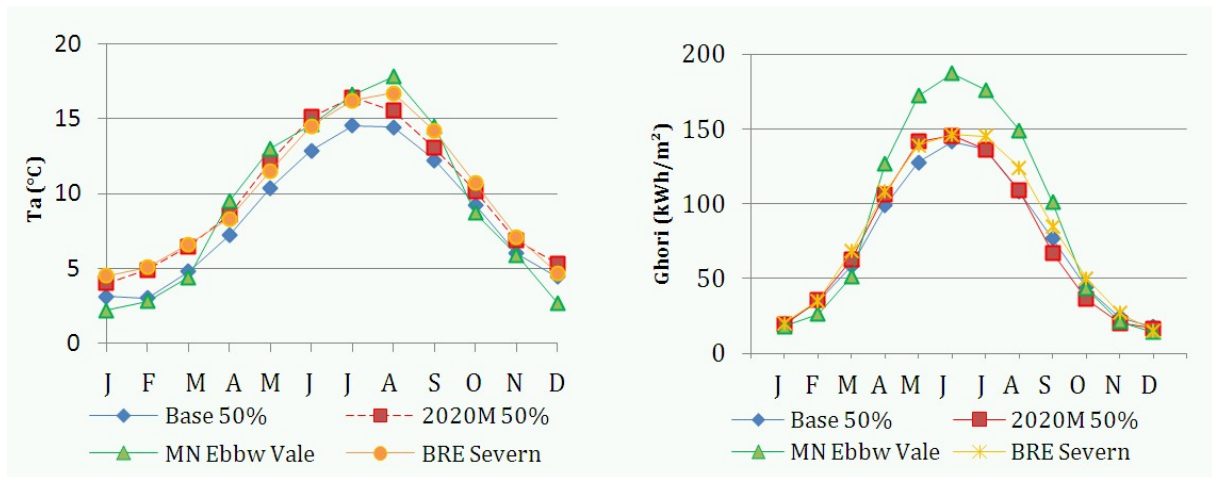


Figure 10. Monthly mean ambient temperature and Global Horizontal Irradiation, Ebbw Vale (3200210): Comparison of 5km2 Baseline 50th percentile, 5km2 2020(M) 50th percentile, Meteonorm (MN) Ebbw Vale (site) and BRE Severn (region 6)

Comparison of ambient temperatures predicted by different climate data sets and across time periods shows that the Baseline (1961-1990) 50th percentile temperature is consistently lower than the 2020 50th percentile, as might be anticipated through climate change. Notably the Severn data (BRE region 6), which represents the current regional data set for Passivhaus certification in the location of Ebbw Vale [10], is significantly warmer than the Met Office Baseline and exceeds even the 2020 50th percentile temperatures for much of the year. There is good agreement between the datasets for the global horizontal irradiation, with the exception of the Meteonorm site-specific data, which predicts significantly higher solar irradiation levels during the summer months (Figure 10).

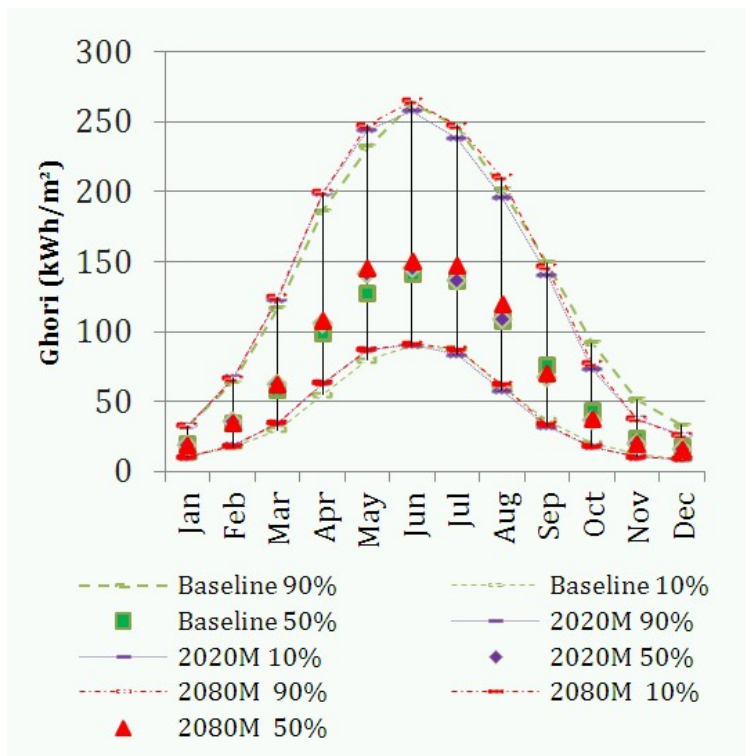


Figure 11. Global Horizontal Irradiation, Ebbw Vale (3200210): 90th, 50th and 10th percentiles showing 5km² Baseline, 5km² 2020M and 5km² 2080M evolution

Global irradiation is not directly affected by Green House Gas (GHG) concentrations and therefore does not evolve in the same way over time as ambient temperatures [7]. Slightly higher levels of global irradiation are seen under the 2080(M) scenario particularly in the summer months however the winter months remain largely unchanged. The changes seen in predicted global irradiation levels are most likely due to changes in the absolute amount of cloud cover and humidity levels. Variation between the 50th and 90th percentile is greater than the variation between the 10th and 50th percentile and this range is more pronounced during the summer months (Figure 11). This significant variation in irradiation levels occurring at different percentiles during the summer months is likely to have a significant impact on overheating risks when both temperature and irradiation distributions occur above the 50th percentile due to inter seasonal variability.

4.2 Results of different case studies

In order to compare the influence of the climate data sets in context, the datasets were entered into a common PHPP model of the certified ‘Larch’ Passivhaus at Ebbw Vale. Figures 12-14 show the resultant annual space heating demand normalised to the treated floor area (q_H) of the Passivhaus dwelling. A clear progression from the historic baseline to future probabilistic levels for the 50th percentile year can be seen.

The current baseline appears to correspond well to the mean performance predicted by the Meteonorm software. By contrast, use of the BRE regional data would lead to a significant under estimation of the space heating demand, to a level that falls significantly below even the 2080M 50th percentile projection for the Ebbw Vale location.

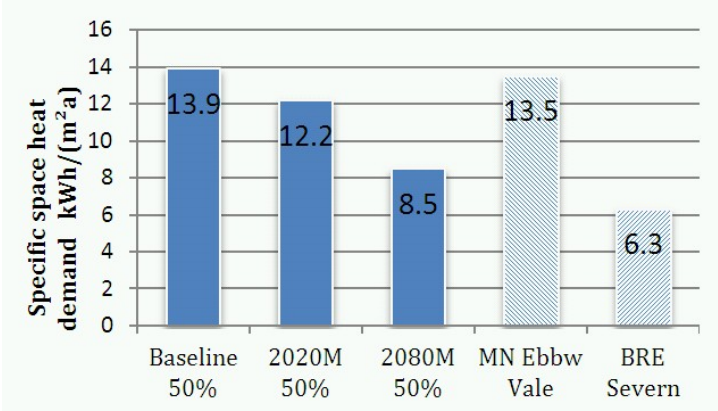


Figure 12 PHPP heating demand, Ebbw Vale: as predicted by 5km2 Baseline, 5km2 2020M, 5km2 2080M, Meteonorm (MN) Ebbw Vale (site), & BRE Severn (region 6)

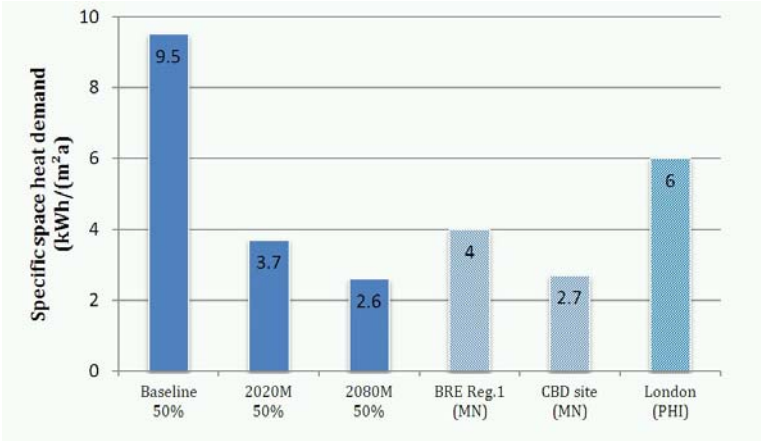


Figure 13. PHPP Heating demand London CBD (5350185) : as predicted by 5km2 Baseline, 5km2 2020M, 5km2 2080M, Meteonorm (MN) London CBD (site), BRE Central London (region 1), PHI original London TRY

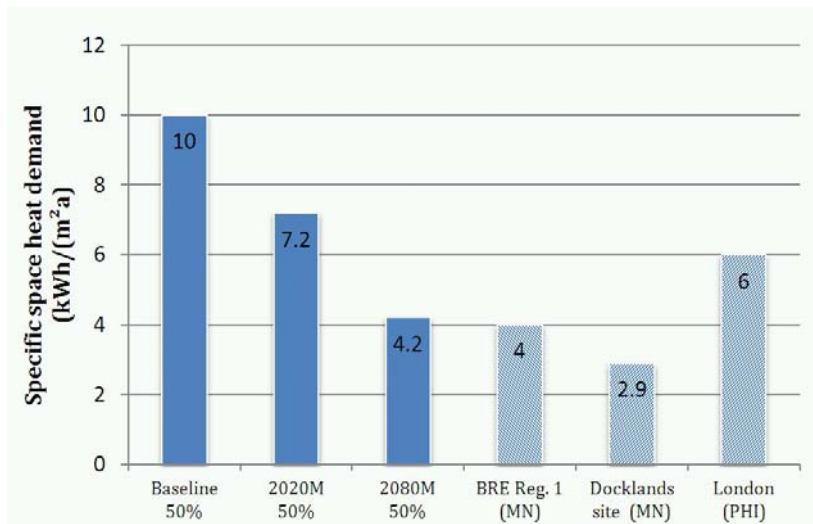


Figure 14. PHPP Heating demand London Docklands (5450185); as predicted by 5km² Baseline, 5km² 2020M, 5km² 2080M, Meteororm (MN) London Dockland (site), BRE Central London (Region 1)

When comparing the results for both of the London locations for the predicted heating demand, it can be seen that there is a rapid evolution towards fewer heating degree hours. Consequently, it will become significantly easier to achieve the Passivhaus (q_H) requirement in the future, in all of the regions assessed, particularly so in areas affected by the Urban Heat Island (UHI).

Analysis of the range of performance predictions here suggests that the misapplication of regional data is likely to lead to highly inaccurate design predictions. This can be seen most noticeably in the case of the London Docklands (5450185) grid cell (Figure 14). As a result of using the current BRE regional data set it appears likely that projects modelled outside the London CBD (but within Greater London) may be designed with significant under-prediction of the current day heating demand. In the Dockland region the UKCP data suggests that the current heating demand may be more than 100% higher than the BRE regional data suggests (Figure 14). In both London cases, Meteororm (MN) site-specific interpolation leads to an even more pronounced under estimate of the heating demand than the BRE regional data. This is likely to be a result of the location used for the BRE Region 1 interpolation (Latitude 51.517° Longitude -0.117°) [11]; which is 1.5 miles due west of the London CBD site specific interpolation point, and therefore further from the influence of the UHI.

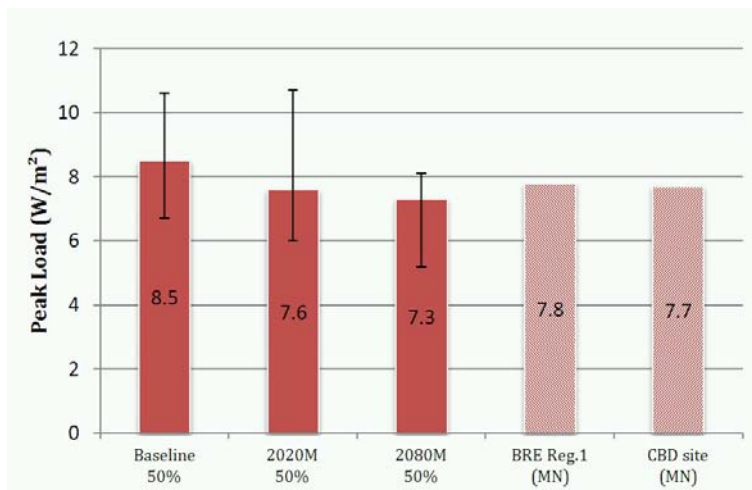


Figure 15 London CBD (5350185) comparison of peak loads showing ranges for 50th percentiles, with error bars indicating 10th and 90th percentiles

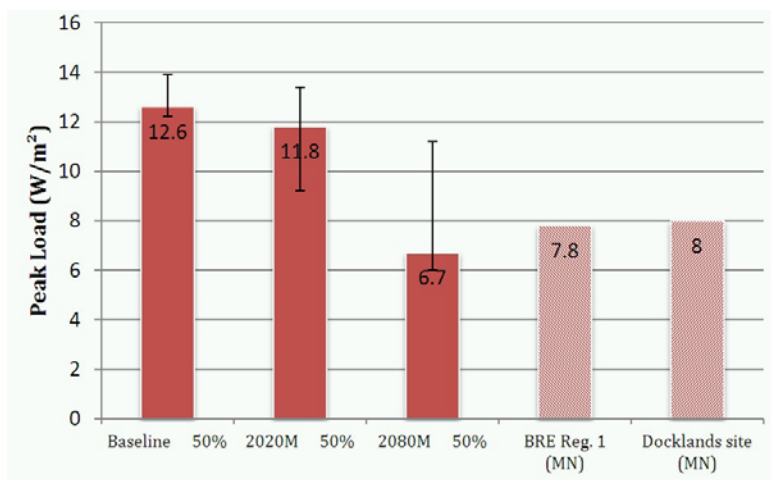


Figure 16 London CBD (5350185) transitional cooling loads and overheating risk

Figure 15 and Figure 16 show the results for the peak loads for the two London locations. There is good agreement between the Central London regional data and the CBD 5km² 2020M data at the 50th percentile. However the Docklands 5km² data shows that significantly higher peak loads are predicted just outside the CBD. This marked variance is likely to illustrate the localised influence of the UHI effect in the underlying 5km² baseline data. Overall these results suggests that the current BRE Central London (Region 1) data - appears to significantly underestimate present day peak loads in Greater London, even allowing for variability predicted between the 10th and 90th percentile ranges.

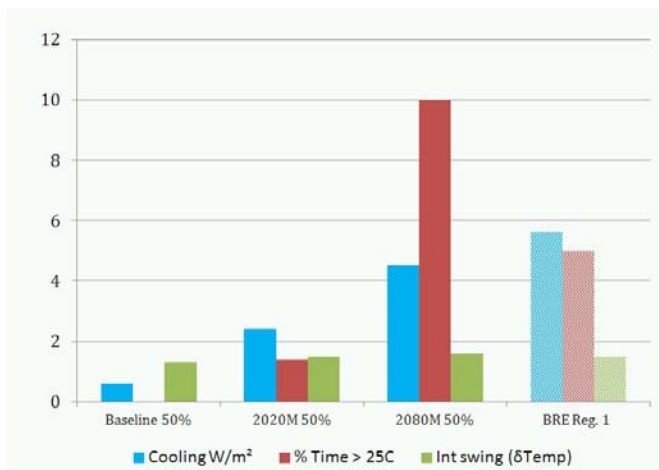


Figure 17 London CBD (5350185) transitional cooling loads and overheating risk

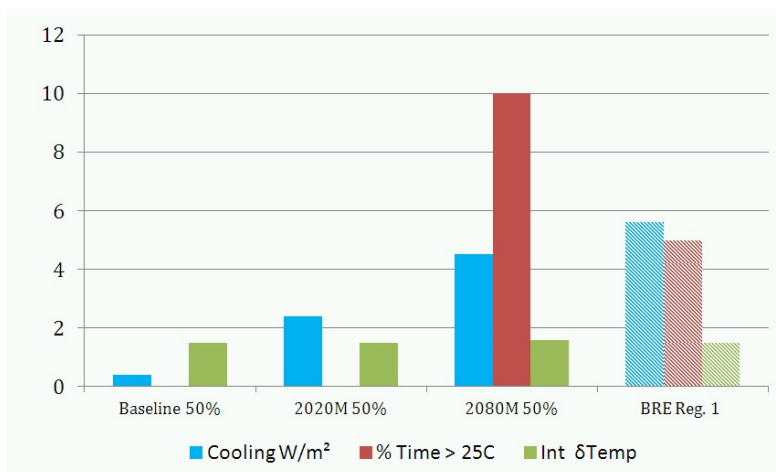


Figure 18 London Docklands (5450185) transitional cooling loads and overheating risk

In Figure 17 and Figure 18 the overheating risk for London CBD and London Docklands is compared. It can be seen that there is an earlier onset of overheating risk in the London CBD location, as might be anticipated by the more pronounced influence of the UHI. In terms of consistency between the data sets, the Central London (BRE Region 1) data seems to significantly overestimate the current day overheating risk when evaluated at the 50th percentile. Overheating risk is however highly dependent upon which percentile the weather year is sampled from, and assessing future overheating risks on a probabilistic basis is an area for further research. By 2080, during a typical 50th percentile year, even with external roller blinds in place and night purge ventilation operating the building modelled here is likely to overheat for 10% of the year in both of London locations studied. This finding is significant since Rouvel [46] defines the exceedance of 25°C for greater than 10% of the

year as the threshold at which active cooling is required. The same limiting standard is also applied in the German DIN standard 4108-2 (2003) [47]. Research by Voss et al [48], involving post-occupancy evaluation studies of low energy office buildings in Europe, suggests that the 10% threshold above 25°C represents the upper limit of acceptability. Voss et al [48] recommend that a lower target of 5% overheating frequency should be the goal of building designers.

Some caution is necessary with respect to the future changes predicted by the UKCP09 scenarios in dense urban areas. At the 25 km² resolution of the HadRM3 model the largest urban areas can be seen to exert some influence on the local simulated climate [49]. Since an explicit representation of urban areas was not included in the HadRM3 model the UKCP09 projections cannot fully incorporate the transient effects of the urban areas in the probabilistic predictions [50]. Studies including those carried out by Watkins et al. [51] have shown that, on average, the Urban Heat Island (UHI) effect for London lies between about 2.5 - 3 °C in summer [51] and 1.0 - 3.2°C during winter [53].

However, according to the UKCP the projections of future climate available from the WG do include the current effects of urbanisation at the 5km² scale. It follows therefore that if the UHI effect does not change significantly in the future, it is reasonable to add the UKCP09 climate change projections to the observed urban climate in order to generate future urban climate predictions [54]. Conversely if future changes occur in the amount of energy dissipated in cities (e.g. cooling systems become widespread), or if the density of a city changes then these factors could alter the current UHI effect, and projecting future climates in cities will then require additional techniques to be employed [54].

Comparative temperature measurements taken at an inner city location (St. James Park) and a suburban site in Surrey suggest that London's nocturnal UHI has intensified by approximately 0.5°C on average since the 1960s [55], partly as a consequence of increased Human Energy Production (HEP), denser urbanisation, and the changing frequency of weather patterns. It is likely that only a relatively small component of these evolutionary changes are missing from the 5km² UKCP baseline data (which was based on data collated over the 1961-1990 period).

Whilst the mean monthly shifts induced by the UHI are reasonably well documented [50, 55] the local amplitude and temporal profile of the daily UHI effect during heat waves should be carefully evaluated by those attempting to accurately evaluate peak overheating risks under extreme conditions. Data from Graves et al [56] indicates that the intensity of the nocturnal UHI peak for Westminster, London has occasionally exceeded 7K during the summer months. Since the most pronounced effects typically occur between 3am -9am [55] the timing of this phenomenon will substantially dampen the natural diurnal cooling range, with consequential impacts for buildings reliant on night purge cooling. Generating an improved understanding of the future evolution of localised UHI's is a complex and important area for building simulation, where significant further research is needed.

5.0 CONCLUSIONS

A new method for the generation of current and future probabilistic micro regional climatic data in Passivhaus design is proposed. The approach is based on the use of data generated using the UKCP09 Weather Generator (version 2) which combines historic baseline recorded data with probabilistic outputs from the RCM. Using this methodology data can be generated on a 5km² grid for the entire UK landmass, across 10-year time intervals spanning from the historic (1961-1990) baseline through to 2080 and for three distinct future climatic scenarios (SRES Low, Medium and High). For each location and scenario, the data can be interrogated at any percentile of the CFD distribution, allowing the creation of both mean and extreme climate data sets. This approach provides designers with the high resolution data needed to optimise and future proof Passivhaus and low energy designs in a site-specific manner. Furthermore the ability to group multiple 5km² grid cells outputs from the WG creates the possibility to generate representative regional climate data sets underpinned by a common statistical model.

The key outputs from the new methodology, when assessed at the 50th percentile, showed generally good agreement with other data sources. When evaluated in the PHPP building model the results showed good correlation with the Meteonorm interpolation software data generated for the same location. When compared with the regional certification data currently used for both the Severn and Central London regions [10] a significant difference was observed in the predicted specific heating demand and peak loads. These preliminary findings suggest that the use of proxy regional data could, in some instances, lead to a significant underestimation of the specific annual heat demand and peak loads. In one example, in the London Docklands

region, the UKCP data indicates that the actual current heating demand may be more than 150% greater than the BRE regional data suggests (Figure 14). These findings reiterate those of other studies, which have found significant differences between the use of local and regional default data in PHPP design predictions [16, 25]. Since the current method of deriving data for Passivhaus design is based on the use of TRY data (which is effectively an historic mean weather year) designers need to be acutely aware of the limitations inherent in this approach particularly with respect to peak loads.

In the context of this study further research is needed in order to establish the robustness of the approach used in terms of predicting peak heating and cooling loads. The approach used here is based on the use of a time constant [18] and the sensitivity associated with this approach may require further calibration against empirical studies and established uncertainty analysis methods [57]. Further parametric studies, including a detailed analysis of peak heating and cooling loads, are proposed in order to fine-tune and validate this new methodology.

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NOMENCLATURE

C cloud cover coefficient (0.0 = clear sky, 1.0 = totally overcast)

$CDF_{i,m,y}$ Cumulative Distribution Function of variable i , in month m , year y

FS_{m,y} Finkelstein Schafer statistic month m , year y

G_{irrad} Global irradiation on a horizontal plane (kwh/m².month)

K coefficient for cloud height (0.34 cloud <2km, 0.18 for >2km<5km, 0.06 for > 5km)

RH percentage relative humidity

T thermodynamic temperature (K)

T_a ambient temperature (°C)

T_d	calculated dew point temperature (°C)
T_{sky}	effective sky temperature in Kelvin, entered into the PHPP model in (°C)
$W1$	peak load climatic data during coldest clear winter design period
$W2$	peak load climatic data during the cloudiest winter design period
WS	wind speed
ε	sky emissivity (approximated to 0.736, for dew point temperature range here)
φ_l	downward longwave irradiation flux (W/m ²)
σ	Stefan-Boltzmann constant (5.67*10 ⁻⁸ Wm ⁻² K ⁻⁴)

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