## APPLICATION AND LIMITATIONS OF REGIONAL AND FUTURE PREDICTIVE CLIMATE DATA IN PASSIVHAUS DESIGN

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### ABSTRACT

According to the Passivhaus Institute (PHI) the verification of a Passivhaus design must be carried out using the Passivhaus Planning Package (PHPP). A number of methods are now available for designers to access climatic data for use in PHPP design predictions. The original climate data provided for design and certification in the UK was derived from the reverse engineering of TRY data from dynamic simulations, for a limited number of locations.

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 based on the UKCP09 climate projections. The data generated is compared to alternative sources, and the implications discussed in a case study of a certified Passivhaus dwelling in Wales.

### INTRODUCTION

The Passivhaus Planning Package (PHPP07) is a simplified steady state building simulation tool that is primarily targeted at assisting architects and mechanical engineers in designing well performing Passivhaus buildings (Feist et al, 2010). PHPP has been validated using dynamic thermal simulations and measured data from a large number of completed Passivhaus projects and generally shows good agreement between measured and predicted results including those derived from dynamic simulation (Feist et al, 2001). The PHPP thermal model conforms to the calculation methods set out in EN ISO 13790 for determining annual heating demand.

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 Heat Demand ( $Q_H$ )  $\leq 15$  kWh/m<sup>2</sup>.yr or a Peak Load ( $P_H$ )  $\leq 10$  W/m<sup>2</sup>, together with a Specific Primary Energy Demand  $\leq 120$  kWh/m<sup>2</sup>.yr relative to the Treated Floor Area (TFA). Where a cooling requirement exists this must also be  $\leq 15$  kWh/m<sup>2</sup>.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 the internal gains (residential, 2.1 W/m<sup>2</sup>) 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 load calculations could have real consequences. 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 the UK 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' (Marion and Urban, 1995).

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 mean annual heating demand. However, since it is possible to obtain Passivhaus certification based on peak loads, questions were raised about the use of a single complete UK climate data set (Manchester) as a proxy for calculations across the entire UK (McLeod et al., 2010). This situation has recently improved with the production of 22 UK regional datasets using Meteonorm interpolation, which have been cross-checked against EPW climate files and ratified by PHI (BRE, 2011).

This paper presents a new method of obtaining highresolution climatic data for current and future probabilistic scenario modelling generated using the UKCP09 Weather Generator (Met Office, 2011). The results were compared to both site specific and regional proxy data (BRE 2011) generated using the Meteonorm software interpolation methods.

## METHODOLOGY

#### Generating Climate Data in PHPP format

To calculate the annual heating demand PHPP uses monthly mean climatic data. The primary inputs required are: mean ambient temperature, global horizontal irradiation and slope beam irradiation. Additional values such as sky temperature and ground temperature were 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 slope irradiance components at source (Figure 1). Historically slope irradiance data for PHPP was derived using a reverse engineering process which involved changing the aperture area in a dynamic simulation model and recording the resultant impact upon monthly heating demand for each of the cardinal points (Feist, 2005; Oberrauch, 2008). Such a method is robust in one sense since it begins with 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. 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.

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 <sup>2</sup> .month)						
Monthly mean slope irradiation (kWh/m <sup>2</sup> .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) the PHPP climate file also contains data for determining the peak loads. 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. 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 (Schneiders, 2003: Schneiders, 2010). Further discussion of this time constant follows in the Methodology section. Figure 2 (below) 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 milder temperatures (Bisanz, 1999). 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 peak load climate data was isolated from a TRY data set, and this is still considered by the PHI as the accepted method. Since a TRY is effectively a mean weather year designers need to be aware of the limitations of this approach with respect to peak load plant sizing.

	Heating	Heating Load				
	Weather 1	Weather 2	Radiation			
	Radiatio	Radiation: W/m <sup>2</sup>				
ſ	-3.3	1.4	21.9			
	8	2	43			
1	18	2	58			
П	56	1	74			
	20	2	73			
╓╫	25	4	113			
╢╢	3d	3d	3d			
			11.2			
	6.2	6.2	15.8			
Πſ	Peak ambient design temperature (°C)					
Mean peak slope irradiance (W/m <sup>2</sup> )						
	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

# 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 straight forward 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 portal (Eames et al., 2010) 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 using various tools such as the Meteonorm software, or data morphing procedures. Belcher et al (2005), Crawley (2008) and Jentsch et al (2008) 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 also provides specific procedure's for shifting the ambient temperature in Urban Heat Islands. Such methods are limited by the spatial distribution of the baseline TRY datasets and the amplitude of the climate change input signals which was initially taken from a 50km grid model. In addition to using a much finer spatial resolution the more recent PROMETHEUS files include morphing of the future wind speed and direction which was absent from many earlier climate generator models (Eames et al 2010).

#### 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 (Feist, 1993). 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 (2010) 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 metastudies, 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 generated by the BRE (2011) 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.

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 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.



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

# 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. 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 contains a baseline dataset for the period 1961-1990, coupled with the possibility to sample future probabilistic scenarios at 10-year intervals from 2020 to 2080. Outputs for three of the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES) climate scenarios are available: Low (A1F1), Medium (A1B) and High (B1). Further information on the SRES scenarios can be found in IPCC (2000).

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. 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 (DEFRA, 09). Further variables are subsequently calculated from the core variables using appropriate formulae. Hourly global solar irradiation, for example, is only recorded at approximately 80 Met-office sites around the UK so additional algorithms based on the work of Cowley (1978) and Muneer (2004) were used to derive the global direct and diffuse irradiation components from the daily sunshine duration.

Validation work carried out by the WG team shows good agreement between the modelled direct and diffuse irradiation predictions and measured data from selected reference sites (UKCP 2011). This intermediate validation check is particularly 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 for each scenario.



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

# 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 is 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 (2006). 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 (Finkelstein and Schafer, 1971). 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 comparing this to the overall cumulative distribution function for each month considered, using the following equation.

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

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 (Eames 2010). 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.

 $FS_{sum,i} = w_1 FS_i(Temp) + w_2 FS_i(G_{Irrad}) + w_3 FS_i(WS)$ (2)

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.

#### 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 50<sup>th</sup> 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 10<sup>th</sup> or 90<sup>th</sup> percentile, as appropriate. Transposing this data into a format suitable for use in the PHPP model requires several additional steps.

Monthly irradiation data (kWh/m<sup>2</sup>.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 (2004) 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 (Muneer, 2004).

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 (1994) and Remund (2010). 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<sub>a</sub>), relative humidity (RH) and cloud cover (C).

The Swinbank formula (Swinbank, 1963) was used to calculate the downward long wave radiative flux  $(W/m^2)$ :

$$\varphi_{\downarrow} = (1 + KC^2) * 8.78 * 10^{-13} * T^{5.852} * RH^{0.07195}$$
(3)

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

$$T_{sky} = \left(\frac{\varphi_{\downarrow}}{\varepsilon \sigma}\right)^{0.25} \tag{4}$$

Dew Point temperature was calculated by rearranging Magnus-Tetens formula for vapour pressure (Barenbrug, 1974) to provide the following expression, which is valid for the range  $0^{\circ}C < T < 60^{\circ}C$ , 0.01 < RH < 1.00,  $0^{\circ}C < Td < 50^{\circ}C$ 

$$T_{d} = \frac{b \cdot \alpha(T_{a}, RH)}{a - \alpha(T_{a}, RH)}$$
(5)  
where:  
$$a = 17.27, b = 237.7 (^{\circ}C)$$
and:  
$$\alpha(T, RH) = \frac{\alpha.T}{b+T} + \ln(RH)$$
(6)

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 for the peak loads calculation:

$$t_{peak} = \frac{\kappa}{U} \tag{7}$$

Where K is the total thermal capacity per unit treated floor area (Wh/K.m<sup>2</sup>) and  $\overline{U}$  is the average area weighted U value of the thermal elements (W/m<sup>2</sup>K) Typical peak load time constants for Passivhaus dwellings are in the order of 3-7 days (Schneiders, 2003, 2010). In this study W1 this was selected by creating a macro which isolates 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.

Having isolated the three daily mean global horizontal irradiation levels for both W1 and W2 this is entered in to an anisotropic daily slope irradiation model (Muneer, 2004) and broken down into the cardinal compass directions (N,E,S,W) for a 90 degree tilt 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 slightly more accurate refinement, leading to slightly different slope values for East and West facing surfaces would be to use an hourly slope model and then average the values over the period of the peak load time constant.

## **RESULTS**

### Results and comparison of data generated

Of the climate data required by the PHPP model, the two dominant variables affecting the specific heating demand are the mean ambient air temperature and the solar irradiation. In the case study here we assume that climate change progresses broadly in line with a 'Medium' SRES scenario. Under this scenario for the Welsh valley location (Ebbw Vale) analysed here it is likely that mean summer temperatures will rise by as much as 4.5°C and winter temperatures by approximately 4°C, by 2080. Within any given timeframe, the variation between the 10th and 90th percentile temperatures is significantly greater +/-7°C, and this remains relatively consistent over time. Global irradiation does not evolve in the same way over time as ambient temperatures. 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 in global irradiation are most likely due to changes in the absolute amount of cloud cover. Variation between the  $50^{\text{th}}$  and  $90^{\text{th}}$ percentile is greater than the variation between the  $10^{\rm th}$  and  $50^{\rm th}$  percentile and this range is more pronounced during the summer months (Figure 5).



Figure 5. Global Horizontal Irradiation: 90th, 50th and 10th percentiles for Baseline, 2020M and 2080M

Comparison of ambient temperatures between different modelling approaches and periods shows that the Baseline (1961-1990) 50th percentile temperature is consistently lower than the 2020 50th percentile. Notably the Severn region data, which represents the appropriate regional data set for Passivhaus certification in the location of Ebbw Vale (BRE, 2011), is significantly warmer than the Baseline and exceeds even the 2020 50<sup>th</sup> percentile during the autumn months. There is good agreement between the datasets for the global horizontal irradiation, with the exception of the Meteonorm sitespecific data, which predicts significantly higher solar irradiation levels during the summer months (Figure 6).



Figure 6. Global Horizontal Irradiation: Baseline 50%, 2020 50%, MN Ebbw Vale and BRE Severn

#### Case study – 3 bedroom Passivhaus at Ebbw Vale

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 7 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, the BRE Severn region data leads to a significant under estimation of the space heating demand, to a level that falls below even the 2080M 50th percentile for this location.



Figure 7. PHPP heating demand predicted by Baseline, 2020M, MN Ebbw Vale & BRE Severn

In terms of peak load calculation the methodology used here predicted slightly higher peak loads than were predicted by other data sources for the Baseline period.

### **CONCLUSION**

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 high-resolution 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 5km by 5km grid for the entire UK landmass, across 10-year time slices spanning from the historic (1961-1990) baseline to 2080 and for three distinct future climatic scenarios. For each location and scenario, the data can be interrogated at any percentile to expose both mean and extreme climate scenarios. This approach provides designers with the data needed to optimise and future proof Passivhaus and low energy designs in a site-specific manner.

The key outputs from the new methodology, when assessed at the 50<sup>th</sup> percentile, showed generally good agreement with other data sources. When evaluated in the PHPP building simulation model the results showed good correlation with the Meteonorm interpolation software data generated for the same location. When compared with regional data

generated for the Severn region (BRE, 2010) a significant difference was observed in the predicted specific heating demand. These preliminary finding suggests that the use of proxy regional data would, in this instance, lead to a significant underestimation of the specific annual heat demand. This finding reiterates that of other studies, which have found significant differences between the use of local, and regional default data in PHPP design predictions.

In terms of peak loads, it is thought that the method currently being used to sort the peak load climate data could be improved by applying the FS statistic method to reduce the risk of daily variability occurring within a given percentile month from skewing the peak load results. Further parametric studies are proposed to fine-tune and validate this new methodology.

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## NOMENCLATURE

С	cloud cover coefficient $(0.0 = \text{clear sky}, 1.0)$
	= totally overcast)
CDF <sub>i,m,y</sub>	Cumulative Distribution Function of
	variable i, in month m, year y
FS <sub>m,y</sub>	Finkelstein Schafer statistic month m, year y
G <sub>irrad</sub>	Global irradiation on a horizontal plane
	(kwh/m <sup>2</sup> .month)
К	coefficient for cloud height (0.34 cloud
	<2km, 0.18 for >2km<5km, 0.06 for > 5km)
RH	percentage relative humidity
Т	thermodynamic temperature (K)
Ta	ambient temperature (°C)
T <sub>d</sub>	calculated dew point temperature (°C)
T <sub>sky</sub>	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
3	sky emissivity (approximated to 0.736, for
	dew point temperature range here)
$\phi_{\downarrow}$	downward longwave irradiation flux (W/m <sup>2</sup> )
σ	Stefan-Boltzmann constant
	$(5.67*10^{-8} \mathrm{Wm}^{-2} \mathrm{K}^{-4})$

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