

Evaluation of three model estimations of solar radiation at 24 UK stations

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Abstract

Meteorological station records often consist only of precipitation and air temperature data. There is therefore a need for appropriate methods to estimate solar radiation data to enable complete data set creation, by combining observed and estimated data. It is important to know the quality and characteristics of the estimates made in order to understand what impacts the data may have on the use to which they are put. This paper describes a detailed evaluation of the performance and characteristic behaviour of two air temperature based models and one sunshine duration conversion method of estimating solar radiation, for 24 meteorological stations in Britain. Comparisons were made using a fuzzy-logic based multiple-indices assessment system (Irad) and tests of the temporal distribution of mean errors over a year. The conversion from sunshine duration to solar radiation produces the best overall estimates, but shows systematic seasonal errors. The two air temperature based methods can be reliable alternatives when only air temperature data are available. Fundamentally, the study demonstrates the value and importance of using a range of assessment methods to evaluate model estimates.

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1. Introduction

A large number of applications require complete weather data sets, for example, studies using simulation models, which represent biological and physical processes (climate change, hydrological, ecological and agronomic studies). Similarly, data gathered from outdoor-based observations and experiments may require associated, temporally synchronised weather data to enable suitable analysis. However, meteorological records tend to consist primarily of pre-

cipitation and air temperature, when there is an increasing demand for data sets that also include solar radiation, wind speed, evapotranspiration, cloud cover etc. The dearth of even semi-complete, synoptically synchronised weather data is a serious limit on the application of agricultural, hydrological and ecosystem models (i.e. Wilks, 1999; Hoogenboom, 2000; Lexer and Honninger, 2004), and analysis of field based research and experiments (i.e. Milne et al., 2002). Missing observed individual data values can be estimated, e.g. Acock and Pachepsky (2000), which enables the temporal completion of observed data sets. To expand the range of weather variables within a data set, observed and estimated data can be combined. Methods exist to estimate solar radiation (i.e. Bristow and Campbell, 1984; Muneer et al., 1996;

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Hansen, 1999), reference evapotranspiration (i.e. Donatelli et al., 2003), relative humidity etc., that utilise observed variables.

Estimates made by simulation models, particularly in site-specific studies when using weather data as input, are determined by the inter-relationships between the weather variables. Weather variables as inputs can have significant impacts on simulation model estimates (i.e. Aggarwal, 1995), particularly when due to introduced errors arising from supplementary estimated data (Rivington et al., 2003). Introduced errors in input data can manifest themselves in terms of a model's incorrect estimations of quantities, rates, patterns, timing and synchronisation of events. Models that represent multiple entities with complex biophysical interactions between them therefore require meteorological data that maintains the true behaviour of the interactions. Appropriate location-specific data are also essential for model calibration. Calibration using non-representative meteorological data will result in unsuitable parameters for the place of model application. Similarly, the analysis of observed data from experimental studies (i.e. plant growth in outdoor conditions), where it may be desirable to investigate the response (or relationships) of a biological or physical entity to the weather, becomes severely restricted when appropriate meteorological data are not available.

In order to create complete weather data sets with the required data types, it is therefore necessary to use appropriate, reliable data estimation methods and have an understanding of their performance and behaviour. The method employed may partly be determined by the resources available (amount and quality of observed data, computing, time and expertise), and level of precision and accuracy required. Precipitation and air temperature are commonly recorded, but their spatial variability and the distribution of meteorological stations can still leave significant gaps. Solar radiation is rarely observed, with records typically covering short time periods (Thornton and Running, 1999; Bechini et al., 2000; Rivington et al., 2002) and absent for a particular place of interest (i.e. Grant et al., 2004). Very few stations in Britain observe daily precipitation, air temperature and solar radiation together. Those that do often have records covering only 1–5 years. More stations have records of sunshine duration (hours) covering longer periods. The ratio between meteorological stations recording solar radiation and those recording temperature could be as low as 1:500 on a global scale (Thornton and Running, 1999). Hence there is great potential for the enhancement of observed data sets to include estimated solar radiation.

This paper investigates the quality of three methods to estimate daily global solar radiation (the total amount of direct beam and diffuse solar radiation received by a flat surface at ground level ($\text{MJ m}^{-2} \text{ day}^{-1}$)), in Britain based on observed variables. These models were chosen as they utilise commonly available data and are representative of the best state of such model development (further details are given in Section 3.2). The aim was to determine the performance of each method and identify patterns of characteristic behaviour of estimates. Such information was considered as important when deciding which method to use to provide supplementary data in observed data sets.

2. Related research

2.1. Sunshine duration conversion

A range of methods are available for conversion of sunshine duration to daily global solar radiation values (i.e. Ångström, 1924; Revfeim, 1997). The Ångström method requires the estimation of site-dependent parameters, normally using a regression technique based on the least squares method (Sen, 2001). Hybrid models based on the Ångström method (i.e. Bahel et al., 1987; Yang et al., 2000a) require detailed parameterisation. Johnson et al. (1995) developed a method for use in tropical rainforest canopies, which was later applied by Woodward et al. (2001) to pastures in New Zealand. This model (JW, Appendix A) has only daily sunshine duration (hours) and latitude as input and contains a single empirical parameter (F , see Eq. (13)), representing the relative intensity of diffuse solar radiation from cloudy skies. The parameter F shows limited variability with geographical location, indicating the potential for meaningful spatial interpolation (in preparation). The JW model was refined and tested by Rivington et al. (2002) and found to produce good results for the regression coefficient of determination (R^2) at three sites (min, mean and max $R^2 = 87.0, 91.5$ and 94.4 , respectively, with $n = 70$ years). However, the physical mechanism used in observation of sunshine hours can result in large measurement errors, in the range of $\pm 20\%$ (BADC, 2004).

2.2. Air temperature based

Air temperature-based estimation models use maximum and minimum air temperature to estimate atmospheric transmissivity (e.g. Bristow and Campbell, 1984; Richardson and Wright, 1984). The Donatelli and

Campbell (1998) (CD) and Donatelli and Bellocchi (2001) (DB) models, as used in this paper, are detailed in Appendix A. These models assume that daily maximum air temperature will decrease with reduced transmissivity (increased cloud cover), whilst minimum air temperature will increase due to the cloud emissivity. Conversely, clear skies will increase maximum air temperature due to higher short wave radiation input, and minimum air temperature will decrease due to higher transmissivity. These models have substantial potential for application due to the greater availability of air temperature data, but do require some observed solar radiation data for parameter optimisation. Therefore, an important restriction is the ability to interpolate parameter values to locations without solar radiation data.

2.3. Model assessment

Many assessments made of model performance use statistical measures, most commonly squared correlation coefficients (R^2) of the line estimates versus measurements, Root Mean Square Error (RMSE) and mean bias error (MBE), either singularly (i.e. Weiss and Hays, 2004) or together (i.e. Muneer et al., 1996; Hunt et al., 1998; Iziomon and Mayer, 2001). Podestá et al. (2004) compared solar radiation estimated from sunshine duration with that estimated from temperature based models, finding that the former produced lower RMSE ($1.5 \text{ MJ m}^{-2} \text{ day}^{-1}$ versus $3.2 \text{ MJ m}^{-2} \text{ day}^{-1}$). Similarly, Chen et al. (2004) compared sunshine duration and temperature based methods at 48 locations in China, using the Nash-Sutcliffe (Nash and Sutcliffe, 1970) coefficient of model efficiency assessment. Based on this single index, these authors concluded that the temperature based models tested were unsuitable for solar radiation estimation in China. Ball et al. (2004) tested a range of methods at thirteen sites in North America, using RMSE and R^2 . The best performing model (the Hargreaves-Samani model with site-specific parameters) gave RMSE values of $3.50 \text{ MJ m}^{-2} \text{ day}^{-1}$ and R^2 of >0.87 . Based on these results these authors concluded that the models tested provide precise and accurate results and that the models did not require further modification.

However, there are limitations in evaluating models when using only a single test statistic, or separate multiple statistics (e.g. Yang et al., 2000b). Bellocchi et al. (2002) present the case that model evaluations are difficult using such statistics, and interpretation of which becomes descriptive rather than based on statistical significance (Willmott, 1982). Each statistic will assess a single component of model behaviour. It is

possible that a model can be deemed unsuitable and rejected based on an assessment by one statistic assessing one form of model performance, whilst other attributes of the model may be desirable. Similarly a model's performance may be seen as acceptable based on one statistic, but still contain poor qualities not assessed by appropriate tests.

One approach to overcome this problem is to use a fuzzy logic based multiple-indices assessment system (Bellocchi et al., 2002). This enables the calculation of a single indicator made up from a number of individual indices representing different statistical tests for model behaviour. Such an approach provides a more comprehensive assessment and makes it easier to identify best performing models.

3. Materials and methods

3.1. Database and data source

The UK Meteorological Office supplied meteorological data via the British Atmospheric Data Centre (BADC) website (<http://badc.nerc.ac.uk/home/index.html>). Data were compiled within an Oracle database for 24 locations in the UK (Fig. 1). Errors, duplicates and anomalies in the original data were identified during the database loading process. Missing values were filled using a search and optimisation method (LADSS, 2004). Sites were only included if they had daily observed maximum and minimum air temperature ($^{\circ}\text{C}$), global solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$) and sunshine duration (hours) data for a minimum of 5 years. Years where >31 consecutive days of data were missing were excluded, as were years where there were >50 missing days in total.

3.2. Solar radiation estimation

For each site and year of available data, daily solar radiation ($\text{MJ m}^{-2} \text{ day}^{-1}$) values were estimated using the following models (Appendix A) and written to the database:

- Sunshine duration conversion model (JW), based on Johnson et al. (1995) and Woodward et al. (2001).
- Campbell-Donatelli (CD) air temperature model (Donatelli and Campbell, 1998).
- Donatelli-Bellocchi (DB) air temperature model (Donatelli and Bellocchi, 2001).

These models were chosen as they utilise readily available weather data inputs and are representative of

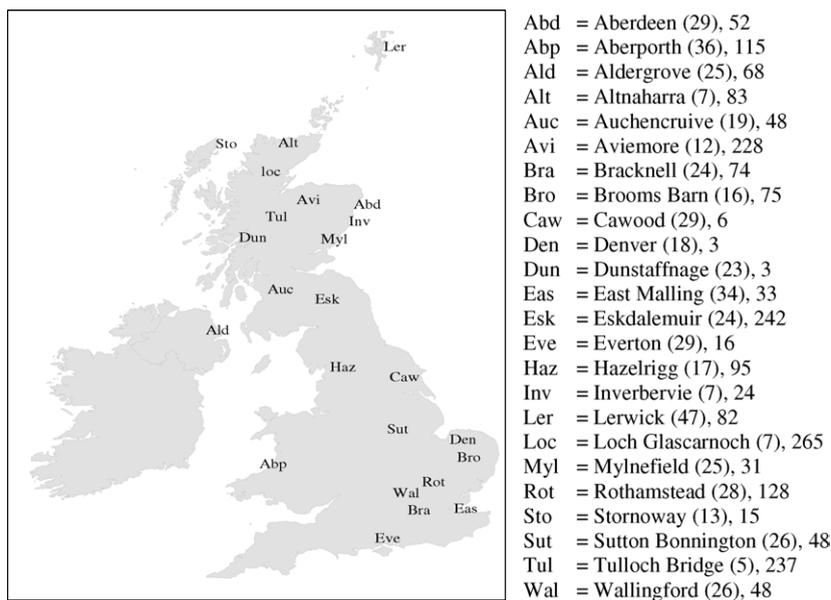


Fig. 1. Sites of observed meteorological data (number of years of data) and elevation (m a.s.l.).

the current best state of development of such models. The authors are unaware of the JW model being used elsewhere, other than the studies by the original developers of Johnson et al. (1995) and subsequently by Woodward et al. (2001), despite its promising potential (Rivington et al., 2002). It has only one empirical parameter (F), compared to multiple parameters of others, for example the Ångström model. Models based on air temperature have a strong physical basis (Bellocchi et al., 2002, 2003), and utilise readily available input data. Further to this, the CD and DB models exist within the freely available PC implemented software tool RadEst (SIPEAA, 2004) and have been applied in specific studies, i.e. Mavromatis et al. (2002). The CD model has also been implemented within a number of crop models and weather data generating tools, i.e. CropSyst/ClimGen (Stöckle et al., 2003), Marksim (Jones and Thornton, 2000) and CRITERIA (Marletto et al., 2001). The CD and DB models have been tested in a wide range of locations worldwide, i.e. 20 by Bellocchi et al. (2003) and approx. 200 (unpublished, for parameter dataset see SIPEAA, 2004), but have not been applied to a large number of sites in a single country, such as Britain, with a maritime climate.

The CD and DB models required the calculation of extra-terrestrial solar radiation (R_a) and atmospheric transmissivity (τ_i) and clear sky transmissivity (τ). These values were calculated according to the methods described in the RadEst documentation (SIPEAA,

2004). Parameters for the three models were optimised using observed solar radiation data for each site. The optimisation method for the JW model empirical parameter (F —see Eq. (13), Appendix A) is detailed in LADSS (2005). The RadEst tool (SIPEAA, 2004) was used to produce site representative parameters for the CD and DB models. These optimised parameters help ensure both a site-specific and generic temporal representation, i.e. a single parameter value was used for one site for all years.

3.3. Model testing

The performance of the JW, CD and DB models were initially tested using single statistical indices: Root Mean Square Error (RMSE) and standard deviation. The models were then tested using the fuzzy-logic based multiple-indices assessment system of Bellocchi et al. (2002). This method permits a flexible structure in which a range of indices and test statistics can be aggregated into a single modular indicator (Irad), based on an expert weighting expression of the balance of importance of the individual indices and their aggregation into modules. The indices used were (Table 1): Relative Root Mean Square Error (RRMSE), modelling efficiency (EF), the probability of equal means by the paired Student t -test ($P(t)$), the correlation coefficient of the estimates versus measurements (R) and two Pattern Indices, one computed versus day of year (PI_{doy}), and the other versus

Table 1
Multiple-indices assessment method (Irad) modules and statistical index content

Module	Index	Abbreviation	Value range and purpose
Accuracy (magnitude of residuals)	Relative Root Mean Square Error	RRMSE	0 to infinity. The smaller RRMSE, the better the model performance. A dimensionless index allowing comparisons among a range of different model responses regardless of units
	Modelling Efficiency	EF	1 to negative infinity. Best performance given when EF = 1 Negative values of EF indicate that the average values of all measured values is a better predictor than the model
	Paired Student <i>t</i> -test of probability means being equal	<i>P</i> (<i>t</i>)	0 to 1. Best value is <i>P</i> (<i>t</i>) = 1 and the worst is 0
Correlation (between estimates and measurements)	Correlation coefficient of the estimates versus measurements	R	–1 (full negative correlation) to 1 (full positive correlation). The closer values are to 1, the better the model
Pattern (presence or absence of patterns in residuals)	Pattern Index by day of year	PI _{day}	0 to infinity. The closer values are to 0 the better the model. Units are MJ m ⁻² day ⁻¹ . Day of year is an independent variable
	Pattern Index by minimum air temperature	PI _{T_{min}}	0 to infinity. The closer values are to 0 the better the model. Units are MJ m ⁻² day ⁻¹ . Daily minimum air temperature is an independent variable

minimum temperature (PI_{T_{min}}). Further details on the Pattern Indices are given in Donatelli et al. (2004). These were calculated between the daily observed and estimated solar radiation for each year and site.

Yearly values of each index were then aggregated into modules (Fig. 2). A module is an evaluation index calculated via a fuzzy-based procedure from one or more basic statistics. For each module, a dimensionless value between 0 (best model response) and 1 (worst model response) is calculated. The Sugeno method of fuzzy inference was adopted (Sugeno, 1985). Three membership classes are defined for all indices, according to an expert judgment, namely favourable (*F*), unfavourable (*U*) and partial (or fuzzy) membership, using S-shaped curves as transition probabilities in the range *F* to *U*:

$$S(x; a; b) = \begin{cases} 0 & x \leq a \\ 2\left(\frac{x-a}{b-a}\right)^2 & a \leq x \leq c \\ 1 - 2\left(\frac{x-b}{b-a}\right)^2 & c \leq x \leq b \\ 1 & x \geq b \end{cases} \quad (1)$$

where *x* is the value of the index, *a* is the lower bound of the interval [min(*F*, *U*)], *b* is the upper bound of the interval [max(*F*, *U*)], *c* = (*a* + *b*)/2.

According to (1), if *a* = *F*, then *x* ≤ *a* means *x* = *F*, and *S*(*x*; *a*; *b*) gives the degree of membership of the index value *x* to the set *U*. Its complement, 1 – *S*(*x*; *a*; *b*), gives the degree of membership of the index value *x* to

the set *F*. A two-stage design of a fuzzy-based rules inferring system is applied (Table 1): first, several indices are aggregated into modules and then, using the same procedure, the modules are aggregated in a second level integrated index (again, ranging from 0 to 1), called *indicator* (Irad). The Modules represent the criteria that the performance assessment should consider: (i) the ability of the model to produce small residuals; (ii) the extent to which estimates are correlated with measurements and (iii) how residuals are uniformly distributed over the range of two independent variables (e.g. where day of year is used as one of the independent variables it is possible to assess how well the model represents the temporal pattern of solar radiation distribution over a single year).

The control rules for estimating module values were based on logic relationships between inputs and outputs, expressed in linguistic terms by if-then statements. For example, when two input variables are aggregated, four rules are formalized as follows:

Premise	Conclusion
if <i>x</i> ₁ is <i>F</i> and <i>x</i> ₂ is <i>F</i>	then <i>y</i> ₁ is <i>B</i> ₁
if <i>x</i> ₁ is <i>F</i> and <i>x</i> ₂ is <i>U</i>	then <i>y</i> ₂ is <i>B</i> ₂
if <i>x</i> ₁ is <i>U</i> and <i>x</i> ₂ is <i>F</i>	then <i>y</i> ₃ is <i>B</i> ₃
if <i>x</i> ₁ is <i>U</i> and <i>x</i> ₂ is <i>U</i>	then <i>y</i> ₄ is <i>B</i> ₄

where *x_i* is an input variable, *y_i* is an output variable and *B_i* is a decision rule (or expert weight). The value of each conjunction (... and ...) is the minimum of the

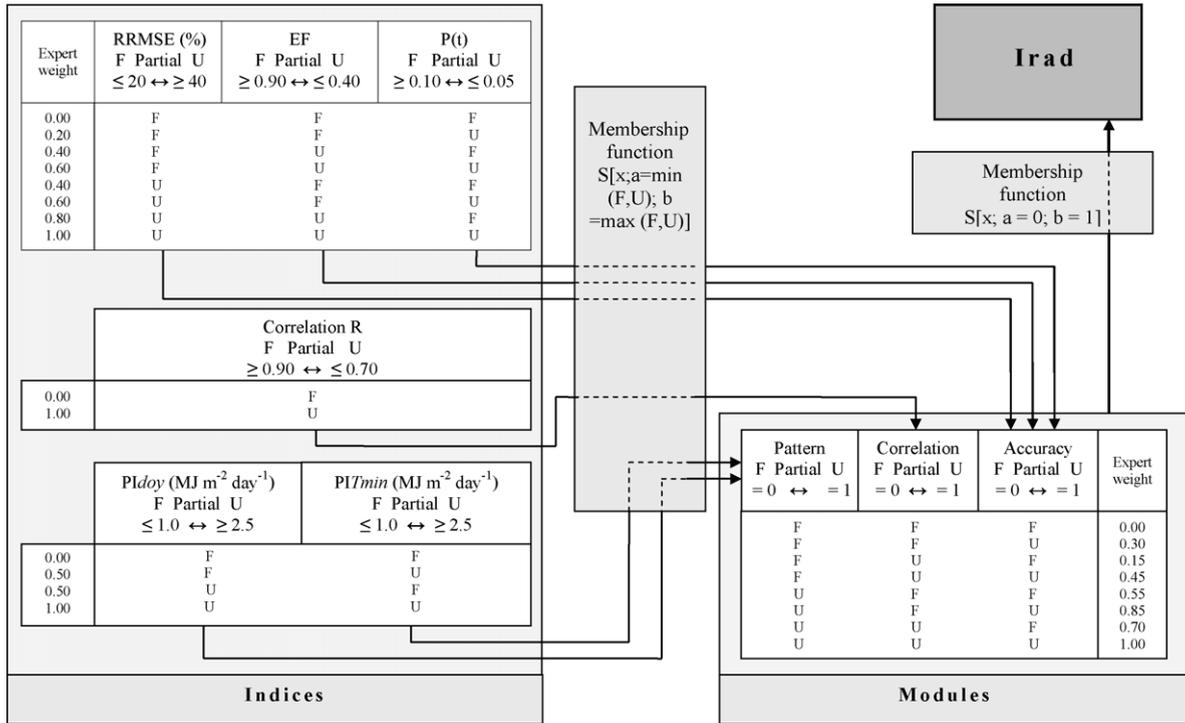


Fig. 2. Structure of the Irad model assessment method, where: RRMSE, Relative Root Mean Square Error; EF, modelling efficiency; $P(t)$, Student t -test probability of equal means; correlation R , correlation coefficient of the estimates vs. measurements; PI_{doy} , Pattern Index by day of year; $PI_{T_{min}}$, Pattern Index by minimum temperature (see also Table 1); F , favourable; U , Unfavourable; S , membership function; x , value of index a , Minimum value of F ; b , maximum value of U ; Irad, single modular indicator.

quantified fuzzy sets, as obtained from complementary S-shaped distribution curves. The output fuzzy sets for all the rules are then aggregated into a single fuzzy set. This set encompasses a range of output values, and is de-fuzzified in order to resolve a single crisp output value from the set. The centroid method was selected to obtain the representative non-fuzzy value for the output, as commonly adopted in the Sugeno-type systems. The expert reasoning runs as follows: if all input variables are F , the value of the module is 0 (good agreement between estimates and measurements); if all indices are U , the value of the module is 1 (bad agreement), while all the other combinations assume intermediate values. The weights were chosen on the basis of the authors' own experience in handling each statistic. Based on the authors' judgment, a decreasing importance was assigned to the modules: Accuracy, Pattern and Correlation.

The mean Irad values per site were calculated and ranked in increasing size per location for each model (Table 3). The Irad method was implemented within the database containing the weather data. Tests were performed to ensure that the results gained from the database were identical to those gained from the

original implementation of Irad in the IRENE_DLL system for model evaluation (Fila et al., 2003).

3.4. Observed versus estimated daily mean difference

For a selected number of locations (including the sites with the lowest mean Irad values per model), the difference between mean daily observed versus estimated solar radiation \underline{D} was calculated from all available years at the site:

$$D \text{ has elements } d_i = \bar{e}_i - \bar{o}_i \tag{2}$$

where \bar{e}_i is the mean estimated solar radiation for day i over n years, and \bar{o}_i is the mean observed solar radiation for day i over n years with

$$\bar{e}_i = \frac{1}{n} \sum_{j=1, n} e_{ji} \tag{3}$$

and

$$\bar{o}_i = \frac{1}{n} \sum_{j=1, n} o_{ji} \tag{4}$$

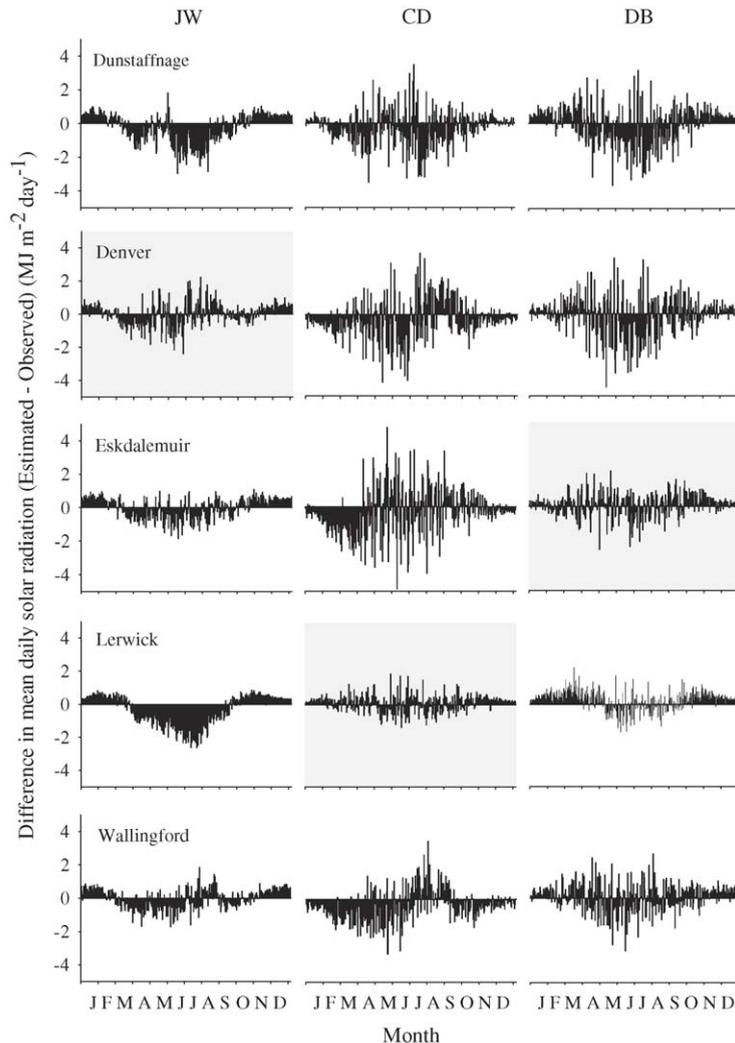


Fig. 3. Difference in mean estimated versus observed daily solar radiation for Johnson-Woodward (JW), Campbell-Donatelli (CD) and Donatelli-Bellocchi (DB) models at selected sites (grey shaded graphs are locations with the lowest Irad values per model).

where e_{ji} is the estimated solar radiation on day i of year j , and o_{ji} is the observed solar radiation on day i of year j . This difference in daily means (Fig. 3) helps to illustrate the temporal distribution of mean daily errors over the period of a year, indicating systematic model behaviour.

4. Results

For several sites individual years of data had to be rejected as it was considered that an excessive number of daily observations were missing in the original data. Noticeably these sites tended to be in remote locations with semi-automatic weather stations, where sensory equipment failure may go undetected for long periods of time. This serves as an illustration of the difficulties in compiling a complete daily data set, even for sites

where observations are made. At four sites (Altnaharra, Inverbervie, Loch Glascarnoch and Tulloch Bridge) it was not possible to test the JW model due to the absence of sunshine duration data. Several sites (Aberdeen, Aberporth, Dunstaffnage and Hazelrigg) had fewer years when sunshine duration data were available than temperature data. Results for the basic level statistics of RMSE and standard deviation are given in Table 2. The ranked mean values per location and model for Irad are given in Table 3, whilst the individual Irad indices results are detailed in Table 4.

4.1. Overall model performance

The JW model gave the best results for all locations, with a mean Irad of 0.146 compared with 0.525 and

Table 2

Mean values for Root Mean Square Error (RMSE) and standard deviation for Johnson-Woodward (JW), Campbell-Donatelli (CD) and Donatelli-Bellocchi (DB) models at each site

Location	<i>n</i>	RMSE			Standard deviation		
		(MJ m ⁻² day ⁻¹)			(MJ m ⁻² day ⁻¹)		
		JW	CD	DB	JW	CD	DB
Aberdeen	29 (9)	2.229	4.874	4.962	7.466	6.855	6.530
Aberporth	40 (36)	2.803	4.897	4.869	8.046	7.201	7.012
Aldergrove	25	2.356	3.135	3.276	7.327	6.643	6.126
Altnaharra	7 (0)		3.901	4.545		6.615	6.117
Auchincruive	19	2.570	4.398	4.473	7.408	7.253	6.731
Aviemore	8	2.761	3.959	4.001	6.840	6.445	5.868
Bracknell	28	2.324	3.719	3.730	8.160	7.320	6.629
Brooms Barn	16	2.372	4.446	4.624	8.007	7.201	6.794
Cawood	29	2.382	4.277	4.390	7.346	7.072	6.621
Denver	18	2.285	4.329	4.491	7.720	7.118	6.682
Dunstaffnage	25 (13)	2.392	4.741	4.874	7.526	7.218	6.726
East Malling	34	2.426	4.570	4.693	8.280	7.181	6.519
Eskdalemuir	25	2.156	3.212	3.203	7.132	7.016	6.654
Everton	29	2.872	4.980	4.947	8.734	7.818	7.129
Hazlerigg	17 (6)	2.356	5.048	5.110	7.921	7.076	6.784
Inverbervie	7 (0)		4.610	4.504		7.505	7.162
Lerwick	41	2.149	3.329	3.449	6.690	6.659	6.421
Loch Glascarnoch	7 (0)		3.865	3.820		6.387	6.032
Mylnefield	23	2.586	4.715	4.860	7.420	6.857	6.496
Rothamstead	30	2.515	4.309	4.475	8.075	6.959	6.544
Stornoway	15	2.421	4.270	4.236	7.075	6.414	6.085
Sutton Bonington	26	3.129	4.435	4.455	7.426	6.821	6.263
Tulloch Bridge	6 (0)		4.751	4.533		7.802	7.245
Wallingford	26	2.314	4.172	4.243	7.483	6.959	6.523
Mean		2.470	4.289	4.365	7.604	7.017	6.570

n Values in parenthesis refer to years of available sunshine duration data.

0.522 for the CD and DB models, respectively. However, each model showed abilities to provide the best estimates for different individual indices whilst also providing the worst for others, i.e. the DB model had the best results for the paired *t*-test, *P*(*t*) at all but nine sites, but had the poorest performance when assessed by the Relative Root Mean Square Error (RRMSE). The case was the opposite for the JW model, with good RRMSE but poor results for the paired *t*-test, *P*(*t*).

4.2. Sunshine duration model (JW)

The JW had consistently the lowest RMSE values between all the models for all sites, with a mean of 2.470 (MJ m⁻² day⁻¹), but had the highest standard deviation of 7.604 (MJ m⁻² day⁻¹). The JW model showed consistently low mean Irad values at all sites. The lowest and highest means were 0.034 (Denver) and 0.254 (Auchencruive), respectively. At all but two sites (Aviemore and Dunstaffnage) the JW model gave Irad

values of 0.000 at least once. The largest single year's value of Irad (0.870) was found at Sutton Bonington. In a spatial context, lower values of Irad tended to be found at sites in lowland eastern parts of Britain. Exceptions were Eskdalemuir (242 m a.s.l.), with a mean Irad of 0.086, and conversely, Sutton Bonington (48 m a.s.l.) with a mean Irad of 0.242. Higher values of Irad were found at west coast sites, such as Dunstaffnage (0.202), Lerwick (0.240), Aberporth (0.246) and Auchencruive (0.254). However, the highest mean Irad value for the JW model (0.254) was still lower than the smallest means for the CD and DB models (0.301 and 0.322, respectively).

For individual Irad indices, JW gave the best results for RRMSE, modelling efficiency (EF) and correlation coefficient (*R*) at all sites where sunshine duration data were available. JW also gave the best results for the day of year Pattern Index (PI_{doy}) at 12 sites and minimum temperature Pattern Index (PI_{T_{min}}) at 15 sites. However, the JW model performed relatively poorly compared with the DB, and to a lesser extent CD, using the paired

Table 3

Ranked mean Irad values for Johnson-Woodward (JW), Campbell-Donatelli (CD) and Donatelli-Bellocchi (DB) models at each site

Ranked mean Irad values					
Site	JW	Site	CD	Site	DB
Denver	0.034	Lerwick	0.301	Eskdalemuir	0.322
Bracknell	0.044	Aldergrove	0.330	Lerwick	0.352
East Malling	0.086	Eskdalemuir	0.377	Bracknell	0.374
Eskdalemuir	0.086	Bracknell	0.392	Aldergrove	0.410
Aberdeen	0.089	Auchincruive	0.456	Wallingford	0.450
Hazelrigg	0.104	Inverbervie	0.462	Auchincruive	0.456
Brooms Barn	0.109	Aviemore	0.474	Inverbervie	0.472
Cawood	0.113	Stornoway	0.477	Brooms Barn	0.511
Wallingford	0.126	Rothamstead	0.536	Aviemore	0.511
Aldergrove	0.137	Wallingford	0.538	Denver	0.513
Rothamstead	0.139	Dunstaffnage	0.543	Cawood	0.524
Everton	0.150	Denver	0.548	Altnaharra	0.528
Mylnefield	0.162	Brooms Barn	0.560	Stornoway	0.535
Stornoway	0.167	Altnaharra	0.575	Tulloch Bridge	0.556
Aviemore	0.196	Cawood	0.580	Rothamstead	0.557
Dunstaffnage	0.202	Mylnefield	0.584	Sutton Bonington	0.565
Lerwick	0.240	Loch Glascarnoch	0.585	East Malling	0.580
Sutton Bonington	0.242	East Malling	0.590	Dunstaffnage	0.592
Aberporth	0.246	Sutton Bonington	0.592	Loch Glascarnoch	0.595
Auchincruive	0.254	Tulloch Bridge	0.596	Aberporth	0.604
		Everton	0.604	Hazelrigg	0.606
		Hazelrigg	0.608	Mylnefield	0.607
		Aberdeen	0.642	Everton	0.643
		Aberporth	0.642	Aberdeen	0.663
Mean	0.146		0.525		0.522

t -test, $P(t)$. The model achieved good values for both the PI_{doy} and $PI_{T_{\text{min}}}$, with means of 1.28 and 1.08 ($\text{MJ m}^{-2} \text{day}^{-1}$), respectively.

4.3. Campbell-Donatelli model (CD)

The CD model gave a mean RMSE for all sites of 4.289 ($\text{MJ m}^{-2} \text{day}^{-1}$), which was slightly better than the DB model. For standard deviation the CD gave the second best overall result of 7.017 ($\text{MJ m}^{-2} \text{day}^{-1}$). The CD model produced Irad indices values that were very similar to those of the DB model. In comparison between all three models, the CD performed marginally worse than the DB model, with a mean Irad value of 0.525 across all sites. The best mean Irad result was at Lerwick (0.301), and the highest mean Irad at Aberporth (0.642). There was a less well defined pattern in the spatial distribution of sites with low and high values of Irad, compared with the JW model. The CD model was able to produce solar radiation data that resulted in comparatively low Irad values at a diverse range of sites, i.e. Lerwick in the Shetland Islands (0.301), Aldergrove in Northern Ireland (0.330) and Bracknell, lowland south-east England (0.392). There

was no clear relationship with distance between sites: Rothamstead (0.536) and Wallingford (0.538) are 56 km apart, whereas Aberdeen (0.642) and Inverbervie (0.462) are only 32 km apart. Similarly the model was able to produce similar Irad values at different elevations, i.e. Aldergrove, 68 m a.s.l. (0.330) and Eskdalemuir, 242 m a.s.l. (0.377).

For individual indices, the CD was slightly better than the DB for RRMSE, though the size of differences was very small. The CD model gave the best results for the paired t -test, $P(t)$ at only six sites, but all values were similar to the best performing model, DB. For R the model had near identical values as to those of the DB, and only very slightly smaller than those of the JW. For the Pattern Indices, the CD gave the best results for PI_{doy} at six sites, and at seven for $PI_{T_{\text{min}}}$, the remaining values being similar to the other models, but with the overall highest means of 1.55 ($\text{MJ m}^{-2} \text{day}^{-1}$) for PI_{doy} and 1.38 ($\text{MJ m}^{-2} \text{day}^{-1}$) for the $PI_{T_{\text{min}}}$.

4.4. Donatelli-Bellocchi model (DB)

The DB model produced the highest mean RMSE values between the three models, of 4.365

Table 4
Index values used within multiple-indices assessment method, for Johnson-Woodward (JW), Campbell-Donatelli (CD) and Donatelli-Bellocchi (DB) models for all sites

Location	Mean Index Values																		
	<i>n</i> (years)	RRMSE			<i>t</i> -test			EF			Correlation			PI _{doy}			PI _{T_{min}}		
		JW	CD	DB	JW	CD	DB	JW	CD	DB	JW	CD	DB	JW	CD	DB	JW	CD	DB
Aberdeen	29 (9)	26.84	57.80	58.86	0.21	0.38	0.48	0.90	0.53	0.51	0.96	0.76	0.74	0.89	1.62	1.44	0.72	1.22	1.42
Aberporth	40 (36)	27.86	48.47	48.17	0.27	0.23	0.24	0.87	0.62	0.62	0.94	0.80	0.80	1.80	2.01	1.90	1.49	1.90	1.56
Aldergrove	25	26.67	35.46	37.01	0.23	0.06	0.04	0.75	0.68	0.68	0.90	0.86	0.85	2.05	1.77	2.22	1.52	1.36	1.37
Altnaharra	7 (0)		53.91	56.12		0.22	0.12		0.63	0.60		0.83	0.83		1.65	1.44		1.57	1.72
Auchincruive	19	28.73	49.04	49.90	0.14	0.51	0.48	0.88	0.64	0.63	0.94	0.82	0.80	1.67	1.26	1.43	1.52	1.01	1.04
Aviemore	8	26.54	42.88	43.78	0.02	0.00	0.00	0.90	0.74	0.73	0.95	0.88	0.88	1.61	1.84	2.46	0.75	1.06	1.12
Bracknell	28	23.89	38.29	38.39	0.22	0.25	0.22	0.90	0.73	0.73	0.96	0.87	0.86	0.80	1.43	1.09	1.10	1.25	1.07
Brooms Barn	16	24.47	45.96	47.81	0.19	0.26	0.54	0.89	0.62	0.59	0.96	0.81	0.78	1.15	1.27	0.77	1.05	1.80	1.47
Cawood	29	26.92	48.06	49.36	0.16	0.22	0.35	0.88	0.62	0.60	0.95	0.82	0.79	1.14	1.67	1.08	1.01	1.40	1.22
Denver	18	23.42	44.47	46.13	0.34	0.35	0.44	0.90	0.64	0.61	0.96	0.82	0.79	0.96	1.45	0.97	0.70	1.46	1.33
Dunstaffnage	25 (13)	28.06	55.35	56.95	0.12	0.31	0.35	0.90	0.60	0.58	0.95	0.80	0.77	1.57	1.06	1.54	1.10	1.16	1.15
East Malling	34	25.02	47.25	48.51	0.19	0.32	0.40	0.89	0.61	0.59	0.96	0.80	0.78	0.91	1.74	1.37	0.99	1.50	1.12
Eskdalemuir	25	27.02	40.17	40.06	0.23	0.20	0.25	0.90	0.78	0.78	0.95	0.90	0.89	1.08	1.37	0.98	0.98	1.30	1.35
Everton	29	26.73	46.44	46.11	0.17	0.32	0.38	0.86	0.58	0.59	0.95	0.80	0.78	1.15	1.74	1.70	1.18	1.63	1.94
Hazelrigg	17 (6)	25.34	54.99	55.64	0.24	0.41	0.52	0.90	0.55	0.54	0.96	0.76	0.75	0.99	1.44	1.18	1.23	1.38	1.14
Inverbervie	7 (0)		51.39	50.15		0.55	0.56		0.63	0.65		0.82	0.82		1.26	1.34		1.34	1.34
Lerwick	41	28.04	43.28	44.35	0.13	0.35	0.35	0.91	0.78	0.77	0.96	0.89	0.88	1.76	1.09	1.37	1.14	1.05	1.17
Loch Glascarnoch	7 (0)		56.21	55.16		0.37	0.32		0.61	0.63		0.81	0.80		1.88	2.04		1.90	1.72
Mylnefield	23	28.33	53.73	55.46	0.19	0.27	0.34	0.89	0.59	0.57	0.95	0.79	0.76	1.33	1.49	1.58	0.92	1.20	1.25
Rothamstead	30	26.96	46.08	47.85	0.15	0.18	0.27	0.87	0.64	0.61	0.95	0.82	0.79	0.89	1.16	0.97	1.10	1.47	1.25
Stornoway	15	25.29	49.69	49.60	0.07	0.22	0.34	0.92	0.68	0.68	0.96	0.83	0.83	1.54	1.96	2.24	1.04	1.43	1.59
Sutton Bonington	26	35.27	49.63	49.89	0.39	0.21	0.23	0.77	0.59	0.59	0.89	0.80	0.78	1.13	1.50	1.34	1.15	1.37	1.16
Tulloch Bridge	6 (0)		56.61	54.61		0.33	0.08		0.56	0.59		0.81	0.81		1.87	1.08		1.04	1.36
Wallingford	26	24.87	44.97	45.76	0.12	0.20	0.34	0.89	0.65	0.63	0.95	0.82	0.81	1.12	1.57	1.05	0.89	1.41	0.96
Mean		26.81	48.34	48.98	0.19	0.28	0.32	0.88	0.64	0.63	0.95	0.82	0.81	1.28	1.55	1.44	1.08	1.38	1.33

Greyed areas show the best result per index (*n* values in parenthesis are the sample sizes for years of available sunshine duration data).

(MJ m⁻² day⁻¹). However, it gave the lowest overall standard deviation of 6.570 (MJ m⁻² day⁻¹). The DB model had similar Irad values to the CD, with a slightly lower mean of 0.522. The lowest Irad was at Eskdalemuir (0.322) and the highest at Aberdeen (0.663). As with the CD model, DB produced solar radiation data that gave low Irad values at a diverse range of sites. The highest Irad ranges were found at similar sites to the CD model, notably Aberdeen (0.663) and Everton (0.643). The model was able to produce solar radiation estimates that gave low Irad values at sites as diverse as Lerwick (0.352) and Bracknell (0.374).

For individual Irad indices, the DB model was the best when assessed by the paired *t*-test, *P*(*t*) at 15 sites. Mean values for EF and R were similar to the CD model, being generally good, with values approaching +1. For the Pattern Indices, DB gave the lowest values at six locations for PI_{doy}, and three for PI_{T_{min}}, whilst giving lower mean values than the CD model (1.44 and 1.33 MJ m⁻² day⁻¹, respectively).

4.5. Observed versus mean daily difference

Fig. 3 illustrates the temporal distribution characteristics, for each model, of daily mean errors and the observed daily mean solar radiation for selected sites. The JW consistently over-estimates solar radiation values in the winter, early spring and late autumn period (approximately January to end of March and mid October to end of December). There is a tendency to under-estimate values in the late spring, summer and early autumn (start of April to mid October), best illustrated by the Lerwick results. The lowest Irad value for JW was at Denver (0.034), where the temporal distribution of daily mean errors fluctuates around the observed mean values throughout the summer period. The JW model has a built-in function of estimating a base level of diffuse solar radiation under cloudy conditions for each day of the year, determined by day length (see Eq. (5), Appendix A), so that days with 0 h of sunshine still result in approximations of solar radiation values. The results suggest that the model requires further refinement to reduce the over-estimation caused by the daily base level diffuse radiation component estimation ($J_{0,d}$), and an increase in the estimates resulting from the direct beam radiation estimation ($J_{0,s}$) in the summer period.

The CD model's temporal distribution of errors shows that it tends towards under-estimation in the winter and early spring period, i.e. Wallingford and Eskdalemuir. The CD has an overall tendency for the

errors to fluctuate about those of the observed data, i.e. very short time periods between switching from under- to over-estimation. The site with the lowest Irad value for CD, Lerwick (0.301) also had very good patterns of error distribution, with limited over-estimation in the winter, spring and early autumn period, and fluctuations about the observed daily mean in the summer. Conversely, Eskdalemuir had the CD's third best Irad value, but there is a constant under-estimate in the winter and large summer-time fluctuation about the observed mean.

The DB model showed similar patterns of daily mean error as the CD. The model has a tendency towards over-estimation in the winter, early spring and autumn periods, and though there is fluctuation in daily mean errors about the observed mean, there is a greater level of under- than over-estimation. The lowest Irad value for DB was at Eskdalemuir, where Fig. 3 shows there was an even balance in the fluctuation of the mean daily errors about the observed daily mean.

5. Discussion

5.1. Model performance

The three models tested were able to produce solar radiation data that in general represented both the quantities and patterns of observed data. The JW model gave the best overall results in terms of individual indices and Irad. The two air temperature based models produced higher Irad values than the JW model, but when examining the individual indices, i.e. the paired *t*-test, *P*(*t*) indicated that the DB model gave the better performance for that particular form of estimate behaviour. The JW model was clearly the best in respect of Root Mean Square Error (RMSE), Relative Root Mean Square Error (RRMSE), modelling efficiency (EF), correlation coefficient (*R*) and minimum temperature Pattern Index (PI_{T_{min}}), but there was a more even spread considering the mean response across all locations for day of year Pattern Index (PI_{doy}).

Localised climates could be attributed to some results for each model. The air temperature based model's behaviour may be influenced by site-specific characteristics. Aberdeen has an occasional summer sea fog that affects air temperatures, potentially distorting the basis of the CD and DB model interpolation method, reflected in the higher Irad values (0.642 and 0.663, respectively). Similarly, Everton is a coastal site, which often experiences strong localised sea-breeze (advection) effects on clear sky days. Such events will alter the temperature measurements and distort the relationship

with solar radiation, even though the DB model contains a component (weighing ΔT with the mobile weekly ΔT , Eq. (15)) to dilute advection effects.

The results indicate variability in the spatial capability of each model, given the differences in results between locations. The JW model's worst performances were at the west coastal sites of Aberporth (0.246) and Auchencruive (0.254), which have a greater amount of cloud cover than east coast sites, i.e. Aberdeen (0.089). Conversely, ranking of the air temperature based models performance indicated that they perform better in locations experiencing more cloudy conditions than those with generally clearer skies.

This investigation has used generic optimised parameters, which over multiple years are crude estimates, but do provide location defining values of general use for any application in the same site. The JW model appears less sensitive to variation in its single empirical parameter (F) than the CD and DB models are to their respective multiple parameters. The spatial application of the models tested, and others, is limited by the ability to provide appropriate site-representative parameters that also capture the temporal variability. Specific geographical locations will obviously have particular characteristics which causes the parameters to deviate from a general model, but a method of model optimisation for each site has additional problems. Restrictions in data availability, noise in available datasets and the requirements of model parameter optimisation place real limits on what can be accomplished using the types of model discussed here.

The use of neural networks has potential, as an alternative to the types of models tested here, for generating parameter values in non-linear model development where data is noisy or the relationships between parameters is unclear (Moisen and Frescino, 2002; Aitkenhead et al., 2003; Laffan and Lees, 2004), with the only requirement being that a dataset exists from which the neural network can be trained. Neural networks are not a perfect solution to the above problem, however. The issue of spatial parameter interpolation remains, although they can be used to provide a degree of interpolation provided additional information is available (e.g. Shen et al., 2004; Cornet et al., 2004). For the current example of solar radiation modelling, parameters such as elevation, spatial location, and distance to coastline may provide this type of information. Additionally, training a neural network does require sufficient data points to explore a sufficient proportion of parameter phase space, in terms of data point density and likely range of parameters.

5.2. Assessment method

The Irad assessment method as applied here demonstrates its ability to identify the quality of model estimates and for use in between-model comparisons. Conventional methods (RMSE, R^2 etc.) for model assessment have provided an indication of the magnitude of differences between observed and estimated values and their correlations, but this research has demonstrated that a more detailed investigation reveals valuable information about a model's behaviour. The combined approach of using a multiple-indices assessment method such as Irad and graphical displays of temporal patterns of difference in daily means gives a comprehensive set of information on which to base judgement as to which is the best model to use.

Although this method is reliable for model performance testing, examples of exceptions exist, depending on what form of model behaviour is being observed, i.e. when comparing Denver (JW = 0.034) and Lerwick (CD = 0.301), the CD at Lerwick has a better difference in daily mean pattern. Similarly, the JW at Wallingford had a larger Irad (0.126) than Denver (0.034), but better temporal distribution pattern of errors (Fig. 3). These exceptions and the results for indices values indicate that an important consideration in choosing a model for data estimation is how the estimates are used and what is important. Using the JW model, with its tendency to under-estimate solar radiation in the UK growing season, when used in, for example, a crop model to estimate mean yields, would lead to an under-estimation of biomass accumulation. Conversely, crop model estimates would be different using the CD or DB, with their fluctuating values of solar radiation about the daily mean, as over- and under estimates cancel each other out (Rivington et al., in press). If the estimates are to be used within experimental analysis, i.e. a biological process influenced by the weather, then the precision and accuracy of the daily estimates becomes more important. In such cases the long-term mean response becomes less relevant and individual indices such as RRMSE, EF, correlation (R) and Pattern Indices indicate the best model options.

The results gained call into question the ability of a model's performance to be assessed by single assessment indices. Some authors, i.e. Ball et al. (2004) and Chen et al. (2004), have reached conclusions about the accuracy and precision, or unsuitability (respectively) of model performance based on single indices. Our research indicates that such conclusions should only be reached following the application of a detailed multiple-indices and graphical representation approach.

The level of detail given here to model evaluation becomes important were such methods are used for data set enhancement, as the results provide valuable information (a form of meta-data to accompany the data set), on the degree of uncertainty that estimated data may introduce. Errors in estimates will introduce uncertainty (difference between observed and estimated values) into data sets, which when used for modelling or experimental analysis purposes, will be propagated through to the final results. Knowledge of such uncertainty (i.e. magnitude and patterns of errors) will help when interpreting results from models and experimental analysis.

6. Conclusions

Where sunshine duration data are available, it is preferable to use the JW model to estimate solar radiation, rather than the models based on air temperature. However, given the greater availability of temperature data, both spatially and temporally, the two air temperature based methods tested here will make reliable estimates to enable the creation of complete data sets. The results have demonstrated that each model is capable of making good estimates at some locations and poorer ones at others. The JW model has a systematic under-estimation error in the late spring, summer and early autumn period. The CD model tends to under-estimate values in the winter to early spring period. The DB model tends to over-estimate values in the winter to early spring period.

There is a need to consider how the estimates are to be used when deciding which model to use, i.e. be aware of when in the year each model makes under- and over-estimates. Consideration should be given to the overall model performance as illustrated by the *Irada* value and the individual assessment indices, supported by some form of graphical representation of the temporal pattern of error distribution. Hence researchers and practitioners wanting to create complete weather data sets, i.e. observed precipitation and temperature supplemented with modelled solar radiation, need to be aware of the behaviour of the models and how introduced errors may manifest themselves in the purposes to which the data are put. Similar consideration needs to be given to localised weather phenomena, with practitioners being aware of how this may impact on model estimates.

The results gained have shown the value of using a combination of assessment methods to provide a comprehensive illustration of model performance and behaviour. Such an approach is recommended in order to provide valuable information on the magnitude and

pattern of errors that may occur when estimated data are combined with observed data to create complete data sets.

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Appendix A

A.1. Estimation of solar radiation from sunshine duration—JW model

Johnson et al. (1995) and Woodward et al. (2001) used sunshine duration to estimate solar radiation. The model accounts for latitude, solar declination and elevation, day length and atmospheric transmissivity on a daily basis and has only daily sunshine duration (hours) as input. Total daily irradiance (J_0) is given by:

$$hJ_0 = SJ_{0,s} + hJ_{0,d} \quad (5)$$

where h is day length, S is the sunshine duration, $J_{0,s}$ is the direct beam and $J_{0,d}$ the diffuse components. Day length in hours is calculated by:

$$h = \frac{24}{\pi} \cos^{-1}(-\tan\lambda \tan\delta) \quad (6)$$

where λ is the latitude and δ is the solar declination in radians. Pi (π) is 3.14159265. Solar declination for each day of the year is given by:

$$\delta = -0.4084 \cos\left(2\pi \frac{d+10}{365}\right) \quad (7)$$

where d is the Julian day of year.

Following Campbell (1977), the direct beam component $J_{0,s}$ is given by:

$$J_{0,s} = 1367 \frac{2p}{\pi} \sin\phi(\tau^{1/\sin\phi}) \quad (8)$$

where p is the fraction of radiation in full spectrum sunlight (here 1 is used) and 1367 is the solar constant ($\text{J m}^{-2} \text{s}^{-1}$). τ is the atmospheric transmissivity (the

method used to estimate transmissivity in the JW model was the same as that of the CD and DB models). ϕ is the solar elevation at solar noon, in degrees from horizontal:

$$\sin\phi = \sin\lambda\sin\delta + \cos\lambda\cos\delta \quad (9)$$

The diffuse portion of total irradiance is represented by $J_{0,d}$ (cloud conditions and from blue sky scattering simultaneously), following List (1971), can be calculated by:

$$J_{0,d} = J_{0,p}(f_{\text{blue}}(1 - c) + f_{\text{cloud}}c) \quad (10)$$

where c is the mean daily fraction of cloud cover, where invoking the Taylor Hypothesis (Stull, 1988) gives: $c = 1 - (S/h)$, being a dimensionless value between 0 (complete cloud cover) and 1 (no cloud cover).

$J_{0,p}$ is the potential total clear sky mean daily irradiance:

$$J_{0,p} = 1367 \frac{P}{\pi} \sin\phi(1 + \tau^{1/\sin\phi}) \quad (11)$$

The values of f_{blue} and f_{cloud} represent the relative different radiation intensities under blue sky and cloud conditions, respectively:

$$f_{\text{blue}} = \frac{1 - \tau^{1/\sin\phi}}{1 + \tau^{1/\sin\phi}} \quad (12)$$

$$f_{\text{cloud}} = F f_{\text{blue}} \quad (13)$$

To determine the parameter F (Eq. (13)) for each site, values were fitted for each day per year to give daily optimised F values (LADSS, 2005). The mean value per year was calculated, then the mean of these values used to represent a particular site. Woodward et al. (2001) determined an F of 1.11 for New Zealand. For the UK there was a range in mean F between 0.69 and 0.87 (individual year and location range of 0.391–1.047, overall mean of 0.688). The JW model imposes a base-line amount of diffuse radiation, variable with h , such that an input of 0 sunshine hours will still produce a value of irradiance for a given day of year.

A.2. Estimation of solar radiation from air temperature—DB and CD models

Daily values of solar radiation at ground level can be estimated as the product of solar radiation outside the Earth's atmosphere times a coefficient of radiation transmission through the atmosphere. General routines, based purely on solar geometry, are available to calculate extra-terrestrial solar radiation for a location on any given day of the year (e.g. Stine and Harrigan, 1985; Spitters et al., 1986; Pickering et al., 1994). The

transmissivity coefficient (tt_i) is modelled daily from air temperature ($^{\circ}\text{C}$) according to alternative functions, two of them used here:

Campbell-Donatelli (CD) model (Donatelli and Campbell, 1998):

$$tt_i = \tau[1 - \exp(-b f(T_a)\Delta T_i^2 f(T_n))] \quad (14)$$

Donatelli-Bellocchi (DB) model (Donatelli and Bellocchi, 2001):

$$tt_i = \tau \left[1 + f(i) \right] \left[1 - \exp\left(\frac{-b\Delta T_i^2}{\Delta T_{\text{week}}}\right) \right] \quad (15)$$

where τ is the clear sky transmissivity (reference value equal to 0.75), b is the temperature range coefficient, ΔT_i is the daily air temperature range, equal to:

$$\Delta T_i = T_{xi} - 0.5(T_{ni} + T_{ni+1}) \quad (16)$$

where T_{xi} is the daily maximum air temperature ($^{\circ}\text{C}$) and T_{ni} is the daily minimum air temperature ($^{\circ}\text{C}$). ΔT_{week} is the mobile average daily temperature range over 7 days around the current day. The function of average air temperature, $f(\bar{T})$ is given by:

$$f(\bar{T}) = 0.017\exp(\exp(-0.053T_{ai})) \quad (17)$$

where T_{ai} is the daily average air temperature, equal to

$$T_{ai} = 0.5(T_{xi} + T_{mi}) \quad (18)$$

The function of daily minimum air temperature, $f(T_n)$ is equal to:

$$f(T_n) = \exp\left(\frac{T_{ni}}{T_{nc}}\right) \quad (19)$$

where T_{nc} is the summer night air temperature factor and $f(i)$ is the seasonality function, equal to

$$f(i) = c_1 \left(\sin\left(i_r c_2 \frac{\pi}{180}\right) + \cos\left(i_r f(c_2) \frac{\pi}{180}\right) \right) \quad (20)$$

where c_1 is the first seasonality factor, c_2 is the second seasonality factor (varying from 0 to 0.5 and from 1 to 1.5) and i_r is a reverse option ($i_r = i$ for no reverse; $i_r = 361 - i$ for reverse), with $f(c_2)$ being a function of c_2 , equal to:

$$f(c_2) = 1 - 1.90(c_2 - [c_2]) + 3.83(c_2 - [c_2])^2 \quad (21)$$

where $[c_2]$ is the integer of c_2 .

Both models are based on the approach of Bristow and Campbell (1984) and are part of a suite of models contained within the RadEst global solar radiation estimation tool (Donatelli et al., 2003), available through the web site <http://www.sipeaa.it/tools>. The

data input requirements are daily values of maximum and minimum air temperature, and location-specific parameters (τ , b , T_{nc} , c_1 , c_2 , i_r). Model CD includes the summer night air temperature factor originally developed by Donatelli and Marletto (1994) to adjust underestimations at times observed with the approach of Bristow and Campbell (1984) during either the months July–August (Northern hemisphere) or January to February (Southern hemisphere). A trigonometric function was originally introduced by Donatelli and Bellocchi (2000) as a seasonality function to prevent estimates from showing systematic patterns at a large range of latitudes (including tropical sites) and, with further improvements, has become the seasonality component of the model DB. Model parameters for a sample of about 200 sites world-wide can be downloaded from the RadEst web page (RadEst, 2004), as obtained via optimisation procedures over multiple year radiation data-sets.

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