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Testing the spatial applicability of the Johnson–Woodward method for estimating solar radiation from sunshine duration data

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ABSTRACT

Solar radiation is a driving variable for a wide range of processes in both natural and human systems. On-site measurement of solar radiation is much rarer than for other meteorological variables (approximately 40 sites of more than 2000 in the current UK network, with many of these only having records in the last 10 years). Hence a number of models have been developed to estimate solar radiation values based on more frequently observed variables such as temperature and sunshine hours. One of the principal limitations of these methods is that they require calibration using on-site measured solar radiation data and it is therefore open to question how transferable these calibration values are to other locations. This paper follows on from previous research that compared the performance of three models to estimate solar radiation (Campbell–Donatelli, Donatelli–Bellocchi and Johnson–Woodward), and that concluded the Johnson–Woodward (JW) model, estimating solar radiation values from sunshine hours duration, had an overall superior performance for UK sites. The JW model has a single empirical parameter (*F*) that indicates the intensity of diffuse solar radiation from cloudy skies. We investigate the use of spatial interpolation methods to provide estimates of *F* at locations without solar radiation measurements. Six simple spatial interpolation methods were tested with the best found to be ordinary kriging with first order polynomial trend removal. The performance of the interpolations was assessed using cross-validation. The magnitudes of the errors from cross-validation were compared with the year-to-year variability of the *F* parameter and found to be acceptable for the intended application. The analysis indicated the importance of stations near the geographic and altitudinal boundaries of the region, with significant errors associated for sites that have greater cloud cover than would be expected from other sites in their immediate vicinity. This suggested that other local factors may need to be included within the spatial interpolation. The paper concludes by suggesting possible improvements to the spatial interpolation methodology.

1. Introduction

1.1. *Rationale*

There is an increasing requirement to provide simulation models and field-based experimental analyses with site-specific weather variables. Since these data are expensive to collect (or effectively impossible to collect when absent from historical records), there is a consequent demand for methods that can estimate the variables needed. These models may either supplement limited data resources or generate entirely new data sets. One example of a rarely observed, sparsely available variable is global solar radiation, with records that

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typically cover short time periods (Thornton and Running, 1999; Bechini et al., 2000; Rivington et al., 2002) or are absent for a particular place of interest (Grant et al., 2004). Solar radiation is a key variable as it is the primary driver for photosynthesis, evapotranspiration, surface energy budgets, etc. Hence the substantial spatial and temporal gaps that exist in the meteorological data record pose a handicap for a significant number of applications where solar radiation data are required. Examples include agricultural, ecological and hydrological simulation modelling (Wilks, 1999; Hoogenboom, 2000; Lexer and Honninger, 2004), field based biological research (Milne et al., 2002), building design (Muneer et al., 2000a) and solar energy systems. On-site observations of temperature and/or sunshine duration are more numerous and tend to have longer runs of years. There have thus been several approaches developed that use these variables within models to estimate solar radiation (see Section 2.1). The main limiting factor for the applicability of such models is the need for the tuning of their calibration parameters. While it is possible to use limited on-site solar radiation records to calibrate models and subsequently generate longer runs of data, the use of such models for sites without solar radiation data, depends on assumptions about the transferability of calibration parameters.

1.2. *Approach*

This paper builds on a previous investigation that compared a number of models that derived solar radiation (total downward surface shortwave flux that includes direct and diffuse solar radiation, S_o, MJ m^{-2} day^{-1}) from other meteorological variables (Rivington et al., 2005). This paper concluded using data from 25 UK meteorological stations that overall the Johnson–Woodward (JW) method (Johnson et al., 1995; Woodward et al., 2001) was superior to other methods. There were several caveats to this conclusion. First that the superiority was likely to be application-specific, in this case used within a multi-crop simulation model CropSyst (Stockle et al., 2003). Second, that the JW method has a small but systematic bias in prediction with a seasonal pattern. Third, that the empirical calibration factor (*F*) was site-specific and would need to be estimated for sites without solar radiation records.

In this paper we address the latter concern by investigating how successfully the *F* parameter can be interpolated between sites. A range of spatial interpolation methods are parameterised and used to derive interpolated values for the long term average (LTA) *F* parameter across Great Britain and Eire. The spatial interpolations are tested using cross-validation and contextualized by comparing the errors introduced by spatial interpolation with the temporal variability of the *F* parameter. Finally the effect of interpolation errors on calculation of solar radiation (S_o) using the JW model is explored.

2. Related work

2.1. *Solar radiation models*

Numerous methods exist to estimate S_o using other weather variables, i.e. air temperature (Bristow and Campbell, 1984; Muneer et al., 1996; Hansen, 1999; Donatelli and Bellocchi, 2001), precipitation and air temperature (Castellvi, 2001) and multiple variables such as sunshine duration, cloud amount and temperature (Muneer et al., 2000b). These models require some observed S_o data to enable calibration. Several methods are available to convert observations of sunshine duration (hours) into values of S_o (i.e. Ångström, 1924; Revfeim, 1997). The Ångström method requires the estimation of site-dependent parameters, normally using a regression method (Sen, 2001). A number of hybrid models have been developed based on the Ångström method (i.e. Bahel et al., 1987; Yang et al., 2000a). Johnson et al. (1995) developed a sunshine duration to S_o conversion method for use in tropical rainforest canopies. This method was later applied by Woodward et al. (2001) to pastures in New Zealand. This model accounts for latitude, solar declination, elevation, day length and atmospheric transmissivity on a daily basis and has only daily sunshine duration (hours) and latitude as input. The method contains a single empirical parameter (*F*) representing the relative intensity of diffuse S_o from cloudy skies.

2.2. *Model parameterisation and testing*

Such models, regardless of their data inputs, are limited by their requirement for site-specific parameterisation. Several models exist as freely available software with parameter optimisation functions (i.e. RadEst, 2005). These however, have a minimal requirement for some observed S_o in order to perform the optimisation process. There is therefore, a need for methods to enable the spatial interpolation of empirically derived, optimised, parameters to enable utilisation of observed weather variables at sites where S_o is not available for model parameterisation.

There are limitations in evaluating models when a single test statistic (such as root mean squared error [RMSE]), or separate multiple statistics are used (e.g. Yang et al., 2000b). A single statistic will assess a particular component of model behaviour. It is possible that a model can be deemed to produce unsuitable estimates 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 accepted based on one statistic, but still contain poor qualities not assessed by appropriate tests. To resolve this, estimates of S_o made by the JW model have previously been assessed (Rivington et al., 2005) using the fuzzy logic based multiple-indices methods of Bellocchi et al. (2002). This method calculates a single indicator (*Irad*) made up from a number of individual indices representing different statistical tests for model behaviour. Such an approach provides a more comprehensive assessment of model performance.

2.3. *Spatial interpolation*

Spatial interpolation methods are employed to predict values at unknown locations from a set of point data where the property under investigation is known to exhibit spatial dependency. A variety of related techniques exist, such as Inverse Distance Weighting, Radial Basis Functions, and Kriging. These have regularly been used in the study of environmental data, such as soil properties (e.g. Uehara et al., 1985; Laslett et al., 1987), temperature (e.g. Legates and Willmott, 1990; Lennon and

Turner, 1995) and rainfall (e.g. Phillips et al., 1992; Hutchinson, 1995; Jeffrey et al., 2001). Differences between the techniques relate principally to the way in which weights applied to surrounding values are calculated. No single technique has found universal favour; indeed many studies in geostatistics have involved the comparison of techniques in order to assess the applicability of interpolation methods for a given variable (e.g. Dubrule, 1984; Voltz and Webster, 1990; Laslett, 1994; Gotway et al., 1996; Schloeder et al., 2001). The selection of an adequate interpolation method with appropriate parameters for a particular application is considered crucial (Mitas and Mitasova, 1998).

Inverse Distance Weighting (IDW) is an exact local deterministic interpolation technique which assumes that each point has a local influence that diminishes with distance (Johnston et al., 2001). The value at any unsampled location is a distance-weighted average of values at sampled points within a selected search neighbourhood. The neighbourhood may be defined by distance (and optionally direction), or by the number of surrounding sample values to be included in the interpolation. For dense datasets the search neighbourhood is commonly defined by distance and direction, whilst with sparse datasets the number of surrounding data points is usually defined. Since the dataset in question in this study is small, the latter option was chosen. The degree to which sample values influence the value at the unsampled point can be controlled by altering the power parameter (see Johnston et al., 2001). This generates smoother or rougher surfaces, with optimum values of the power parameter depending on the number of neighbouring points included.

Radial Basis Functions (RBFs) are a series of exact local deterministic interpolators which are generally used for calculating smooth surfaces from data points. Conceptually, the process involves the fitting of a flexible membrane to the data points so that the total curvature of the surface is minimised. They differ from IDW in that they allow the prediction of values above the maximum measured value and below the minimum measured value (Johnston et al., 2001). The functions produce generally good results for gently varying surfaces, but are inappropriate where there are large changes in surface values within a short horizontal distance. Although the dataset in this study is relatively sparse, it was anticipated that the F varied gently across the study area. Examples of RBFs used within this paper include completely regularised splines (CRS), splines with tension (S&T), thin plate splines (TPS), multi-quadratic (MQ) and inverse multiquadratic (InvMQ).

Kriging is a *geostatistical technique* that uses the statistical properties of the data points to make predictions of values at intervening points on the surface. This contrasts with IDW and RBFs, which are *deterministic techniques* that create surfaces based on either the extent of similarity of surrounding points or the degree of smoothing respectively. Kriging uses the semivariogram – a structural model of the data which links position, direction, and the squared difference between values of data points – to quantify spatial autocorrelation in the data. It also takes into account the configuration of the data points so that clustered points carry less weight individually than isolated points at the same distance. The autocorrelation values are then used within the interpolation to determine the weights assigned to each measured value (Journel and Huijbregts, 1978). A variety of kriging methods exist. Simple Kriging uses a known constant mean. Ordinary Kriging assumes a constant but unknown mean, whilst Universal Kriging replaces the mean with some user-defined deterministic function – usually a polynomial of order 1, 2, or 3. The success of kriging-based techniques is principally due to the use of a customised statistical distance rather than a geometric (or euclidean) distance in its attempt to decluster the available sample data (Isaaks and Srivastava, 1989, p.321).

3. Materials and methods

3.1. Meteorological data

The UK Meteorological Office provided meteorological data via the British Atmospheric Data Centre (BADC),[1] for the UK sites. Met Éireann provided data for the three sites in Eire. Sites were only included if they had daily observed global solar radiation (MJ m^{-2} 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. Daily values for the required variables were available for 25 sites (Fig. 1), for varying lengths of records between 1952 and 2000 (see Table 1). Errors, duplicates and anomalies in the original data were identified during the database (Oracle) loading process. Missing data values were filled using a search and optimisation method (Rivington et al., 2005). Post-processing checks for other abnormalities in the data were also carried out, and one years' data from one site (Bracknell – 1999) was removed from the dataset. Latitude and longitude for all sites were converted to Ordnance Survey British National Grid co-ordinates and all sites projected for analysis (Ordnance Survey, 2006).

3.2. Supporting data

For final presentation of the interpolation maps a generalised 300 m contour map of the UK was used to indicate the elevation above which interpolation of F could not be considered valid. The 300 m value was chosen since the meteorological station with the highest elevation was 242 m (average height of all stations = 75 m) which allowed for a limited extrapolation from 242 to 300 m. The 300 m contour was extracted (from the Ordnance Survey 10 m Digital Elevation Data in GB and the LandMap 25 m DEM for Eire)[2] and then buffered by 2 km, merged, and eroded by 2 km in ArcInfo (see Harlow et al., 2005). This generalisation process eliminated finger valleys and ensured a better representation of the 300 m contour at the scale of the displayed map.

3.3. F Estimation and spatial interpolation

A previously published method (Rivington et al., 2005) for estimating the F parameter was used to derive yearly values per site. The method optimises daily values of F such that the

[1] http://badc.nerc.ac.uk/home/index.html.

[2] http://www.landmap.ac.uk/download/100k_grids_selector_v2.htm.

Fig. 1 – Meteorological station locations.

JW method accurately predicts the measured S_o values using sunshine hours as the input. Yearly and long term average values for F are then derived from the daily values. Daily S_o (MJ m^{-2} day^{-1}) values can then be estimated for every year for which sunshine hours are available, using the JW model (see Johnson et al., 1995 and Rivington et al., 2005 for details of the implementation used here).

Seven different spatial interpolation techniques were performed for the annual, long-term[3] mean of the F parameter for each station. These methods were chosen for this first investigation of the spatial properties of the F parameter since they are relatively simple to implement and do not depend on the availability of secondary datasets to act as co-variates. Minimising the computational complexity and data requirements are important if the JW method is to be more widely used. The interpolations were undertaken using ESRI's ArcGIS Geostatistical Analyst (Johnston et al., 2001).

3.4. *Exploratory data analysis*

Exploratory data analysis of the LTA F data showed the dataset to have a regional scale NW-SE downwards trend. The dataset had a slight positive skew of 0.492 with a mean value of 0.81 and a median value of 0.80. The normal QQ plot, in which the quantiles of a normal distribution and the distribution are plotted relative to each other, was close to a straight line (see Johnston et al., 2001, p88). All of these tests confirmed that the dataset was near-normally distributed and did not require transformation prior to interpolation.

[3] The number of records contributing to the mean value varied between 11 and 48 (Table 1).

Table 1 – Distribution of years with data available per site

Station	1952	1953	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Aberdeen																*	*	*	*	*	*	*	*	*	*																								
Aberporth							*	*	*	*	*	*	*	*	*	*	*	*	*			*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*			*	*
Aldergrove																		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
Altnaharra																																										*						*	
Auchincruive																									*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Aviemore																																	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Bracknell																				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
Brooms Barn																													*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
Cawood																		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*			
Denver																														*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
Dunstaffnage																															*	*	*		*	*	*	*	*	*	*	*	*	*					
East Malling													*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*			
Eskdalemuir																				*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*					
Everton																			*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
Hazelrigg																																											*	*	*	*	*	*	
Lerwick	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
Mylnefield																							*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		
Rothamsted																		*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Stornoway																															*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Sutton Bonington																			*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Wallingford																					*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Jersey																	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*		*	*		
Leeds																																														*	*	*	
Hemsby																															*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	
Belmullet																																		*	*	*	*	*	*	*	*	*	*	*					
Malin Head																																		*	*	*	*	*	*	*	*	*	*	*					
Valentia																																		*	*	*	*	*	*	*	*	*	*	*					

3.5. Parameterisation of the spatial interpolation methods

For all the methods referred to above, there are parameters or design choices that require to be made. To ensure a fair comparison of the spatial interpolation methods for the LTA *F* dataset the parameterisation of each interpolation method was investigated.

The IDW was carried out using both a circular (or isotropic) and elliptical (or anisotropic) search neighbourhood for a variety of neighbourhood sizes (4–24). For each case the power parameter was optimised by cross-validation. By using an anisotropic search neighbourhood rather than a circular search neighbourhood, slight improvements in the error measurements could be observed.

The optimal value for the smoothing parameter of the RBFs was found by minimising the prediction errors using cross-validation. For splines, both tension and smoothing parameters were again set to minimise the predictive error estimated by cross-validation (Mitasova et al., 1995). The spline routines were run with varying numbers of points (from 4 to 24 stepping by 2 points), with the smoothing parameter optimised for each case. The larger the number of points considered, the smoother the interpolated surface.

For kriging, a variety of semivariogram models exist with which to model the behaviour of the experimental semivariogram cloud. Among the most commonly used of these are spherical, exponential, and gaussian models. The spherical model is frequently used in the interpolation of climatic variables. While care is required in ensuring that the empirical variogram behaviour near the origin is well represented by the model fitted, it requires a "gross mis-specification of the variogram model to have a dramatic impact on kriging estimates" (Chiles and Delfiner, 1999, p.175). As a result, the spherical semivariogram model was selected for the interpolation of the LTA *F* dataset. Simple Kriging was immediately discounted, since the mean of the stationary random function was unknown. The NW-SE trend, identified in the exploratory analysis of the dataset, had to be removed if the stationarity assumptions for Ordinary Kriging (OK) were to be met. Options for trend removal included 1st, 2nd, or 3rd order polynomials, before kriging the residuals. OK was implemented using the three orders of polynomial trend removal, each combined with isotropic or anisotropic search neighbourhoods. The size of the search neighbourhood for each combination was varied from 4 to 24 points.

Surfaces were generated using each of the methods and clipped to match the Great Britain (GB) and Eire coastline (from Ordnance Survey and MIMAS, respectively). To create a surface that covered all land areas of GB and Eire it was necessary, given the layout of the meteorological stations, to extrapolate (up to 10 km) in northern Shetland, the easternmost edge of East Anglia and west of Valentia in Eire. The surfaces output by each interpolation method were compared using the metrics defined in the next section (supplemented for OK by the kriging standard error surface generated as part of the interpolation process).

3.6. Interpolation accuracy assessment metrics

Due to the relatively small number of sites in this study, a cross-validation strategy was used. Data points were consecutively removed from the sample and the value at the removed point interpolated using the remainder of the data. Recent research has questioned the traditional practice of reporting RMSE as the sole measure of interpolation accuracy (Willmott and Matsuura, 2006) Consequently, prediction errors were calculated using a range of accuracy indicators and one measure of effectiveness (the G-measure). RMSE is the square root of the mean of the squared residuals (predicted minus observed value) and gives a high level indication of the overall accuracy of the interpolated surface. Mean absolute error (MAE) is a measure of the sum of the residuals. Small MAE values indicate a method with few errors overall. Mean error (ME) is a measure of the bias of the residuals. The MAE and ME were reported to give an indication of the size of the errors and the overall bias respectively. The G-measure gives an indication of how effective a prediction is, relative to that using the sample mean alone (Agterberg, 1984; Reich et al., 2004). A value of 100% indicates a perfect fit while a value of 0% describes no significant improvement to using the sample mean alone. The G-measure is calculated in the following manner:

$$G = \left(1 - \left\{\frac{\sum_{i=1}^{n}[z(x_i) - \hat{z}(x_i)]^2}{\sum_{i=1}^{n}[z(x_i) - \bar{z}]^2}\right\}\right) \times 100$$

where $\hat{z}(x_i)$ is the predicted value at point x_i and $\bar{z}$ is the sample mean. These metrics can be used both during parameterisation of individual interpolation methods and in the between-method comparisons.

3.7. Year-to-year variability testing

The year-to-year variability dataset provided a context for assessing the magnitude of the cross-validation errors that resulted from interpolating the LTA *F* parameter. Following interpolation of the LTA *F* dataset, interpolations of Year-specific *F* were attempted for each individual year between 1985 and 1995 to give a map view of how the *F* parameter varied through time and space. The range of years selected represented those years with the greatest number of available stations in the network (see Table 1). However, due to the already low density of station points, the increased variability of the datasets caused instability in the semivariograms to such an extent that it became impossible to use them for spatial interpolation for some of the years. As a result, this approach was discontinued.

3.8. Solar radiation predictions

S_o values were estimated using the site optimised LTA *F* parameter values (F_O), and the interpolated LTA *F* parameter values (F_I), for each site. This gave an indication of the level of error in the calculation of solar radiation being introduced by using interpolated F_I values against the F_O. Evaluations of estimate quality were made using the fuzzy logic based multiple-indices assessment system of Bellocchi et al. (2002) as applied by Rivington et al. (2005) and Diodata and Bellocchi (2007). This method permits a flexible structure in which a range of indices and test statistics can be aggregated into modules which are then 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, and modules into *Irad*. The indices used were: Relative Root Mean Square Error (RRMSE), Modelling Efficiency (EF), the probability of paired Student's-*t* test (P(*t*)), forming the module 'Accuracy'; the correlation coefficient of the estimates versus measurements (*R*), forming the module 'Correlation'; and two Pattern Indices, one computed versus day of year (PI*doy*), and the other versus minimum temperature (PI*Tmin*), forming the module 'Patterns'. Further details on the Pattern Indices are given in Donatelli et al. (2004).

Further to this, the difference between mean daily observed S_o and that derived from the F_O values and the F_I values were estimated. The difference between the daily S_o derived from the F_O values and the F_I values were also estimated.

4. Results

4.1. Parameterisation of interpolation methods

Table 2 shows the cross-validation results of the parameterisation testing conducted for IDW RBFs, and OK for the LTA *F* dataset. The statistics for the most successful parameterisation for each interpolation method are highlighted. Table 3 shows the effect of different combinations of trend removal (1st, 2nd, and 3rd order polynomials) and isotropic and anisotropic search neighbourhoods for OK.

4.2. Maps of LTA F

Fig. 2 shows the surfaces produced with each interpolation method, using the best parameterisations found in testing. The interpolated surfaces are presented as choropleth maps with nine steps across the range of surface values. The kriging standard error map associated with the OK surface is also presented. Fig. 3 shows the surface generated with OK in more detail and with the land areas above 300 m masked.

4.3. Variability in F parameter

Table 4 shows the year-to-year variation in the *F* parameter for the 25 stations used in the interpolations together with the interpolation errors for the optimal surface. The table shows for the *F* parameter the mean (observed *F*), range, predicted *F* via OK, the difference between the observed *F* and the predicted value, standard deviation, coefficient of variation (%) and the number of years of available data. The final column expresses the value of the absolute difference (AD) as a proportion of on-site *F* standard deviation. This gives an indication of the level of cross-validation error when compared to the variability of *F* at any given site.

Fig. 4 shows the year-to-year variation in the *F* parameter at a number of representative sites together with the variation in the mean annual for each year between 1952 and 2000.

4.4. Effect of interpolation errors on solar radiation predictions

Fig. 5 shows the difference between mean daily S_o data derived from F_O and F_I parameter values for the periods 1981–98 at Denver (where the interpolated *F* parameter was under-estimated), and 1967–76 at Aberdeen (where the interpolated *F* parameter was over-estimated). The systematic error existing in the JW model, as also observed by Rivington et al. (2005) can be seen, where the model over-estimates in the winter and under-estimates in the summer (most noticeable at Aberdeen). The S_o data derived from F_I shows very little difference from those from F_O (mean daily difference of -0.229 and 0.280 MJ m^{-2} day^{-1}, see Fig. 5, and annual total difference of -83.54 and 100.69 MJ m^{-2} day^{-1} at Denver and Aberdeen, respectively). These under- and over-estimated annual totals are comparable to the amount of S_o received over approximately 3–4 summer days. This indicates that the OK interpolation method introduces only a very small addition error to the estimation of S_o using the JW model.

The results for individual years of daily S_o data derived from F_O and F_I parameter (1987 for Denver, and 1991 for Aberdeen) again show close similarity (mean daily difference of -0.242 and 0.278 MJ m^{-2} day^{-1}, and an annual total difference of -88.15 and 101.39 MJ m^{-2} day^{-1} at Denver and Aberdeen, respectively). Again, these can be translated into an annual total under- and over-estimation error equivalent to about 3–4 days of summer S_o. The JW model produces some large errors, i.e. at Aberdeen (the largest being an under-estimation of 15 MJ m^{-2} day^{-1}). These large errors are possibly due to the sea-fog (Haar) effect commonly found there, which would distort the role of the *F* parameter. Whilst these are errors of an occasionally large magnitude, they exist consistently throughout the year as over- and under-estimations (Fig. 5), hence the impact of the data on end use, i.e. within a crop model will be reduced due to the compensating error effect.

Table 5 shows the results of testing the S_o data derived from F_O and F_I parameters using the *Irad* multiple-metrics evaluation method. Here metrics are assigned weightings and aggregated into modules, which are also assigned weightings. A further level of aggregation of the modules produces the single indicator *Irad* (0 = good estimate quality, 1 = poor estimate quality). The mean for each metric value across all sites show very little change. Generally the F_I values are very slightly higher, except for the pattern indices (PI*doy* and PI*Tmin*), which are marginally lower. The mean *Irad* values across all sites shows that the S_o data derived from F_O and F_I parameters are very similar (F_I *Irad* = 0.147, F_O *Irad* = 0.166).

The individual metrics used to determine *Irad* per site show very little change between S_o data derived from the F_O and F_I parameter. The F_I S_o data occasionally show an improvement, both in individual metrics and *Irad*, over the F_O S_o data. These improvements in *Irad* values can be attributed to the lower values for individual metrics, primarily the pattern indices (PI*doy* and PI*Tmin*), and the weightings assigned to them and their respective modules. For example at Aberporth there is an improvement in the pattern indices from using F_I, leading to the *Irad* value decreasing from 0.246 for the F_O derived S_o data, to 0.073. Other sites where a similar change in pattern indices and *Irad* occur are all west coast locations (i.e. Aldergrove, Belmullet, Dunstaffnage), which generally have greater amounts of cloud cover. Weightings for the pattern indices and the Pattern module favour reduction in *Irad*. These changes in *Irad* have to be put into context of the overall multiple-metric assessment approach, as the magnitude of

Table 2 – Cross-validation results with anisotropic search neighbourhoods (OK includes 1st order polynomial trend removal)

Interpolation method	Accuracy or effectiveness measure	Neighbourhood										
		4	6	8	10	12	14	16	18	20	22	24
IDW	RMSE	0.0565	0.0559	0.0564	**0.0547**	0.0558	0.0567	0.0562	0.0568	0.0572	0.0572	0.0573
	MAE	0.0468	0.0457	0.0435	**0.0423**	0.0441	0.0446	0.0442	0.0446	0.0448	0.0449	0.0449
	ME	−0.0084	−0.0113	−0.0129	**−0.0109**	−0.0105	−0.0116	−0.0117	−0.0126	−0.0127	−0.0127	−0.0127
	G-Measure	46.9	47.9	47.1	**50.1**	48.1	46.6	47.4	46.2	45.6	45.5	45.4
CRS	RMSE	0.0582	0.0579	0.0580	**0.0566**	0.0581	0.0588	0.0585	0.0589	0.0580	0.0582	0.0583
	MAE	0.0465	0.0460	0.0439	**0.0431**	0.0449	0.0451	0.0446	0.0448	0.0445	0.0446	0.0448
	ME	−0.0076	−0.0096	−0.0092	**−0.0074**	−0.0057	−0.0056	−0.0055	−0.0057	−0.0043	−0.0035	−0.0026
	G-Measure	43.6	44.3	44.0	**46.6**	43.9	42.5	43.1	42.3	43.9	43.6	43.3
S&T	RMSE	0.0577	0.0573	0.0576	**0.0561**	0.0578	0.0587	0.0584	0.0589	0.0582	0.0583	0.0584
	MAE	0.0464	0.0456	0.0437	**0.0427**	0.0448	0.0450	0.0443	0.0444	0.0444	0.0445	0.0448
	ME	−0.0077	−0.0100	−0.0098	**−0.0077**	−0.0058	−0.0058	−0.0056	−0.0059	−0.0044	−0.0035	−0.0025
	G-Measure	44.5	45.3	44.7	**47.7**	44.4	42.7	43.3	42.2	43.7	43.4	43.2
TPS	RMSE	0.1438	0.0987	0.1011	0.0906	0.0982	0.0956	0.0949	0.0946	0.0946	0.0891	**0.0881**
	MAE	0.1015	0.0755	0.0788	0.0730	0.0776	0.0752	0.0735	0.0737	0.0728	0.0702	**0.0699**
	ME	−0.0002	0.0089	0.0079	0.0029	−0.0034	−0.0019	−0.0029	−0.0019	−0.0019	0.0002	**0.0006**
	G-Measure	−244.4	−62.3	−70.2	−36.5	−60.5	−52.0	−49.8	−49.0	−49.0	−32.1	**−29.2**
MQ	RMSE	0.0657	0.0638	0.0635	0.0633	0.0642	0.0631	0.0635	0.0631	**0.0619**	**0.0619**	0.0620
	MAE	0.0538	0.0526	0.0530	0.0524	0.0532	0.0527	0.0532	0.0530	**0.0479**	**0.0524**	0.0524
	ME	−0.0057	−0.0034	−0.0015	−0.0019	−0.0027	−0.0018	−0.0027	−0.0023	**−0.0016**	**−0.0013**	−0.0014
	G-Measure	28.0	32.2	32.9	33.4	31.4	33.6	32.9	33.6	**36.2**	**36.2**	36.0
InvMQ	RMSE	0.0558	0.0556	0.0568	**0.0543**	0.0580	0.0602	0.0601	0.0613	0.0613	0.0619	0.0624
	MAE	0.0463	0.0460	0.0436	**0.0416**	0.0451	0.0456	0.0447	0.0456	0.0463	0.0465	0.0472
	ME	−0.0081	−0.0123	−0.0139	**−0.0095**	−0.0068	−0.0075	−0.0074	−0.0078	−0.0059	−0.0048	−0.0034
	G-Measure	48.2	48.5	46.4	**51.0**	44.0	39.7	39.9	37.5	37.4	36.2	35.3
OK	RMSE	0.0536	0.0525	0.0504	0.0502	0.0497	0.0477	0.0493	0.0495	**0.0484**	0.0487	0.0488
	MAE	0.0444	0.0424	0.0418	0.0407	0.0409	0.0405	0.0404	0.0408	**0.0395**	0.0402	0.0400
	ME	−0.0079	−0.0048	−0.0039	−0.0020	−0.0012	−0.0022	−0.0012	−0.0007	**−0.0005**	−0.0011	−0.0010
	G-Measure	52.2	54.1	57.8	58.1	58.8	58.9	59.5	59.2	**61.0**	60.5	60.3

Table 3 – Effects of trend removal and search shape for ordinary kriging of JW-*F*

	1st order trend removal		2nd order trend removal		3rd order trend removal	
	Isotropic	Anisotropic	Isotropic	Anisotropic	Isotropic	Anisotropic
Optimal neighbourhood	**20**	**18**	**20**	**6**	**20**	**6**
RMSE	**0.0484**	0.0490	0.0587	0.0579	0.1108	0.1106
MAE	**0.0395**	0.0401	0.0472	0.0475	0.0751	0.0766
ME	**−0.0005**	0.0007	−0.0014	−0.0005	0.0038	0.0033
G-measure (%)	**61.0**	60.0	42.7	44.1	−104.3	−103.7

the change is relative to the overall range (0–1), where any *Irad* value below approximately 0.3 indicates good estimate quality. The calculation of *Irad* follows an 'S' shaped curve (0–1), whereby a change from 0.246 to 0.073 occurs at the near asymptotic phase, and hence does not reflect a substantial improvement in estimate. These results also indicate the possible limitation of the original optimisation method used to produce the F_O value, which aimed to minimise the difference

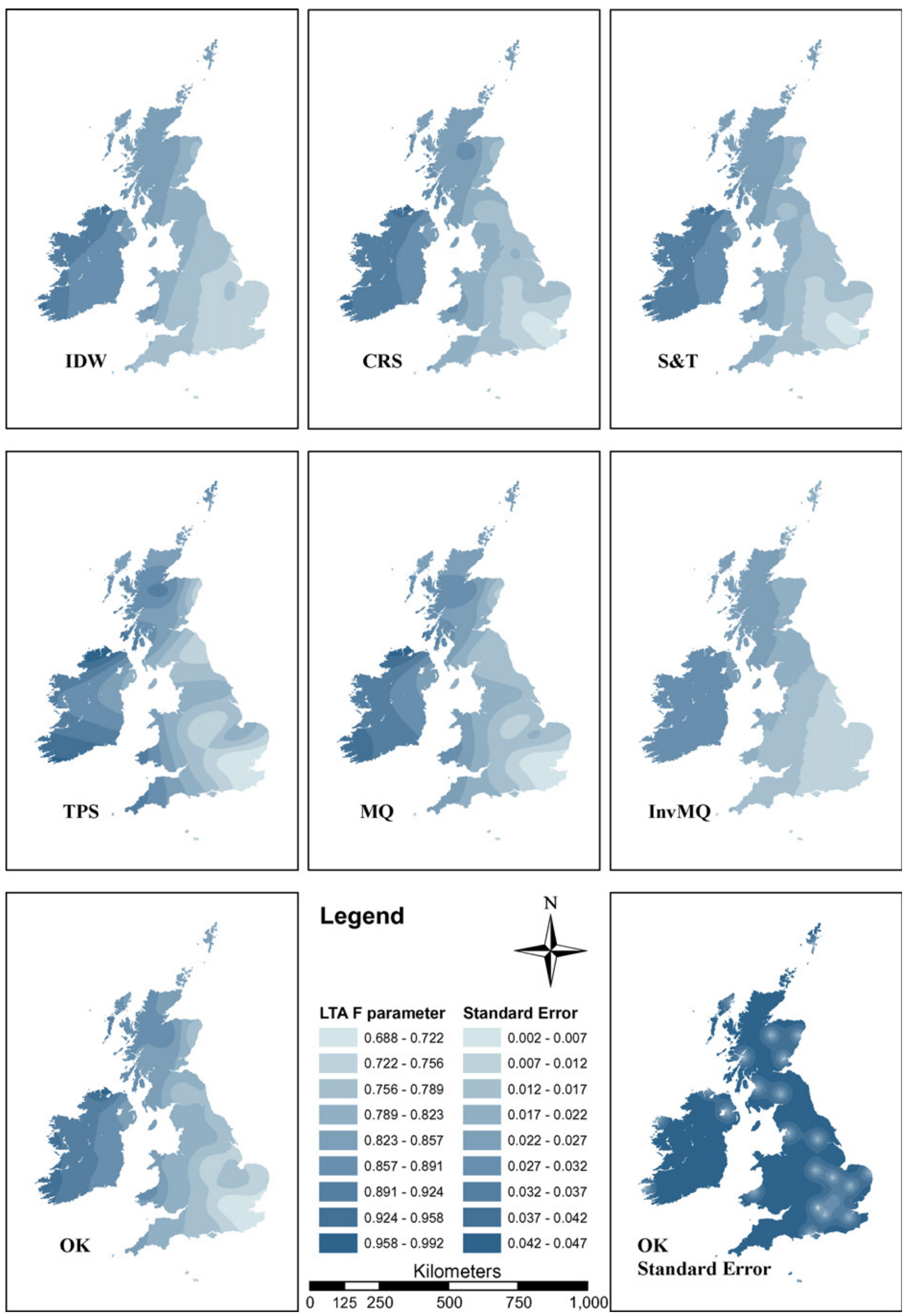

Fig. 2 – Comparison of the spatial interpolations of long term average (LTA) *F* value.

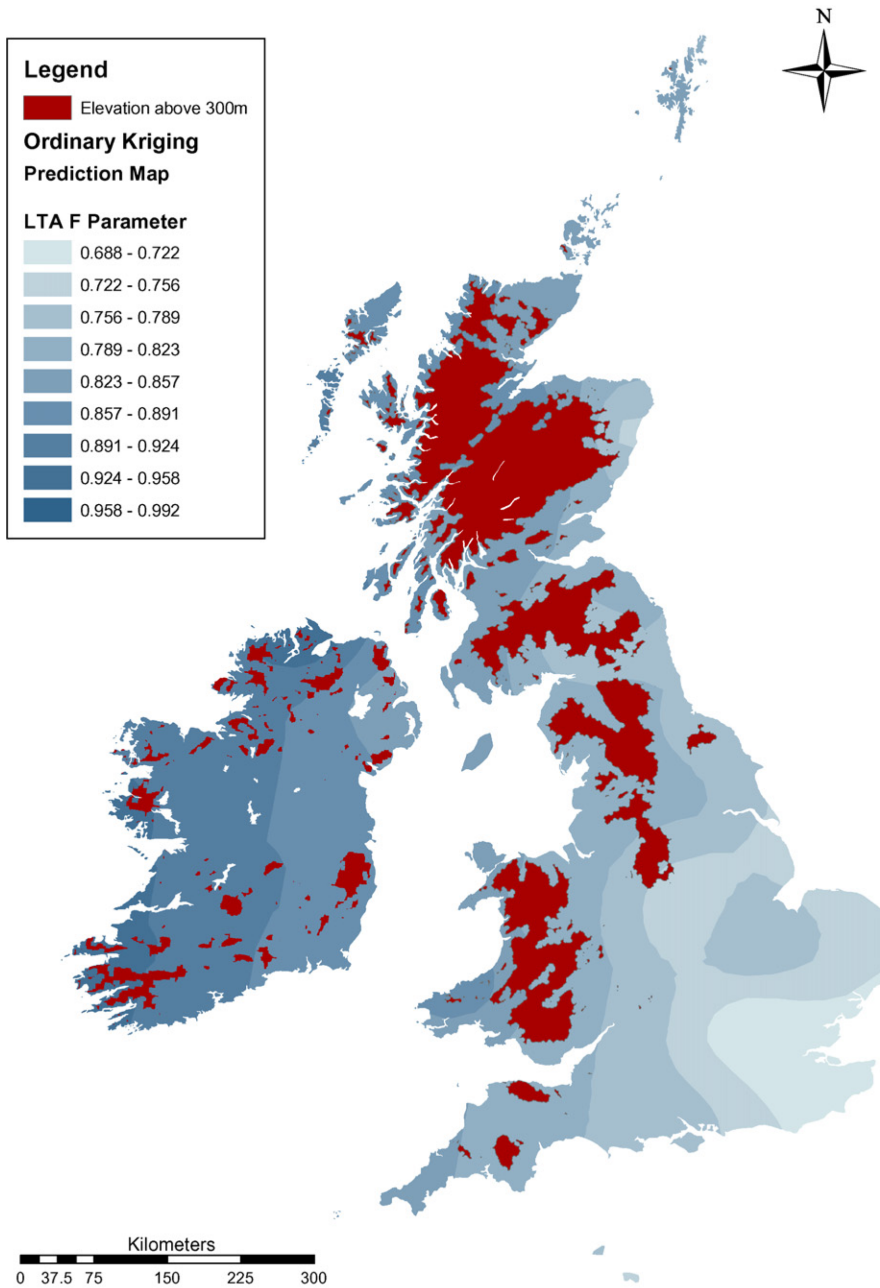

Fig. 3 – Interpolation of long term average – *F* values masked by 300 m contour.

in daily means between observed and estimated S_o data, rather than more detailed aspects such as patterns.

5. Discussion

5.1. *Interpolation methods*

The testing of alternative spatial interpolation methods was useful as it confirmed the need for care when selecting interpolation methods and in their parameterisation. The most successful of the methods tested for the *F* parameter was OK with a G-measure of 61.0%, compared with the two next best methods InvMQ (G = 50.9%) and IDW (G = 50.1%), (see Table 4). Indeed inspecting Table 2 shows that OK remains more accurate than the deterministic methods even with small numbers of points in the search neighbourhood. Visually all interpolations capture the broad NW-SE trend in the *F* parameter. Ordinary kriging can be seen to achieve a higher level of detail in the interpolated surface than is achieved by the IDW and InvMQ while not suffering from the artefacts, indicated by negative G-measure values, of TPS or MQ (see Fig. 2).

While it is possible to conclude that *F* parameter may be interpolated, the magnitudes of the errors associated with the process are significant. Overall measures of accuracy such as RMSE tend to mask areas where the interpolation is less robust. The largest errors (highlighted in Table 4) in the cross-validation are often associated with sites at the edges of

Table 4 – Year-to-year variability of JW-*F* compared with interpolation errors for optimal surface (OK)

Station	Observed *F*	Range (max–min)	Predicted *F*	Difference (Observed *F* – predicted *F*)	Standard deviation	Coefficient of variation (%)	N (years)	AD/ standard deviation
Aberdeen	0.737	0.278	0.821	0.084	0.083	11.21	10	**1.01**
Aberporth	0.884	0.292	0.824	−0.060	0.068	7.68	39	0.88
Aldergrove	0.839	0.220	0.870	0.031	0.048	5.67	30	0.65
Auchincruive	0.850	0.237	0.840	−0.010	0.064	7.51	24	0.16
Aviemore	0.890	0.138	0.833	−0.057	0.040	4.47	16	**1.43**
Belmullet	0.909	0.316	0.947	0.038	0.086	9.52	11	0.44
Bracknell	0.723	0.209	0.724	0.001	0.047	6.43	28	0.02
Brooms Barn	0.754	0.188	0.736	−0.018	0.055	7.25	19	0.33
Cawood	0.797	0.332	0.771	−0.026	0.075	9.47	29	0.34
Denver	0.806	0.167	0.738	−0.068	0.041	5.14	18	**1.64**
Dunstaffnage	0.846	0.377	0.866	0.020	0.097	11.41	13	0.21
East Malling	0.688	0.281	0.725	0.037	0.066	9.62	34	0.56
Eskdalemuir	0.760	0.183	0.818	0.058	0.051	6.77	25	**1.13**
Everton	0.786	0.344	0.759	−0.027	0.077	9.84	29	0.35
Hazelrigg	0.802	0.063	0.803	0.001	0.029	3.57	6	0.03
Hemsby	0.760	0.167	0.706	−0.054	0.044	5.76	18	**1.23**
Jersey	0.752	0.243	0.768	0.016	0.057	7.51	30	0.28
Lerwick	0.850	0.202	0.794	−0.056	0.043	5.09	48	**1.29**
Malin Head	0.992	0.191	0.879	−0.113	0.046	4.63	11	**2.46**
Mylnefield	0.817	0.301	0.823	0.006	0.070	8.61	25	0.09
Rothamsted	0.689	0.347	0.738	0.049	0.086	12.51	31	0.57
Stornoway	0.833	0.133	0.896	0.063	0.034	4.11	18	**1.84**
Sutton Bonington	0.713	0.347	0.782	0.069	0.073	10.21	30	0.95
Valentia	0.947	0.159	0.936	−0.011	0.045	4.72	11	0.25
Wallingford	0.727	0.359	0.742	0.015	0.087	12.03	28	0.17
Overall mean	0.806	0.243	0.806	0.000	0.060	7.63	23.2	0.73
Standard deviation	0.079	0.085	0.067	0.049	0.019	2.68	10.2	0.64

geographic and altitudinal space, for example Aberdeen (N&E), Aviemore and Eskdalemuir (altitude), Hemsby (E), Lerwick (N) and Stornoway (N&W). This points to the strictly limited ability of the methods to extrapolate. Another error of note is that for Malin Head where cloud cover is significantly greater than for other sites in the immediate vicinity, due both to its greater than average distance from other sites and its exposed situation on the west coast. The mean value of the absolute errors in prediction expressed in standard deviations is 0.73, (Table 4). The closer this value is to zero, the better the predicted value of *F* corresponds with the observed value of *F*, so the errors introduced by spatial interpolation using even

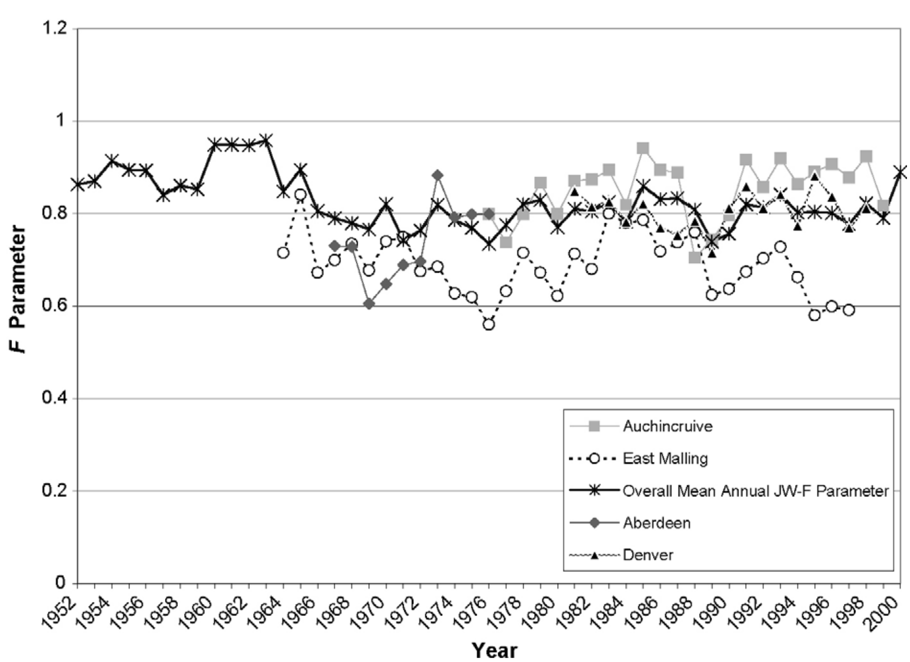

Fig. 4 – Year to year variability in JW-*F* for selected sites.

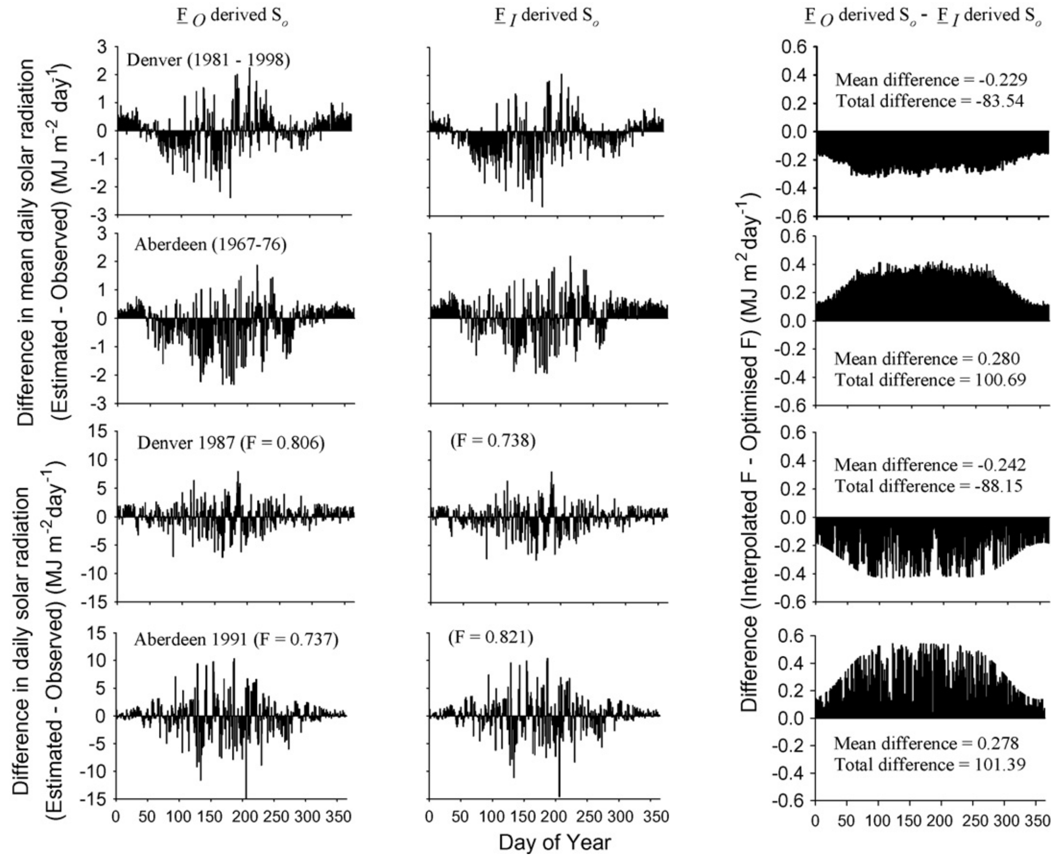

Fig. 5 – Difference in mean daily (top left four plots) and daily (bottom left four plots) solar radiation (F_O derived S_o – observed S_o and F_I derived S_o – observed S_o). The right hand plots show the daily mean and annual total differences (F_O derived S_o – F_I derived S_o) (MJ m^{-2} day^{-1}).

the best of the tested methods are significant. Comparing the difference values with the range of annual values in Table 4, it is, however, clear that the errors introduced by spatial interpolation are much smaller than those that might be introduced by using a year specific value for F rather than a long term average value.

A significant limitation of the analysis is the sparse network of observation stations for which data were available. It is not possible to say whether data from 25 points is enough to capture the spatial variability of F across the British Isles. The prediction standard error map for the OK generated surface (Fig. 3) is an indication (for geographic space) of the spatial pattern of uncertainty (but does not provide a map of uncertainty associated with changes in elevation which may be a significant factor). It shows that other than for areas very close to actual observed values (i.e. the observation stations), and other than the south-east of England where the concentration of observation stations is most dense, the prediction errors are uniform across much of the study area. Only by substantially increasing the network of observation stations would this problem be overcome (and this is of course impossible for historical cases).

5.2. *Solar radiation estimation*

The effect of the spatial interpolation errors in the F parameter on S_o calculation are not substantial. Whilst the JW model, using a site-optimised F (derived from observed S_o), makes some large over- and under-estimates (i.e. at Aberdeen, 1991, Fig. 5), the additional error introduced by the interpolation is very small. The total difference, as illustrated in Fig. 5, equates to an error of approximately 3–4 days of summer S_o within a year. In relation to the end use of the F_I derived S_o, the mean daily difference would have a negligible impact if used in a crop model. Whilst differences in crop model estimates will exist when using observed S_o and F_O derived S_o, due to limitations of the JW S_o method (or any other model), additional errors resulting from using F_I derived S_o will be small. For example, for a light to biomass conversion value of 3 (g of biomass per MJ m^{-2} day^{-1} S_o) over a 21 day period (day 170–190) at Denver, where the observed mean S_o is 18.56 MJ m^{-2} day^{-1} (1981–98) would produce 55.7 g of biomass per day and 1169.3 g over the 21 days. Using the mean daily error from Denver (−0.242 MJ m^{-2} day^{-1} in 1987) from using the F_I gives a daily mean S_o of 18.32 MJ m^{-2}, which would produce 54.6 g of biomass per day (1.1 g less) and 1146.6 over the 21 days (22.7 g less). Using actual, as opposed to 21 day mean values of S_o (with day to day variability) would produce similarly small differences, due to the compensating error effect of over- and under-estimates of S_o. These errors would be less for other times in the year, as the period of day 170–190 exemplifies the time of year when the JW model makes its largest over- and under-estimates (i.e. Fig. 5). Hence the overall

Table 5 – Individual metrics and derived *Irad* results for the site optimised F (F_O) and interpolated F (F_I)

Location	N (years)	Mean index values													
		RRMSE		Paired *t*-test		EF		Correlation		PI*doy*		PIT*min*		Mean Irad values	
		F_O	F_I	F_O	F_I	F_O	F_I	F_O	F_I	F_O	F_I	F_O	F_I	F_O	F_I
Aberdeen	9	26.84	29.37	0.205	0.287	0.899	0.876	0.956	0.941	0.894	0.919	0.719	0.693	0.080	0.080
Aberporth	36	27.86	23.52	0.271	0.338	0.865	0.898	0.936	0.951	1.802	1.345	1.485	1.126	0.246	0.073
Aldergrove	25	26.67	25.56	0.227	0.342	0.745	0.895	0.904	0.951	2.049	1.157	1.519	1.086	0.201	0.060
Auchincruive	19	28.73	28.10	0.143	0.185	0.876	0.882	0.941	0.943	1.667	1.583	1.520	1.471	0.266	0.257
Aviemore	8	26.54	24.44	0.021	0.336	0.898	0.909	0.951	0.955	1.614	1.172	0.751	0.815	0.063	0.196
Belmullet	10	27.56	28.04	0.073	0.052	0.876	0.869	0.940	0.937	2.035	2.043	1.624	1.672	0.288	0.196
Bracknell	28	23.89	23.95	0.224	0.131	0.898	0.897	0.961	0.961	0.802	0.841	1.097	1.149	0.044	0.032
Brooms Barn	16	24.47	23.88	0.190	0.167	0.891	0.896	0.958	0.959	1.150	1.061	1.053	0.935	0.109	0.049
Cawood	29	26.92	27.12	0.164	0.297	0.879	0.878	0.946	0.946	1.140	1.069	1.011	0.984	0.172	0.138
Denver	18	23.42	23.92	0.340	0.180	0.899	0.895	0.956	0.954	0.958	0.997	0.701	0.710	0.034	0.017
Dunstaffnage	13	28.06	29.68	0.122	0.168	0.899	0.884	0.951	0.943	1.571	1.472	1.098	1.126	0.207	0.113
East Malling	34	25.02	24.88	0.187	0.162	0.890	0.891	0.960	0.960	0.908	0.899	0.992	1.005	0.086	0.096
Eskdalemuir	25	27.02	26.61	0.231	0.306	0.901	0.903	0.953	0.954	1.076	0.976	0.979	1.011	0.086	0.082
Everton	29	26.73	26.69	0.166	0.202	0.862	0.862	0.948	0.948	1.154	1.144	1.184	1.173	0.147	0.098
Hazelrigg	6	25.34	29.81	0.240	0.227	0.905	0.867	0.957	0.936	0.986	1.298	1.233	1.097	0.171	0.176
Lerwick	41	28.04	28.95	0.131	0.010	0.909	0.902	0.956	0.953	1.763	1.860	1.144	1.222	0.222	0.301
Malin Head	10	24.09	25.81	0.011	0.020	0.914	0.901	0.958	0.955	1.939	2.129	1.433	1.633	0.246	0.287
Mylnefield	23	28.33	27.55	0.193	0.183	0.887	0.883	0.946	0.948	1.325	1.325	0.916	0.967	0.140	0.139
Rothamsted	30	26.96	26.66	0.148	0.134	0.873	0.876	0.954	0.955	0.885	0.880	1.100	1.090	0.135	0.150
Stornoway	15	25.29	25.01	0.075	0.304	0.916	0.917	0.959	0.959	1.535	1.249	1.044	0.857	0.131	0.051
Sutton Bonington	26	35.27	34.37	0.394	0.157	0.766	0.780	0.893	0.899	1.127	1.075	1.147	1.036	0.228	0.255
Valentia	10	25.77	25.43	0.207	0.219	0.894	0.895	0.947	0.948	2.258	2.270	1.599	1.645	0.278	0.285
Wallingford	26	24.87	24.74	0.124	0.174	0.891	0.892	0.953	0.953	1.123	1.122	0.887	0.874	0.240	0.240
Mean		26.68	26.70	0.178	0.199	0.880	0.885	0.947	0.948	1.381	1.299	1.141	1.103	0.166	0.147

impact of using F_I is not only small, but can also be quantified in relation to the end use of the F_I derived S_o.

The small differences between F_O and F_I derived S_o demonstrates that a moderate degree of variability in the F parameter has no appreciably detrimental effect on calculation of S_o estimates. This further demonstrates the robustness of the JW model and confirms that interpolation of the F parameter is a viable option when observed S_o is not available for model calibration.

However, the results gained from use of F_I compared with those from F_O indicate that the JW model's performance was improved in some cases. Rivington et al. (2005) showed that the JW model has a systematic bias, where the model over-estimates in the winter and under-estimates in the summer. The F parameter controls the relative contribution of diffuse radiation on cloudy days, and is thought to determine the seasonal over- and under-estimation errors. The reduced *Irad* values seen in the F_I derived S_o data at some locations may be due to an unintended reduction in this systematic bias seen in the F_O derived S_o estimates. Using the F_O value appears to provide an introduced compensating error that partially reduces the systematic error at some locations. Again, the magnitude of these errors is still relatively small. However, what these results show is that care is needed to determine how the interpolation of a model parameter influences model estimates. In this case the interpolation of F resulted in an improvement in model performance at some locations, but a slight deterioration at others. The important point is that, however parameter values are derived (spatial interpolation as here, statistical or empirical methods, etc.), model outputs should be assessed to determine how the derivation method introduces uncertainty and how the errors manifest themselves.

6. Conclusion

The aim of this paper was to conduct an initial investigation into how well the F parameter could be spatially interpolated with the intention of using the interpolated values as a basis for calibrating the JW model at sites without on-site solar radiation measurements. The ordinary kriging approach produced the best method for the spatial interpolation of the F parameter. It is concluded that the spatial interpolation of the F parameter is feasible and does not introduce unacceptable errors (at least in UK and Eire and regions with similar densities of meteorological station networks). There are very small differences between solar radiation data estimated using an on-site long term average F and those derived from the interpolated F. Therefore, in this example, the interpolation process does not introduce a significant error. Indeed, due to the systematic error known to exist with the JW model, the interpolated F in some cases results in compensating errors within the estimation of solar radiation, unintentionally improving the JW model performance. The research has also shown that the JW model is robust and has relatively low sensitivity to variations in the F parameter. Thus the application of the JW method at sites without on-site solar radiation measurements is possible.

The spatial interpolation techniques used were deliberately chosen for their simplicity S_o as not to introduce additional data or parameterisation requirements. They thus rely entirely on the spatial structures within the datasets. Since the definition of F relates to sunshine duration, it may thus be possible to use co-variates in the spatial interpolation of the F value. Examples would include altitude (relatively widely available from DEMs), distance to the sea (definable within a GIS from coastline data) and most significantly cloud type and cover. A relationship between F and rainfall would be particularly useful since rainfall is measured at a much greater number of sites across the UK However, there can be a wide range in correlations between amount of rain and amount of sunshine.

Fundamentally, this research demonstrates that careful selection, and use, of appropriate interpolation techniques allows the application of robust models, with basic parameterisation requirements, to locations where parameterisation using observed data is not possible.

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