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Evaluating uncertainty introduced to process-based simulation model estimates by alternative sources of meteorological data

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Abstract

Models that represent biophysical processes in hydrology, ecology and agricultural systems, when applied at specific locations, can make estimates with significant errors if meteorological input data are not representative of the sites. This is particularly important where the estimates from the models are used for decision support, strategic planning and policy development, due to the impacts of introduced uncertainty. This paper investigates the impacts of meteorological data sources on a cropping systems simulation model's estimate of crop yield, and quantifies the uncertainty that arises when site-specific weather data are not available. In the UK, as elsewhere, many meteorological stations record precipitation and air temperature, but very few also record solar radiation, a key driving input data set. The impacts of using on-site observed precipitation and temperature with estimated solar radiation, and off-site entirely observed meteorological data was tested on the model's yield estimates. This gave two scenarios: on-site observed versus partially modelled data; and on-site observed versus substitute data from neighbouring sites, for 24 meteorological stations in the UK.

The analysis indicates that neighbouring meteorological stations can often be an inappropriate source of data. Of the 24 stations used, only 32% of the nearest neighbours were able to provide the best substitute off-site data. On-site modelled data provided better results than

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observed off-site data. The results demonstrate that the range of alternative data sources tested are capable of having both acceptable and unacceptable impacts on model performance across a range of assessment metrics, i.e. on-site data sources each produced yield over- or under-estimate errors greater than 2 t ha^{-1}. A large amount of uncertainty can be introduced to the model estimates due to the data source. Therefore, the applications of models that represent biophysical process where meteorological data are required, need to include the quantification of input data errors and estimate of the uncertainty that imperfect data will introduce.

Keywords: Meteorological data; Solar radiation; Simulation model; Uncertainty; Error propagation; Decision support; CropSyst

1. Introduction

There often exists a significant difference between the sophistication of models developed to represent natural processes and our ability to provide the required biophysical input data at a particular place of model application (PoMA). It may be desirable to apply a detailed model for a site-specific case study where biophysical data does not exist, hence the model becomes redundant if the quality of the input data leads to unreliable estimates. The lack of location-specific input data for spatially and temporally variable entities means that a model's site-specific estimates have potentially large and unquantified uncertainties.

There is a serious limit on the application of agricultural, hydrological and ecosystem models if weather data are not directly available (Hoogenboom, 2000; Bechini et al., 2000). The weather is one of the primary driving variables in biophysical processes and in determining human intervention through management responses. This is particularly the case in farming systems. The influence of the weather on biological processes tends to be non-linear (i.e. Nonhebel, 1994a), and is dependent on the correlations between individual weather variables. Models that represent multiple entities with complex biophysical interactions between them therefore require meteorological data that maintains appropriate values and correlations between variables.

Inappropriate choices of data source can have significant impacts on model estimates (Rivington et al., 2002), introducing uncertainties which manifest themselves as incorrect estimations of magnitudes, absolute values, relative timing and synchronisation. Appropriate location-specific data are also essential for model calibration and parameterisation, as non-representative data will result in unsuitable parameters for the PoMA. The consequences of data source choices are particularly important when models are used as components for decision support systems (DSS), strategic planning and policy development (i.e. in climate change impact studies; Rivington et al., 2004). Errors may be propagated through the model, leading to incorrect conclusions, recommendations or policy formulation. Using model estimates for decision support requires that the quality of model estimates is assessed in advance, or that the DSS outcomes be made insensitive to the prediction uncertainty (Norton, 2003). Hence the source of the data then becomes critical in ensuring the reliability of the model estimates and subsequent DSS outputs. Assumptions made about the impacts of introduced uncertainty often go unspecified.

Our aim was to illustrate how using substitute meteorological data introduces uncertainty to the yield estimates made by a simulation model. Uncertainty and the role of input meteorological data is discussed. The methodological approach taken reflects the practical problems that people applying models face when they are required to choose a data source for a PoMA. We examined the impacts on yield estimates of using either observed on-site precipitation and temperature with estimated solar radiation (three methods), or observed off-site alternative meteorological station data. A range of assessment metrics help illustrate the way in which introduced uncertainty manifest themselves. Whilst this provides valuable information on the introduced uncertainty arising from the choice of weather data source, it does not distinguish between the data types and their individual contribution to estimate uncertainty.

2. Related research

This section looks at the introduction of uncertainty to models, particularly by meteorological data, then considers the range of options for data source selection, reflecting the practical choices that people applying models have to make. There is an emphasis on solar radiation data estimation methods, as this is a rarely observed data type which is essential for many modelling functions.

2.1. Uncertainty in model estimates

Few researchers quantify the impacts that data and parameter uncertainty have on the quality of model estimates. In applications of models to engineering problems, assessments are often made of the uncertainty that input data quality may introduce (J.P. Norton, personal comment, Law and Kelton, 1991). However, it is rare that natural systems researchers publish the uncertainty in model estimates that may arise as a result of the quality of input data. Martorana and Bellocchi (1999) discuss uncertainty relevant to agro-ecosystem models, highlighting a classification of five uncontrolled variable sources of uncertainty: inputs; initial values; measurement errors in observations; structural and operational uncertainty. It is useful, in order to reduce it, to distinguish uncertainty arising from the lack of information (degree of confidence) and that due to temporal and spatial variability (Heuburger and Janssen, 1994). Weather data can be seen to fall into both categories, as errors can occur when measurements are made and they have potentially large, and either continuous (i.e. temperature) or discontinuous (i.e. precipitation) spatial and temporal variability. Whilst a number of methods exist to investigate the relationships between model estimates and inputs, the more easily applied methods may still give inaccurate estimates of uncertainty. Methods that do, tend to be either difficult to apply or require considerable computational effort (Tyagi and Haan, 2001). This implies that, in order for a basic level of uncertainty analysis to be applied more regularly to model applications, a simple but reliable method is required.

2.2. Meteorological data as a source of uncertainty

Heinmann et al. (2002) showed that the accuracy of rainfall observations is critical for the simulation of yield and that the variability of simulated estimates is directly correlated to the accuracy of model inputs. This emphasizes the importance of data quality (accuracy of measurement), as well as site-specific representation. Xie et al. (2003) evaluated the importance of input variables on the yield estimates made for maize and sorghum by the ALMANAC model. They concluded that, in a dryland environment, rainfall and then solar radiation were the most important of the meteorological variables for non-irrigated crops, and solar radiation where irrigation was applied. These authors recommended the use of the closest weather station as an appropriate substitute source of meteorological data. However, Rivington et al. (2003) found there could be substantial levels of uncertainty introduced by using neighbouring station data. Aggarwal (1995) tested the relationships between the uncertainty in crop, soil and meteorological inputs with the resulting uncertainties in estimates of yield, evapotranspiration and crop nitrogen uptake, within a deterministic crop growth model. It was then possible to identify the 'uncertainty importance' of an input for a given scenario, concluding that in rain fed environments soil and weather inputs were dominant over crop parameters in introducing uncertainty.

Solar radiation is a key variable as it is used, amongst other things, as part of the estimation of evapotranspiration (ET) and biomass accumulation. Bellocchi et al. (2003) tested the impacts of three air temperature based methods for estimating solar radiation data on the estimates made on reference crop ET and subsequent determination of above ground biomass (AGB) by CropSyst, a daily time step, multi-crop and year cropping systems model (Stöckle et al., 2003), at 20 locations worldwide. The solar radiation models tested where able to provide both good and poor estimates, with subsequent propagation of errors in ET and AGB. The results showed that each source had different levels of performance, in terms of yield estimates, with each geographical location and seasonal patterns.

Hudson and Birnie (2000) showed that the time period from which meteorological data were taken had an impact on the results of a land capability classification model. This implies that model output determined from meteorological data from one time period vary from those derived from another. Nonhebel (1994a), showed that average weather data produced different simulation results than daily data (an over-estimation in potential production of 5–15% and up to 50% in water limited production in dry conditions), due to (i) the response of non-linear relationships within the model used, where average input did not give average output, and (ii) the large variability in daily weather data being different from the average value. Similarly, Nonhebel (1994b) found that inaccuracies in solar radiation of 10% and temperature of 1 °C resulted in yield estimation errors of up to 1 t ha^{-1}, and up to 10 days difference in vegetative period between emergence and flowering. These findings indicate similarities between the impacts on model estimates of both spatial and temporal variability.

2.3. Meteorological data sources

Problems exist in compiling a complete meteorological data-set (i.e. precipitation, temperature and solar radiation) for a PoMA, due to the differences in their spatial and temporal availability and quality of observed data. The spatial distribution of meteorological stations (Met) can leave significant gaps in terms of their coverage. Precipitation and air temperature data records are relatively long, thus sufficient to represent temporal variability. The Met station network for observing other data types has a lower spatial density and typically with shorter temporal records. Solar radiation is rarely observed, with records typically covering short time periods (Thornton and Running, 1999; Bechini et al., 2000; Rivington et al., 2002). Very few meteorological stations in Britain observe daily precipitation, air temperature and solar radiation simultaneously, often with records covering only 1–5 years. More stations record sunshine duration (hours) (approximately 76), with a large range in the length of records.

In the absence of site-specific data, practitioners applying models have a choice of meteorological data source: nearby alternative meteorological stations; data modelled from measurements made on the site (e.g. solar-radiation interpolated from air temperature); spatially interpolated from a Met station network (e.g. Lennon and Turner, 1995; Thornton et al., 1997; Jeffrey et al., 2001; Jarvis et al., 2002), or artificial data derived from stochastic weather generators e.g. LARS-WG (Barrow and Semenov, 1995), ClimGen (Stöckle et al., 2001). An advantage of using a substitute Met station is that the data will maintain synoptic synchronisation, with the correlations between weather variables that influence the behaviour of the model being preserved. However, local characteristics, i.e. microclimatic factors, distance to the sea, elevation and spatial configuration of shelter features in relation to prevailing weather patterns, will all influence the differences between neighbouring Met stations. The criteria for choosing an appropriate data source for simulation model input will depend on whether any observed data are available, what the model requirements are and how it will be used.

2.4. Solar radiation estimated from other weather variables

Methods are available for conversion of sunshine duration (hours) to solar radiation values (i.e. Ångström, 1924; Revfeim, 1997; Suehrcke, 2000), which have a number of empirical, site specific parameters. Johnson et al. (1995) developed a method (here referred to as JW) which was applied by Woodward et al. (2001) then refined and tested by Rivington et al. (2002), producing good results for the regression coefficient of determination (r^2) for measured versus estimated solar radiation data 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 ±20% (BADC, 2004a). The JW model accounts for latitude, solar declination, elevation, day length and atmospheric transmissivity on a daily basis and has only daily sunshine duration (hours) as input. It has a single empirical parameter (FF) representing the relative intensity of solar radiation from cloudy skies, which can be optimised when observed solar radiation is available.

Numerous air temperature-based estimation models use maximum and minimum air temperature to estimate solar radiation, i.e. Donatelli and Campbell (1998) (CD) and Donatelli and Bellocchi (2001) (DB), whilst others also include precipitation, i.e. Weiss and Hays (2004). These models assume that daily maximum air temperature will decrease with reduced transmissivity (increased cloud cover, aerosols, humidity, etc), 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. The advantage of these methods is that temperature data is readily available. However, interpolation is required for their empirical parameters where no solar radiation data exists for calibration purposes.

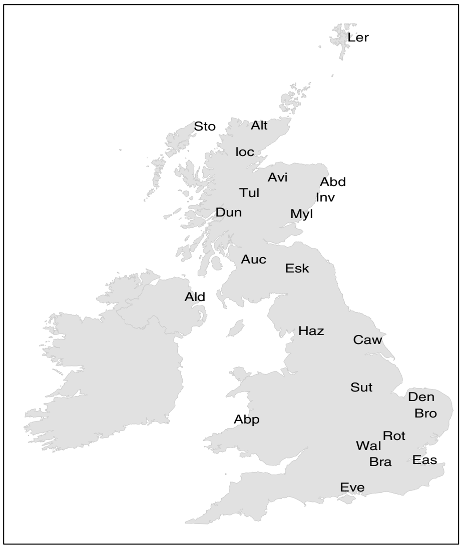
2.5. Neighbouring meteorological station data

The simplest alternative source of substitute meteorological data for the PoMA is to use that observed at a neighbouring location. Large distances may exist however, between a Met station with the full compliment of data types required, and the PoMA. Hunt et al. (1998) working in Ontario, Canada, determined a distance threshold for substitution of solar radiation data of 390 km. Beyond this distance they recommended the use of an interpolation method to provide missing data. In previous studies in the UK (Rivington et al., 2002, 2003), there was inconsistency in the ability of the nearest Met station (NMS) to provide the best observed data substitute. Indeed, for some locations, Met stations at greater distances provided the best substitute, occurring in sufficient cases to imply that the nearest station is not an automatic choice of substitute. The Met station network density, topographical character and temporal span of the data record determined which site provided the closest matching substitute. However, the impacts on crop model estimates using a substitute Met station varied depending on the form of output assessment metric used.

3. Materials and methods

3.1. Database and data source

The UK Meteorological Office supplied meteorological data via the British Atmospheric Data Centre website (BADC, 2004b). 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



Abd = Aberdeen (29), 52
Abp = Aberporth (36), 115
Ald = Aldergrove (25), 68
Alt = Altnaharra (7), 83
Auc = Auchencruive (19), 48
Avi = Aviemore (12), 228
Bra = Bracknell (24), 74
Bro = Brooms Barn (16), 75
Caw = Cawood (29), 6
Den = Denver (18), 3
Dun = Dunstaffnage (23), 3
Eas = East Malling (34), 33
Esk = Eskdalemuir (24), 242
Eve = Everton (29), 16
Haz = Hazelrigg (17), 95
Inv = Inverbervie (7), 24
Ler = Lerwick (47), 82
Loc = Loch Glascarnoch (7), 265
Myl = Mylnefield (25), 31
Rot = Rothamstead (28), 128
Sto = Stornoway (13), 15
Sut = Sutton Bonnington (26), 48
Tul = Tulloch Bridge (5), 237
Wal = Wallingford (26), 48

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

included if they had daily observed precipitation (mm), maximum and minimum air temperature (°C), global solar radiation ($MJ^{-1}\ m^{-2}\ day^{-1}$) and sunshine duration (hours) data for a minimum of 5 years. Table 1 details the four meteorological data-sets created within the database for each site.

3.2. Solar radiation estimation

For each site, solar radiation was estimated using the sunshine duration conversion method (JW) and the Campbell–Donatelli (CD) and Donatelli–Bellocchi (DB) air temperature based models (implemented in freely available software, Donatelli et al., 2003). Output from each model was used to create the data-sets described in Table 1. The CD and DB models required the calculation of extraterrestrial 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

Table 1
Data-sets created within the database

Data-set	Contents
Base	Observed precipitation (mm), maximum and minimum air temperature (°C), solar radiation ($MJ^{-1}\ m^{-2}\ day^{-1}$) and sunshine duration (h)
JW	Base but solar radiation converted from sunshine duration
CD	Base but solar radiation calculated by the Campbell–Donatelli model from air temperature
DB	Base but solar radiation calculated by the Donatelli–Bellocchi model from air temperature

documentation (RadEst, 2004). Empirical parameters used within the three models were optimised for each site using observed solar radiation data, giving individual optimal values per site applied across all years. This represented the scenario of near ideal data interpolation (site – but not temporal specific).

3.3. Impacts on crop model estimates

The CropSyst cropping systems simulation model was used for this study. It is a multi-crop and multi-year daily time step crop growth simulation model, capable of representing a wide range of cropping systems. The model represents a number of physical, biological and management process interactions. It models soil water, crop-soil water and nitrogen budgets, crop phenology, canopy and root growth, yield and biomass production and organic residue decomposition. Inputs to the model are weather, soil, crop physiology parameters and management data. The model requires daily precipitation, maximum and minimum air temperature and solar radiation. The accumulation of thermal time (degree days) controls crop phenological development and management events can be created, the timings of which can be set in relation to crop phenology.

A standardised scenario for a spring barley crop simulation was created within CropSyst. For comparisons between data sources the only differences between simulations were the input meteorological data. The simulation was parameterised so as to produce estimates consistent with national level grain yield statistics (mean of 5.5 t ha^{-1} grain dry matter) from the observed meteorological data. Initialisation and management parameters were set so that the crop was neither water nor nitrogen limited at the onset of growth. Soil texture was set to the percent sand, silt and clay values at the interface between sandy clay loam, loam and clay loam. The Priestley–Taylor model within CropSyst calculated evapotranspiration and a finite difference model was used for soil water infiltration. Sowing date was always the 16th March and harvest occurred 10 days after the crop reached physiological maturity.

CropSyst simulations were run using the Base, JW, CD and DB data-sets (Table 1) for each site. Estimated crop yield (t ha^{-1}) from CropSyst was compared for years where there were corresponding meteorological data available:

- on-site (Base vs. JW, CD and DB models);
- off-site (PoMA Base vs. nearest, 2nd and 3rd nearest neighbour Bases).

The on-site comparison represents the scenario of partial data availability for the PoMA. The off-site comparison represents the scenario of using the neighbouring Met station data as input for the PoMA.

The CropSyst estimate used for assessment was the harvestable grain yield (t ha^{-1}). Yield was chosen as it is a singular representation of the culmination of many different biophysical processes. Crop yield is also a product of all four meteorological data variables acting in conjunction with each other. As such, yield represents the cumulative impact of all variances within the climate data. Yield is also a key model estimate used by DSS. Uncertainty is defined as the difference between model estimates of yield arising from the use of ideal (complete observed site-specific) and imperfect (incomplete sitespecific or neighbouring site) input weather data. The assessment metrics applied to investigate the introduced uncertainty to yield estimates were:

- sum total;
- total difference;
- mean;
- difference in mean;
- absolute difference (sum of over- and under-estimates);
- maximum over- and under-estimation error;
- standard error.

The results for total yield difference and absolute difference, in the off-sites analysis, were normalised by dividing the results by the number of corresponding years (n) to enable comparisons between sites with differing lengths of data records, i.e. absolute difference/n.

4. Results

Options for analysis were constrained due to the number of years for which meteorological data was rejected. Altnaharra, Loch Glascarnoch and Tulloch Bridge had insufficient data to enable meaningful off-site comparisons of CropSyst estimates. Data for Lerwick were unable to be used to produce yield results in CropSyst due to slow accumulation of thermal time, hence restricting phenological development. Comparisons were also limited by the number of data types available for corresponding years at a site, thus illustrating the type of practical problems that arise in providing meteorological data for use in models.

4.1. On-site data source comparisons

When comparing the mean yield values for all metrics at all the sites within the on-site data source scenario (Table 2), JW provided the best overall results, with the exception of the sum total of yields. Across all sites, each model was able to produce solar radiation data that resulted in both closely matching and largely different CropSyst yield estimates for all types of assessment metric. All three model sources gave good estimated results for mean yield and low standard errors. Each source also produced large over- and under-estimates. However, at some sites, i.e. Wallingford and Aldergrove, the temperature based CD and DB models produced better results for all metrics than the sunshine hours based JW. At some sites, i.e. Cawood all three models produced the best result for at least one metric. Generally one model would dominate the best results for all metrics at a site (i.e. JW at Rothamstead, DB at Wallingford), or there would be an even split between two models (i.e. JW and DB at Hazelrigg). The distance between sites did not infer that the best model at

Table 2
Difference between observed weather data (Base) derived CropSyst yield (t ha^{-1}) and estimates simulated with solar radiation from JW, CD and DB models (on-site data source comparisons)

Site	Aberdeen			Aberporth			Aldergrove			Altnaharra			Auchencruive			Aviemore		
Model	JW	CD	DB	JW	CD	DB	JW	CD	DB	JW	CD	DB	JW	CD	DB	JW	CD	DB
Total yield diff (t ha^{-1})	*4.32*	15.43	8.84	−12.68	−7.93	*1.28*	−10.05	*−5.81*	−11.21		−3.97	*−3.85*	−11.54	*−0.70*	−4.85	*−4.56*	−7.18	−11.12
Mean yield diff (t ha^{-1})	0.43	0.51	*0.29*	−0.32	−0.19	*0.04*	−0.39	*−0.22*	−0.43		*−0.41*	−0.53	−0.58	*−0.04*	−0.24	*−0.41*	−0.65	−1.01
Absolute diff (t ha^{-1})	5.02	20.37	14.66	14.15	17.37	*12.41*	15.11	*10.38*	15.85		*3.53*	7.43	12.45	*4.28*	6.31	*4.65*	7.18	11.12
Max over est. (t ha^{-1})	*0.34*	0.82	0.68	1.26	1.49	*1.10*	1.05	*0.68*	1.07		1.64	*0.01*	1.29	*1.05*	1.07	*0.87*	1.19	1.45
Max under est. (t ha^{-1})	*−1.57*	−2.00	−1.61	*−0.34*	−0.98	−0.94	−1.76	*−1.57*	−1.73		*−0.33*	−1.33	−0.46	−0.55	*−0.38*	*−0.05*	−0.28	0.58
Standard error (t ha^{-1})	*0.51*	0.54	0.54	*0.35*	0.52	0.43	0.56	0.46	*0.45*		*0.66*	0.88	0.46	*0.34*	0.37	0.27	*0.21*	−0.28
n (years)	10	30	30	40	40	40	26	26	26		7	7	20	20	20	11	11	11
	Bracknell			Brooms Barn			Cawood			Denver			Dunstaffnage			East Malling		
Total yield diff (t ha^{-1})	*1.43*	−2.00	−6.12	−1.41	*0.24*	1.23	−7.22	*−1.22*	1.81	−1.20	−3.10	*−0.82*	−12.92	*−3.71*	−5.49	*1.21*	−1.38	−6.91
Mean yield diff (t ha^{-1})	*0.05*	−0.07	−0.22	−0.09	*0.02*	0.08	−0.25	*−0.04*	0.06	−0.07	−0.17	*−0.05*	−0.52	*−0.15*	−0.22	*0.04*	*−0.04*	−0.20
Absolute diff (t ha^{-1})	*4.31*	6.51	6.90	*2.27*	2.47	3.31	9.75	8.12	*7.25*	2.78	3.79	*2.62*	13.45	*8.76*	9.50	*3.88*	8.52	8.54
Max over est. (t ha^{-1})	*0.24*	1.11	0.79	0.59	*0.29*	0.39	1.14	0.72	*0.71*	0.43	0.56	*0.33*	*1.15*	1.77	2.08	*0.33*	0.89	1.15
Max under est. (t ha^{-1})	−0.48	−0.43	*−0.16*	*−0.13*	−0.44	−0.40	*−0.53*	−0.95	−1.13	−0.24	*−0.16*	−0.19	*−0.12*	−0.47	−0.77	−0.39	−0.53	*−0.33*
Standard error (t ha^{-1})	*0.19*	0.34	0.25	0.22	*0.17*	0.18	0.40	0.39	*0.37*	0.18	0.20	*0.16*	*0.31*	0.48	0.53	*0.16*	0.33	0.28
n (years)	28	28	28	16	16	16	29	29	29	18	18	18	25	25	25	34	34	34

	Hazelrigg			Eskdalemuir			Everton			Inverbervie		Loch Glascarnoch			Mylnefield		
	JW	CD	DB	JW	CD	DB	JW	CD	DB	CD	DB	JW	CD	DB	JW	CD	DB
Total yield diff (t ha^{-1})	−0.84	−2.53	*−0.91*	−3.20	−7.16	*−0.46*	−2.54	−5.12	−7.77	*0.24*	0.77		*−3.01*	−4.13	−4.75	*−2.83*	−6.21
Mean yield diff (t ha^{-1})	−0.14	−0.15	*−0.05*	−0.16	−0.36	*−0.02*	*−0.09*	−0.18	−0.27	*0.03*	0.11		*−0.50*	−0.69	−0.19	*−0.11*	−0.25
Absolute diff (t ha^{-1})	1.92	5.57	*4.91*	*5.80*	13.78	6.54	*5.01*	9.04	9.46	*1.94*	2.06		*3.01*	4.13	11.73	*9.76*	10.68
Max over est. (t ha^{-1})	*0.50*	0.74	0.76	*0.72*	1.12	1.22	*0.84*	1.13	0.96	0.62	*0.29*		*1.24*	1.43	1.22	*0.80*	0.87
Max under est. (t ha^{-1})	*0.36*	−0.97	−0.52	*−0.54*	−0.92	−1.32	-0.40	−0.54	*−0.30*	*−0.55*	−0.67		*−0.01*	−0.28	−2.05	−1.55	*−1.41*
Standard error (t ha^{-1})	*0.13*	0.31	0.38	*0.32*	0.65	0.49	*0.27*	*0.38*	0.30	0.40	0.38		0.48	*0.45*	0.58	0.52	*0.48*
n (years)	6	17	17	20	20	20	29	29	29	6	6	0	6	6	25	25	25
	Rothamstead			Stornoway			Sutton Bonnington			Tulloch Bridge		Wallingford			Mean for all sites		
Total yield diff (t ha^{-1})	*−0.63*	−2.98	−0.70	−6.53	*−2.97*	−6.37	*−6.27*	−5.20	−5.81	1.04	*0.39*	−4.31	−3.41	*0.68*	−4.40	*−3.89*	−4.24
Mean yield diff (t ha^{-1})	*−0.02*	−0.10	*−0.02*	−0.38	*−0.17*	−0.37	*−0.23*	−0.19	−0.22	0.21	*0.08*	−0.17	−0.13	*0.03*	*−0.06*	−0.16	−0.16
Absolute diff (t ha^{-1})	*6.50*	8.26	8.09	9.09	*8.81*	9.49	*7.18*	8.55	8.18	*2.06*	2.69	6.77	6.21	*4.05*	*6.77*	8.51	8.39
Max over est. (t ha^{-1})	*0.57*	1.03	0.59	0.93	*0.81*	0.94	0.91	0.98	*0.82*	*0.51*	1.03	1.11	0.57	*0.35*	*0.81*	1.15	1.12
Max under est. (t ha^{-1})	*−0.60*	−0.61	−0.64	−0.79	−1.12	*−0.78*	*−0.26*	−0.60	−0.39	−0.95	*−0.69*	−0.51	*−0.34*	−0.53	*−0.63*	−0.98	−0.98
Standard Error (t ha^{-1})	*0.28*	0.39	0.33	*0.45*	0.58	0.50	*0.28*	0.37	0.30	*0.60*	0.80	0.32	0.27	*0.20*	*0.34*	0.48	0.47
n (years)	31	31	31	17	17	17	30	30	30	5	5	26	26	26			

Italicised values indicate the best results per assessment metric.

one site would be best at closely neighbouring sites. For example, JW had the best results for metrics at Rothamstead and Bracknell, but not the nearby site of Wallingford. The following results per assessment metric are detailed in Table 2.

4.1.1. Total yield difference

There was a wide range in the abilities of the on-site data sources to provide a close match between measured and estimated total yield. The lowest and highest total yield difference (t ha^{-1}) were for JW −0.63 (Rothamstead, $n = 31$) and −12.92 (Dunstaffnage, $n = 25$); for CD 0.24 (Brooms Barn, $n = 16$) and 15.54 (Aberdeen, $n = 30$); for DB −0.46 (Eskdalemuir, $n = 20$) and −11.21 (Aldergrove, $n = 26$), respectively. All three models gave an overall under-estimation of total yield difference. At Aberporth, the DB model's total yield difference from the Base results was 1.28 (t ha^{-1}), whereas the JW model gave −12.68 (t ha^{-1}), where $n = 40$. Conversely, at Bracknell, JW gave 1.43 (t ha^{-1}) and DB gave −6.12 (t ha^{-1}), where $n = 28$. Comparing the above results with those for absolute difference indicates that the differences in total yield for Aberporth and Bracknell for JW and CD can be attributable to the balance of errors in over and under-estimations. At Aberporth, DB has a low total difference (1.28 t ha^{-1}) but an absolute difference of 12.41 (t ha^{-1}), hence over and under-estimations are cancelling themselves in the calculation of total difference.

4.1.2. Difference in mean yield

For all three models, only seven out of 24 sites had a difference in mean yield greater than 0.5 t ha^{-1}. This indicates that the models were able to maintain a close match to the mean yield across the majority of geographical locations. The difference in mean yield compared with the Base mean for all sites was −0.06, −0.16 and −0.16 (t ha^{-1}) for the JW, CD and DB models respectively, reflecting the overall pattern of under-estimating yield. Each model was able to produce both large and small differences, variable across sites. The lowest and highest difference in mean yield (t ha^{-1}) were: for JW, −0.02 (Rothamstead, $n = 31$) and −0.58 (Auchencruive, $n = 20$); for CD, 0.02 (Brooms Barn, $n = 16$) and −0.65 (Aviemore, $n = 11$); for DB, −0.02 (both Rothamstead, $n = 31$ and Eskdalemuir, $n = 20$) and −1.01 (Aviemore, $n = 11$), respectively.

4.1.3. Absolute difference in yield

There was a varied response in the model's impacts on the absolute difference in yield (t ha^{-1}), again with each model producing low and high differences (Table 2). The mean absolute differences were 6.77, 8.51 and 8.39 for JW, CD and DB, respectively. The range in absolute differences (as a function of n) varied between 2.27 ($n = 16$) and 15.11 ($n = 40$) for JW, 2.47 ($n = 16$) and 20.37 ($n = 30$) for CD, and 2.62 ($n = 18$) and 15.85 ($n = 26$) for DB. The JW model gave high absolute differences of 12.45 at Auchencruive ($n = 19$), 15.11 at Aldergrove ($n = 26$), 13.45 at Dunstaffnage ($n = 25$) and 11.73 at Mylnefield ($n = 25$). These are all coastal sites. The CD and DB models produced similar high absolute differences at Aberdeen, Aberporth, Aldergrove and Mylnefield, which are again coastal sites. The DB model gave a high absolute value at Aviemore of 11.12, whilst the CD model gave 13.78 at Eskdalemuir. All three models gave lower absolute values at lowland inland sites, i.e. Rothamstead, Hazelrigg, Wallingford, Brooms Barn, Denver and East Malling. This implies that there may be errors in the parameter values used within the three models at the coastal sites.

4.1.4. Over- and under-estimation errors

The maximum and minimum errors (over- and under-estimates) (t ha^{-1}) for a single years' yield estimation showed similar variation, with means of 0.81, 1.15, 1.12 and −0.63,−0.98, −0.98 for the JW, CD and DB models, respectively. Each data source produced small and large errors. The smallest and largest estimation errors were: for JW −0.05 (Aviemore, $n = 11$) and −2.05 (Mylnefield, $n = 25$); for CD −0.16 (Denver, $n = 18$) and −2.00 (Aberdeen, $n = 30$); for DB −0.16 (Bracknell, $n = 28$) and 2.08 (Dunstaffnage, $n = 25$), the largest single error. All sources produced errors of >1 t ha^{-1} in at least one site. These large errors may in part be due to the use of generic optimal parameter values (within the solar radiation estimation models) applied across all years, rather than year specific values.

4.1.5. Standard error

The JW produced lowest, mean and highest standard errors (t ha^{-1}) of 0.16 (East Malling, $n = 34$), 0.34 and 0.58 (Mylnefield, $n = 25$), respectively. The results for CD were 0.17 (Brooms Barn, $n = 16$), 0.48 and 0.65 (Eskdalemuir, $n = 20$), and for DB, 0.16 (Denver, $n = 18$), 0.47 and 0.88 (Altnaharra, $n = 7$), respectively.

4.2. Off-sites data source comparisons

The results for impacts on yield estimates arising from the use of the three nearest substitutes to a PoMA are shown in Table 3. There can be large differences in the ability of a substitute to produce comparable yield estimates with some substitutes introducing substantial errors, varying with the type of assessment metric used. At only two sites, Mylnefield and Wallingford, did the NMS (Inverbervie, 32 km, and Bracknell, 33 km, respectively), provide the best results for all metrics. For total yield difference/n (t ha^{-1}), there were only six nearest substitutes, out of 23, that provided the best results. For mean yield difference (t ha^{-1}), only five nearest substitutes provided the best results. Similarly for absolute difference (t ha^{-1}), nine nearest sites gave the best results. For over- and under-estimations, eight and nine nearest sites gave the best results, respectively. This equates to approximately only 32% of the NMS being able to provide the best matching results for these metrics.

The occurrence and magnitude of errors was not directly related to distance. Substitute sites that were close together could still produce large errors, i.e. Aberdeen and Inverbervie (32 km) had a maximum under-estimation error of −1.29 tha^{-1}, whilst Wallingford and Rothamstead (57 km) had a maximum under-estimation error of −1.27 t ha^{-1} with a relatively high standard error. Conversely sites at larger distances apart produced closely matching results, i.e. Aldergrove and Dunstaffnage (206 km), where all metrics, except maximum over-estimation error, had good matches. The mean maximum and minimum over- and under-estimations across the three NMS's were 1.28 and 0.95 t ha^{-1} respectively. Table 5 shows the sites producing the 10 lowest absolute difference/*n* results and distance. The lowest absolute difference/*n* (0.189 t ha^{-1}) occurred between Aberdeen and Inverbervie (32 km). The 10th lowest (0.447 t ha^{-1}) was between Bracknell and Wallingford (33 km), with other sites higher up the order and at distances as high as 206 km, producing lower values.

4.3. On-site versus off-site data source comparisons

The use of observed precipitation, temperature and estimated solar radiation (on-site data) introduced smaller errors than using complete, observed off-site Met station data (Table 4). Examination of the mean metric values for all sites and data sources shows that the mean results for the best matching nearest Met station are worse than the three on-site sources, except for the size of over- and underestimations and standard error, which were better than for those of CD and DB.

5. Discussion

The results demonstrate the variability in model estimates that arise as a result of the input data source. The sources tested here were capable of producing both good and poor estimates of yield. In both the on-site and off-site comparisons no single data source can be identified as being more suitable than another for all sites. It is preferable though to use incomplete on-site data (observed precipitation and temperature) with estimated solar radiation data, rather than substituting a neighbouring Met stations data. This helps preserve the site-specific characteristics within the model, in terms of precipitation and temperature effects. The range of response across the assessment metrics indicates that a data source can appear to be appropriate using one metric, but inappropriate with another. For example, at Aldergrove the DB model had its worst total yield difference value (-11.21 t ha^{-1}), but also gave the best response for standard error (0.45 t ha^{-1}) at the site, i.e. all errors were under-estimates. This contradictory indication of performance is typical across most sites and sources. Model assessments need to consider the variation in impacts of data source which manifest themselves differently depending on the type of assessment metric used.

5.1. Use of on-site data sources

The JW model was the best performing on-site source overall, but not at all sites and for all metrics. There were sufficient cases, where either the CD or DB gave better results, to exclude the assumption that use of on-site observed sunshine hours converted to estimates of solar radiation would be an automatic choice of data source. The yield estimates indicate spatial variation in the suitability of each of the models used to provide solar radiation data. The JW model's better performance at inland sites suggests that coastal climatic effects may not be as well represented by the CD

Table 3
Difference between CropSyst yield estimates (t ha^{-1}) for the place of model application (PoMA) and estimates gained using off-site substitute meteorological station data (off-site data source comparisons), assessed by total yield difference/n, mean yield difference, absolute difference/n, maximum and minimum over- under-estimations and standard error, where n = number of corresponding years

Site (PoMA)	Aberdeen			Aberporth			Aldergrove			Auchencruive			Aviemore		
Substitute	Inv	Myl	Avi	Sut	Haz	Wal	Auc	Esk	Dun	Esk	Dun	Ald	Tul	Loc	Myl
Distance (km)	32	94	102	238	241	246	140	206	206	88	121	140	65	86	95
Total yield diff/n (t ha^{-1})	−0.59	−0.82	*0.13*	1.76	*0.62*	2.36	−0.24	1.68	*0.23*	1.88	0.48	*0.24*	*−0.04*		−1.21
Mean yield diff (t ha^{-1})	−0.59	−0.86	*0.13*	1.76	*0.56*	1.96	−0.24	1.59	*0.18*	1.88	0.45	*0.24*	*−0.04*		−1.21
Absolute diff (t ha^{-1})	0.59	1.04	*0.58*	1.76	*0.70*	2.36	*0.33*	1.68	0.56	1.88	0.61	*0.33*	*0.84*		1.21
Max over est. (t ha^{-1})	*−0.15*	1.70	1.24	3.86	*1.54*	3.27	*0.33*	3.16	1.24	2.97	1.31	*0.77*	0.79		*−0.66*
Max under est. (t ha^{-1})	−1.29	−2.63	*−0.64*	0.47	*−0.35*	0.98	−0.77	1.02	*−0.30*	1.34	−0.49	*−0.33*	*−0.88*		−1.58
SE (t ha^{-1})	*0.41*	0.57	0.45	0.52	*0.39*	0.53	*0.31*	0.38	0.40	*0.27*	0.35	0.32	na		0.32
n (years)	3	22	7	18	9	15	17	18	17	6	18	17	2	0	7
	Bracknell			Brooms Barn			Cawood			Denver			Dunstaffnage		
	Wal	Rot	Eas	Den	Rot	Eas	Haz	Sut	Den	Bro	Rot	Sut	Tul	Auc	Avi
Distance (km)	33	51	84	40	81	109	109	111	171	40	103	114	64	121	129
Total yield diff/n (t ha^{-1})	0.34	−0.25	*−0.13*	*0.05*	−0.25	*−0.05*	−1.47	*−0.02*	−0.24	*−0.05*	−0.37	0.18	1.26	*−0.45*	1.21
Mean yield diff (t ha^{-1})	0.37	−0.25	*−0.13*	*0.05*	−0.25	*−0.05*	−1.47	*−0.02*	−0.33	*−0.05*	−0.37	0.15	1.26	*−0.45*	1.04
Absolute diff (t ha^{-1})	0.39	*0.35*	0.46	*0.33*	0.38	0.66	1.48	*0.52*	0.69	*0.33*	0.53	0.47	1.26	*0.58*	1.21
Max over est. (t ha^{-1})	1.27	*0.47*	1.56	0.90	*0.49*	2.46	*0.05*	1.40	1.04	0.90	*0.76*	0.82	na	*0.61*	1.43
Max under est. (t ha^{-1})	*−0.22*	−1.28	−1.08	*−0.57*	−1.30	−1.42	−3.07	*−1.25*	−2.08	*−0.57*	−1.54	−0.70	na	−1.31	*0.09*
SE (t ha^{-1})	0.42	*0.39*	0.51	*0.40*	0.49	0.63	0.62	*0.50*	0.58	*0.43*	0.54	0.47	na	*0.51*	0.88
n (years)	23	23	24	15	15	16	15	21	14	15	17	13	2	19	6

	East Malling			Eskdalemuir			Everton			Hazelrigg			Inverbervie		
	Rot	Bra	Bro	Auc	Myl	Haz	Bra	Wal	Rot	Caw	Esk	Sut	Abd	Myl	Avi
Distance (km)	81	84	109	88	128	147	95	101	146	109	147	166	32	65	102
Total yield diff/n (t ha^{-1})	−0.10	0.13	*0.05*	−1.77	*−1.48*	−2.15	1.07	1.63	*0.95*	*1.30*	2.15	1.51	0.59	−0.49	*−0.08*
Mean yield diff (t ha^{-1})	−0.10	0.13	*0.05*	−1.88	*−1.48*	−2.15	1.20	1.56	*0.95*	1.47	2.15	*1.21*	0.59	−0.58	*−0.08*
Absolute diff (t ha^{-1})	0.51	*0.46*	0.66	1.77	*1.53*	2.15	*1.15*	1.70	1.19	*1.31*	2.15	1.54	0.59	*0.49*	0.64
Max over est. (t ha^{-1})	*0.63*	1.08	1.42	−1.34	*0.46*	−1.23	*2.70*	2.73	2.72	3.07	*2.84*	3.42	1.29	*−0.13*	0.56
Max under est. (t ha^{-1})	−2.42	*−1.56*	−2.46	−2.97	−3.36	*−2.84*	−1.16	*−0.85*	−1.50	*−0.05*	1.23	−0.11	*0.15*	−1.38	−0.72
SE (t ha^{-1})	0.83	*0.62*	0.81	0.42	0.67	*0.41*	0.75	*0.72*	1.00	0.59	*0.51*	0.54	0.87	*0.29*	na
n (years)	27	24	16	17	18	11	27	24	26	17	11	12	3	6	2

	Mylnefield			Rothamstead			Sutton Bonington			Wallingford		
	Inv	Abd	Avi	Bra	Wal	Eas	Caw	Den	Rot	Bra	Rot	Eve
Distance (km)	65	94	95	51	57	81	111	114	129	33	57	101
Total yield diff/n (t ha^{-1})	*0.49*	0.82	1.21	0.23	0.72	*0.10*	*0.02*	−0.18	−0.45	*−0.31*	−0.72	−1.56
Mean yield diff (t ha^{-1})	*0.58*	0.86	1.21	0.25	0.72	*0.10*	*0.02*	−0.15	−0.40	*−0.37*	−0.72	−1.56
Absolute diff (t ha^{-1})	*0.49*	1.04	1.21	*0.33*	0.75	0.53	*0.47*	*0.47*	0.50	*0.36*	0.75	1.63
Max over est. (t ha^{-1})	*1.38*	1.89	1.58	*1.28*	2.40	2.42	1.25	0.70	*0.30*	*0.22*	0.34	0.85
Max under est. (t ha^{-1})	*0.13*	−1.59	0.66	−0.47	*−0.34*	−0.63	−1.40	*−0.82*	−1.97	*−1.27*	−2.40	−2.73
SE (t ha^{-1})	*0.09*	0.71	*0.35*	0.35	0.53	0.61	0.61	*0.43*	0.47	*0.43*	0.60	0.51
n (years)	6	22	7	25	23	26	23	13	22	25	23	25

Italicised areas indicate substitute site providing the best result per assessment metric.

and DB models. Based on the results here, all three models are suitable methods for providing solar radiation at lowland inland sites, but there is generally an increasing size in errors with elevation for the air temperature based models (an exception is the DB model at Eskdalemuir), and with proximity to the sea for the JW model.

The relative importance of solar radiation as a data input is reflected in the magnitude of yield errors arising from using estimated values, which are of significant size and occurring sufficiently often as to cause potentially misleading interpretations in assessing the inter-year variability of crop yield. However, the yield results are based on using optimised parameters within the solar radiation models. Hence, when no observed data are available, more generalised parameter values would have to be used, reducing the quality of the estimated solar radiation and subsequently introducing greater uncertainty to the yield estimates. Further study is required to determine what impact using imperfect solar radiation model parameters would have on process-based simulation model estimates.

Table 4
On-site versus off-site comparisons for assessment metrics

Assessment metrics	Mean metric values (t ha^{-1})					
	Base	On-site data			Off-site data	
		JW	CD	DB	Best matching site	Three nearest sites
Total difference		−4.04	*−3.89*	−4.24	6.16	11.18
Mean	5.69	5.63	5.53	5.53	5.42	5.35
Difference in mean		*−0.06*	−0.16	−0.16	−0.27	−0.34
Absolute difference		*6.77*	8.51	8.39	10.16	13.95
Max. over estimate		*0.81*	1.15	1.12	0.84	1.41
Max. under estimate		*−0.63*	−0.98	−0.98	−0.69	−1.21
Standard error		*0.341*	0.482	0.472	0.418	0.515

Italicised values indicate the best results per assessment metric.

Table 5
Lowest 10 absolute difference (ABS)/*n* values in yield (t ha^{-1}) related to distance between PoMA and best substitute

Site	Substitute	Distance (km)	(ABS/*n*) (t ha^{-1})
Abd	Inv	32	0.189
Ald	Auc	140	0.342
Den	Bro	40	0.354
Caw	Den	171	0.366
Den	Rot	103	0.403
Loc	Avi	86	0.413
Ald	Dun	206	0.413
Bro	Rot	81	0.429
Alt	Loc	68	0.436
Bra	Wal	33	0.447

5.2. Use of off-site data sources

The off-site data produced both good and poor matches of yield estimates compared with the Base data. The nearest Met station infrequently provides the best substitute, with near-by substitutes introducing larger errors than substitutes from further away and without any direct relationships with distance. Some sites where able to function as good quality substitutes for all assessment metrics, i.e. Brooms Barn for Denver (40 km apart), whilst others introduced large errors, i.e. Hazelrigg for Cawood (109 km). The best matching substitute sites were still able to produce large individual over- or under-estimates. The implications are that even after carefully selecting a substitute, there can still be large uncertainties introduced to the model estimates.

Off-site data sources introduced a greater amount of uncertainty than the on-site sources, partly due to different temperature data introducing errors via the impacts on the rate of phenological development and time for biomass accumulation (and timing of management events). Differences in solar radiation and precipitation between sites will impact on biomass accumulation quantities and soil–crop water balance components, respectively. Therefore, substitute Met station data change the overall model behaviour through impacts on a range of functions, due to differences in response of biophysical process (i.e. non-linearity responses of model components, highlighted by Nonhebel, 1994a,b). This has impacts on DSS outputs, i.e. where labour and machinery resource scheduling is based on estimates of crop phenology (temperature differences), irrigation planning (precipitation differences), or both simultaneously.

5.3. Suitability of data sources

The relationship between the spatial variability of a data type and how it is used within a model is a key consideration in selecting an appropriate data source. If a model's estimates are primarily determined by temperature, then the distance threshold between a PoMA and substitute may be higher than if the output is more influenced by precipitation. However, estimates from models such as CropSyst are determined by the accumulated influence of four data variables acting in conjunction with model sub-components. This implies that the distance threshold should be set at the lowest of all the data types. In practical terms, practitioners applying models are faced with a third choice of using near-by met stations with partital data sets, and models to estimate additional data. This would reduce the distance from a PoMA to the nearest Met station, due to the higher density of sites where precipitation and temperature are observed but would still introduce potentially large uncertainties.

The length of the data record influences the suitability of a substitute. Meteorological records consisting of a short time period are less likely to capture the growth of data variance with time. This limits the ability of the model to represent the year to year variability in crop yield. Also, neighbouring Met stations may show greater levels of weather data similarity outside of the growing season, with a temporal distribution of accuracy: a spring barley crop will only reflect the period of say, mid-March to late summer/early autumn. Parallels exist between the spatial differences in weather data and the temporal variability, implying that simulations need to be run for sufficient time periods in order to capture the natural growth of variance in estimates.

5.4. Model estimates used within DSS

This study used a range of assessment metrics which reflect those forms of model estimates that may be used within research studies and DSS. Total yield may be used to estimate a land uses' overall financial return, or for inputs into livestock feed budgets. Errors introduced by data choice leading to differences in total yield will result in incorrect gross margin or net present value estimation, or propagation of errors into livestock feed resource allocation and subsequent live weight gain. Over- and under-estimate errors have the same effect. Mean yield is used for indicative purposes, i.e. for summarising crop performance in response to climate change, management practises, etc. Errors introduced to the mean yield may, for example, lead to inappropriate recommendations on crop management.

The results given here indicate that the value of DSS interpretations can be improved by considering combinations of metrics in order to gain greater clarity of the meaning of results. The value of individual assessment metrics is increased when used in conjunction with others, for example, absolute difference and total yield difference. However, in research studies and DSS applications, metrics tend to be used separately. Where models are used as an integral part of DSS, the overall system needs to include a mechanism whereby introduced uncertainty can be quantified and tracked through to the final outputs. This will allow DSS outputs to be appraised in a more honest and reliable manner.

6. Conclusion

Large uncertainties in process-based simulation model estimates can result from the choice of meteorological input data. The JW solar radiation model used with on-site observed precipitation and temperature data was identified as being the best at reducing the amount of uncertainty at the majority of sites. Both on- and off-site meteorological data source were capable of producing good and poor estimates of yield. There was sufficient variation in the yield results from the off-site sources to exclude the assumption that the nearest meteorological station with complete data provides the most appropriate substitute. Only 1 in 3 of the nearest meteorological stations were capable of providing the best substitute. Where precipitation, maximum and minimum air temperature data are available, it is preferable to use one of the solar radiation models to complete the data-set, rather than use a neighbouring stations' complete data-set as a substitute. Data sources and subsequent model estimates can appear to be suitable when assessed with one metric, but inappropriate with another. Practitioners need to be aware of the variation between results as described by different assessment metrics. The use of multiple metrics for assessment of introduced uncertainty is recommended.

Model errors of the magnitude found here may have a significant impact when used for decision support, strategic planning or policy analysis. A single data source can produce both low and high uncertainty across the range of assessment metrics, implying a need to relate the range of uncertainty to the type of metrics used. This has implications on how model estimates are used and interpreted within a DSS, for strategic planning or policy development. Practitioners applying models that represent biophysical processes therefore need to quantify the uncertainty that the input data sources introduce. It is recommended that a range of assessment metrics be used to describe the different responses in model estimates, and that these differences be considered when interpreting DSS output.

Both the on-site and off-site data source impacts on estimates imply that models applied to a site without observed meteorological data should be calibrated, parameterised and individual runs made with data from a range of sources. This would allow practitioners to understand the sensitivity of a simulation to alternative choices of meteorological data, and demonstrate variability of both parameters and estimates, as a first step towards quantifying the uncertainty. Stated assumptions about input data need to be supplemented with an indication as to what the impacts are of using imperfect data. Where no meteorological data exist for a place of model application, modellers need to determine with which substitute the site can be best represented.

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