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A process-based model designed for filling of large data gaps in tower-based measurements of net ecosystem productivity

Zisheng Xing[a,e], *Charles P.-A. Bourque*[a,b,*], *Fan-Rui Meng*[a], *Roger M. Cox*[c], *D. Edwin Swift*[c], *Tianshan Zha*[d], *Lien Chow*[e]

[a] *Faculty of Forestry and Environmental Management, University of New Brunswick, Fredericton, New Brunswick, Canada E3B 6C2*
[b] *Lanzhou Regional Climate Centre, 2070 Donggang East Road, Lanzhou, 730020, Gansu, PR China*
[c] *Natural Resources Canada, Canadian Forest Service, Atlantic Forestry Centre, P.O. Box 4000, Fredericton, New Brunswick, Canada E3B 5P7*
[d] *Climate Research Branch, Environment Canada, 11 Innovation RD, Saskatoon, Saskatchewan, Canada S7N 3H5*
[e] *Potato Research Centre, 850 Lincoln Road, P.O. Box 20280, Fredericton, New Brunswick, Canada E3B 4Z7*

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ABSTRACT

In this paper we present a simple hybrid gap-filling model (GFM) designed with a minimum number of parameters necessary to capture the ecological processes important for filling medium-to-large gaps in Flux data. As the model is process-based, the model has potential to be used in filling large gaps exhibiting a broad range of micro-meteorological and site conditions. The GFM performance was evaluated using "*Punch hole*" and extrapolation experiments based on data collected in west-central New Brunswick. These experiments indicated that the GFM is able to provide acceptable results ($r^2 > 0.80$) when >500 data points are used in model parameterization. The GFM was shown to address daytime evolution of NEP reasonably well for a wide range of weather and site conditions. An analysis of residuals indicated that for the most part no obvious trends were evident; although a slight bias was detected in NEP with soil temperature. To explore the portability of the GFM across ecosystem types, a transcontinental validation was conducted using NEP and ancillary data from seven ecosystems along a north-south transect (i.e., temperature–moisture gradient) from northern Europe (Finland) to the Middle East (Israel). The GFM was shown to explain over 75% of the variability in NEP measured at most ecosystems, which strongly suggests that the GFM maybe successfully applied to forest ecosystems outside Canada.

1. Introduction

Data gaps in flux measurements (in particular, net ecosystem productivity, NEP) are an ever-present challenge for flux researchers (Greco and Baldocchi, 1996; Aubinet et al., 2000). In general, 17–50% of flux observations are reported as missing or rejected (Falge et al., 2001a,b; Hui et al., 2004). The gaps are caused (*i*) during inclement weather, especially during heavy rainfall and during periods of freezing rain; (*ii*) by equipment failures, maintenance shut-downs, and power outages; or (*iii*)

* *Corresponding author at*: Faculty of Forestry and Environmental Management, University of New Brunswick, Fredericton, New Brunswick, Canada E3B 6C2. Tel.: +1 506 453 4930; fax: +1 506 453 3538.
E-mail address: cbourque@unb.ca (C.P.-A. Bourque).
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by low wind conditions (Xing et al., 2008). Occasional data gaps in the data stream cause problems by (*i*) reducing the value and integrity of the data, (*ii*) making it difficult to estimate annual NEP budgets and to determine sink–source status of ecosystems, and (*iii*) biasing climatic relationships with NEP, reducing the level of validation (Falge et al., 2001a,b; Hui et al., 2004; Amiro et al., 2005).

The data gaps must be filled in order to derive annual trends and to investigate the time-dependency of the derived quantities (i.e., NEP). Poor gap filling may cause misinterpretation of the data and lead to incorrect conclusions. In previous research, Xing et al. (2007a) have summarized the features of an effective gap-filling protocol. In particular, the method should: (*i*) be easy to implement, (*ii*) be able to capture prominent features of the modelled system and address interactions among relevant environmental controls, (*iii*) have limited number of model parameters for auto-parameterization (parameter optimization), and (*iv*) have few inter-correlated parameters so that model parameterization is internally consistent.

Many gap-filling methodologies have been developed over the past decade, each with their strengths and weaknesses. Some of these methods include the application of (*i*) lookup tables (LUT), (*ii*) non-linear regression (NLR), (*iii*) artificial neural networks (ANN), (*iv*) multiple imputation (MI), and (*v*) ecosystem models (EM). LUT use a randomly or systematically chosen value from individual observations that have similar values on other variables (Falge et al., 2001a,b; Greco and Baldocchi, 1996). LUT, typically consider only the effects of light and temperature in their formulation, restricting the portability of the method to regimes of unchanging soil water content. NLR is used to estimate missing values with mathematical functions generated by regressing dependent variables against explanatory (independent) variables. Most often, one or two explanatory variables are used. Such functions, seldom consider interaction between environmental controls, again restricting their application to a small subset of cases.

ANN generates predictive models (networks) of simple processing elements (i.e., neurons) by iterative learning (Aubinet et al., 2000). The approach is based on a black-box application of statistical formulations (rules) with little biophysical-ecological realism. In order to match training data, the network evolves and adopts almost any parameter value in its search for perfect agreement. In doing so, the network produces ecologically meaningless quantities. If not carefully applied, ANN can over fit (over-generalize) the training dataset and produce unreasonable output. Also, ANN can adopt different solution strategies with the same training data, rendering its application very difficult. Moffat et al. (2007) point out, all ANN methods are complex to implement and require smoothing or regularization to ensure good reliability in the annual NEP sums. Smoothing and regularization introduce their own level of uncertainty in the final results. MI provides a set of values through standard statistical techniques (Hui et al., 2004) often difficult to implement in gap filling.

Ideally, EM provide the best overall solution to gap filling, however, their complicated structures and parameterization requirements make EM cumbersome to use. Additionally, because of the presence of many inter-correlated parameters and non-linearities in the models, auto-parameterization is usually difficult because of internal inconsistencies and problems associated with solution divergence. Typically, parameterization of EM is done by trial and error and is very time consuming. As a general rule, as the number of model parameters increases, the statistical stability of the model decreases.

Some parameters may be set only through specific field measurement techniques, including some for which current instrumentation may be inadequate or does not exist. Available models are designed to serve specific applications with specific spatial and temporal resolutions. Also, time series from variables that are hard to fill reflect the outcome of complex biological interactions among different ecosystem components. Simple linear interpolation and other statistical methods may be good for filling small data gaps lasting a few hours, but are less reliable for filling large gaps lasting more than a few days to a few weeks. To address large gaps, a simple model which combines the flexibility of statistical models with the precision of EM is required to best address gaps in NEP flux measurements. This model should technically balance relevant ecological detail with the number of inter-correlated parameters in model structure.

In Moffat et al.'s (2007) publication, a process-based Biosphere Energy-Transfer Hydrology model (BETHY; Knorr and Kattge, 2005) was used to demonstrate the potential of using process-based models in gap filling of very long periodically interrupted time series of flux data, because of their reduced dependence on existing observations. Xing et al. (2007a,2008) provide two versions of a simplified gap-filling model (GFM) which can be automatically parameterized based on a few available measurement episodes. These GFM's are robust with handling small to intermediately-sized gaps by addressing variations (*i*) in light interception, as a result of differences in sun elevation, sky cloudiness, and partitioning of incident photosynthetically active radiation (PAR) into its direct and diffused components (Xing et al., 2007a, with small gaps), and (*ii*) in air and soil temperatures (Xing et al., 2008, with intermediate-size gaps). Although, the GFM's were shown to underestimate in instances of water stress conditions (Xing et al., 2008), consideration of environmental controls of light and air and soil temperatures on NEP has made the methods very practical in dealing with these two gap-size categories, as long as the input data (mostly meteorological in nature) are available. For large gaps, the leading environmental controls should include water conditions which affect plant growth (and NEP) through either diurnal fluctuations in air relative humidity (RH) and/or long-term fluctuations in soil water content.

In this study, our objectives are to: (*i*) develop an ecosystem-based model with the least number of parameters for gap filling of *large data gaps*; and (*ii*) evaluate the performance of the newly developed GFM for selected scenarios by comparing model results to flux measurements collected at a Fluxnet-Canada Research Network (FCRN) site in west-central New Brunswick (NB), Canada, and seven CarboEurope project sites (as a second validation experiment) using "*Punch hole*" (interpolation, Hui et al., 2004) and various "extrapolation" experiments.

2. Materials and methods

2.1. Primary research site and measurements

The primary research site, from which a significant portion of the NEP flux and ancillary data is obtained, is located in a predominantly balsam fir [*Abies balsamea* (L.) Mill; BF] site about 1 km east of *Nashwaak Lake* (NWL_BF) in central New Brunswick (NB), northwest of the City of Fredericton (i.e., 46°28′20N, 67°06′0W; Xing et al., 2008), New Brunswick, Canada. The site is located in hilly terrain with elevations ranging from 320 to 350 m. Situated in the Central Uplands Eco-region (Ecosystem Classification Working Group, 2003), the site is characterized by warm, rainy summers and mild, snowy winters. The mean annual air temperature for the growing season is 10.8 °C. The mean annual rainfall is 1392 mm. The average number of growing degree days for this region is about 1302 °C. The soil is a well-drained sandy loam, with an average duff thickness of 6–7 cm. The site is very rocky with some large boulders interspersed throughout the site. Mixedwood forests in the region is primarily composed of sugar (*Acer Saccharum* Marsh.) and red maple (*Acer rubram* L.), red spruce (*Picea rubens* Sarg.) and white spruce (*Picea glauca* [Moench] Voss), and BF. Balsam fir makes up more than 95% of the total volume (Xing et al., 2005) on the NWL_BF site.

At the site, a 20-m high triangular tower was used to host a series of eddy-covariance (EC) sensors to collect high-frequency (10 Hz) measurements of water vapor and CO_2 concentrations (expressed in mixing ratios), horizontal, lateral, and vertical wind velocities, and air temperatures. EC-sensors were placed above the forest canopy (13.5 m high) at a height of about 16.5 m above ground. The EC-sensors included a close path infrared gas analyzer (IRGA, LI-7000, Li-COR, Lincoln, Nebraska), a three-dimensional (u, v, w) sonic anemometer [CSAT3, Campbell Scientific (Canada), Edmonton, Alberta], and a fine-wire thermocouple. Meteorological sensors on the tower included a series of photosynthetically active radiation (PAR) sensors (LI-190SA, Li-COR, Lincoln, Nebraska), a series of temperature and relative humidity sensors (5 HMP45C T-RH probes; CSC) placed at regular intervals along the length of the tower, and a CNR1 net radiation sensor (CSC) installed several metres above the forest canopy. Ancillary site information collected included soil temperature and soil moisture profiles [using a series of 107 thermisters (CSC) for temperature and CS616 probes for soil moisture] in two separate pits about 5–7 m west to northwest of the flux tower. All information was recorded on a CR5000 datalogger (CSC).

Flux data were recorded on a 1-GB flash card and regularly downloaded for storage on high-capacity hard drives for off-site archiving. The high-frequency data were processed with the FLUX-CAL software written in Visual FORTRAN (Intel®, Visual FORTRAN Compiler version 9.0) from which 30-min averages of NEP were calculated after spike removal (based on values >3rd standard deviation) and coordinate rotation.

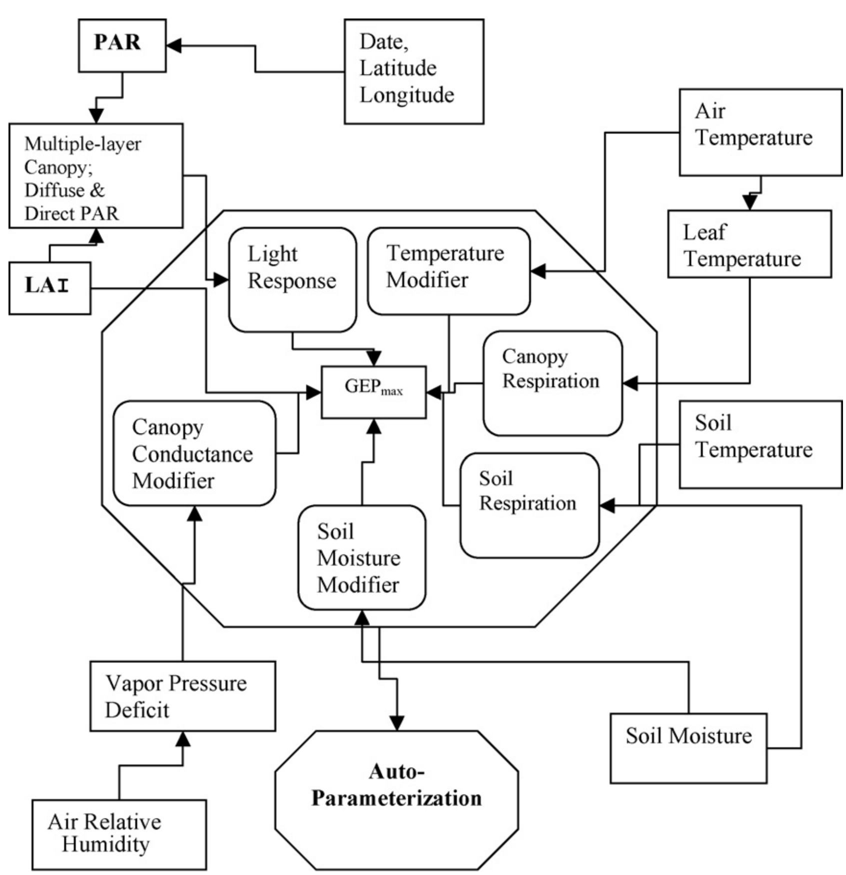

Fig. 1 – Conceptual structure of the gap filling model (GFM) for large data gaps.

2.2. Model description

The flowchart of the GFM appears in Fig. 1. The model has six main control functions, which are indicated by rounded rectangular boxes (except for the two larger ones) in Fig. 1. Beside GEP_{max}, the other rectangular boxes stand for either the input variables or calculated intermediate variables.

In the GFM, the canopy is divided into four layers and each layer is divided into shade and sunlit leaves in the representation of NEP (μmol CO_2 $m^{-2}\,s^{-1}$; Xing et al., 2007a), i.e.,

$$\begin{aligned} NEP = & \sum_{i=1}^{n} GEP_{max} f_{temp} f_{sm} f_{cond} \\ & \times \left\{ \begin{array}{l} 1 - L_{sun}[i] \cdot \exp\left[-\alpha \times (PAR_{sun}[i])\right] - \\ L_{shade}[i] \cdot \exp\left[-\alpha \times (PAR_{shade}[i])\right] \end{array} \right\} \\ & \times \frac{LAI}{n - Rp} - R_s \times f_{sm} \end{aligned} \tag{1}$$

where GEP_{max} (μmol CO_2 $m^{-2}\,s^{-1}$) is the maximum photosynthesis per unit leaf area index (LAI). Variable f_{temp} is the temperature modifier (Xing et al., 2008) and is defined as

$$f_{temp} = \begin{cases} f(T_o), & if \quad T_a < T_{opt} \\ f(T_1) \times f(T_o), & if \quad T_a \geq T_{opt} \end{cases}, \tag{2}$$

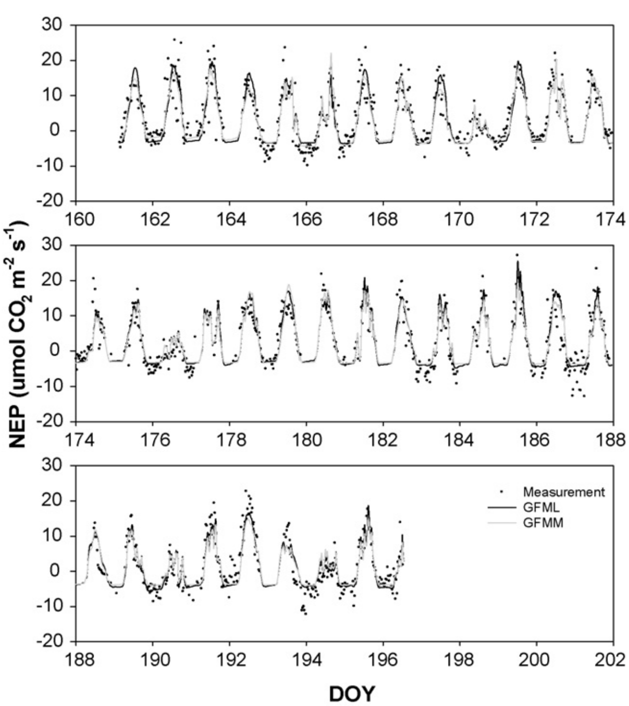

Fig. 2 – Time series of modelled vs. measured NEP for DOY 161 through to 196 with an earlier version of the GFM designed to handle medium-sized gaps (GFMM in the Figure; Xing et al., 2008) and the current GFM for large-sized gaps (GFML in the Figure; developed in this paper). Measured data comes from the NWL_BF-FCRN site in west-central NB.

with

$$f(T_o) = \frac{1}{\exp[(T_a - T_{opt})^2 / K_{rt}]}, \tag{3}$$

and

$$f(T_1) = \left(\frac{T_a - T_{min}}{T_{opt} - T_{min}} \right) \times \left(\frac{T_{max} - T_a}{T_{max} - T_{opt}} \right)^{(T_{max} - T_{opt})/(T_{opt} - T_{min})} \tag{4}$$

where T_a is the air temperature (in °C), T_{opt} is the optimum air temperature for photosynthesis (set at 17.5 °C for BF), K_{rt} is a equation parameter which is used to adjust the slope of temperature curve with values ranging from 100 to 1200 (°C^2), and T_{max} and T_{min} are air temperature thresholds (in °C) for which photosynthetic activity ceases (Landsberg and Waring, 1997).

Variable f_{sm}, is the soil moisture modifier (Fig. 1), calculated from equations introduced in Bourque et al. (2000, 2006), in particular

$$f_{sm} = \max(0, \kappa \xi^{\alpha} (1 - \xi)^{1/\alpha} \tag{5}$$

where

$$\xi = \begin{cases} 0 & if \quad sm < sm_{min} \\ \dfrac{sm - sm_{min}}{sm_{max} - sm_{min}} & if \quad sm_{min} < sm < sm_{max} \\ 1 & if \quad sm > sm_{max} \end{cases}$$

$$\alpha = \sqrt{\frac{\chi}{1 - \chi}},$$

and

$$\kappa = \frac{1}{\chi^{\alpha} (1 - \chi)^{1/\alpha}}$$

and

$$\chi = \frac{\psi - sm_{min}}{sm_{max} - sm_{min}} \quad \text{with } sm_{min} \leq \psi \leq sm_{max}$$

Parameters sm_{min}, sm_{max}, and Ψ represent minimum, maximum and optimum soil moisture (SWC; in % of saturation) for a given species (BF, in this instance). If $sm = \Psi$, then $f_{sm} = 1$; if $sm = 0$ or 1.0, $f_{sm} = 0$.

Variable f_{cond} is the stomatal conductance modifier (see Fig. 1) and follows formulation in Landsberg and Waring (1997), Kelliher et al. (1993), and Kelliher et al. (1995) with some modification, i.e.,

$$f_{cond} = e^{(-(1 - RH/100) e_{sat} V_k)} \tag{6}$$

where RH is the relative humidity of the air (%), V_k is a parameter which is determined during model fitting with a value range from 0.1 to 5 $(kPa)^{-1}$, and e_{sat} is the saturation vapor pressure (kPa), given by

$$e_{sat} = e^{(52.57633 - 6970.4985/(T_a + 273.16) - 5.0208 \ln(T_a + 273.16))}. \tag{7}$$

$L_{sun}[i]$ and $L_{shade}[i]$ are the sunlit and shade leaf fraction of the i^{th} canopy layer at a given solar elevation (and time of day), while n is the number of canopy layers ($n = 4$, for this research;

De Pury and Farquhar, 1997), α is a parameter which defines the photosynthesis efficiency (μmol^{-1} CO_2 s). Here, T_{max} and T_{min} are set to 35 °C and 0 °C, respectively. R_p is the canopy respiration (μmol CO_2 m^{-2} s^{-1}; see Fig. 1), i.e.,

$$R_p = \frac{R_{c\,max}}{1 + \exp[-R_{c\beta}(T_a - R_{copt})]} \tag{8}$$

where R_{cmax} is the maximum canopy respiration (μmol CO_2 m^{-2} s^{-1}). $R_{c\beta}$ is an adjustable equation parameter having values ranging between 0.01 and 0.999 (°C^{-1}), and R_{copt} is another adjustable equation parameter with values ranging between 15 and 25 (°C). R_s is the soil respiration (μmol CO_2 m^{-2} s^{-1}; Lloyd and Taylor, 1994; Gu et al., 1999; Lavigne, 2003, see also

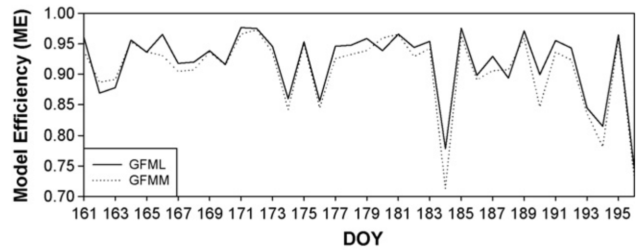

Fig. 3 – A comparison of model efficiency (ME) for the earlier version of the GFM designed to handle medium-sized gaps (GFMM; Xing et al., 2008) and the current GFM for large-sized gaps (GFML). MEs are based on data from Fig. 2.

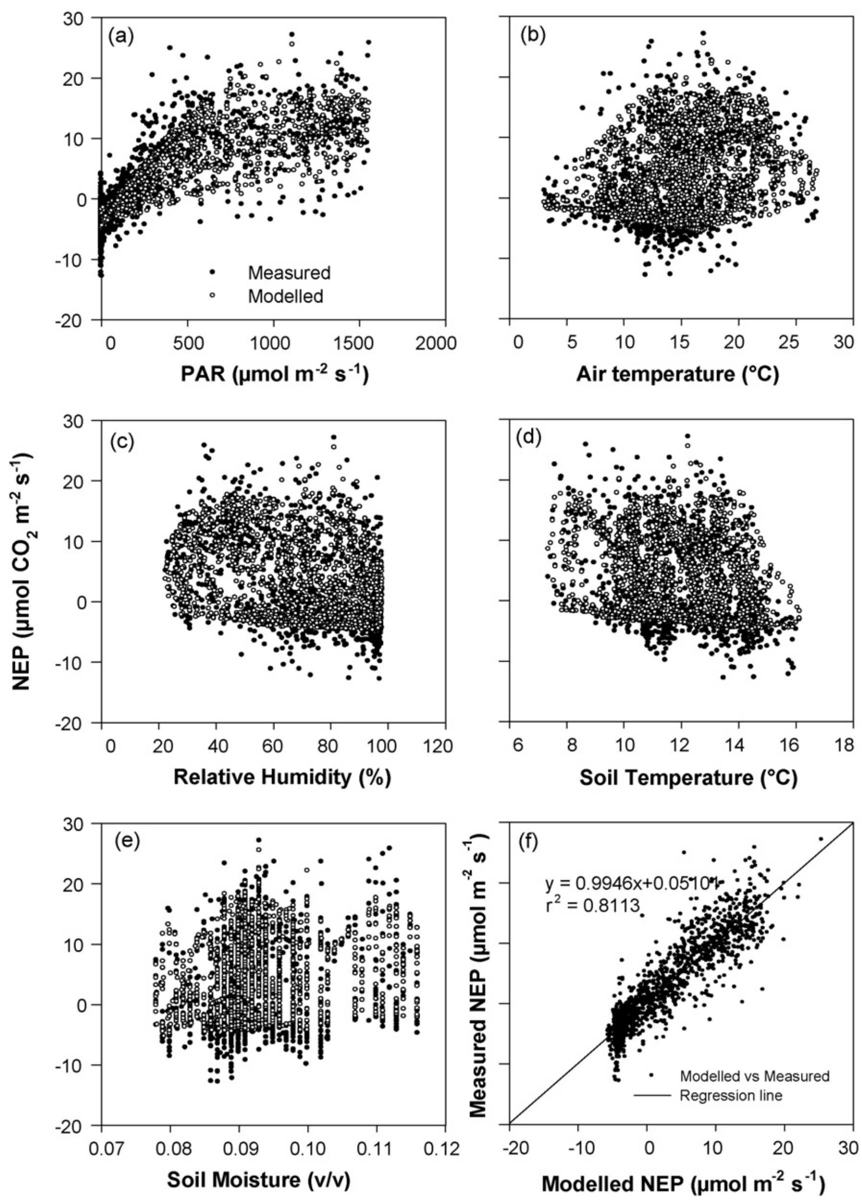

Fig. 4 – NEP response as functions of PAR (a), air temperature (b), RH (c), soil temperature (d), and SWC (e) based on implementation of the current GFM. Graph (f) gives overall model performance as a function of data point alignment to the 1:1 line, regression line fitted to the modelled-vs.-measured data pairs, and coefficient of determination (r^2).

Fig. 1),

$$R_s = R_{s\,max}\ \exp\left\{R_{s\alpha} \times \left[R_{s\beta} - \frac{1}{(T_s - 227.13)}\right]\right\}, \quad (9)$$

where R_{smax} is the maximum soil respiration (defaulted to 2.26 μmol m^{-2} s^{-1}), T_s is the soil temperature (in K), and $R_{s\alpha}$ and $R_{s\beta}$ are equation parameters set to 308 (K; Gu et al., 1999) and 0.017825 (K^{-1}), respectively.

2.3. Model parameterization and optimization

Iterative numerical methods, such as Levenberg-Marquardt and Nelder-Mead Simplex method, are frequently used in non-linear model parameterization. This is accomplished by minimizing the difference between the model's results and target data (observations), provided in terms of the weighted sum of square and expressed as:

$$\chi^2 = \sum \frac{(P_j - O_j)^2}{Er^2} \quad (10)$$

where O_j is the target value, P_j the calculated value, Er the uncertainty associated with the data values predetermined by the user, and j represents a specific target data-prediction data pair.

2.4. Model evaluation

Five methods were used to evaluate model performance including:

(1) *Modelling efficiency* (ME), given as:

$$ME = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(|P_i'| + |O_i'|)^2} \quad (11)$$

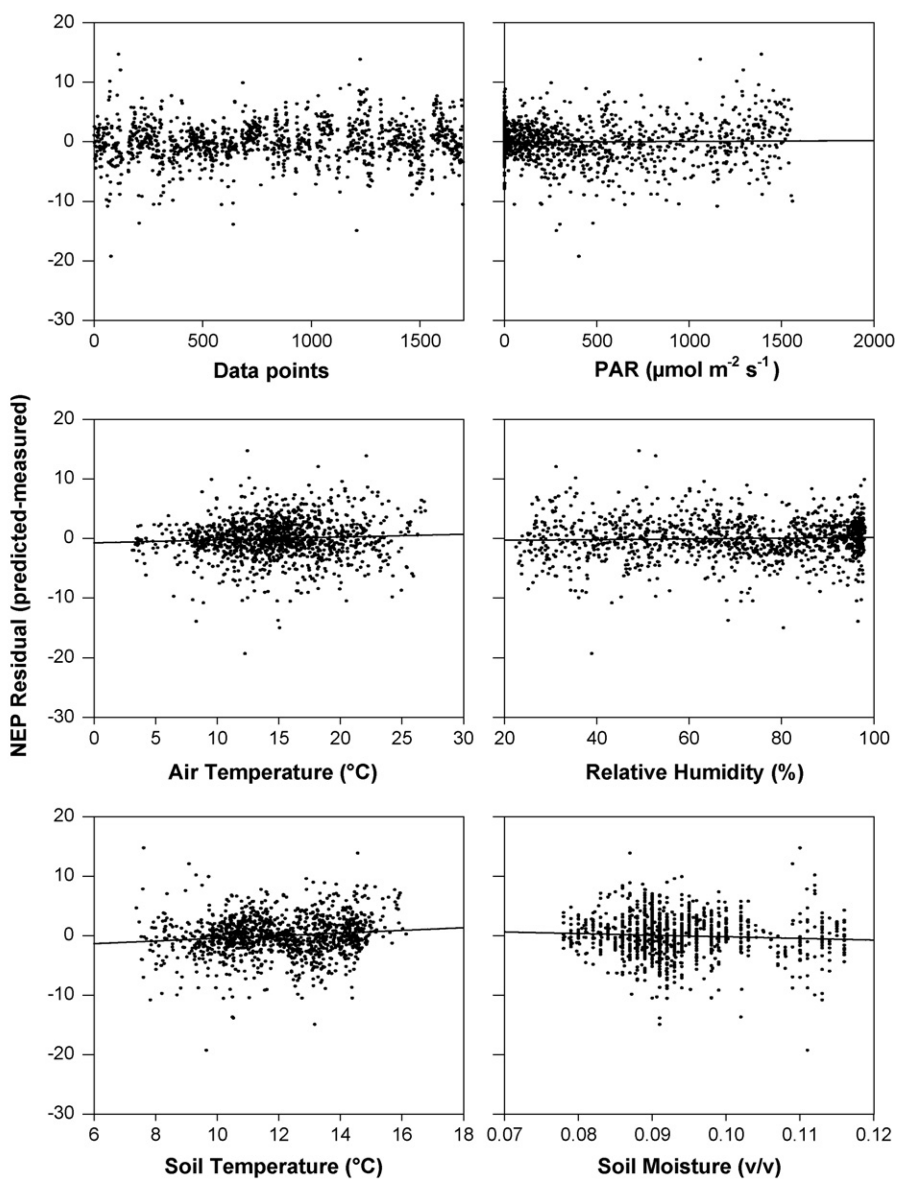

Fig. 5 – Residual plots with respect to the different controlling variables of the current GFM.

where $P_i' = P_i - \bar{O}$; $O_i' = O_i - \bar{O}$; and $\bar{O}$ is the mean of the observations, (Willmott, 1981; Leuning et al., 1998). The ME ranges from ME = 1 to ME = 0 as agreement between predicted values and observations vary from prefect to absolutely no agreement.

(2) *Relative error (RE)* for analyzing model bias. RE is given as

$$RE = \left[\frac{(\text{Predicted} - \text{Measured})}{\text{Measured}}\right] \times 100\%. \tag{12}$$

(3) *Residual analysis*, based on the difference between measured and modelled values, provides a useful tool in testing model structure (Medlyn et al., 2005). The technique is commonly used in flux research (Chen et al., 2002). In this research, model residuals are plotted against the controlling variables of PAR, T_a, RH, T_s, and SWC to examine model performance in relation to output data structure.

(4) "*Punch hole*" experiments involve removing data from the observation data stream before model parameterization and predicting the removed values. In contrast, *extrapolation* experiments consist of using entire, pre-defined sections of the data stream for model parameterization and estimating values in other sections downstream from the sections used in model parameterization.

(5) *Cross-site validation* by applying the final GFM to other datasets not involved in the development of the model. In this test, the model uses data from 12 datasets from selected ecosystems monitored as part of the CarboEurope project (Papale et al., 2006).

2.5. *Analysis platform*

ModelMaker v. 3.0 (Cherwell Scientific Ltd. Oxford, UK) provides an object-oriented modelling platform for the development, parameterization, and testing of the GFM. Data

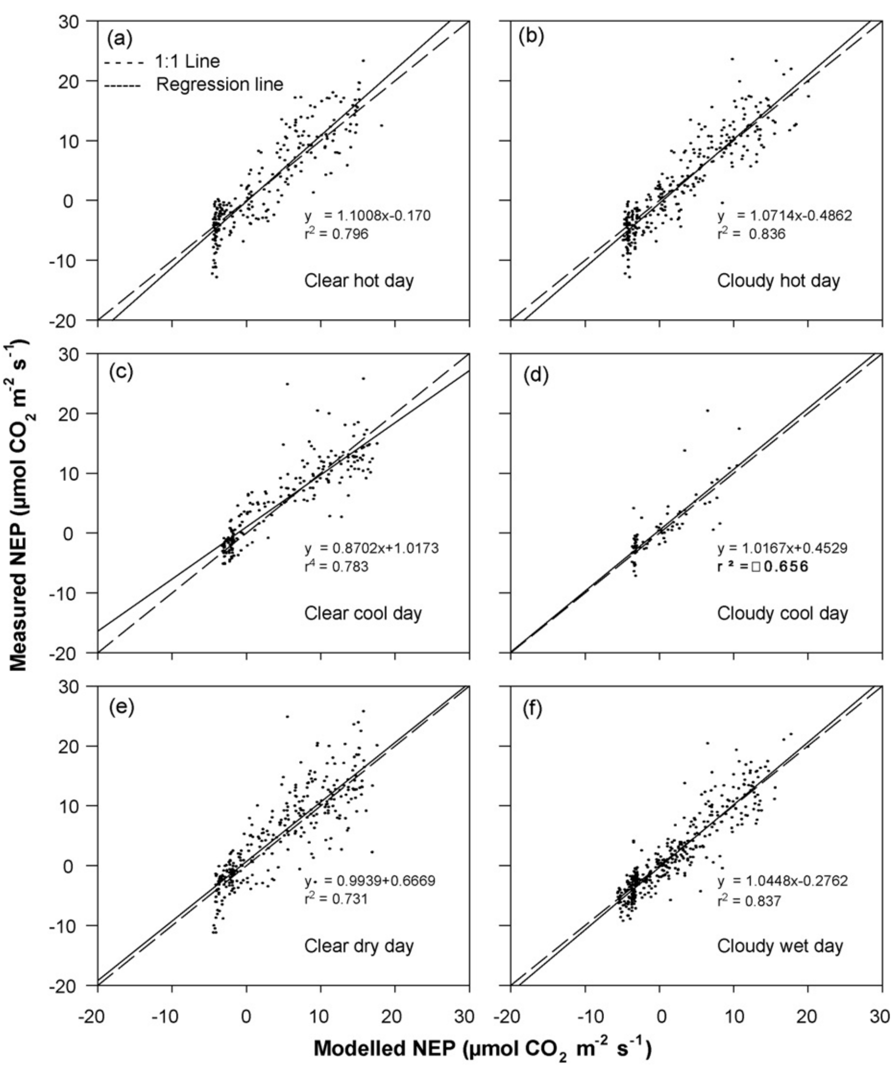

Fig. 6 – Model performance as a function of six day categories, namely (a) 6 clear-hot days (defined as PAR > 800 μmol m^{-2} s^{-1} and T_a > 20 °C); (b) 8 cloudy-hot days (PAR < 800 μmol m^{-2} s^{-1} and T_a > 20 °C); (c) 5 clear-cool days (PAR < 800 μmol m^{-2} s^{-1}, and T_a < 20 °C); (d) 2 cloudy-cool days (PAR < 800 μmol m^{-2} s^{-1} and T_a < 20 °C); (e) 8 clear-dry days (PAR > 800 μmol m^{-2} s^{-1} and RH < 60%); and (f) 12 cloudy-wet days (PAR < 800 μmol m^{-2} s^{-1} and RH > 60%).

analysis in this paper was carried out in MS Excel, and SPSS (SPSS Inc., Chicago, USA).

3. Results and discussion

3.1. *Model evaluation – based on NWL_BF data*

Fig. 2 provides the NEP output from an earlier version of the GFM (designed to address medium-sized gaps; Xing et al., 2008) and the current GFM. GFM performs better than the earlier model for most of the days, except for DOY 162, 163, and 180. The mean relative error (RE) is about 0.2% with a standard error (SE) of ±15.35%. Although the absolute values of RE can be large (i.e., >|100%|) for some points, the median is approximately −10%, which suggest that the model may underestimate NEP by about 10%. Variance analysis shows that GFM rectified underestimation by the earlier model (Xing et al., 2008) for some points during DOY 161, 162, 163, 164, 171, and 179 when RH <40%, and underestimations of some other points during DOY 192, when RH is <60% and DOY 165, 166, 176 and 187 when RH is >90%. Biases observed between measured and modelled NEP on DOY 162 are not statistically significant (i.e., F/F_{crit}, 0.15, and $p = 0.69$). The regression analysis between model and measured values provided an r^2 of 0.81, suggesting that the variables in GFM were able to explain 81% of the variability in the measured NEP values. As in earlier versions of the GFM, prediction of daytime NEP is far superior to prediction of nighttime NEP, although daytime performance varied from day to day. Nineteen percent of variation in current NEP measurements remains unexplained by GFM, which is reasonable. As Grant et al. (2005) rationalizes, 20% or more of the variation in CO_2 fluxes measured by means of EC remains unexplained by process models, even when they have detailed mass and energy transfer formulations. The authors explain that the variation observed could be reasonably caused by random error in flux measurements, due to the statistical nature of turbulent-transport processes involved (Wesely and Hart, 1985; Grant et al., 2005).

Average ME associated with GFM increases by 1.4%, compared to the earlier model (Fig. 3). The figure shows the day-to-day variation of ME. In general, both models have problems in modelling larger-than-normal and mostly unexplained variation in the NWL_BF-FCRN site data.

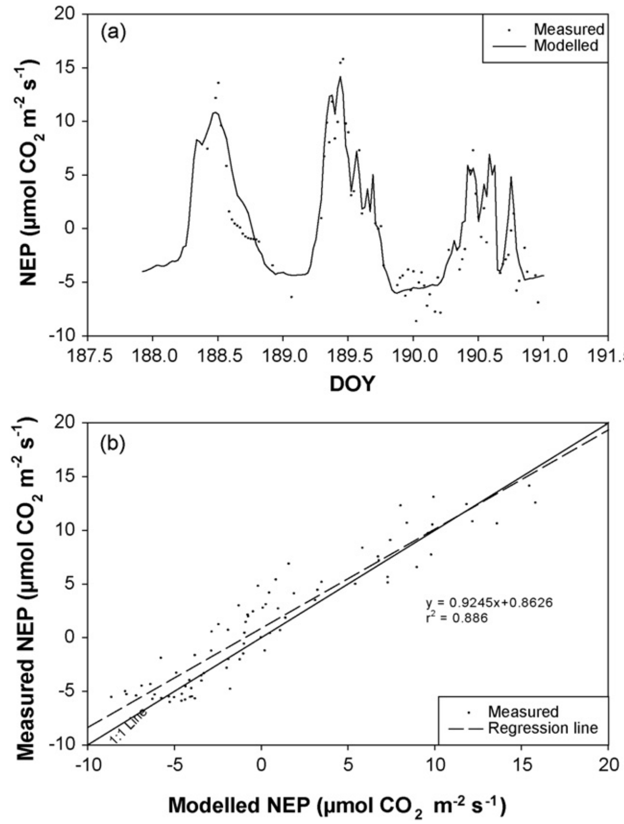

Fig. 7 – "*Punch hole*"-interpolation experiment: (a) time series of measured (dots) and modelled (line) NEP; (b) linear regression applied to modelled-vs.-measured data pairs, where the 1:1 line represents complete agreement between modelled and measured NEP values.

Fig. 4 displays the distribution patterns of modelled and measured NEP values plotted against PAR, T_a, RH, T_s, and SWC. In general, the distribution patterns of NEP associated with the different controlling variables coincide reasonably well for most cases. Discrepancies between modelled and measured

Table 1 – Parameter values determined from model parameterization using specified sections of the dataset (column 1)

Data section	α	GEP_{max}	$R_{c\beta}$	R_{cmax}	R_{copt}	K_{rt}	V_k	R_{smax}	$R_{s\alpha}$	$R_{s\beta}$	r^2
1–120	0.00521	1.1002	0.06666	0.5023	15	1000	1.1	1.5182	0.01012	350.0	0.6979
1–240	0.00370	1.0270	0.2127	1.5286	15	995	1.5	1.6800	0.01020	304.2	0.7650
1–480	0.00229	1.2677	0.1473	1.2387	15	1000	1.5	1.5919	0.01000	350.0	0.7790
1–960	0.00248	1.4233	0.1212	1.0589	15	1000	1.3	1.5000	0.00100	350.0	0.8115
1–1440	0.00247	1.7079	0.1139	1.0956	15	1000	1.2	1.5100	0.01013	350.0	0.8110
Entire dataset (1–1700)	0.00300	2.2485	0.0451	0.7032	15.4	1000	0.9	1.7356	0.23265	350.0	0.8137
480–960	0.00238	1.5100	0.0987	0.9793	15	1000	1.5	3.7974	0.01000	349.99	0.8605
960–1440	0.00221	1.8720	0.0101	1.2872	17.8	1000	1.5	3.7992	0.01430	349.89	0.8203

[a] GEP_{max} is the maximum GEP, based on LAI/4, where 4 represents the number of canopy layers; α is a light use efficiency parameter, K_{rt} is the parameter to determine temperature influence on photosynthesis, V_k is the parameter relating to stomatal conductance modifier, R_{cmax}, $R_{c\beta}$ and R_{copt} are the parameters determining the maximum canopy respiration, a shape factor of canopy respiration, and the reference temperature at which the highest canopy respiration occurs, R_{smax}, $R_{s\alpha}$, and $R_{s\beta}$ are parameters for soil respiration, and r^2 is the coefficient of determination associated with the degree a model can explain the variability in measured data.

values are examined in order to understand the limitations of the current GFM.

Fig. 4a provides the distribution patterns of modelled and measured NEP as a function of PAR. Underestimation of high NEP values can be observed when PAR is <500–600 μmol m^{-2} s^{-1}. Three reasons potentially contribute to these underestimations: (i) at these low PAR levels, plant growth is generally more sensitive to light variations; (ii) when the model is parameterized using the available dataset, invariably an average trend is derived. However, when the resultant model is applied to predict specific data points, the actual combination of environmental controls (input variables) may not be the same as the "averaged" combination of environmental controls used to derive the averaged trend. This may ultimately lead to imprecision in some of the predictions; (iii) Vertical variation in canopy respiration and photosynthesis (Lewis et al., 2000) is not addressed in the model, which may cause the model to fail from capturing specific peaks in NEP. When PAR >600 μmol m^{-2} s^{-1} and NEP closed to 0 or slightly negative, obvious discrepancies result between measured and modelled NEP. These discrepancies are likely caused by measurement noises or difficult-to-predict fluctuations in daily respiration. Although the bias is large for some data points (i.e., RE >50%), the data points most affected accounted for <10% of the entire dataset. Further statistical analysis showed that *RE* (relative error) for low light conditions is −8.15%, when PAR <10 μmol m^{-2} s^{-1}, and for high light conditions, RE is −13%, when PAR is between 10 and 500 μmol m^{-2} s^{-1}, and 2.29% when PAR is >500 μmol m^{-2} s^{-1}, respectively.

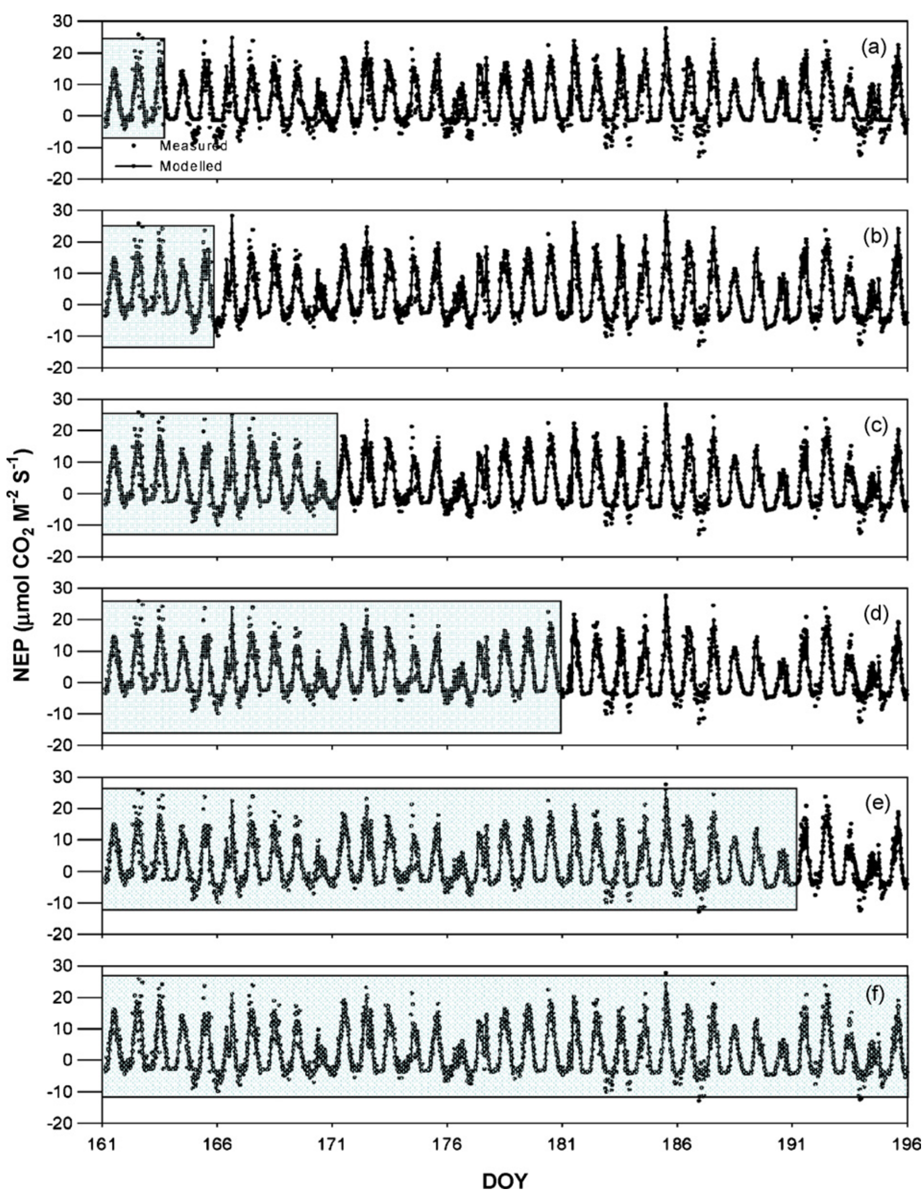

Fig. 8 – "Extrapolation experiments" consisting of (a) 120, (b) 240, (c) 480, (d) 960, (e) 1440 data points, and (f) the entire dataset (1700 data points) for model parameterization. Parameter values derived for each data section (represented by the box) appear in Table 1. The model is subsequently used to estimate (extrapolate) the remaining (unboxed sections) of the dataset based on the data section-specific parameter values.

Over the entire temperature range, there is a slight overestimation of about 5% of the data points (Fig. 4b). Overestimation of this level is common in detailed ecosystem models (Grant et al., 2005), because temperature, as a multiple-phase factor, influences NEP non-linearly by affecting plant growth and plant respiration processes at the same time. In comparison, GFM provides a better fit when temperature > 20 °C. For temperatures between 5 and 20 °C, GFM underestimates ~1% of the data points. Further statistical analysis indicates that *RE* is −51%, −0.49%, and 2.49% for air temperature <10 °C, between 10 and 20 °C, and >20 °C, respectively. Although a large *RE* is associated with air temperatures <10 °C, the error, manifested as an underestimation, affects about 15.3% of the data points. The general NEP-temperature response suggests that 85% of the data points can be accurately represented with GFM.

Distribution of modelled and measured NEP values as a function of RH are similar except for a slight overestimation in about 6% of the data points and an underestimation in <1% of the data points (Fig. 4c). When RE is examined as a function of RH, RE is −6.13% when RH <40%, −3.19% when between 40 and 80%, 2.78% when between 80 and 90%, and 26% when >90%. These results suggest that the model performs well when RH <90%, covering about 71% of the total number of data points, and poorly, when RH >90%.

Although modelled and measured NEP-soil temperature response fits well, there is an obvious cut-off at the low NEP extreme (Fig. 4d). A small portion of data display large biases during the respiration-dominated portion of the day. Statistical analysis shows that GFM performs better when soil temperature is >10 °C (RE = 19%) than when soil temperature <10 °C (RE = −35%). Currently, parameters in the soil respiration function of GFM are set constant based on literature values. If these same parameters are calibrated with soil respiration measurements from soil chambers (unavailable for this study), model results could potentially be improved for the respiration-dominated periods of the day.

General patterns of responses between the modelled and measured NEP to soil moisture (SWC) are nearly similar except that an underestimation of NEP can be found during respiration-dominated period of the day (Fig. 4e). Statistical analysis shows that RE for SWC (*sm*) <0.09 is about 30%, −15.79 for SWC (*sm*) = (0.09–0.10), and −12.57% for SWC (*sm*) > 0.10, based on SWC measured at NWL_BF.

The slope of the regression line (0.995) applied to the modelled-vs.-measured NEP data pairs is close to the 1:1 correspondence line indicating that on average the model balances underestimation with an equal amount of overestimation; the high r^2-value (0.81; Fig. 4f) obtained from this research equally illustrates this point with an overall improvement in performance from the GFM designed for medium-sized gaps ($r^2 = 0.77$, and Fig. 3; Xing et al., 2008).

Overall, residual plots (Fig. 5a–f) show no organized structure, except a slight linear trend in the residual plot for soil temperature. From this, we can conclude that the model structure is mostly correct.

3.2. *Model response to various weather conditions – based on NWL_BF data*

To investigate the model's performance under various weather conditions, data from 41 days were selected from the dataset and partitioned according to six day-types: namely, (*i*) clear-hot days (comprising of 6 days), (*ii*) clear-cool days (5 days), (*iii*) cloudy-hot days (8 days), (*iv*) cloudy-cool days (2 days), (*v*) clear-dry days (8 days), and (*vi*) cloudy-wet days (12 days). The model provides reasonable fits for hot days, yielding a slope of 1.1 and 1.07, and r^2 of 0.796 and 0.836 for clear-hot and cloudy-hot days, respectively (Fig. 6a and b). For both hot and cold days, the model tends to slightly underestimate NEP values during periods of high positive NEP and during periods of high respiration. However, on cool days (Fig. 6c and d), the model does not perform as well. Obviously, some data points (measured NEP > 10 μmol m^{-2} s^{-1}; Fig. 6d) critically

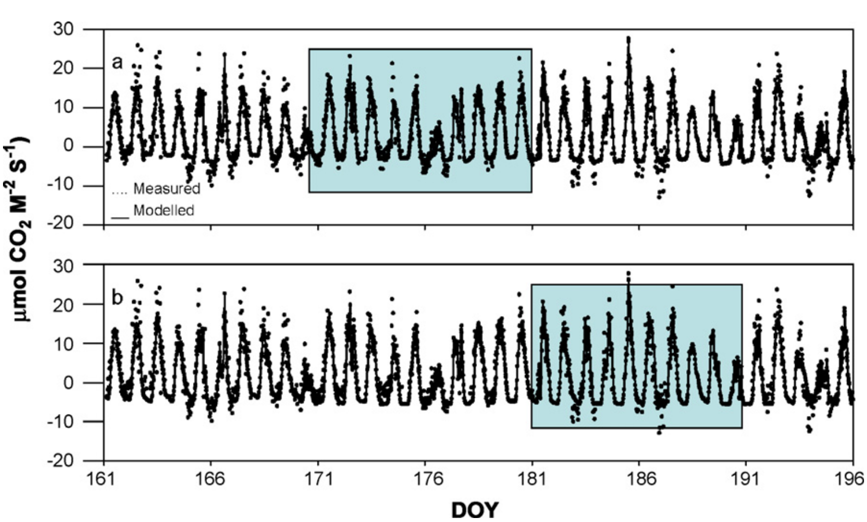

Fig. 9 – "Extrapolation experiment"using 480 data points for model parameterization (sections indentified by boxes). Graph (a) provides the results based on model parameters generated from data points 480 to 960, and (b) the results, based on model parameters generated from data points 960 to 1440. The resultant models are used to predict the data on either side of the data section employed in model parameterization (the unboxed portion of the dataset).

affected model parameterization, which caused the resultant model to misrepresent portions of the dataset. Those data points may be "problematic" as noted by Medlyn et al. (2005), due to the lack of turbulence and trunk-space ventilation (i.e., u^*, above canopy friction velocity, <0.25 m s^{-1} for NWL_BF, Coursolle et al., 2006). Alternatively, the model performs better on cloudy-wet days (Fig. 6e) than on clear-dry days (Fig. 6f). From this analysis, it is reasonable to conclude that the model yields reasonable estimates of NEP for most weather conditions, although a certain level of discrepancy remains.

3.3. "Punch hole" interpolation experiment

To test model performance by means of interpolation, 3 days worth of measurements (DOY 188 through to 190) were removed from the dataset prior to the parameterization of the model using the remaining data. The model was then used to generate the data for removed data points (Fig. 7a). Although the model slightly underestimates NEP on DOY 190, the model captures most of the variation. Regression analysis for the 3 days shows that the model slightly overestimates NEP (Fig. 7b). Maximum bias was around 8%. The model explains about 89% of the variation in the measured NEP data. The experiment suggests that the GFM can produce reasonable estimates of NEP by interpolation.

3.4. Extrapolation and large data gap interpolation experiments

To test the GFM's ability to extrapolate data values for large data gaps and to determine the correlation between data input amounts and model output quality, several experiments were conducted by using the first 120, 240, 480, 960, 1440 data points, and the entire dataset (1700 data points) for model parameterization. Following parameterization (Table 1), the model was then used to estimate the unremoved data points (Fig. 8). Further testing of the model was conducted by using two

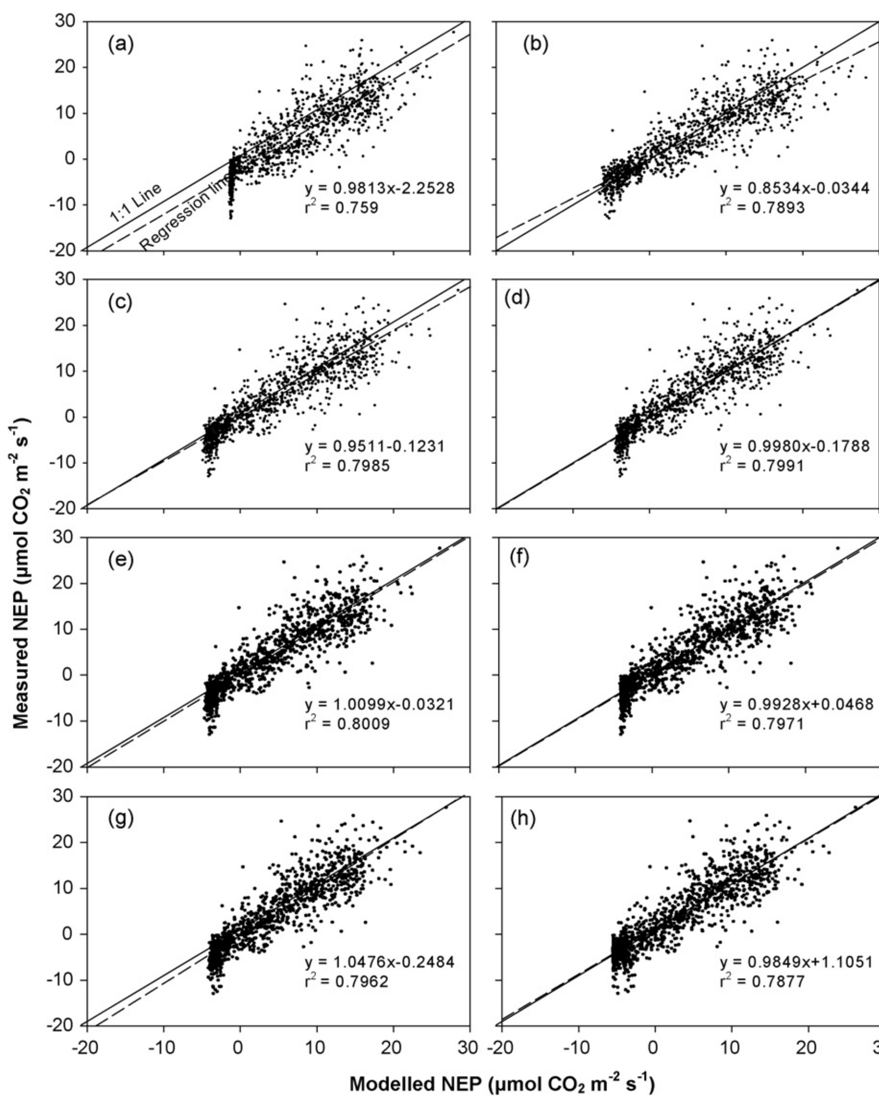

Fig. 10 – Linear regressions applied to modelled-vs.-measured NEP data pairs representative of different parameterization strategies identified in Fig. 9, i.e., (a) first 120, (b) 240, (c) 480, (d) 960, and (e) 1440 data points, and (f) the entire dataset (1700 data points), (g) data points 480–960; and (h) data points 960–1440.

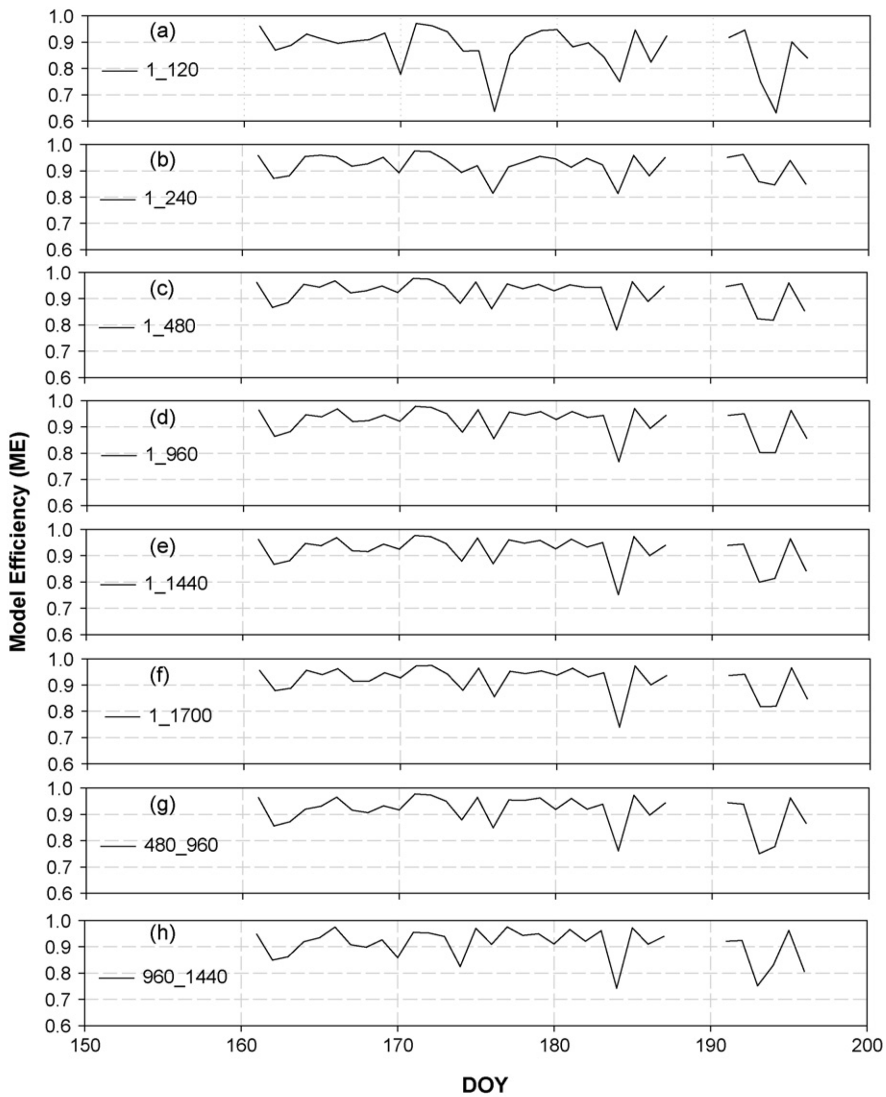

Fig. 11 – Model efficiencies (ME) for the different parameterization and extrapolation strategies (based on Figs. 8 and 9).

large middle sections of the dataset (data points 480–960 and 960–1440) to parameterize the model, then to interpolate large data gaps (Fig. 9) both upstream and downstream from the data section employed in model parameterization.

The first extrapolation experiment consistently underestimates NEP by ~50% (Figs. 8a and 10a; based on 120 data points). This underestimation is caused either by employing too few data points for proper model parameterization or abnormal variation in observed values within the first 120 data points (first 3 days). However, by doubling the number of data points to 240, improvement results in the intercept, by bringing it closer to 0 and increasing the r^2-value from 0.76 to 0.79 (Figures 8b and 10b). The slope of the regression line, however, is negatively affected by bringing the slope of nearly 0.98 down to 0.85. These changes are reasonable responses to additional data points, covering greater variation in NEP and environmental controls along with their combined effects on model parameterization.

Significant improvement results with the intercept (close to 0), slope (95%), and r^2-value (0.80) when the number of data points is further doubled to 480; however, there is an apparent slight underestimation (Figs. 8c and 10c). Even more improvement is obtained when 960 data points are used, giving a slope of 0.998, a near-zero intercept, and a high r^2-value (0.80; Figs. 8d and 10d). Further doubling of the data points beyond 960 only provides minor improvement (Figs. 8e, 8f, 10e, and 10f). Fig. 8g and h (480 data points) illustrate similar model results to the 480-data point scenario (Fig. 10c). These tests suggest that a minimum of 480 data points are required for reasonable model fitting of the dataset. Fig. 11 shows variation in ME for the different parameterization schemes, in compliance with results in Figs. 8–10. The model appears to provide satisfactory interpolative and extrapolative projections when >480 data points are used in model parameter fitting.

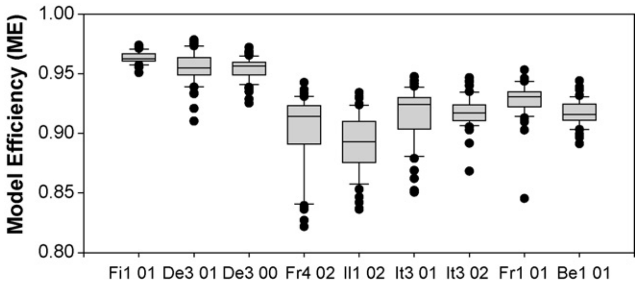

Fig. 12 – Model efficiencies (ME) for the different CarboEurope sites. Each letter designation on the *x*-axis stands for the flux dataset used in the evaluation of the current GFM and its associated year (last two numbers); Fi1 stands for the Hyytiala site in Finland, De3 for the Hainich site in Germany, Fr1 and Fr4 for the Hesse and Puechabon site in France, Il1 for the Yatir forest site in Israel, It3 for the Roccaresp site in Italy, and Be1 for the Vielsalm site in Belgium.

3.5. *Further model validation – based on CarboEurope project datasets*

To test the portability of the model to other forest ecosystems globally, the model was applied to a selection of ecological sites along a latitudinal, temperature–moisture gradient from northern Europe (Finland) to Israel. In this study, nine datasets extracted from the CarboEurope project were used to validate GFM for multiple artificial gap sizes, running from single gaps lasting only half an hour to larger gaps, lasting over 12 consecutive days. Artificial gap scenarios were constructed following procedures described in Ajtar (http//www.bgc-jena.mpg.de/gf_workshop/). For each gap type, 10 scenarios were generated by varying the gap locations along the time series. In total, 450 gap scenarios were generated, yielding 50 gap scenarios per site per year.

The results showed that the model was able to produce reasonable NEP estimates for all scenarios considered. ME varied from 0.89 to 0.97 for the different sites and for the different years (Fig. 12). The r^2-values (between measured and modelled NEP for artificial gaps only) generated varied from 0.68 to 0.83, depending on the site and the particular year of comparison. The comparatively poor fitting associated with the Israeli site (Il1 02) was related to the fact that only PAR and T_a were available; all other input requirements were assumed constant or were estimated from surrogate variables. With a full compliment of model input, the model is expected to generate r^2-values >0.75 (between measured and modelled NEP for artificial gaps only). For a given site, model performance with single and small-gap scenario data is slightly poorer than with large-gap scenario data, although the variation is quite minor. The evaluation results suggest that GFM can reasonably capture a significant portion of the variation in NEP for most ecosystems investigated. Clearly, the current GFM has the potential to be applicable to other forest ecosystems outside Canada and, as a result, provides a powerful foundation for gap filling of tower-based measurements of NEP regardless of location. Further detail on the validation of the GFM with CarboEurope flux datasets will be covered in a separate paper.

4. Conclusions

After introducing air and soil moisture modifiers in an earlier version of the GFM, designed specially to address medium-sized gaps (Xing et al., 2008), the current GFM performed consistently better for large gaps.

- Although average ME for GFM was only 1.4% higher than the average ME obtained with the earlier model, the model corrected inaccuracies associated with extremely low and high RH's (i.e., RH < 40% and RH > 80%).
- NEP response to different environmental factors indicated a reasonable level of agreement between modelled and measured NEP. As a comparison, NEP response to air temperature showed a better fit than it did with PAR or RH; NEP response to soil temperature was generally not as good.
- Residual analysis confirmed that the model's structure was generally correct as no structured patterns were obvious in the residual plots created for individual controlling variables.
- Detailed examination of the model's performance for various day-types indicated that the model may provide reasonable predictions for different weather conditions, yielding r^2-values >0.7 for most of the cases examined. In general, the model output provided the best comparison to data collected on hot days.
- A 3-day gap experiment indicated that the model provided reasonable estimates when data gaps were small and when interpolation was used. Regression statistics revealed relatively high r^2-values (~0.88), a slope within 92% of the 1:1 line, and an intercept close to 0.
- Further testing of the model suggested that a minimum of 480 data points were required for the best representation of a 34-day dataset. When the number of data points increased beyond 480, there were no additional gains in representation. It appears that datasets lasting for at least 10 days are sufficiently long enough to generate acceptable model parameters and model output.
- Cross ecosystems validation indicated that the model was easily portable to other forest ecosystems to deal with many different types of data gaps and obtain a reasonable performance with r^2-values >0.75 when a full compliment of input data were provided. With minimum model inputs provided (in this case, PAR and T_a for the Israeli site), the model captured ~68% of the variation in NEP.

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