

Semi-empirical modeling of abiotic and biotic factors controlling ecosystem respiration across eddy covariance sites

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Global Change Biology

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Semi-empirical modeling of abiotic and biotic factors controlling ecosystem respiration across eddy covariance sites

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Abstract

69 In this study we examined ecosystem respiration (R_{ECO}) data from 104 sites belonging to 70 FLUXNET, the global network of eddy covariance flux measurements. The main goal was to 71 identify the main factors involved in the variability of R_{ECO} : temporally and between sites as 72 affected by climate, vegetation structure and plant functional type (PFT) (evergreen needleleaf, 73 grasslands, etc.).

mporal variability in the data and that the depended to be included as an additional driver of R_{ECOMAX}) had an additional effect that explained t (the respiration at reference temperature Tref=1: synthetic activity and w 74 We demonstrated that a model using only climate drivers as predictors of R_{ECO} failed to 75 describe part of the temporal variability in the data and that the dependency on gross primary 76 production (GPP) needed to be included as an additional driver of R_{ECO} . The maximum seasonal 77 leaf area index (LAI_{MAX}) had an additional effect that explained the spatial variability of 78 reference respiration (the respiration at reference temperature Tref=15°C, without stimulation 79 introduced by photosynthetic activity and without water limitations), with a statistically 80 significant linear relationship (r^2 =0.52 p<0.001, n=104) even within each PFT. Besides LAI_{MAX}, 81 we found that the reference respiration may be explained partially by total soil carbon content. 82 For undisturbed temperate and boreal forest a negative control of the total nitrogen deposition on 83 the reference respiration was also identified.

84 We developed a new semi-empirical model incorporating abiotic factors (climate), recent 85 productivity (daily GPP), general site productivity and canopy structure (LAI_{MAX}) which 86 performed well in predicting the spatio-temporal variability of R_{ECO} , explaining >70% of the 87 variance for most vegetation types. Exceptions include tropical and Mediterranean broadleaf 88 forests and deciduous broadleaf forests. Part of the variability in respiration that could not be 89 described by our model could be attributed to a range of factors, including phenology in 90 deciduous broadleaf forests and management practices in grasslands and croplands.

92 Keywords: Ecosystem Respiration, Productivity, FLUXNET, Eddy Covariance, Leaf Area 93 Index, Inverse Modeling

Introduction

97 Respiration of terrestrial ecosystems (R_{ECO}) is one of the major fluxes in the global carbon cycle 98 and its responses to environmental change is important for understanding climate-carbon cycle 99 interactions (e.g. Cox *et al.*, 2000, Houghton *et al.*, 1998). It has been hypothesized that relatively

100 small climatic changes may impact respiration with the effect of rivalling the annual fossil fuel 101 loading of atmospheric CO₂ (Jenkinson et al., 1991, Raich & Schlesinger, 1992).

 $\overline{7}$ 102 Recently, efforts have been made to mechanistically understand how temperature and other 103 environmental factors affect ecosystem and soil respiration, and various modeling approaches have 104 been proposed (e.g. Davidson *et al.*, 2006a, Lloyd & Taylor, 1994, Reichstein & Beer, 2008, Reichstein *et al.*, 2003a). Nevertheless, the description of the conceptual processes and the complex interactions controlling R_{ECO} are still under intense research and this uncertainty is still hampering bottom-up scaling to larger spatial scales (e.g. regional and continental) which is one of the major challenges for biogeochemists and climatologists.

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are usually described as a function of air of
ontent (e.g. Lloyd & Taylor, 1994, Reichstein *et a*ctional form of these relationships varies from
lominant role of reaction kinet Heterotrophic and autotrophic respiration in both data-oriented and process-based biogeochemical models are usually described as a function of air or soil temperature and 111 occasionally soil water content (e.g. Lloyd & Taylor, 1994, Reichstein *et al.*, 2005, Thornton *et al.*, 112 2002), although the functional form of these relationships varies from model to model. These functions represent the dominant role of reaction kinetics, possibly modulated or confounded by 114 other environmental factors such as soil water content or precipitation, which some model 115 formulations include as a secondary effect (e.g. Carlyle & Ba Than, 1988, Reichstein *et al.*, 2003a, Richardson *et al.*, 2006).

A large number of statistical, climate-driven models of ecosystem and soil respiration have been 118 tested and compared using data from individual sites (Del Grosso *et al.*, 2005, Janssens & 119 Pilegaard, 2003, Richardson & Hollinger, 2005, Savage *et al.*, 2009), multiple sites (Falge *et al.*, 2001, Rodeghiero & Cescatti, 2005), and from a wide range of models compared across different ecosystem types and measurement techniques (Richardson et al., 2006).

Over the course of the last decades, the scientific community has debated the role of productivity 123 in determining ecosystem and soil respiration. Several authors (Bahn *et al.*, 2008, Curiel Yuste *et* 124 *al.*, 2004, Davidson *et al.*, 2006a, Janssens *et al.*, 2001, Reichstein *et al.*, 2003a, Valentini *et al.*, 125 2000) have discussed and clarified the role of photosynthetic activity, vegetation productivity and their relationship with respiration.

Linking photosynthesis and respiration might be of particular relevance when modelling R_{ECO} across biomes or at the global scale. Empirical evidence for the link between GPP and R_{ECO} is 129 reported for most, if not all, ecosystems: grassland (e.g. Bahn *et al.*, 2008, Bahn *et al.*, 2009, Craine 130 *et al.*, 1999, Hungate *et al.*, 2002), crops (e.g. Kuzyakov & Cheng, 2001, Moyano *et al.*, 2007), 131 boreal forests (Gaumont-Guay *et al.*, 2008, Hogberg *et al.*, 2001) and temperate forests, both 132 deciduous (e.g. Curiel-Yuste *et al.*, 2004, Liu *et al.*, 2006) and evergreen (e.g. Irvine *et al.*, 2005). 53 55129 59 60132

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133 Moreover, several authors have found a time lag between productivity and respiration response. 134 This time lag depends to the vegetation structure it is related to the translocation time of assimilates 135 from aboveground to belowground organs through the phloem. Although the existence of a time lag 136 is still under debate, it has been found to be a few hours in grasslands, and croplands and a few 137 days in forests (Baldocchi *et al.*, 2006, Knohl & Buchmann, 2005, Moyano *et al.*, 2008, Savage *et* 138 *al.*, 2009).

While the link between productivity and respiration appears to be clear, to our knowledge, few model formulations include the effect of productivity or photosynthesis as a biotic driver of respiration and these models are mainly developed for the simulation of soil respiration using a 142 relatively small data set of soil respiration measurements (e.g. Hibbard *et al.*, 2005, Reichstein *et* 143 *al.*, 2003a).

of soil respiration measurements (e.g. Hibbard *e* increasing availability of ecosystem carbon, by means of the eddy covariance technique (e.g types (PFTs) at more than 400 research sites, rep and interactions behind carbo In this context, the increasing availability of ecosystem carbon, water and energy flux measurements collected by means of the eddy covariance technique (e.g. Baldocchi, 2008) over different plant functional types (PFTs) at more than 400 research sites, represents an useful tool for understanding processes and interactions behind carbon fluxes and ecosystem respiration. These data serve as a backbone for bottom-up estimates of continental carbon balance components (e.g. 149 Ciais *et al.*, 2005, Papale & Valentini, 2003, Reichstein *et al.*, 2007) and for ecosystem model 150 development, calibration and validation (e.g. Baldocchi, 1997, Hanson *et al.*, 2004, Law *et al.*, 151 2000, Owen *et al.*, 2007, Reichstein *et al.*, 2003b, Reichstein *et al.*, 2002, Verbeeck *et al.*, 2006). The database includes a number of added products such as gap-filled net ecosystem exchange (NEE), gross primary productivity (GPP), ecosystem respiration (R_{ECO}) and meteorological drivers (air temperature, radiation, precipitation etc) aggregated at different time-scale (e.g. half-hourly, 155 daily, annual) and consistent for data treatment (Papale *et al.*, 2006, Reichstei *et al.*, 2005)

In this paper we analyze with a semi-empirical modeling approach the R_{ECO} at 104 different sites belonging to the FLUXNET database with the primary objective of synthesizing and identifying the 158 main factors controlling i) the temporal variability of R_{ECO} , ii) the between-site (spatial) variability and *iii*) to provide a model which can be used for diagnostic up-scaling of R_{ECO} from eddy covariance flux sites to large spatial scales.

Specifically, the analysis and the model development followed these two steps:

1. we developed a semi-empirical R_{ECO} model site by site (site-by-site analysis) with the aim of clarifying if and how GPP should be included into a model for improving the description of R_{ECO} and which factors are best suited for describing the spatial variability of reference respiration (i.e. the daily R_{ECO} at the reference temperature without moisture limitations). 166 We follow these three steps:

- o the analysis of RECO data was conducted by using a purely climate driven model: *'TP* 168 *Model'* (Raich et al., 2002). The accuracy of the model and the main bias were 169 analyzed and discussed;
- \circ we evaluated the inclusion of biotic factors (i.e. GPP) as drivers of R_{ECO}. A range of 171 different model formulations, which differ mainly in regard to the functional responses of R_{ECO} to photosynthesis, were tested in order to identify the best model formulation for the daily description of R_{ECO} at each site;
	- o we analyzed variability of the reference respiration estimated at each site with the aim of identifying, among the different site characteristics, one or more predictors of the spatial variability of this crucial parameter. This can be extremely useful for the application of the model at large spatial scale;
	- 2. we optimized the developed model for each PFT (PFT analysis) with the aim of generalizing the model parameters in a way that can be useful for diagnostic, PFT-based, up-scaling of R_{ECO} . The accuracy of the model was assessed by a cross-validation technique and the main weak points of model were critically evaluated and discussed.

Material and Methods

Data set

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variability of this crucial parameter. This can be

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developed model for each PFT (PFT analysis) wit

ters in a way that can be useful for diagnostic, 1

y of the model was assessed b The data used in this analysis is based on the dataset from the FLUXNET ([www.fluxdata.org\)](http://www.fluxdata.org/) eddy covariance network (Baldocchi, 2008, Baldocchi et al., 2001). The analysis was restricted to 104 sites (cf. Table in Appendix I and II) on the basis of the ancillary data availability (i.e. only sites containing at least both leaf area index (LAI) of understorey and overstorey were selected) and of the time series length (all sites containing at least one year of carbon fluxes and meteorological data of good quality data were used). Further, we only analyzed those sites for which the relative 193 standard error of the estimates of the model parameters E ⁰ (activation energy) and reference 194 respiration (R_0) (please see further sections for more details on the meaning of parameters) were 195 less than 50% and where E₀ estimates were within an acceptable range (0–450 K).

The latitude spans from 71.32° at the Alaska Barrow site (US-Brw) to -21.62 $^{\circ}$ at the Sao Paulo $Cerrado (BR-Sp1)$. The climatic regions include tropical to arctic.

All the main PFTs as defined by the IGBP (International Geosphere-Biosphere Programme) 199 were included in this study: the selected sites included 28 evergreen needleleaf forests (ENF), 17

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200 deciduous broadleaf forests (DBF), 16 grasslands (GRA), 11 croplands (CRO), 8 mixed forests 201 (MF), 5 savannas (SAV), 9 shrublands (SHB), 7 evergreen broadleaved forests (EBF) and 3 202 wetlands (WET). Due to limited number of sites and their similarity, the class SAV included both 203 the sites classified as savanna (SAV) and woody savannas (WSA), while the class SHB included both the open (OSH) and closed (CSH) shrubland sites. For abbreviations and symbols refer to Appendix III. 10_{204} 11 12 20 5 13

Daily R_{ECO}, GPP and the associated uncertainties of NEE data, together with daily 207 meteorological data such as mean air temperature (T_A) and 30-day precipitation running average (P), were downloaded from the FLUXNET database. 14 15 16 17 18208 19

209 At each site data are storage corrected, spike filtered, u *-filtered according to Papale et al. (2006) and subsequently gap-filled and partitioned as described by Reichstein et al. (2005). Only days 211 containing both meteorological and daily flux data with a percentage of gap-filled half hours below 212 15% were used for this analysis. The median of the u^{*} threshold applied in the FLUXNET database for the site-years used in the analysis are listed in the Appendix II. The average of the median u^* values are lower for short canopies (e.g. for grasslands 0.075 ± 0.047 ms⁻¹) and higher for tall canopies (e.g. for evergreen needleleaf forests $0.221 \pm 0.115 \text{ ms}^{-1}$). 20^{209} 25212 27213

for Forested, spike filtered, u_{*}-filtered accordical and partitioned as described by Reichstein ogical and daily flux data with a percentage of ganalysis. The median of the u_{*} threshold applied in the analysis are list Along with fluxes and meteorological data, main ancillary data such as maximum ecosystem LAI (overstory and understory for forest sites) (LAI_{MAX}), LAI of overstory (LAI_{MAX₀), stand age} for forests (StandAge), total soil carbon stock (SoilC) and the main information about disturbance (date of cuts, harvesting) were also downloaded from the database. Total atmospheric nitrogen deposition (N_{deno}) is based on the atmospheric chemistry transport model *TM3* (Rodhe et al., 2002) and calculated at $1^{\circ}x1^{\circ}$ resolution. These data are grid-average downward deposition velocities and 222 do not account for vegetation effects. The data used for the selected sites are shown in the Appendix $^{44}_{45}$ 223 II. 32216 34217 41221

Development of the ecosystem respiration model

Site-by-site analysis – TP Model description

For the analysis of R_{ECO} we started from a widely used climate-driven model: '*TP Model*' (Eq. 1) 230 proposed by Raich et al. (2002) and further modified by (Reichstein *et al.*, 2003a). Here we used the 231 59 '*TP Model*' for the simulation of R_{ECO} at the daily time-step using as abiotic drivers daily T_A and P: 60 232 57

$$
233 \t R_{ECO} = R_{ref} \cdot f(T_A) \cdot f(P) \t (1)
$$

235 where R_{ref} (gC m⁻²day⁻¹) is the ecosystem respiration at the reference temperature (T_{ref}, K) 236 without water limitations. $f(T_A)$ and $f(P)$ are functional responses of R_{ECO} to air temperature and 237 precipitation, respectively.

238 Here temperature dependency $f(T_A)$ is changed from the Q_{10} model to an Arrhenius type equation 239 (Eq. 2). E_0 (K) is the activation energy parameter and represents the ecosystem respiration 240 sensitivity to temperature, T_{ref} is fixed at 288.15 K (15°C) and T_0 is fixed at 227.13 K (-46.02°C):

$$
f(T_A) = e^{-E_0 \left(\frac{1}{T_{ref} - T_0} - \frac{1}{T_A - T_0}\right)}
$$
(2)

We refine the approach of Reichstein *et al.* (2003) and propose a reformulation of the response 245 of R_{ECO} to precipitation (Eq. 3), where k (mm) is the half saturation constant of the hyperbolic 246 relationship and α is the response of R_{ECO} to null P.

$$
f(P) = \frac{\alpha k + P(1 - \alpha)}{k + P(1 - \alpha)}
$$
(3)

Although soil water content is widely recognized as the best descriptor of soil water availability, we preferred to use precipitation since the model developed is oriented to up-scaling and soil water maps are more affected by uncertainty than precipitation maps.

(2)

th of Reichstein *et al.* (2003) and propose a refor

(Eq. 3), where *k* (mm) is the half saturation co

esponse of R_{ECO} to null P.

(3)

ontent is widely recognized as the best descriptor

pitation since the model 253 The model parameters – R_{REF} , E_0 , α , k - were estimated for each site in order to evaluate the 254 accuracy of the climate-driven model. At each site the Pearson's correlation coefficient (*r*) between *'TP Model'* residuals (R_{ECO} observed minus R_{ECO} modelled) and GPP was also computed.

Site-by-site analysis - Effect of productivity on the temporal variability of R_{ECO}

The role of GPP, as an additional biotic driver of R_{ECO} that has been included into Eq. 1, was analysed at each site using three different formulations of the dependency of ecosystem respiration 261 on productivity $f(\text{GPP})$:

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265 Beside the linear dependency the exponential and Michaelis-Menten responses were tested. 266 According to different authors (e.g. Hibbard et al., 2005, Reichstein et al., 2007) we hypothesized 267 that respiration might saturate at high productivity rates in a similar way to the Michaelis-Menten 268 enzyme kinetics. This saturation can also occur by a transition of carbon limitation to other 269 limitations. The exponential curve was used as another formulation of a saturation effect.

270 We tested two different schemes for the inclusion of *f*(GPP) (Eqs. 4, 5, 6) in the *'TP Model'* $(Eq.1)$:

f(GPP) was included by replacing the reference respiration at reference temperature 274 (R_{ref} in Eq. 1) with the sum of a new reference respiration (R_0) and the f(GPP):

$$
R_{ref} = R_0 + f(GPP) \tag{7}
$$

 23276 2) *f*(GPP) was included as an additive effect into the *'TP Model'*. In this case one part of ecosystem respiration is purely driven by biotic factors (e.g. independent from temperature) and the other one by abiotic ones.

For All the sum of a new reference respiration (R₀) and the sum of a new reference respiration (R₀) and the $R_{ref} = R_0 + f(GPP)$ **(7) sincluded as an additive effect into the** *TP Modspiration* **is purely driven by biotic fa** 280 In Table 1, R_0 is the new reference respiration term (i.e. ecosystem respiration at T_{ref} , when the 281 GPP is null and the ecosystem is well watered). This quantity is considered to be an indicator of the ecosystem respiration of the site, strictly related to site conditions, history and characteristics, while k_2 , R_2 , R_{max} and h_{Rmax} describe the assumed functional response to GPP.

285 **[TABLE1]**

287 The model parameters - R_0 , E_0 , α , k and the parameters of $f(GPP)$ - were estimated for each site in order to evaluate which model formulation best describes the temporal variability of R_{ECO} .

With the aim of confirming the existence of a time lag between photosynthesis and the 290 respiration response we ran the model with different time lagged GPP time-series (GPP_{lag,*i*}), starting from the GPP estimated on the same day (GPP $_{\text{lac},0}$), and considering daily increments back to GPP estimated one week before the measured R_{ECO} (GPP_{lag,7}).

GPP and R_{ECO} estimated with the partitioning method used in the FLUXNET database are derived from the same data (i.e. $GPP=R_{ECO}-NEE$) and this may to some extent introduce spurious correlation between these two variables. In literature two different positions on that can be found: Vickers *et al.*, (2009) argue that there is a spurious correlation between GPP and R_{ECO} when these 297 component fluxes are jointly estimated from the measured NEE (i.e. as estimated in the FLUXNET 298 database). Lasslop *et al.*, 2009 demonstrated that, when using daily sums or further aggregated data, 60_{297}

299 self-correlation is important because of the error in R_{ECO} rather than because R_{ECO} being a shared 300 variable for the calculation of GPP.

301 Lasslop *et al.*, 2010 further suggested a 'quasi'-independent GPP and R_{ECO} estimates (GPP_{LASS}) 302 and RECO-LASS). The method by Lasslop *et al.,* (2010) do not compute GPP as a difference, but 303 derive R_{ECO} and GPP from quasi-disjoint NEE data subsets. Hence, if existing, spurious correlations is minimized.

To understand whether our results are affected or not by the 'spurious' correlation between GPP and R_{ECO} estimated in FLUXNET, we also performed the analysis using the GPP and R_{ECO} estimated by the partitioning method of Lasslop *et al.*, (2010). The details of the analysis are described in the Appendix IV. The results obtained confirmed (Appendix IV) that the data presented and discussed in follow are not influenced by the possible 'spurious' correlation between RECO and GPP reported in the FLUXNET data set.

312 Site-by-site analysis – Spatial variability of reference respiration (R_0)

dix IV. The results obtained confirmed (Appen n follow are not influenced by the possible 'spurited the FLUXNET data set.
 Spatial variability of reference respiration (R_0) I formulation was defined, we analyzed the Once the best model formulation was defined, we analyzed the site-by-site (i.e. spatial) 315 variability of R_0 : the relationships between the estimated R_0 at each site and site-specific ancillary data were tested, including LAI_{MAX}, LAI_{MAX,o}, N_{depo}, SoilC and Age. Leaf mass per unit area and aboveground biomass were not considered because these are rarely reported in the database for the sites studied and poorly correlated with spatial variability of soil respiration, as reported by Reichstein et al. (2003a). In this analysis the sites with incomplete site characteristics were removed (Age was considered only for the analysis of forest ecosystems). On the basis of this analysis the 321 model was reformulated by adding the explicit dependency of R_0 on the site characteristics that best explained its variability.

PFT–Analysis

In this phase we tried to generalize the model parameters in order to obtain a parameterization useful for diagnostic PFT-based up-scaling. For this reason model parameters were estimated 328 including all the sites for each PFT at the same time. The dependency of R_0 was prescribed as a 329 function of site characteristics that best explain the spatial R_0 variability within each PFT class.

The model was corroborated with two different cross-validation methods:

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332 1) Training/evaluation splitting cross-validation: one site at a time was excluded using the 333 remaining subset as the training set and the excluded one as the validation set. The model 334 was fitted against each training set and the resulting parameterization was used to predict the R_{ECO} of the excluded site.

k-fold cross-validation: the whole data set for each PFT was divided into *k* randomly 337 selected subsets (*k*=15) called a fold. The model is fitted against *k-1* remaining folds 338 (training set) while the excluded fold (validation set) was used for model evaluation. The 339 cross-validation process was then repeated *k* times, with each of the *k* folds used exactly once as the validation set.

342 For each validation set of the cross-validated model statistics were calculated (see 'Statistical Analysis' section). Finally, for each PFT we averaged the cross-validated statistics to produce a single estimation of model accuracy in prediction.

Statistical analysis

348 *Model parameters estimates*

of the cross-validated model statistics were ca

1y, for each PFT we averaged the cross-validate

El accuracy in prediction.
 Formally are averaged the cross-validate
 Formally are extended using the Levenberg-Marquardt Model parameters were estimated using the Levenberg-Marquardt method, implemented in the data analysis package "PV-WAVE 8.5 advantage" (Visual Numerics, 2005), a non-linear regression analysis that optimize model parameters finding the minimum of a defined cost function. The cost function used here is the sum of squared residuals weighted for the uncertainty of the observation 354 (e.g. Richardson et al., 2005). The uncertainty used here is an an estimate of the random error associated with the night-time fluxes (from which R_{ECO} is derived).

Model parameter standard errors were estimated using a bootstrapping algorithm with $N=500$ random re-sampling with replacement of the dataset. As described by Efron and Tibshirani (1993), 358 the distribution of parameter estimates obtained provided an estimate of the distribution of the true model parameters.

361 *Best model formulation selection*

363 For the selection of the 'best' model from among the six different formulations listed in Table 1 and the *'TP Model'* we used the approach of the information criterion developed by Akaike (1973) 365 which is considered a useful metric for model selection (Anderson *et al.*, 2000, Richardson *et al.*,

366 2006). In this study the Consistent Akaike Information Criterion (cAIC, eq. 8) was preferred to the 367 AIC because the latter is biased with large datasets (Shono, 2005) tending to select more 368 complicated models (e.g. many explanatory variables exist in regression analysis):

$$
{}_{14}^{10}370 \t\t cAIC = -2\log L(\Theta) + p[\log(n) + 1] \t\t(8)
$$

372 where $L(\Theta)$ is the within samples residual sum of squares, p is the number of unknown parameters 373 and n is the number of data (i.e. sample size). Essentially, when the dimension of the data set is fixed, cAIC is a measure of the trade-off between the goodness of fit (model explanatory power) and model complexity (number of parameters), thus cAIC selects against models with an excessive number of parameters. Given a data set, several competing models (e.g different model formulations proposed in Table 1) can be ranked according to their cAIC, with the formulation having the lowest cAIC being considered the best according to this approach.

379 For the selection of the best set of predictive variables of R_0 we used the stepwise AIC, a multiple regression method for variable selection based on the AIC criterion (Venables & Ripley, 381 2002, Yamashita *et al.*, 2007). The stepwise AIC was preferred to other stepwise methods for 382 variable selection since can be applied to non normally distributed data (Yamashita *et al.*, 2007).

384 *Evaluation of model accuracy*

umber of parameters), thus cAIC selects against a
Given a data set, several competing model
1 Table 1) can be ranked according to their cA
eing considered the best according to this approac
the best set of predictive vari Model accuracy was evaluated by means of different statistics according to Janssen and Heuberger (1995): RMSE (Root Mean Square Error), EF (modelling efficiency), determination 388 coefficient (r^2) and MAE (Mean Absolute Error). In particular EF is a measure of the coincidence between observed and modelled data and it is sensitive to systematic deviation between model and 390 observations. EF can range from $-\infty$ to 1. An EF of 1 corresponds to a perfect agreement between model and observation. An EF of 0 (EF = 0) indicates that the model is as accurate as the mean of the observed data, whereas a negative EF means that observed mean is a better predictor than the model. In the PFT-analysis for each validation set the cross-validated statistics were calculated. The average of cross-validated statistics were calculated for each PFT both for the training/evaluation 395 splitting (EF_{cv} , RMS E_{cv} , r^2_{cv}) and for the *k-fold* cross-validation ($EF_{\text{kfold-cv}}$, RMS $E_{\text{kfold-cv}}$, $r^2_{\text{kfold-cv}}$).

Site-by-Site analysis

TP Model Results

The RMSE and EF obtained with *'TP Model'* fitting (Table 2) showed a within-PFT-average EF ranging from 0.38 for SAV to 0.71 for ENF and an RMSE ranging from 0.67 for SHB to 1.55 gC $405 \text{ m}^{-2} \text{d}^{-1}$ for CRO.

[TABLE 2]

The importance of productivity is highlighted by residual analysis. A significant positive 410 correlation between the *'TP Model'* residuals (*z*) and the GPP was observed with a systematic underestimation of respiration when the photosynthesis (i.e. GPP) was intense.

412 In Fig. 1a, the mean *r* between the residuals and GPP for each PFT as a function of the time lag is summarised.

FABLE 2]
 FORMALE 21
 FORMALE 31
 414 The lowest correlation was observed for wetlands (r=0.29±0.14). The mean *r* is higher for herbaceous ecosystems such as grasslands and croplands $(0.55\pm0.11$ and 0.63 ± 0.18 , respectively) than for forest ecosystems (ENF, DBF, MF, EBF) which behaved in the same way (Fig. 1a), with a *r* ranging from 0.35 ± 0.13 for ENF to 0.45 ± 0.13 for EBF. No time lag was observed with the residuals analysis.

Gross Primary Production as driver of RECO

The effect of GPP as an additional driver of R_{ECO} was analyzed at each site by testing 6 different models with the three different functional responses (Eqs. 4, 5 and 6) of respiration to GPP (Tab. 1). The model ranking based on the cAIC calculated for each different model formulation at each site showed agreement in considering the models using the linear dependency of R_{ECO} on GPP 426 ('LinGPP') as the best model formulation (Tab. 2), since the cAICs obtained with 'LinGPP' were lower than those obtained with all the other formulations. This model ranking was also maintained 428 when analysing each PFT separately, except for croplands in which the 'addLinGPP' formulation 429 provided the minimum cAIC although the difference between the average cAIC estimated for the

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430 two model formulations was almost negligible (cAIC was 38.22 ± 2.52 and 38.26 ± 2.45 for 431 'addLinGPP' and 'LinGPP', respectively) and the standard errors of parameter estimates were 432 lower for the 'LinGPP' formulation. In general, the cAIC obtained at all sites with the 'LinGPP' 433 model formulation (39.50 [37.50 – 42.22], in squared parentheses the first and third quartile are 434 reported) were lower than the ones obtained with the *'TP Model'* (41.08 [39.02 - 44.40]), although the 435 complexity of the latter is lower (one parameter less). On this basis we considered the 'LinGPP' as the best one model formulation.

The statistics of model fitting obtained with the 'LinGPP' model formulation are reported in Table 2. The model optimized site by site showed a within-PFT-average of EF between 0.58 for EBF to 0.85 for WET with an RMSE ranging from 0.53 for SAV to 1.01 gC m^{-2} day⁻¹ for CRO. On average EF was higher than 0.65 for all the PFTs except for EBF. In terms of improvement of 441 statistics, the use of 'LinGPP' in the *'TP Model'* led to a reduction of the RMSE from 13.4 % for shrublands to almost one third for croplands (34.8%) , grasslands (32.5%) and savanna (32.0%) with 443 respect to the statistics corresponding to the purely climate driven *'TP Model'*.

[FIGURE 1]

th an RMSE ranging from 0.53 for SAV to 1.01 g
than 0.65 for all the PFTs except for EBF. In t
GPP' in the *'TP Model'* led to a reduction of the
third for croplands (34.8%) , grasslands (32.5%) a
rresponding to the pu No time lag between photosynthesis and respiration response was detected. In fact using GPP_{lag,-i} as a model driver we observed a general decrease in mean model performances for each PFT (i.e. 449 decrease of EF and increase of RMSE) for increasing *i* values (i.e. number of days in which the GPP was observed before the observed R_{ECO}). The only exception were DBFs in which we found a time lag between the GPP and R_{ECO} response of 3 days as shown by the peak in average EF and by the minimum in RMSE in Fig. 1b, although the differences were not statistically significant.

Spatial variability of reference respiration rates

456 The reference respiration rates (R_0) estimated site by site with the 'LinGPP' model formulation represent the daily ecosystem respiration at each the site at a given temperature (i.e. 15° C), without 458 water limitation and carbon assimilation. Hence, R_0 can be consider the respiratory potential of a 459 particular site. R₀ assumed highest values for the ENF (3.01 \pm 1.35 gC m⁻² day⁻¹) while the lowest values were found for SHB (1.49 \pm 0.82 gC m⁻² day⁻¹) and WET (1.11 \pm 0.17 gC m⁻² day⁻¹), possibly 461 reflecting lower carbon pools for shrublands or lower decomposition rates due to anoxic conditions or carbon stabilization for wetlands.

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463 By testing the pairwise relationship between R_0 and different site characteristics we found that 464 the ecosystem LAI_{MAX} showed the closest correlation with R_0 ($R_0 = 0.44(0.04) L A I_{MAX} + 0.78(0.18)$, 465 $r^2=0.52$, $p<0.001$, n=104, in parentheses standard errors of model parameters estimates were 466 reported), thus LAI_{MAX} was the best explanatory variable of the retrieved R_0 variability (Fig 2a). 467 Conversely, LAI_{MAX,0} correlated weakly (r^2 =0.40, p <0.001, n=104) with R₀ (Fig. 2b) indicating that, for forest sites, understorey LAI must be also taken into account. A very weak correlation was 469 found with SoilC $(r^2=0.09; p<0.001, n=67)$ and no significant correlation with Age, N_{depo} and T_{MEAN} were found for forest sites (Fig. 2 c-f).

472 **[FIGURE 2]**

The multiple regression analysis conducted with the stepwise AIC method including 475 simultaneously all sites, showed that the two best predictors of R_0 were LAI_{MAX} and SoilC 476 (Multiple r^2 =0.57; p<0.001; n=68) which were both positively correlated with R₀ (Tab. 3). LAI_{MAX} 477 was the best predictor of spatial variability of R_0 for all sites confirming the results of the pairwise regression analysis above mentioned but the linear model which included the SoilC as additional predictor led to a significant, though small, reduction in the AIC during the stepwise procedure.

FIGURE 2]
sion analysis conducted with the stepwise
showed that the two best predictors of R_0 v
91; n=68) which were both positively correlated v
spatial variability of R_0 for all sites confirming the
nentioned bu Considering only the undisturbed temperate and boreal forest sites (ENF, DBF, MF), the 481 predictive variables of R₀ selected were LAI_{MAX} and N_{depo}. (Multiple r^2 =0.67; *p*<0.001; n=23). For 482 these sites both LAI_{MAX}, which was still the main predictor of spatial variability of R_0 , and N_{depo} 483 controlled the spatial variability of R_0 , with N_{depo} negatively correlated to R_0 (Tab. 3). This means 484 that for these sites, once removed the effect of LAI_{MAX} , N_{depo} showed a negative control on R_0 with a reduction of 0.025 gC m⁻² day⁻¹ in reference respiration for an increase of 1 kg N ha⁻¹year⁻¹. Considering only the disturbed forest sites we found that SoilC and T_{MEAN} were the best predictors 487 of spatial variability of R_0 (Multiple $R^2 = 0.80$, p<0.001, n=10).

488 In Table 5 (left column) the statistics of the pairwise regression analysis between R_0 and LAI_{MAX} for each PFT are reported. The best fitting was obtained with the linear relationship for all PFTs except for deciduous forests for which the best fitting was obtained with the exponential 491 relationship $R_0=R_{\text{LAI}=0}(1-e^{-a\text{LAI}})$.

493 **[TABLE 3 AND TABLE 4]**

495 **PFT-Analysis**

497 *Final formulation of the model*

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499 On the basis of the aforementioned results, the GPP as well as the linear dependency between R_0 500 and LAI_{MAX} were included into the *'TP Model'* leading to a new model formulation (Eq 9). The final formulation is basically the *'TP Model'* with the addition of biotic drivers (daily GPP and LAI_{MAX}) and hereafter referred to as *'TPGPP-LAI Model'*, where the suffixes GPP and LAI reflect the inclusion of the biotic drivers in the climate-driven model:

505
$$
R_{ECO} = \left(\underbrace{R_{LAI=0} + a_{LAI} \cdot LAI_{MAX}}_{R_0} + k_2GPP\right) \cdot e^{E_0\left(\frac{1}{T_{ref}-T_0} - \frac{1}{T_A-T_0}\right)} \cdot \frac{\alpha k + P(1-\alpha)}{k + P(1-\alpha)}
$$
(9)

LAI_{MAX}, the section of the base of $k + P(1-\alpha)$
 B_{LAI} LAI_{MAX}, describes the dependency of the base of $k + P(1-\alpha)$

and B_{LAI} LAI_{MAX}, describes the dependency of the base of R_0 , in the final model formulational 507 where the term, $R_{\text{LAI=0}} + a_{\text{LAI}} L A I_{\text{MAX}}$, describes the dependency of the basal rate of respiration (R_0) in Table1) on site maximum seasonal ecosystem LAI. Although we found that SoilC and N_{depo} may 509 help to explain the spatial variability of R_0 , in the final model formulation we included only the LAI_{MAX} . In fact the model is primarily oriented to the up-scaling and spatial distributed information of SoilC, N_{depo} and disturbance may be difficult to be gathered and usually are affected by high uncertainty. 24507 33512

The parameters $R_{\text{LAI}=0}$ and a_{LAI} listed in Table 4 were introduced as fixed parameters in the 'TPGPP-LAI Model'. For wetlands and mixed forests the overall relationship between LAI_{MAX} and 515 38 R ⁰ was used. For wetlands, available sites were insufficient to construct a statistically significant relationship while for mixed forests the relationship was not significant ($p=0.146$). 40516

517 PFT specific model parameters (k ², E ⁰, k, α) of *'TPGPP-LAI Model'* were then derived using all data from each PFT contemporarily and listed with their relative standard errors in Table 4. No significant differences in parameter values were found when estimating all the parameters 520 simultaneously $(a_{LAI}$, $R_{LAI=0}$, k_2 , E_0 , k , α). 47520

The scatterplots of the observed *vs* modelled annual sums of R_{ECO} are shown in Figure 3, while results and statistics are summarized in Table 5. The model was well able to describe the interannual and intersite variability of the annual sums over different PFTs, with the explained variance varying between 40% for deciduous forests and 97% for shrublands and evergreen broadleaved forests. Considering all sites, the explained variance is 81%, with a mean error of about 17% (132.99 $gCm^{-2}yr^{-1}$) of the annual observed R_{ECO}. 48 49 50 51 52 53 54 55 56 57 58

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528 **[TABLE 5, FIGURE 3]**

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Evaluation of model predictions accuracy and weak points

532 The results obtained with the k-fold and training/evaluation split cross-validation are listed in Table 6.

[TABLE 6]

537 The r_{cv}^2 ranges from 0.52 (for EBF) to 0.80 (for CRO) while the $r_{\text{cv,kfold}}^2$ ranges from 0.58 (for DBF) to 0.81 (for GRA). The cross-validated statistics averaged for each PFT are always higher for 539 the *k*-fold than for the training/evaluation splitting cross-validation.

The cross-validated statistics averaged for each P
ining/evaluation splitting cross-validation.
residuals time series of the deciduous broadleaf
on during the springtime development phase and
fter leaf-fall. A similar beha The analysis of model residuals time series of the deciduous broadleaf forest (Fig. 4) showed a systematic underestimation during the springtime development phase and, although less clear, on the days immediately after leaf-fall. A similar behaviour was also found for croplands and grasslands during the days after harvesting or cuts (Fig. 5).

[FIGURE 4,5]

DISCUSSION

Gross primary production as driver of ecosystem respiration

551 The results obtained with the purely climate-driven model (*'TP Model'*) and the best model formulation selected in the site-by-site analysis (i.e. 'LinGPP', Tab. 1) confirm the strong relationship between carbon assimilation and R_{ECO} highlighting that this relationship must to be included into models aimed to simulate temporal variability of R_{ECO} .

Respiration appears to be strongly driven by the GPP in particular in grasslands, savannas and 556 croplands as already pointed out by several authors in site-level analysis (Bahn *et al.*, 2008, Moyano *et al.*, 2007, Wohlfahrt *et al.*, 2008a, Xu & Baldocchi, 2004). For croplands and grasslands growth respiration is controlled by the amount of photosynthates available and mycorrhizal respiration, 559 which generally constitutes a large component of soil respiration (e.g. Moyano *et al.*, 2007, Kuzyakov & Cheng, 2001).

561 For wetlands instead the weak relationship between respiration and GPP can be explained by the 562 persistence of anaerobic conditions, decomposition proceeds more slowly with an accumulation of

563 organic matter on top of the mineral soil layer and respiration is closely related to temperature and 564 water table depth rather than to other factors (Lloyd, 2006).

565 The lower correlation observed for forest ecosystems than for grasslands and croplands may be 566 due to the higher time for translocation, in trees, of substrates from canopy to roots, related to the 567 rates of phloem carbon transport (Nobel, 2005), which affect the reactivity of the respiration and the release of exudates or assimilates from roots as response to productivity (Mencuccini & Höltta, 2010). This is very often cause of time lags between photosynthesis and respiration response but may justify the reduction of correlation between model residuals and GPP estimated at the same $\frac{17}{18}$ 571 day.

Free GPP and R_{ECO} response was not detected.

he analysis conducted with the '*LinGPP*' mod

sence of a time lag with the only exception of Dlugh the results were not statistically significant. I

to confirm or reject t A clear time lag between GPP and R_{ECO} response was not detected. In fact both the residual analysis (Fig. 1a) and the analysis conducted with the 'LinGPP' model formulation (Fig. 1b) confirmed the general absence of a time lag with the only exception of DBF where a time lag of 3 days was observed although the results were not statistically significant. However, in our opinion, 576 these results do not help to confirm or reject the existence of a time lag for several reasons: *i*) in 577 some studies (e.g. Baldocchi *et al.*, 2006, Tang & Baldocchi, 2005) a lag on the sub-daily time scale was identified and the lags on the daily time scale were attributed to an autocorrelation in weather patterns (i.e. cyclic passage of weather fronts with cycles in temperature or dry and humid air masses) which modulates the photosynthetic activities, since our analysis focused on daily data we were not able to identify the existence of sub-daily time lags; *ii*) lag effects may be more 582 pronounced under favorable growing conditions or during certain periods of the growing season, the analysis of which analysis is out of scope of present study.

585 *Spatial variability of reference respiration rates*

587 The relationship between reference respiration rates (R_0) derived by using the 'LinGPP' model formulation, and LAI_{MAX} (Fig. 2a) is particularly interesting considering that the productivity was already included into the model (i.e. daily GPP is driver of 'LinGPP'). While daily GPP describes the portion of R_{ECO} that originates from recently assimilated carbon (i.e. root/rhizosphere respiration, mychorrizal and growth respiration), LAI_{MAX} is a structural factor which has an additional effect to the short-term productivity and allows to describe the overall ecosystem respiration potential of the ecosystem. For instance, high LAI means increased autotrophic maintenance respiration costs. Moreover LAI_{MAX} can be considered both as an indicator of the 595 general carbon assimilation potential and as an indicator of how much carbon can be released to soil 596 yearly because of litterfall (in particular for forests) and leaf turnover which are directly related to

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597 basal soil respiration (Moyano *et al.*, 2007). At recently disturbed sites, this equilibrium between 598 LAI $_{\text{MAX}}$ and soil carbon (through litter inputs) may be broken, for example thinning might lead to a 599 reduction of LAI_{MAX} without any short-term effect on the amount soil carbon, while ploughing in 600 crops or plantations leads solely to a reduction in soil carbon content and not necessarily in LAI. Also in cut or grazed grasslands maximum LAI does not correspond well with litter input because most of this carbon is exported from the site and only partially imported back (as organic manure). This explains why the multiple linear model including LAI_{MAX} and SoilC was selected as the best by the stepwise AIC regression using all the sites contemporarily and why considering only 605 disturbed forest ecosystems we SoilC was selected as best predictor of R_0 (Tab. 3).

is also the negative control of N_{depo} on R₀ with a
sae of 1 kg N ha⁻¹year⁻¹. The reduction of heteroti
deposition load was already described in literatur
to different processes. For instance soil acidific
osition Particularly interesting is also the negative control of N_{depo} on R₀ with a reduction of 0.025 gC m⁻ 607 $\frac{2}{3}$ day⁻¹ in R₀ for an increase of 1 kg N ha⁻¹year⁻¹. The reduction of heterotrophic respiration in sites with high total nitrogen deposition load was already described in literature and in some site-level analysis and attributable to different processes. For instance soil acidification at high N_{depo} loads may inhibit litter decomposition suppressing the respiration rate (Freeman et al., 2004, Knorr et al., 2005) and increasing in N_{depo} can increase N concentration in litter with a reduction of litter 612 decomposition rates (Berg & Matzner, 1997, Persson *et al.*, 2000) and the consequent reduction of respiration. The latter process is more debated in literature because increased N supply may lead to higher N release from plant litter, which results in faster rates of N cycling and in a stimulation of litter decomposition (e.g. Tietema et al., 1993). However this process is not always clear (e.g. Aerts 616 et al., 2006): in litter mixtures, N-rich and lignin-rich litter may chemically interact with the formation of very decay-resistant complexes (Berg et al., 1993). In addition, litter with a high 618 concentration of condensed tannins may interact with N-rich litter reducing the N release from decomposing litter as described in Hattenschwiler and Vitousek (2000). Thus, the supposed stimulating effects of N addition on N mineralization from decomposing litter may be counteracted by several processes occurring in litter between N and secondary compounds, leading to chemical immobilization of the added N (e.g. Pastor et al., 1987, Vitousek & Hobbie, 2000)

623 Although the absolute values are a matter of recent debate (De Vries *et al.*, 2008, Magnani *et al.*, 2007, Sutton et al., 2008), it is agreed that N_{depo} stimulates net carbon uptake by temperate and boreal forests. As net carbon uptake is closely related to respiration, once the effect of age is removed, it can be seen that increased N_{depo} has the potential to drive R_{ECO} in either directions. The stimulation of GPP as consequence of the increasing N_{depo} is already include in the model since GPP is a driver. Additionally our analysis suggests that overall an increased total N_{depo} in forests tends to reduce reference respiration. Without considering the effects introduced by N_{depo} in our 630 models we may overestimate R_{ECO} , with a consequent underestimation of the carbon sink strength 51 55626 58 59 60629

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631 of such terrestrial ecosystems. It is also clear that, in managed sites, such interactions apply equally 632 to other anthropogenic nitrogen inputs (fertilizers, animal excreta) (e.g. Galloway *et al.*, 2008). 633 However, considering *i*) that LAI_{MAX} is the most important predictor of R_0 , *ii*) that the uncertainty 634 in soil carbon and total nitrogen deposition maps is usually high, *iii*) that the spatial information on disturbance is often lacking and finally iv) that our model formulation is oriented to up-scaling 636 issues, we introduced LAI $_{\text{MAX}}$ as the only robust predictor of the spatial variability of R_0 in the final model formulation.

The use of LAI_{MAX} is interesting for an up-scaling perspective (e.g. at regional or global scale) since can be derived by remotely sensed vegetation indexes (e.g. normalized vegetation indexes or enhanced vegetation indexes) opening interesting perspectives for the assimilation of remote sensing products into the *'TPGPP-LAI Model'*.

lexes) opening interesting perspectives for the *TPGPP-LAI Model'*.
 FT-based linear regression between R_0 and LAI₃ to 0 ('ideally' bare soil), the lowest R_0 takes placent consystems. The frequent disturbances o 642 The intercepts of the PFT-based linear regression between R_0 and LAI_{MAX} (Tab.4) suggest that, 643 when the LAI_{MAX} is close to 0 ('ideally' bare soil), the lowest R_0 takes place in arid (EBF, SHB and SAV) and agricultural ecosystems,. The frequent disturbances of agricultural soils (i.e. ploughing and tillage), as well as management, reduce soil carbon content dramatically. In croplands, the 646 estimated R_0 is very low in sites with low LAI. However, with increasing LAI_{MAX}, R_0 shows a rapid increase, thus resulting in high respiration rates for crop sites with high LAI. For EBF, SHB and SAV the retrieved slopes are typical of forest ecosystems, while the intercepts are close to zero because of the lower soil carbon content usually found in these PFTs (Raich & Schlesinger, 1992). Because of the few available sites representing and on similarity in terms of climatic characteristics, savannas, shrublands were grouped.

652 In grasslands, the steeper slope (a_{LAI}) value found (1.14 ± 0.33) suggests that R₀ increases 653 rapidly with increasing aboveground biomass as already pointed out in literature (Wohlfahrt *et al.*, 2008a, Wohlfahrt et al., 2005a, Wohlfahrt et al., 2005b), i.e. an increase in LAI_{MAX} leads to a 655 stronger increase in R_0 than in other PFTs.

In forest ecosystems, and in particular in evergreen needleleaf and deciduous broadleaf forests, the physical meaning of the higher intercept may be found in less soil disturbance. In boreal forests, the soil carbon stock is generally high even at sites with low LAI_{MAX}, thus maintaining an overall 659 high R_0 which is less dependent on the LAI_{MAX}.

661 *Final formulation of the model and weak points*

These results obtained with the *'TPGPP-LAI Model'* cross-validation indicate that the developed 664 model describes the R_{ECO} quite well. In particular results indicate a better description of the

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665 temporal variability of R_{ECO} rather than the spatial variability (or across-site variability). In the 666 training/evaluation splitting in fact, the excluded site for each PFT is modelled using a 667 parameterization derived from the other sites within the same PFT. However, the k-fold is more 668 optimistic than training/evaluation splitting cross-validation because the data set is less disturbed and the calibration and validation datasets are statistically more similar. In the training/evaluation splitting, instead, we exclude one site which is completely unseen by the training optimization procedure.

ion is necessary to link of the developed model w
ducts necessary for the estimation of LAI. On
ell formulation is the incorporation of GPP an
inch importance in modeling Reco is above discu
e description of both the tempo The derived parameterization of the *'TPGPP-LAI Model'* reported in Table 4 may be considered as an optimized parameterization for the application of the model at large scale (e.g. continental or global). For this application is necessary to link of the developed model with a productivity model and remote sensing products necessary for the estimation of LAI. One of the main advances introduced by this model formulation is the incorporation of GPP and LAI as driver of the ecosystem respiration, which importance in modeling Reco is above discussed. These variables are necessary to improve the description of both the temporal and spatial dynamics or R_{ECO} . These results imply that empirical models used with remote sensing (e.g. Reichstein et al., 2007, Reichstein et al., 2003a, Veroustraete et al., 2002) underestimate the amplitude of R_{ECO} an might 681 lead to wrong conclusions regarding the interpretation of seasonal cycle of the global $CO₂$ growth rate and annual carbon balance.

683 The values of the *'TPGPP-LAI Model'* parameters (Tab. 4) related to the precipitation (k, α) indicated a much stronger nonlinearity in the response of R_{ECO} to precipitation for shrublands, wetlands and croplands than for forest ecosystems (Fig. 6). Wetlands and croplands reached saturation (no limitation of water on respiration) after a small rain event underlying their insensitivity to precipitation owing to the presence of water in wetland soils and irrigation in 688 croplands. Grasslands are very sensitive to rain pulse as described in Xu & Baldocchi *et al.* (2004), while savannas and evergreen broadleaved forests showed a strong limitation when rainfall was 690 scanty and f(P) saturation exceed 50 mm month⁻¹. The parameters related to GPP dependency (k_2) estimated at PFT level confirm all the results obtained at site level indentifying a clear sensitivity of grasslands and savannah to GPP.

693 **[FIGURE 6]**

However, when comparing these parameterizations, it is very likely that a background correlation between precipitation, short-term productivity and soil respiration confused the apparent 696 response of respiration to water availability in the *'TPGPP-LAI Model'*.

697 Despite the good accuracy, some criticisms and limitations of the *'TPGPP-LAI Model'* were 698 identified, in particular for the deciduous broadleaf forests. The systematic underestimation during 60697

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on et al., (1998) whose showed that the sense glong-term data input is different from short-term onally varying factors. At some DBF sites (US-I r than the modelled ones during the foliaged peri ws that model values are ge 699 the springtime development phase (Fig 4) is very likely related to the peak in autotrophic respiration 700 due to the intense activity of vegetation during bud burst not described by the model. This 701 hypothesis is confirmed by different authors. For instance, Davidson et al. (2006b) pointed out that 702 during spring development, specific root respiration increases with increasing soil temperature and 703 the concomitant root growth increases the amount of respiring tissue. Moreover, during bud burst also leaf growth, starch mobilisation and increased phloem transport may contribute to this pulse in 705 respiration as shown by Knohl *et al.*, (2003). A systematic underestimation was also observed immediately after the leaf-fall, in which the increase in heterotrophic respiration stimulated by the 707 decomposition of fresh litter was not completely described by the model. These results are in accordance with Davidson et al., (1998) whose showed that the sensitivity of respiration to temperature derived using long-term data input is different from short-term sensitivity because it is 710 confused with other seasonally varying factors. At some DBF sites (US-HA1, DE-Hai, Fig 4) the 711 observed fluxes are lower than the modelled ones during the foliaged period. Also the overall plot for DBF in Fig 4 shows that model values are generally higher than observations. These 713 considerations suggest that the link between phenological models describing overall foliar 714 development (Jolly *et al.*, 2005, Migliavacca *et al.*, 2008) and semi-empirical carbon flux models may be useful for the correction of the long-term sensitivity in active spring or summer periods. Another option is the assimilation of remotely-sensed time series from which the main phenological 717 phases may be derived (e.g. derivative methods) and used for instance for the correction of the temporal variability of model parameters.

We also found a similar behaviour of croplands and grassland during the days after harvesting or 720 cuts, when respiration increased because of the decomposition of organic residues (e.g. grass or 721 crop residues) as depicted for example in Fig. 5. In this case, the model was unable to describe increased respiration following the harvest.

725 **Conclusions**

In this study we proposed a model (*'TPGPP-LAI Model'*) for the simulation of R_{ECO} which include the explicit dependency of the respiration to the productivity. We demonstrated that the dependency of respiration on some measure of short-term productivity (e.g. GPP) needs to be included in models simulating ecosystem respiration at regional and global scale in order to improve the description of carbon fluxes and feedbacks between respiration and productivity.

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732 In addition, the general site productivity (using maximum seasonal LAI as a proxy) is another 733 important additional variable which accounts for the spatial variability of reference respiration 734 within different plant-functional types. In other words, the LAI_{MAX} can be used as an indicator of 735 the potential respiration for a specific site related to long-term respiration (i.e. low frequencies of 736 the modelled respiration) while GPP and climate drive the short-term respiration response (i.e. the high frequencies of the modelled respiration). This opens interesting perspectives for assessing properties related to respiration using remote sensing products. Soil carbon content and total atmospheric nitrogen deposition may represent under certain circumstance additional parameters enhancing and suppressing, respectively, reference respiration rates.

We demonstrated that variables related to productivity and site structure are necessary to improve the description of both the temporal and spatial dynamics or R_{ECO} . These results imply that empirical models driven only by climate underestimate the amplitude of R_{ECO} and might lead to 744 wrong conclusions regarding the interpretation of seasonal cycle of the global CO₂ growth rate and annual carbon balance.

It variables related to productivity and site strow f both the temporal and spatial dynamics or R_{ECO} only by climate underestimate the amplitude of ling the interpretation of seasonal cycle of the glober deterization of 746 We provided a parameterization of the *'TPGPP-LAI Model'* for a PFT-based application of the model at large scale (e.g. continental or global). We have shown that the temporal, spatial and interannual variability of ecosystem respiration can be captured quite well by the proposed model. For this application is necessary a link of the developed model with a productivity model (for GPP estimation) and remote sensing products (necessary for the estimation of LAI). One interesting 751 perspective is the integration of the proposed model formulation into the MODIS-GPP/NPP data stream (e.g MOD17 Light Use Efficiency model) for regional and global estimates of R_{ECO} .

Finally, we observed that a part of ecosystem respiration variance not explained by the model may be related to phenology in forests and to management in grasslands and croplands. For these reasons we consider the link between phenological models and/or remotely-sensed time series of 756 vegetation indexes and respiration models as well as the inclusion of total nitrogen deposition as an additional driver for improving the description of ecosystem respiration in both space and time.

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 Table 2 - Statistics of fit for the climate-driven model (*'TP Model'***) and the best model selected among the models listed in Tab. 1 according to the consistent Akaike Information Criterion (cAIC). Statistics are averaged per Plant Functional Type (PFT). Except for croplands (CRO), 'LinGPP' is selected as the best model formulation. EF is the modelling efficiency while RMSE is the root mean square error (Jannsens and Heuberger, 1995). The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET). The list of acronyms is also provided in Appendix II. Values in brackets are the standard deviations.**

Table 3 – Results of the model selection conducted with the Stepwise AIC method for the sites belonging to all the PFT (*All PFTs***) and for undisturbed temperate and boreal forests identified in the Appendix II (***Undisturbed Forests***). Coefficients (a ¹,a ², const), their significance and the statistics of the best model selected are reported. In parenthesis the standard error of the coefficients are reported. The significance of coefficients is also reported (*** p<0.001, ** p<0.01, * p<0.05, . p<0.1).**

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Table 4 – Parameters of the relationships between reference respiration (R0) defined at 15°C and seasonal maximum LAI for each Plant Functional Type (PFT). The standard errors of model parameters are reported in parenthesis. Determination coefficients and statistical significance are also shown.– *'TPGPP-LAI Model'* **parameters estimated for each Plant Functional Type (see Appendix II). Standard errors estimated with the bootstrap algorithm are reported in parentheses. Model statistics are also given.** *''TPGPP-LAI Model'* **is defined in Eq. 9. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).**

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Table 5-Statistics of the modelled (x- axis) vs measured (y-axis) annual R_{ECO} with the *'TPGPP-LAI Model'*. **Number of site-years for each PFT are also reported. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).**

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Table 6 – Results of Training/Evaluation splitting and k-fold cross-validation of the *'TPGPP-LAI Model'* **averaged per plant functional type as defined in the Appendix II. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).**

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Figure Captions

Figure 1 - a) Pearson's correlation coefficients (r) for the residual of observed minus modelled R_{ECO} versus measured GPP and a function of time lag; b) average model performances (EF and RMSE) for deciduous broadleaf forests as a function of the time lag between GPP and R_{ECO} response. Results obtained running the 'LinGPP' formulation with different GPP time series, from the GPP measured at the same day up to the GPP measured one week before the R_{ECO} . Error bars represent the standard deviation of model statistics calculated at each site. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

ET).
 Formulation (R₀) and a) seasonal m

and overstorey, b) overstorey peak leaf area index

b) stand age for forest ecosystems (Age), e) total at

(N_{depo}) and f) mean annual temperature. In panels

nt different PF Figure 2 - Correlation between reference respiration (R_0) and a) seasonal maximum leaf area index (LAI_{MAX}) of understorey and overstorey, b) overstorey peak leaf area index $(LAI_{MAX,0})$, c) total soil carbon content (SoilC), d) stand age for forest ecosystems (Age), e) total atmospheric nitrogen deposition for forest sites (N_{depo}) and f) mean annual temperature. In panels a), b), c), d) and f) different symbols represent different PFT. In panel e) full circles represent disturbed sites while open circles the undisturbed ones. The r^2 , p and number of sites (n) were reported. The regression line and the 95% confidence interval are given if the relationship is significant. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

Figure 3 – Scatterplots of annual observed vs modelled R_{ECO} obtained using the *'TPGPP-LAI Model'*. Each panel represent a different plant functional type (PFT). The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

Figure 4 - Time series of average monthly model residuals for different deciduous broadleaf forest (DBF) sites. The vertical grey dashed lines represent the phenological dates. Average phenological dates were derived for US-Ha1 from literature (Jolly et al. 2005) while for other sites they were retrieved from the FLUXNET database. Average phenological dates, bud-burst and end-of-growing season are respectively: US-Ha1 (115-296),DE-Hai (126-288), FR-Hes (120-290), FR-Fon (125- 292), IT-Ro1 (104-298) and CA-Oas (146-258)..

Figure 5 – Time series of observed (open circles) and modeled (black circles) for the IT-MBo site (a,b) and for the ES-ES2 site (c, d), grey dashed lines represent the dates of cuts indicated in the database (the date may be indicative), the model underestimation of fluxes in the days after each cut is clear.

Figure 6 – Response function of ecosystem respiration to the 30-day running average of daily precipitation (Eq. 2) for each plant functional type (PFT). The parameters in Table 3 were used to draw the curves. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

Figure AI – Box-plot of the differences at each site between the Pearson's correlation coefficient between 'TP Model' residuals and GPP computed using FLUXNET partitioning (r_{TPModel-GPPFLUX}) and Lasslop's partitioning (r_{TPModel-GPPLasslop}). Data were grouped in box-plots for each PFT. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET)

Figure AII – Box-plot of the parameters a) R_0 , b) k_2 , c) EF and d) RMSE estimated using FLUXNET (red boxes) and Lasslop's (Blue boxes) partitioning. The median of the differences of parameters governing the response to GPP (k₂) estimated at each site with the two different datasets are not statistically different from 0 except for ENF and DBF (for both p<0.05). No statistical differences were found for model statistics. Data were grouped in box-plots for each PFT. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

For Review Only

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Appendix List

APPENDIX I – Site Table. ID, Name, country, belonging network, coordinates PFT, climate and LAI_{MAX} of the sites used in the analysis. Climate abbreviations follow the Koeppen classification (Peel et al., 2007). Networks are described in www.fluxdata.org

APPENDIX II – Site characteristics derived from the FLUXNET database. R_0 is the reference respiration estimated with the *LinGPP* model formulation, LAI is the maximum seasonal leaf area index of the ecosystems (understorey and overstorey), LAI_{MAX,o} is the maximum leaf area index of the solely overstorey, SoilC is the total soil carbon content, Age is the stand age, T_{mean} is the annual average mean temperature, Ndepo is the total atmospheric nitrogen deposition derived as described in the method section. Sites with (*) in the column dist (disturbance) represent sites with recent disturbance according to what reported in the FLUXNET database.

APPENDIX III – Acronyms and abbreviations.

APPENDIX IV – Discussion of the 'spurious' correlation between R_{ECO} and GPP.

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APPENDIX I – Site table

Table AI – Site Table. ID, Name, country, belonging network, coord[inates PFT, climat](http://www.fluxdata.org/)e and LAI_{MAX} of the sites used in the analysis. Climate abbreviations follow the **Koeppen classification (Peel et al., 2007). Networks are described in www.fluxdata.org.** The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).—

12	SITE ID	Tower Name	Country	Latitude	Longitude	PFT	<i>Climate</i>	Reference
13	AT-Neu	Neustift/Stubai Valley	Austria	47.12	11.32	GRA	Cfb	(Wohlfahrt et al., 2008b)
14	AU-How	Howard Springs	Australia	-12.49	131.15	WSA	Aw	(Beringer et al., 2007)
15	BE-Lon	Lonzee	Belgium	50.55	4.74	CRO	Cfb	(Moureaux et al., 2006)
	BE-Vie	Vielsalm	Belgium	50.31	5.99	MF	Cfb	(Aubinet et al., 2001)
16	BR-Sp1	Sao Paulo Cerrado	Brazil	-21.62	-47.65	WSA	Aw	(Santos et al., 2004)
17	BW-Ma1	Maun-Mopane Woodland	Botswana	-19.92	23.56	WSA	BSh	(Veenendaal et al., 2004)
18	CA-Ca1	British Columbia- Campbell River - Mature Forest Site	Canada	49.87	-125.33	ENF	Cfb	(Humphreys et al., 2006)
19	CA-Ca3	British Columbia- Campbell River - Young Plantation Site	Canada	49.53	-124.90	ENF	Cfb	(Humphreys et al., 2006)
20	CA-Gro	Ontario- Groundhog River-Mat. Boreal Mixed Wood	Canada	48.22	-82.16	MF	Dfb	(Mccaughey et al., 2006)
21	CA-Let	Lethbridge	Canada	49.71	-112.94	GRA	Dfb	(Flanagan et al., 2002)
22	CA-Mer	Eastern Peatland- Mer Bleue	Canada	45.41	-75.52	WET	Dfb	(Lafleur <i>et al.</i> , 2003)
23	CA-NS1	UCI-1850 burn site	Canada	55.88	-98.48	ENF	Dfc	(Goulden et al., 2006)
24	CA-NS3	UCI-1964 burn site	Canada	55.91	-98.38	ENF	Dfc	(Goulden et al., 2006)
	CA-NS6	UCI-1989 burn site	Canada	55.92	-98.96	OSH	Dfc	(Goulden et al., 2006)
25	CA-Oas	Sask.- SSA Old Aspen	Canada	53.63	-106.20	DBF	Dfc	(Black et al., 2000)
26	$CA-Ojp$	Sask.- SSA Old Jack Pine	Canada	53.92	-104.69	ENF	Dfc	(Kljun et al., 2006)
27	CA-Qfo	Quebec Mature Boreal Forest Site	Canada	49.69	-74.34	ENF	Dfc	(Bergeron et al., 2007)
28	CA-TP4	Ontario-Turkey Point Mature White Pine	Canada	42.71	-80.36	ENF	Dfb	(Arain & Restrepo-Coupe, 2005)
29	CA-WP1	Western Peatland- LaBiche-Black Spruce/Larch Fen	Canada	54.95	-112.47	MF	Dfc	(Syed et al., 2006)
30	CH-Oe1	Oensingen1 grass	Switzerland	47.29	7.73	GRA	Cfb	(Ammann et al., 2007)
31	CN-HaM	Haibei Alpine Tibet site	China	37.37	101.18	GRA	ET	(Kato et al., 2006)
	$CN-Ku1$	Kubuqi_populus forest	China	40.54	108.69	EBF	BSk	
32	$CN-Ku2$	Kubuqi_shrubland	China	40.38	108.55	OSH	BS k	
33	$CN-Xi2$	Xilinhot grassland site(X03)	China	43.55	116.67	GRA	Dwb	
34	DE-Bay	Bayreuth-Waldstein/WeidenBrunnen	Germany	50.14	11.87	ENF	Cfb	(Staudt and Foken 2007)
35	DE-Hai	Hainich	Germany	51.08	10.45	DBF	Cfb	(Knohl et al., 2003)
36	DE-Kli	Klingenberg	Germany	50.89	13.52	CRO	Cfb	
37	DE-Tha	Tharandt-Anchor Station	Germany	50.96	13.57	ENF	Cfb	(Grunwald & Bernhofer, 2007)
38	DK-Ris	Risbyholm	Denmark	55.53	12.10	CRO	Cfb	(Houborg & Soegaard, 2004)
39	ES-ES1	El Saler	Spain	39.35	-0.32	ENF	Csa	(Reichstein et al., 2005)
	ES-ES2	El Saler-Sueca	Spain	39.28	-0.32	CRO	Csa	Carrara A. (P.C.)
40	ES-LMa	Las Majadas del Tietar	Spain	39.94	-5.77	SAV	Csa	
41 42	ES-VDA	Vall d'Alinya	Spain	42.15	1.45	GRA	Cfb	(Gilmanov et al., 2007)

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APPENDIX II – Lists of site characteristics

Table A II – Site characteristics derived from the FLUXNET database. R₀ is the reference respiration estimated with the *LinGPP* model formulation, LAI is the maximum seasonal leaf area index of the ecosystems (understorey and overstorey), $\text{LAI}_{\text{MAX},\text{o}}$ is the maximum leaf area index of the solely overstorey, SoilC is the total soil carbon content, Age is the stand age, T_{mean} is the annual average mean temperature, Ndepo is the total atmospheric nitrogen deposition derived as described in the **method section, u* is the median of the yearly friction velocity threshold identified at each site by using the method described in Papale et al., (2006). Sites with (*) in the column dist (disturbance) represent sites with recent disturbance according to what reported in the FLUXNET database.**

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APPENDIX III – List of acronyms and abbreviations

Table AIII – Acronyms and abbreviations

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APPENDIX IV – Discussion of the 'spurious' correlation between R_{ECO} and GPP.

To understand whether our results were affected by the 'spurious' correlation between GPP and R_{ECO} as reported in FLUXNET (GPP $_{FLUX}$) we also perform the analysis using a 'quasi'-independent Reco and GPP estimates as described by Lasslop et al., (2010) (R_{ECO-LASS} and GPP_{LASS,}). The method by Lasslop et al., (2009) do not compute GPP as a difference, but derive R_{ECO} and GPP from quasi-disjoint NEE data subsets. Hence, if existing, spurious correlations was minimized. The *'TP Model'* was optimized against R_{ECO-LASS} and GPP_{LASS} and the Pearson's correlation coefficient between *'TP Model'* residuals and GPP_{LASS} was calculated (r_{TPModel-GPPLASS}) at each site and for each PFT.

iduals and GPP_{LASS} was calculated ($r_{TPModel-GPPL}$
pared the correlation between *'TP Model'* resificatabase ($r_{TPModel-GPPELUX}$) with the $r_{TPModel-GPPL}$
wo sample paired sign test (Gibbons and Chakra
nedian of the difference between t At each site we compared the correlation between *'TP Model'* residuals and GPP derived exploiting the FLUXNET database $(r_{TPModel-GPPFLUX})$ with the $r_{TPModel-GPPLASS}$. The comparison was conducted by using the two sample paired sign test (Gibbons and Chakraborti, 2003). We test the null hypothesis that the median of the difference between two samples is zero, for a 5% significance level. The sign test was selected instead the t-test because avoids: (i) the normal distribution assumption; and (ii) distribution symmetry.

The paired sign test between r_{TPModel-GPPFLUX} and r_{TPModel-GPPLASS} indicates that the median for the differences of the populations is not statistically different from 0 ($p = 0.187$) confirming that the bias observed in the purely climate driven model it is not imputable to a 'spurious' correlation between Reco and GPP introduced by the partitioning method used in the FLUXNET database. The differences are negligible also if we consider each PFT separately as depicted by the box-plot in Fig. A-I and in Tab. A-IV.

Once the best model formulation including GPP as driver is selected we also compared the parameters of the 'LinGPP' model formulation (i.e. best model selected by the consistent Akaike Information Criterion, cAIC in Table 1) estimated using the GPP and R_{ECO} from FLUXNET and R_{ECO} . LASS and GPPLASS. The statistics in fitting were also compared. The results are summarized in the boxplot in Fig. AII in which k_2 , R_0 and the main statistics in fitting (EF and RMSE) were schematically reported. These results showed that using the two different datasets the results are similar and the overall picture drawn using the Lasslop's method and the FLUXNET database is the same.

Table A IV– Statistics of the sign test between the Pearson's correlation coefficient calculated between residuals of TP Model and GPP computed using FLUXNET partitioning (Reichstein et al., 2005) and Lasslop's partitioning (Lasslop et al., 2010). In the third colums NS means that the median is not significantly different to 0 while * means a significance level of p<0.05. Median of diff. represent the median of differences of two populations, *p* **the level of significance, df the degree of freedom (i.e. number of sites (n) -1). The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).**

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Figure 1 - a) Pearson's correlation coefficients (r) for the residual of observed minus modelled RECO versus measured GPP and a function of time lag; b) average model performances (EF and RMSE) for deciduous broadleaf forests as a function of the time lag between GPP and RECO response. Results obtained running the 'LinGPP' formulation with different GPP time series, from the GPP measured at

the same day up to the GPP measured one week before the RECO. Error bars represent the standard deviation of model statistics calculated at each site. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF),

wetland (WET).

191x108mm (300 x 300 DPI)

Figure 2 - Correlation between reference respiration (R0) and a) seasonal maximum leaf area index (LAIMAX) of understorey and overstorey, b) overstorey peak leaf area index (LAIMAX,o), c) total soil carbon content (SoilC), d) stand age for forest ecosystems (Age), e) total atmospheric nitrogen deposition for forest sites (Ndepo) and f) mean annual temperature. In panels a), b), c), d) and f) different symbols represent different PFT. In panel e) full circles represent disturbed sites while open circles the undisturbed ones. The r2, p and number of sites (n) were reported. The regression line and the 95% confidence interval are given if the relationship is significant. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

177x177mm (600 x 600 DPI)

Figure 3 - Scatterplots of annual observed vs modelled RECO obtained using the 'TPGPP-LAI Model'. Each panel represent a different plant functional type (PFT). The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET). 177x177mm (600 x 600 DPI)

Figure 4 - Time series of average monthly model residuals for different deciduous broadleaf forest (DBF) sites. The vertical grey dashed lines represent the phenological dates. Average phenological dates were derived for US-Ha1 from literature (Jolly et al. 2005) while for other sites they were retrieved from the FLUXNET database. Average phenological dates, bud-burst and end-of-growing season are respectively: US-Ha1 (115-296),DE-Hai (126-288), FR-Hes (120-290), FR-Fon (125- 292), IT-Ro1 (104-298) and CA-Oas (146-258) 379x563mm (150 x 150 DPI)

Figure 5 - Time series of observed (open circles) and modeled (black circles) for the IT-MBo site (a,b) and for the ES-ES2 site (c, d), grey dashed lines represent the dates of cuts indicated in the database (the date may be indicative), the model underestimation of fluxes in the days after each cut is clear. 382x359mm (150 x 150 DPI)

Figure 6 - Response function of ecosystem respiration to the 30-day running average of daily precipitation (Eq. 2) for each plant functional type (PFT). The parameters in Table 3 were used to draw the curves. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET). 313x244mm (150 x 150 DPI)

 $\mathbf 1$ $\overline{2}$ $\overline{\mathbf{4}}$

Figure AI - Box-plot of the differences at each site between the Pearson's correlation coefficient between 'TP Model' residuals and GPP computed using FLUXNET partitioning (rTPModel-GPPFLUX) and Lasslop's partitioning (rTPModel-GPPLasslop). Data were grouped in box-plots for each PFT. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET) 177x177mm (600 x 600 DPI)

Figure AII - Box-plot of the parameters a) R0, b) k2, c) EF and d) RMSE estimated using FLUXNET (red boxes) and Lasslop's (Blue boxes) partitioning. The median of the differences of parameters governing the response to GPP (k2) estimated at each site with the two different data-sets are not statistically different from 0 except for ENF and DBF (for both p<0.05). No statistical differences were found for model statistics. Data were grouped in box-plots for each PFT. The definitions of different PFTs are: evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), grasslands (GRA), croplands (CRO), savannah (SAV), shrublands (SHB), evergreen broadleaf forest (EBF), mixed forest (MF), wetland (WET).

197x177mm (600 x 600 DPI)