Validation of 3D-CMCC Forest Ecosystem Model (v.5.1) against eddy covariance data for ten European forest sites

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33 **Abstract**

34 This study evaluates the performances of the new version (v.5.1) of 3D-CMCC Forest
35 Ecosystem Model (FEM) in simulating gross primary productivity (GPP), against eddy
36 covariance GPP data for ten FLUXNET forest sites across Europe. A new carbon allocation
37 module, coupled with new both phenological and autotrophic respiration schemes, was
38 implemented in this new daily version. Model ability in reproducing timing and magnitude of
39 daily and monthly GPP fluctuations is validated at intra-annual and inter-annual scale,
40 including extreme anomalous seasons. With the purpose to test the 3D-CMCC FEM
41 applicability over Europe without a site-related calibration, the model has been deliberately
42 parameterized with a single set of species-specific parameterizations for each forest
43 ecosystem. The model consistently reproduces both in timing and in magnitude daily and
44 monthly GPP variability across all sites, with the exception of the two Mediterranean sites.
45 We find that 3D-CMCC FEM tends to better simulate the timing of inter-annual anomalies
46 than their magnitude within measurements' uncertainty. In six of eight sites where data are
47 available the model well reproduces the 2003 summer drought event. Finally, for three sites
48 we evaluate if a more accurate representation of forest structural characteristics (i.e. cohorts,
49 forest layers) and species composition can improve model results. In two of the three sites
50 results reveal that model slightly increases its performances although, statistically speaking,
51 not in a relevant way.

52

1 Introduction

Terrestrial ecosystems have a relevant role in the global carbon cycle, acting also as climate regulators (Peters et al., 2007; Bonan, 2008; Huntingford et al., 2009). In fact terrestrial ecosystems store large carbon stocks and cause most of the variance of carbon exchange between the atmosphere and land surface (Batlle Bayer et al., 2012). Among terrestrial ecosystems, forests are an essential component in the global carbon cycle because of their high capacity to store carbon in the vegetation and soil pools (Kramer et al., 2002). Through Gross Primary Production (GPP) plants fix atmospheric carbon dioxide (CO_2) as organic compounds, enabling terrestrial ecosystems to offset part of the anthropogenic CO_2 emissions (Janssens et al., 2003; Cox & Jones, 2008; Battin et al., 2009). Consequently, changes in GPP could have relevant impacts on atmospheric CO_2 concentration. Thus, accurately simulating terrestrial GPP is key to quantify the global carbon cycle and predict the future trajectories of the atmospheric CO_2 concentration (Wu et al., 2015), and taking into account the various spatial and temporal scales of the processes is a major challenge (Yuan et al., 2007). Terrestrial ecosystem models, used to simulate carbon, water and energy fluxes, are valuable tools for advancing the knowledge of the role of ecosystems in maintaining a multitude of their fundamental services, like the provision of products and the regulation of climate (Ibrom et al., 2006). Such numerical models are also useful to: 1) predict the impacts of climate variability on terrestrial biosphere and related carbon fluxes (Ciais et al., 2005; Brèda et al., 2006; Richardson et al., 2007), ranging from long term anomalies (Santini et al., 2014) up to extreme events (Zscheischler et al., 2014); and 2) reproduce biophysical and biogeochemical feedbacks of vegetation cover and change on climate, especially when coupled to atmosphere-ocean climate models through land surface schemes (Bonan, 2008; Arneth et al., 2012; Taylor et al., 2012).

At European level, terrestrial ecosystems have been reported to be a significant sink of CO_2 (Luyssaert et al., 2012), with forests playing a relevant role in absorbing anthropogenic emissions for about 10% (Nabuurs et al., 2003; UNECE and FAO, 2011).

In the last decade some studies have identified systematic errors when modelling terrestrial ecosystem sensitivity to climate variability at multiple time scales (Friedlingstein et al., 2006; Piao et al., 2013; Dalmonech et al., 2015) while sometimes differences in model predictions are very large (Wang et al., 2014a).

84 To improve the models capability in reproducing relevant processes related to the land carbon
85 cycle, detailed representation of missing processes should be increasingly developed (Sykes et
86 al., 2001; Campioli et al., 2013; Nolè et al., 2013; Ciais et al., 2013; Prentice et al., 2014). For
87 instance, spatial and temporal environmental hetereogeneity is known to play an important
88 role in the dynamics of populations and communities (Kobe, 1996; Chesson, 2000; Clark et
89 al., 2010; 2011). However, the implications of this hetereogeneity for developing and testing
90 regional to global scale forest dynamics models that are also able to take into account forest
91 management have still largely to be explored (Zhang et al., 2014). As reported by Wramneby
92 et al. (2008), incorporating increased mechanistic details is expected to improve the
93 explanatory power of a model. Many models for example calculate leaf photosynthesis
94 through the Farquhar model (Farquhar et al., 1980; Farquhar & Sharkey, 1982), while few
95 models take in proper consideration the canopy vertical stratification. Increasing model
96 complexity can sometimes mask a lack of understanding, although models including a larger
97 subset of important processes should be more realistic than a simpler model. However,
98 complex models are tuned to perform well at standard tests but produce widely divergent
99 results when projected beyond the domain of calibration (Prentice et al., 2014). Since
100 European forests are mostly managed and not homogeneous in terms of structure,
101 composition and cohorts, only a few models are able to represent this particular ecosystem
102 complexity and heterogeneity (Grote et al., 2011; Morales et al., 2005; Seidl et al., 2012; Yin
103 et al., 2014). For simulating the impact of forest management on the carbon cycle, it is
104 important to consider the vertical structure of forests and the age-related changes in structure
105 and physiology.

106 In this study we investigate the performance of the new version of the 3D-CMCC Forest
107 Ecosystem Model (3D-CMCC FEM, Collalti et al. 2014) in quantifying GPP across different
108 forest types and climate conditions in Europe. In contrast to Dynamic Global Vegetation
109 Models (DGVMs), 3D-CMCC FEM incorporates accurate process description focusing on the
110 effects of hierarchy in vertical forest structure and ages on productivity and growth at species
111 level. The model has been designed to maintain computational efficiency, as postulated for
112 the Light Use Efficiency (LUE) Models (Monteith, 1977), coupled to the accuracy of the
113 Process-Based Models (PBMs) (Makela et al., 2000). As described by Wang et al. (2014a; b),
114 a model with both high accuracy and computation efficiency is highly desirable for the
115 purpose of simulating long time series of GPP at high spatial resolution.

Thanks to FLUXNET, a global network of flux tower sites, half hourly net CO_2, water and energy eddy covariance (EC) flux measurements (Baldocchi, 2003) are now available for a wide range of forest ecosystems. The network provides a continuously increasing set of annual series of half-hourly data (Balzarolo et al., 2014). These data provide valuable information to investigate seasonal phasing and amplitudes of carbon fluxes (Aubinet et al., 2000; Falge et al., 2002; Gielen et al., 2013; Slevin et al., 2015) and to test terrestrial models at the ecosystem scale (e.g. Richardson et al., 2010; Blyth et al., 2011; Chang et al., 2013; Wißkirchen et al., 2013; Bagnara et al., 2014; Balzarolo et al., 2014; Liu et al., 2014; Wang et al., 2014a; Wu et al., 2015). In the present paper daily meteorological and GPP data are provided by FLUXNET. GPP data are exploited as an independent dataset to compare, over different time-scales, 3D-CMCC FEM simulations for ten European forest stands varying in species composition, forest structure, cohorts and climates.

The objective of this work is to answer the following questions:

1   Does the model reproduce the magnitude and the timing of seasonal fluctuations in GPP and their effects across different forest types and forest canopy structures?

2   Does the model reproduce the observed inter-annual GPP variability?

3   Is the model generic enough so that a single set of species-specific parameterizations (i.e. without a site-related calibration) allows reproducing GPP behaviour across different biomes?

4   Do the model outputs improve when considering a complex heterogeneous three-dimensional canopy structure compared to a simple "big leaf" model canopy representation?

To investigate these issues, we introduced a 3D canopy representation into the 3D-CMCC FEM, while however maintaining its flexibility and the generic features to be applied to different forest ecosystems. The new model can now run on a daily time step and includes as main changes an improved allocation-phenology scheme (with new carbon pools including the non-structural carbon pool, NSC), an implemented water cycle (including snow processes) and the computation of autotrophic respiration.

2   Materials and Methods

2.1   Model description

The three-dimensional Forest Ecosystem Model, 3D-CMCC FEM (Collalti, 2011; Collalti et al., 2014) (source code and executables are available upon request to the corresponding authors and downloadable at http://dev.cmcc.it/git/3D-CMCC-FEM-git) is hybrid between an empirical and a process-based model relying on the concepts of the LUE approach at canopy level for carbon fixation. The 3D-CMCC FEM is designed to simulate forest ecosystems at flexible scale (from hectare to 1km per 1km) and on a daily time step. The model simulates tree growth as well as carbon and water fluxes, at species level, representing ecophysiological processes in hetereogeneous forest ecosystems including complex canopy structures. The 3D-CMCC FEM v.5.1 uses daily meteorological data, site-specific data and ecophysiological data (e.g. maximum canopy conductance, specific leaf area, etc.; see Table S3 and Collalti et al., 2014) to simulate forest processes. The model code architecture allows aggregating trees into representative classes, each characterized with its variables (e.g. carbon pools, leaf area index, tree height) based on their ages, species-specific and structural traits. These variables are identified by the model through four indexes: i.e. species (x index), diameter class (Diameter at Breast Height, DBH) (y index), height class (z index), and age cohort (k index); such indexes represent the main state variables considered by the model in distinguishing ecosystems across sites. To deal with forest hetereogenity within and across different ecosystems, 3D-CMCC FEM v.x.x (all model versions follow the same architecture) uses a species-specific parameterization for each species simulated. Moreover, based on the assumption made by Magnani et al. (2007) that the above-ground net primary production decreases with the ageing of a forest, the model explicitly takes into account all ages within the stand, reproducing a year by year reduction due to senescence (Landsberg & Waring, 1997; Waring & McDowel, 2002). Height classes and the tree position within the forest vertical profile are explicitly treated by the model to estimate the light availability (version 5.1 includes also the albedo effects) using the Monsi-Saeki formulation of exponential attenuation coupled with the "Big-leaf" approach developed for a multi-layered model without considering canopy depth (Collalti et al., 2014; Medlyn et al., 2003). DBH together with stand density control grid cell horizontal canopy coverage (and gaps) through the computation of the single tree crown coverage and then upscale to grid-cell level (Collalti et

176 al., 2014). In this way, the model is able to reproduce different combinations of uneven-aged,

177 multi-layered and multi-species forests, by optional simulation of e.g. light competition, age

178 related decline and different species-specific traits. This aspect makes the model flexible to be

179 theoretically used for a wide range of applications in forests and allows quantifying the effects

180 of a particular simulation of forest structure on model performance.

181 2.2 Model implementations

182 In this study, the 3D-CMCC FEM described in Collalti et al. (2014) has been advanced to

183 version 5.1 to improve the representation of forest processes, like phenology, canopy

184 photosynthesis, including autotrophic respiration, tree carbon allocation and water dynamics.

185 The improved phenology routine is based on a new C allocation scheme, that includes new

186 carbon pools among which the Non-Structural-Carbon (NSC) pool, related to five

187 phenological transitions for deciduous species, and three phenological transitions for

188 evergreen species, both updated once per day. Autotrophic respiration is explicitly simulated

189 and separated into maintenance and growth respiration. Maintenance respiration is the

190 function of the nitrogen content (a new added pool) in the living pools, while growth

191 respiration is computed proportionally to the carbon allocated to the different tree

192 compartments.

193

194 Photosynthesis and net primary production

195 As in the Collalti et al. (2014) the carbon flux is still estimated in 3D-CMCC FEM through

196 the Light Use Efficiency approach multiplying, for a particular species x, the absorbed

197 photosynthetic active radiation (APAR, i.e. the radiation intercepted by the canopy) with the

198 leaf area index (LAI, $m^2 m^{-2}$) with either the prognostic potential radiation use efficiency (ε_x,

199 grams of dry matter MJ^{-1}) or the maximum canopy quantum use efficiency (α_x, µmol CO_2

200 µmol^{-1} PAR) (for a full list of model parameters see Table S3). Parameters ε_x or α_x are

201 controlled by the product of several environmental factors (modifiers) indicated as $mod_{x,k}$

202 (dimensionless values varying between 0 and 1 and differing for each species x and age class

203 k) depending on: vapour pressure deficit, daily maximum and minimum air temperatures, soil

204 water content and site nutrient status (for a full modifiers description see Landsberg &

205 Waring, 1997). Gross Primary Production (GPP; $gCm^{-2}day^{-1}$) is thus calculated using the

206 following equation:

207 $$GPP_{x,y,z,k} = (\varepsilon_x \, or \propto_x) * APAR_z * mod_{x,k} \qquad (1)$$

208 where $APAR_z$ is the absorbed radiation by the trees at the zth layer (where z represents the

209 layer of representative height for each height class).

210 Conversely from the previous version where Autotrophic Respiration (AR) was set as a

211 constant fraction of GPP (Waring & Landsberg, 1998), in this version AR is explicitly

212 simulated. AR is treated distinguishing into Maintenance Respiration (MR), governed by a

213 Q_{10} type response function (Ryan, 1991; Bond-Lamberty et al., 2005) and Growth Respiration

214 (GR) assumed to be a constant proportion (30%) of all new tissues produced (Larcher, 2003).

215 Net Primary Production (NPP), is then calculated as follows:

216 $$NPP_{x,y,z,k} = GPP_{x,y,z,k} - AR_{x,y,z,k} \qquad (2)$$

217 NPP is then partitioned into biomass compartments and litter production following dynamic

218 allocation patterns that reflect environmental constraints (i.e. light and water competition) and

219 age.

220

221 **Daily meteorological forcing and snow dynamics**

222 The model implements a daily time step (previous version was at monthly time step) thanks to

223 the temporal frequency of meteorological forcing input data: daily maximum (T_{max}; °C) and

224 minimum air temperature (T_{min}; °C), soil temperature (T_{soil}; °C), vapour pressure deficit (hPa),

225 global solar radiation (MJ $m^{-2}day^{-1}$) and precipitation amount (mm day^{-1}). In addition, the

226 model uses the day-time (T_{day}; °C) and night-time (T_{night}; C°) average temperature computed

227 as follows (Running & Coughlan, 1988):

228 $$T_{day} = 0.45 * (T_{max} - T_{avg}) + T_{avg} \qquad (3)$$

229 $$T_{night} = (T_{day} + T_{min})/2 \qquad (4)$$

230 Where T_{avg} is the daily average air temperature (°C). When the soil temperature is missing

231 among in situ observed data, the model estimates it for the upper 10 cm of the soil layer

232 through an 11-day running weighted average of T_{avg} and further corrected by the presence of a

233 snowpack as in Thornton (2010), Kimball et al. (1997) and Zeng et al. (1993). The variable

234 related to the snowpack thickness was included as a water cycle component by reproducing

235 the daily amount (mm day^{-1}) of snow melt driven by average air temperature (T_{avg}) and

236 incident net global radiation (Rad_{soil}; W m^{-2}), while snow sublimation is only driven by T_{avg}.

237   In case of snow presence, if T_{avg} is higher than 0°C, considered the melting point as in
238   Running & Coughlan (1988) and Marks et al. (1992), the rate of daily snowmelt is estimated
239   by:

240    $$Snow_{melt} = \left(t_{coeff} * T_{avg}\right) + \left(\frac{Rad_{soil} * \varepsilon_{snow}}{H_{fus}}\right) \qquad\qquad (5)$$

241   where t_{coeff} is the snowmelt coefficient (0.65 Kg m^{-2} °C^{-1}day^{-1}), ε_{snow} is the absorptivity of
242   snow (0.6), H_{fus} is the latent heat of fusion (335 kJ kg^{-1}), Rad_{soil} is the incident net global
243   radiation at the soil surface (kJ m^{-2} day^{-1}).

244   Otherwise, if T_{avg} is lower than 0°C snow sublimation is computed by:

245    $$Snow_{subl} = \left(\frac{Rad_{soil} * \varepsilon_{snow}}{H_{sub}}\right) \qquad\qquad (6)$$

246   where H_{sub} is the latent heat of sublimation (2845 kJ kg^{-1}).

247

248   **Phenology and Carbon allocation**

249   Phenology plays a fundamental role in regulating photosynthesis and other ecosystem
250   processes (e.g. carbon and nitrogen dynamics), as well as inter-individual and inter-species
251   competitive relations and feedbacks to the climate system (Richardson et al., 2012a). In the
252   updated model version phenology and carbon allocation depend on six different carbon and
253   nitrogen pools (while three carbon pools where considered in the previous versions). Five
254   pools represent the main tree organs: foliage, (fine and coarse) roots, stem, branch and bark
255   fraction. One new pool corresponds to non-structural carbon (NSC; starch and sugar) stored in
256   the whole tree. The inclusion of this new pool was necessary to represent NSC mobilization
257   and consequently leaf phenology (e.g. leaf production during spring for deciduous trees) and
258   carbon allocation. Woody pools are furthermore distinguished between live and dead wood.
259   In the new version of 3D-CMCC FEM, LAI values are predicted for sun and shaded leaves
260   (De Pury & Farquhar, 1997; Thornton & Zimmermann, 2007; Wu et al., 2015), minimizing
261   the effects of the "Big-leaf" approach (Monteith, 1965; Sellers et al., 1997), as a function of
262   the amount of carbon allocated to the leaf pool. It is noteworthy that each pool and each
263   structural state variables is daily updated according to the meteorological data, forest structure
264   and simulated fluxes.

265 Following Arora & Boer (2005), for deciduous species the model considers five phenological
266 transitions (being just four in the previous versions: bud burst, peak LAI, leaf fall period and
267 dormancy) that drive the seasonal progression of vegetation through phases of
268 dormancy/quiescence, budburst, maximum growth, active growth, and senescence as in the
269 following:

270 1. Leaf onset starts from quiescence when thermic sum (the sum of the T_{day} air
271 temperatures exceeding the threshold T_{base} value of 5°C) exceeds a species- and site-
272 specific temperature threshold value (Rötzer et al., 2004; Dufrene et al., 2005) and
273 when the LAI value reaches LAI = max(LAI) * 0.5. The costs of expanding buds
274 during this period of high carbon demand are supported by NSC (Landhausser, 2010;
275 Dickmann & Kozlowski, 1970).

276 2. During the budburst phase, carbon and NSC are allocated to the foliage pool, as long
277 as the balance between GPP and AR is positive (Barbaroux & Bréda, 2002; Campioli
278 et al., 2013; Scartazza et al., 2013).

279 3. During the succeeding maximum growth phase and lasting up to peak LAI, carbon is
280 allocated into foliage and fine root pools (Sabatè et al., 2002), based on the pipe model
281 theory (Shinozaki et al., 1964 a; b), to optimize photosynthesis; otherwise, no growth
282 occurs and NSC is used.

283 4. Successively, the full growing phase lasts up to the day when day length (in hours) is
284 shorter than a species-specific threshold value. In this phase carbon is allocated into
285 stem, fine and coarse roots, branch and bark, and into non-structural carbon pools in
286 order to refill the reserves for the next years.

287 5. Finally, during the leaf fall (i.e. yellowing or senescence) phase, lasting until the leaf
288 fall (assumed linear) is complete, the total positive carbon balance is allocated to the
289 NSC pool.

290 Outside the growing season (dormancy) trees consume NSC for fuelling maintenance
291 respiration (Ogren, 2000).

292 For evergreen species the model follows a similar but simplified approach simulating a first
293 maximum growth phase, when the model allocates NSC to foliage and fine roots up to reach
294 peak LAI, and a second full growing phase, when the model allocates to the other pools. As in

295   Lawrence et al. (2011) for litterfall we assume and simplify that there are no distinct periods,

296   but rather a continuous shedding of foliage and fine roots of the previous years.

297   All tree pools are updated at a daily time step depending on NPP balance. Nitrogen

298   concentration for each pool is considered as a C/N ratio following Dufrene et al. (2005) and

299   Thornton (2010). The C/N stoichiometry is constant and depends on species; unfortunately,

300   the model still lacks of an interactive C-N cycle. Forest stand structural attributes, e.g. DBH,

301   tree height, and crown competition are also updated at a daily time step based on species-

302   specific biometric relationships.

303

304   **Autotrophic respiration**

305   Based on the approach of BIOME-BGC model (Thornton, 2010) 3D-CMCC FEM computes

306   the daily AR of all living tissues. MR is a modified Van't Hoff function (Davidson et al.,

307   2006; Mahecha et al., 2010) of temperature with the temperature sensitivity parameter Q_{10}

308   (see below) and a linear function of the nitrogen content ($N_{content}$ = 0.218 kgC kgN^{-1} day^{-1};

309   Ryan, 1991) in the living compartments. The Q_{10} function is an exponential function for

310   which a 10°C increase in temperature relates to a Q_{10} factor change in the rate of respiration.

311   MR is partitioned into day time and night time respiration using, in place of *temp* in Eq.(7):

312   t_{day} and t_{night} for foliage, t_{soil} for fine and live coarse roots, and t_{avg} for live stem and branch.

313    $$MR_{x,y,z,k} = 0.218 * Ncontent_{x,y,z,k} * Q_{10}^{(temp-20)/10} \qquad (7)$$

314    $GR_{x,y,z,k}$ is considered as a fixed ratio (30%) of all newly grown (i.e. living) tissues as

315   proposed by Larcher (2003).

316

317   2.3   Data description

318   Model validation has been performed for ten different forest sites (Table 1) included in the

319   European EC fluxes database cluster (URL: http://www.europe-fluxdata.eu). For each site,

320   3D-CMCC FEM v.5.1 simulations were performed averagely for 10 years, forced with gap-

321   filled daily meteorological data, according to the available time series. The selected sites

322   cover a wide range of European forest ecosystems across different latitudes, landscapes and

323   three climatic zones: temperate, Mediterranean and subalpine.

324 For all sites, daily time series of meteorological variables (maximum and minimum air
325 temperature, precipitation, vapour pressure deficit and incoming solar global radiation) were
326 used as drivers, while GPP was used for model output validation. The GPP derives from Net
327 Ecosystem Exchange (NEE) measurements that have been previously quality checked and
328 processed including storage correction, spike detection, and low turbulence condition (u*)
329 filtering according to the method in Papale et al. (2006) and gap filled using the Marginal
330 Distribution Sampling method (MDS; Reichstein et al., 2005). The GPP is not directly
331 measured by the eddy covariance technique but it is estimated using a partitioning technique
332 as described in Reichstein et al. (2005). In the rest of the paper, we will refer to these data as
333 "measured" or "observed" GPP for simplicity but it is important to highlight that they are
334 obtained using a modeling approach (although strongly based on direct measurements).

335 ## 2.4   Model and experimental set-up

336 Site data needed for model initialization concerned information on forest structure (DBH, tree
337 height, age and density), its species composition, and soil characteristics (e.g. soil depth,
338 texture and bulk density). These data were used for each site to initialize the model, i.e. to
339 describe soil characteristics and the initial forest conditions at which the model starts to
340 simulate forest processes. Initialization data were taken from the BADM (Biological,
341 Ancillary, Disturbance, Metadata) files, available at http://www.europe-fluxdata.eu, for each
342 of the selected sites, and complemented by a literature review and personal contacts with the
343 sites' Principal Investigators. Length of model simulations, basic sites description and forest
344 attributes used for model initialization are shown in Table 1. As a whole, for all sites, the
345 species-specific ecophysiology has been parameterized generically (i.e. not related to the
346 simulated site) using only data from the literature (e.g. Breuer et al., 2003; Mollicone et al.,
347 2003; Pietsch et al., 2005; White et al., 2000) independently from site-related measurements
348 (for a list of model ecophysiological and structural species-related parameters see Table S3).
349 As in White et al. (2000) and in Naudts et al. (2014) in case of multiple values available for a
350 single parameter, the mean values were used. Using the mean parameter estimates avoided
351 hidden model-tuning (i.e. the use of unrealistic value to obtain the best fit) and largely reduces
352 the likelihood that simulation results are biased by hidden calibration.

353 In addition, several studies (Bolstad et al., 1999; Griffin et al., 2001; Ibrom et al., 2006;
354 Misson et al., 2007; Cescatti et al., 2012; Guidolotti et al., 2013; Migliavacca et al., 2015)

claim that beside environmental variables, spatial heterogeneity (horizontal and vertical) of the stand structure and composition (age, species) also plays an important role at the ecosystem level. To evaluate if a more detailed simulation of forest heterogeneity improves model performances, a number of replicated simulations were performed for three heterogeneous sites (BE-Bra, IT-Ren and DE-Tha), based on different model initializations in terms of forest layers, species composition and/or ages (Table 1). These replicates start from a forest representation very close to reality (e.g. cohorts, mixed species composition and different canopy layers) to a more generalized one. For reasons of comparability, in these test sites the model has been forced with the same meteorological input data, and eco-physiological species-related parameterizations, i.e. only model initializations data, related to stand attributes, differ. These data are based on different sources: site measurements and/or literature data and/or experimental settings.

In the case of BE-Bra we initialized the model with near all possible combinations of initialization datasets. The first simulation (BE-Bra P_Q-3L) has explicitly taken into account the site heterogeneity (vertical and horizontal) (following Gielen et al., 2013, and ancillary data sources) consisting in mixed species composition at a different canopy coverage rate of *Quercus robur* (Q) and *Pinus sylvestris* (P) (20 and 80%, respectively), with two cohorts (oaks and pines, 65 and 72 years old, respectively) and three forest layers. In the second simulation (BE-Bra P), only a single-layer of Scots pines was considered (following Janssens et al., 2002 and Verbeeck et al., 2007). In the third, fourth and fifth simulations (BE-Bra Q_3L, BE-Bra Q_2L, BE-Bra Q_1L, respectively) only three, two and one layer of pedunculate oaks (following Curiel Yuste et al., 2005 and experimental set up) were assumed. Additionally, two more experimental set-ups combined two layers of oak and one layer of pine (BE-Bra P_Q-2L) and one layer of oak and pine (BE-Bra P_Q-1L).

For IT-Ren, in the first simulation, two layers and two cohorts were considered (IT-Ren 2L_2C) following Montagnani et al. (2009). In the second case, stand heterogeneity has been grouped into one layer, i.e. minimizing forest structure, and one single averaged cohort (IT-Ren 1L_1C; experimental set up).

For DE-Tha, two species (DE-Tha 2S) (spruce 80% and pine 20%, respectively) were modelled in the first simulation (following Grünwald & Bernhofer, 2007), while in the second experiment only the dominant species (spruce; DE-Tha 1S) was considered (BADM source).

2.5 Validation approach

In order to analyse model performance, we used daily (X_{daily}), monthly ($X_{monthly}$) and annual (X_{annual}) time series for modelled and observed GPP values, which were compared at the different time scales. At first, we conducted a comparison via appropriate performance indices on long-term annual average (i.e. over the full series of all the available years), then we evaluated how the model performed in the different seasons aggregating values for months of the same season.

In addition, to avoid misleading results in the daily and monthly signal comparisons due to the strong seasonality for both daily and monthly signals, we followed the decomposition technique proposed by Zhao et al. (2012). To partially remove the seasonal cycle signal, we build a new daily (Y_{daily}) and a new monthly ($Y_{monthly}$) dataset for both observed and modelled data, respectively. The Y_{daily} is created by subtracting the daily time series from the daily mean of the month, and the $Y_{monthly}$ by substracting the monthly time series from the annual mean (see Table S1-b).

For both X and Y datasets we firstly adopted the Pearson coefficient of correlation (r).Then, we calculated the Normalized Root Mean Square Error (NRMSE) (Anav et al., 2010; Keenan et al., 2012) as a standardized index of error. The NRMSE reports the mean difference between observed and modelled GPP values (GPP_{EC} and GPP_{MD}, respectively) normalized on the variability in the GPP_{EC}, in order to have an indication of the average distance between GPP_{MD} and GPP_{EC}, comparable among the different sites. NRMSE was quantified as:

$$NRMSE_{GPP} = \frac{\sqrt{\sum_{i=1}^{N}\left(GPP_{EC_i}-GPP_{MD_i}\right)^2}}{\sum_{i=i}^{N}\sigma\left(GPP_{EC_i}\right)} \tag{8}$$

where i represents the day (or month), and $\sigma(GPP_{EC})$ is the standard deviation of the full daily (or monthly) series of observed GPP consisting of N records.

In addition, model performances were measured for the same series through the 'Model Efficiency' index (MEF) following Reichstein et al. (2002) and Migliavacca et al. (2015):

$$MEF = 1 - \frac{\sum_{i=1}^{N}\left(GPP_{EC_i}-GPP_{MD_i}\right)^2}{\sum_{i=1}^{N}\left(GPP_{EC_i}-avg(GPP)_{EC}\right)^2} \tag{9}$$

In contrast to correlation coefficient r, the MEF index (Bowman & Azzalini, 1997) measures not only the correlation between modelled and observed data (in other words, how well they

414 reproduce the phase of observations), but also their 'coincidence', i.e. the deviation from the
415 1:1 line, and it is sensitive to systematic deviations between model and observations
416 (Reichstein et al. 2002).

417 Another index used in model evaluation is the standardized Mean Absolute Bias (MABstd)
418 (Li et al., 2010) instead of classical Bias index to avoid compensations for errors of opposite
419 signs and standardized (as for NRMSE) to allow comparison across sites:

420 $$MABstd = \sum_{i=1}^{N} \left(\frac{\left| GPP_{MD_i} - GPP_{EC_i} \right|}{\sigma \left(GPP_{EC_i} \right)} \right) \frac{1}{N} \qquad (10)$$

421 To evaluate the model performances in terms of variability patterns, we adopted a procedure
422 to compare each GPP_{MD} value to both its correspondent GPP_{EC} value and the GPP_{EC}-GPP_{MD}
423 difference, at daily and monthly levels. Since the different sites have different ranges of GPP,
424 we arranged in ascending order GPP_{EC} time series, then divided the whole series in 18 classes,
425 each one containing values of a 5 percentile class. For each group of GPP_{EC} we calculated the
426 median and reported the range. We calculated the same statistics for the values of GPP_{MD}
427 arranged so that dates of GPP_{MD} and GPP_{EC} matched. We chose the median rather than the
428 average because it is less influenced by outliers. We decided to use the range rather than the
429 variance as a measure of variability, because giving information on asymmetry.
430 In order to assess the Inter-Monthly and Inter-Annual Variability (IMV and IAV
431 respectively), individual GPP values for each month and year considered were normalized
432 following Vetter et al. (2008) and Keenan et al. (2012). Shortly, we subtracted the respective
433 observed or modelled average from individual (monthly and yearly) observed and modelled
434 value as follows:

435 $$IMV_{(EC \ or \ MD)i} \ or \ IAV_{(EC \ or \ MD)i} = GPP_{(EC \ or \ MD)i} - avg(GPP)_{(EC \ or \ MD)} \qquad (11)$$

436 where avg(GPP) is the long-term (full series of all the available years) average of monthly
437 (for IMV) or yearly (for IAV) GPP from observations (EC) and modeling (MD), respectively.
438 A kernel density estimation (*kde*) was performed to qualitatively observe probability
439 distribuition functions (PDFs) respectively of the IMV and IAV values (Bowman & Azzalini,
440 1997).

441 To evaluate 3D-CMCC FEM ability in reproducing the observed IMV and IAV, we
442 calculated the NRMSE based on monthly and annual time series of IMV and IAV values,
443 respectively. The NRMSE, adopted as a normalized index of error allowing comparability

444 among different sites, was thus calculated as in Eq. 8 but using IMV and IAV instead of GPP

445 individual values, following the approach of Keenan et al. (2012).

3 Results

3.1 GPP evaluation over long-term annual and seasonal scale

448 Both monthly and daily simulated (MD) GPP show high correlations with EC data and these

449 results are consistent with MEF values as well as with NRMSE and MABstd (Table S1a, and

450 Figure 1-a and 1-b). On average, deciduous forests reveal better correlation between MD and

451 EC data than evergreen forests, with a mean r of 0.86, while evergreen and mixed stands

452 show average *r* of 0.81 and 0.77, respectively. For all stations p<0.0001. These results are

453 confirmed by Taylor diagrams (Taylor, 2001) (Figure 2a) which show that the model

454 performs satisfactorily for daily fluxes, in four (i.e. DE-Hai, DK-Sor, DE-Tha, FI-Hyy) of ten

455 sites falling within ±0.5 normalized standard deviations from the reference point (REF;

456 representing observed data) and having correlation around 0.9. For six sites (all the evergreen

457 needleleaf plus deciduous except FR-Hes), the normalized standard deviation of simulated

458 data is close to that of observed data (represented by reference line with normalized standard

459 deviation, i.e. radial distance from the axis origin equal to 1). Simulated data for IT-Cpz, FR-

460 Hes and FR-Pue have, respectively, a normalized standard deviation of approximately +0.2,

461 +0.3 and +0.4 (as difference from that of observations) consistently with the lower correlation

462 values; BE-Bra shows the highest negative difference, in terms of standard deviation, of

463 around -0.3. On average, the least performing result is for IT-Cpz that shows a correlation

464 below 0.60 and falls outside ±1 normalized standard deviation from the reference point. The

465 Taylor diagram in Figure 2b shows the model's capability to better simulate GPP at monthly

466 scale. For seven sites (all deciduous and evergreen needleleaf), the normalized standard

467 deviations of modelled data are close to that of observations (reference line), the correlation is

468 well above 0.90 and within ±0.5 normalized standard deviation from the reference point. IT-

469 Cpz and BE-Bra show improved results with respect to daily data: respectively, their

470 correlation increases by more than 0.1 units, they fall within the +0.2 and -0.2 units of

471 normalized standard deviation differences with respect to that of observations, and they enter

472 in the field of ±1 and ±0.5 normalized standard deviation from the reference point,

473 respectively, although for IT-Cpz the values for all statistical indexes are consistently the

474 lowest. Although less strongly, FR-Pue monthly data also have better performances than daily

475 data results in terms of higher correlation (0.89) and closer position in terms of normalized

476 standard deviations units from the reference point even if the other indexes are a little bit far

477 from the average values of the other sites.

478 To reduce the effects of seasonality, we also examine model performance using

479 decomposition method (section 2.5). In the daily time-step, the overall model performance is

480 much lower in Y dataset (Figure 1-c and Table S1b) than in X dataset, that is, r= 0.51, MEF =

481 -0.43, NRMSE = 1.18 and MABstd = 0.8 in Y dataset vs r= 0.82, MEF = 0.63, NRMSE =

482 0.57 and MABstd = 0.44 in X dataset. The large model error at synoptic scale have been well

483 recognized by previous studies (Dietze et al., 2011; Zhao et al., 2012). The model shows to be

484 a good predictor for DE-Tha and FR-Pue and to be less predictive for DK-Sor and FR-Hes

485 with respect to the X dataset. Accordingly, for FR-Pue comparisons between X and Y datasets

486 show that this site is less affected by seasonality while DK-Sor is the most affected one. As

487 expected, in the monthly time step, the decomposition technique returns more similar results

488 between X and Y datasets. Worst results are for IT-Cpz while best results are for DE-Hai,

489 DK-Sor, DE-Tha and IT-Ren (see Table S1b and Figure 1-d). Overall, after smoothing the

490 seasonality the model shows to be slightly better predictive with average values among sites

491 consistent with observed data (r = 0.94, MEF = 0.85, NRMSE = 0.36 and MABstd = 0.27).

492 Comparison between X and Y datasets shows that DE-Hai is less affected by seasonality and

493 IT-Cpz is the most affected one. In brief, comparison between X and Y datasets shows similar

494 reconstruction ability in the monthly time step, but very different in the daily time step

495 because X dataset contains the feature of large seasonality. Given that one of the objects of

496 this study focuses on seasonality fluctuation, we mainly show the results based on X dataset

497 hereafter without specification.

498 To summarize, although with similar inter-sites variability, monthly correlations across

499 different sites are higher than daily ones, with average correlations of 0.94 for deciduous, 0.90

500 for evergreen and 0.92 for mixed stand (Figure 1 and Table S1a).

501 Daily and monthly NRMSE are usually less than 1.00. Monthly NRMSE is less than daily

502 NRMSE, 0.41 vs. 0.63 on average, respectively (Table S1a). These results confirm that the

503 model performs better at a monthly than at a daily time scale (Figure 1), likely because of

504 averaging effects of daily variability in GPP estimation.

The same consistency is shown for MEF index that is on average 0.79 (monthly) and 0.57 (daily), with largely lower values for the two Mediterranean forests (IT-Cpz and FR-Pue) at both the daily and monthly time scale (Table S1a and Figure 1).

Considering the annual mean in deciduous forests (Table S1a), the model slightly underestimates the GPP by -2.4% (average among DE-Hai, DK-Sor), while in FR-Hes and IT-Col it shows an overestimation of 5.2% on average. Concerning evergreen forests, we find an overall model underestimation of 2.1%, with higher variability compared to deciduous forests, and more divergent in the case of the two Mediterranean ecosystems, ranging from underestimation of 18.4% (318 gC m^{-2} year^{-1}; IT-Cpz) to overestimation of 12.1% (158 gC m^{-2}year^{-1}; FR-Pue). Results for the mixed forest site of BE-Bra are reasonable, with an underestimation of about 4.4%.

In terms of inter-annual variability of the yearly mean, GPP$_{MD}$ falls well within the range of GPP$_{EC}$ standard deviations for all sites except at IT-Cpz (Figure 3). Deciduous broadleaved and the evergreen needleleaf are the best reproduced.

Performance indices from daily and monthly observed and modelled GPP series analysed at seasonal level are shown in Table S2 and Figures 4 and 5. Winter (DJF) and summer (JJA) correlations were generally lower than those in autumn (SON) and spring (MAM). Specifically, DJF and JJA showed a correlation of 0.45 and 0.46 respectively on a daily scale and a value of 0.59 and 0.50 on a monthly scale; MAM and SON showed on a daily scale an average correlation of 0.72 and 0.77 respectively, while on monthly scale a correlation of 0.82 and 0.86 with two low values of 0.05 and 0.06 for monthly DJF and MAM for IT-Cpz was shown. Winter and summer monthly average NRMSE of 1.13 and 1.00, respectively, were not significantly different to the 0.66 and 0.57 of spring and fall. MEF and MABstd indexes values suggest similar findings than NRMSE.

Figure 6 shows overall modelled vs. observed fluxes over daily and monthly scales, and the absolute difference (ΔGPP MD, i.e. GPP$_{MD}$ minus GPP$_{EC}$) vs. observed fluxes (GPP$_{EC}$) as calculated by the difference matrix described in section 2.5. Overall, the aggregated data reveal high correlation also due to a progressively reduced range of data, and then variability, at higher GPP values (Figures 6; top plots). Figures 6 (bottom plots) show patterns of ΔGPP MD with increasing GPP$_{EC}$. These differences result in strong reduction of discrepancies for GPP$_{EC}$ greater than 8.5 gC m^{-2} d^{-1} for daily, or 7.3 gC m^{-2} d^{-1} for monthly time series.

536 The average intra-annual GPP variations are analysed by calculating the long-term average

537 and standard deviation values for each month of the year (Figure 7). In spring, the modelling

538 results from deciduous forests present a larger variability than the observed data, especially

539 during budburst and in late spring. The model generally matches the observed phenology

540 timing (budburst, peak LAI, leaf senescence and their fall, i.e. length of growing season, data

541 not shown). Consistent biases were observed in late summer.

3.2 Inter-monthly and inter-annual variability

543 The distribution of the IMV for the analysed sites reveals in general lower variance for

544 modelled than observed data (Figure 8 and Table 2). Regarding deciduous forests, both DK-

545 Sor and FR-Hes show IMV_{MD} distributions with a larger interquartile range in comparison

546 with IMV_{EC} (p-value < 0.05). Conversely, for DE-Hai and IT-Col the IMV_{MD} variance is

547 statistically representative for the IMV_{EC}; however IT-Col shows a significantly biased

548 median (p-value < 0.05). Less variability than IMV_{EC} is generally observed for IMV_{MD} of

549 conifers. While DE-Tha shows significant agreement for both variance and central tendency

550 (median) (p-value > 0.05), at FI-Hyy the IMV_{MD} appears statistically in disagreement with

551 IMV_{EC} for both variance and central mean tendency (p-value < 0.05). We find a small

552 difference between IMV_{MD} and IMV_{EC} probability density modal values in IT-Ren (Table 2).

553 Concerning broadleaved evergreen vegetation, we observe very good agreement between

554 observed and modelled IMV central tendency measures in FR-Pue with most of the

555 frequencies between $\pm$ 2 gCm^{-2}d^{-1}. In FR-Pue, however, we notice that the distributions are

556 slightly shifted, especially around the median, with resulted variance from modelled data in

557 disagreement with observed data. We detect high IMV distributions disagreement in IT-Cpz,

558 where the PDF from observed IMV is normally distributed and the one from modelled IMV is

559 not (as resulted by a χ^2 goodness of fit test). IMV_{MD} series in BE-Bra (mixed forest) are in

560 low agreement with those from EC. Modelled variance is low, and positive IMV values are

561 especially scarcely represented. Table 2 also shows the NRMSE for IAV and IMV series.

562 There is no apparent correlation either between sites species and average error, or between

563 distributions uniformity and NRMSE. In fact, the lowest NRMSE for IMV was found in BE-

564 Bra and IT-Col and the highest in DE-Hai and DK-Sor. On average the model has a NRMSE

565 for IMVs of about 1.2.

566   Figure 9 shows the modelled and measured individual IAV values for each studied site. The
567   magnitude of IAV_{MD} was on average of the same order as IAV_{EC}, showing the model's ability
568   to reproduce the inter-annual variability range, and capturing about 62% of the anomalies
569   signs (i.e. timing) for the total set of years. The model generally better captured conifers' IAV
570   sign (i.e. DE-Tha, FI-Hyy, and IT-Ren), with 66% of the times against about 59% for the
571   deciduous forests (i.e. DE-Hai, DK-Sor, FR-Hes, IT-Col) and 55% for the Mediterrenean
572   ones (i.e. FR-Pue and IT-Cpz). However, the IAV difference in magnitude was better
573   represented for deciduous forests rather than conifers, as inferred by the average NRMSE of
574   respectively 1.45 and 1.67 (calculated by averaging values reported in Table 2). Although the
575   model reproduced the timing of anomalies satisfactory in more than half of cases (a little bit
576   more than in a random selection), the correlations had a wide spread across sites.
577   Quantitatively, modelled anomalies suggest better results for FR-Pue (r = 0.76) and worse
578   results for IT-Ren (r = -0.54).

579   In the case of the year 2003 with its summer heat and drought extreme (Ciais et al., 2005;
580   Vetter et al., 2008), the anomaly sign has been well captured by the model for six of the eight
581   sites analyzed for that year (no observations were available for BE-Bra and IT-Ren) (Figure
582   9). At IT-Cpz and DK-Sor, average IAV_{MD} has the opposite sign to IAV_{EC}, while 2003 was
583   recognized as not remarkably anomalous at IT-Col. Similarly, the model results match with
584   that found by Delpierre et al. (2009) about the anomalous carbon uptake during the warm
585   spring of 2007 compared with the decadal mean for FR-Pue, FR-Hes, and DE-Tha.

3.3   Comparison within different forest structure simulations

587   Considering the presence of only one species (either pines or oaks) strongly limits the model
588   to simulate the daily and monthly GPP patterns in BE-Bra (Table 3). This site represents a
589   mixed stand of deciduous and evergreen tree species that assimilates CO_2 all year round,
590   although low temperatures in winter and spring reduce photosynthesis for pines also. The
591   observed GPP fluxes are then caused by the 'mixture', at a varying degree, of both oak and
592   pine trees. Considering BE-Bra as a pure oak forest with a variable number of layers
593   (simulation codes: BE-Bra Q_3L, BE-Bra Q_2L, BE-Bra Q_1L) the model results for annual
594   GPP deviate from -1.2 up to -7.4%; considering a pure pine forest (BE-Bra P) or a
595   combination of pines and one layer of oak (BE-Bra P_Q-1L) the model underestimates
596   annually from -15.9% to -11.5%, respectively. It is noteworthy that the daily GPP values

show a markedly different seasonal distribution on fluxes (data not shown). Conversely, there is no clear evidence that in simulating pines coupled with one, two or three oak layers (BE-Bra P_Q-1L, BE-Bra P_Q-3L BE-Bra P_Q-2L) model results largely benefitted of this differentiation both on a daily, monthly and annual scale. Similar results are obtained for DE-Tha site when simulating one single species (DE-Tha 1S) or two (DE-Tha 2S), since the similar phenology behaviour of modelled species does not cause a marked difference in the seasonal GPP cycle. On the other hand, IT-Ren initialized as a single layer and with one single cohort (IT-Ren 1L_1C) instead of two layers and two cohorts (IT-Ren 2L_2C) differs strongly from observed GPP values overestimating the annual cumulated GPP by 43.2%. However, for this site, the analysis of performance indices based on daily and monthly series shows no evidence of improved model results.

4 Discussion

In this paper, we have analyzed the capability of the latest version of the 3D-CMCC FEM (v.5.1) to simulate intra-annual to inter-annual GPP variability over ten heterogeneous European forest sites, representative of different ecosystems and bioclimatic regions, by comparing model results with observations based on the EC technique. Although the model provides a reasonable reproduction of the observed values, we may evince some critical issues. First, the observed GPP data are affected by high uncertainties (Kenan et al., 2002; Papale et al., 2006; Richardson et al., 2012a, b). According to Luyssaert et al. (2007) these uncertainties in the ten case studies considered here, although at the biome level, have a very high spread, varying from ±557.9 (for FI-Hyy) to ±700 gC m^{-2}yr^{-1} (for IT-Cpz). Besides uncertainty in the EC technique, model assumptions and parameterizations can increase discrepancies compared to observed GPP data.

A potential further source of error in the model runs that may need to be considered or accounted for is related to our choice of not making a site-specific parameterization. Since we used general parameterizations, large uncertainties could be detected especially in the variables that determine, for example, the length of the growing season (Richardson et al., 2010), and the latitudinal differences (acclimation) of the maximum, minimum and optimum temperatures for photosynthesis. Improvement could be achieved with a site-specific parameterization, but this falls beyond our goal to make the model generally applicable. In addition, to avoid a misleading model evaluation coming from strong seasonality (especially for deciduous sites) we followed the decomposition technique proposed by Zhao et al. (2012).

629   On average, 10 years of simulations have been conducted for each site. In addition, in three
630   sites different model initializations (i.e. considering different forest structure, composition and
631   cohorts) were used to quantify improvements in model results when a more detailed
632   heterogeneity forest structure representation and processes are simulated. Modelled GPP
633   results were compared against those from EC observations collected for these sites
634   encompassing three mono-specific (pure) stands of Beech, Holm oak and Scots pine, and
635   three uneven-aged, multi-layered and mixed stands.

636   Based on results, we can now provide answers to the four initial questions:

637   ***1.   Does the model reproduce the magnitude and timing of seasonal fluctuations in***
638   ***GPP and their effects across different forest types, structures and compositions?***

639   Overall, as desirable, the model is skilful in reproducing the annual GPP and its intra-annual
640   (seasonal) cycle, calculated as both daily and monthly value averages, with the monthly scale
641   performing better across all statistical indexes considered. These results can be however
642   considered as a "false positive" due to the strong seasonality of GPP patterns that influences
643   and causes higher values of correlation than the model's capabilities to reproduce GPP fluxes
644   (Zhao et al., 2012). This is clearly related to the tendency to linearize the relationship among
645   CO_2 flux and PAR and/or temperature, as also reported by Ruimy et al. (1995) and Wu et al.
646   (2015). Overall, statistical indexes of daily and monthly modelled values for both X and Y
647   datasets were highly consistent with EC data, except for the Mediterranean sites (where
648   seasonality is less pronounced) (see Table S1a and b). Summer drought stress appeared to be
649   the most limiting factor on photosynthesis at FR-Pue (Falge et al., 2002; Reichstein et al.,
650   2002; Sabatè et al., 2002) while the presence of shallow groundwater table at IT-Cpz seemed
651   to reduce the severity of summer drought. This reduction cause a smoothing of seasonality
652   well highlighted in the Y dataset (see Table S1-b) where IT-Cpz showed to be unanimously
653   one of the worst simulated site at both daily and monthly timescale while FR-Pue and DE-
654   Tha, both evergreens, the less affected by seasonal patterns. This behaviour is confirmed by
655   the daily values of DK-Sor and IT-Col for monthly data, both deciduous, that showed to be
656   the most affected, in other words if we smooth over the seasonal trends results get worse
657   while the model indicated to be less sensitive for those evergreen sites where seasonality is
658   not marked with high values of correlation for DE-Tha, FI-Hyy and Fr-Pue. These results
659   confirm that seasonality has a remarkable effects on a model evaluation.

660 Concerning the seasonality, all statistical indexes divided by seasons in Table S2 are
661 consistent in showing a non-negligible uncertainties in representing GPP patterns, as well as
662 inferred by temporal mismatches in variance. The overall agreement despite temporal
663 mismatches suggested that errors compensated over the year, but are cumulated in specific
664 time windows (e.g. seasons). As reported for other models (Morales et al., 2005 and Naudts et
665 al., 2014), the model's performances are generally worse in winter (DJF) and summer (JJA).
666 Biases and differences in winter GPP variance may be related, among other things, to the
667 model algorithms used to simulate LAI and to the algorithm used to calculate GPP from EC
668 data (Reichstein et al., 2005), since GPP variability should be low during DJF or absent for
669 deciduous forests. However, mismatches are also related to the way in which 3D-CMCC
670 FEM represents winter and early spring ecosystem processes. The model in fact does not
671 consider the influence of ground vegetation that appears to be not negligible in some cases
672 (Kolari et al., 2006). High GPP variance for evergreen species could be strongly related to
673 low temperatures during winter (Del Pierre et al., 2009). Systematic overestimation in winter
674 and spring GPP could then be associated with a lack in representing conifers acclimation or to
675 soil and atmosphere thermal constraints. At high latitudes and altitudes, another source of
676 uncertainty may be related to freezing and thawing dynamics in soil water (Beer et al., 2007)
677 which are not considered by the model, as with snow sublimation and melting, which are still
678 simplistically represented.

679 GPP of deciduous forests in summer and autumn are also affected by uncertainties for
680 surface, which is represented by LAI in the model. In addition, GPP is linear with respect to
681 PAR (Monteith, 1977) over monthly or annual time scales, while the relation is strongly
682 nonlinear at the daily scale (Leuning et al., 1995; Gu et al., 2002; Turner et al., 2003; Wu et
683 al., 2015). The linear response of GPP to PAR led to the underestimation/overestimation of
684 GPP under conditions of low/high incident PAR (Propastin et al., 2012; He et al., 2013). In
685 the case of stress or photoinhibition, leaves reduce or stop photosynthesis at too high levels of
686 radiation, while in normal conditions, photosynthesis is light-saturated at high PAR (Mäkelä
687 et al., 2008) which lets canopy photosynthesis saturate at relatively low PAR even in dense
688 tropical forests with high LAI (Ibrom et al., 2008). The model overestimation of summer GPP
689 may thus be partially related to the lack of representation of the canopy photosynthesis
690 saturation processes.

691   Although adopting a more complex phenology scheme in the comparison between decidous
692   and evergreen forests, our model showed better performances for deciduous compared to
693   evergreen forests. This behaviour is due to the strong seasonality patterns that the deciduous
694   species show, which is consistent with the findings of Zhao et al. (2012) at the two french
695   sites, but contrasts to the results of Morales et al. (2005) who showed that it is generally easier
696   for models to simulate evergreen forests due to the simpler phenology. The present results for
697   evergreen forests are, however, highly affected by the low model performances for the two
698   evergreen Mediterranean forests. As previously stated, overestimation during summer at FR-
699   Pue, and during winter and spring for IT-Cpz, are mostly related to neglecting species-
700   specific drought stress response functions. As in Landsberg & Waring (1997), the water
701   modifier is only based on soil physical characteristics and no consideration is given to the
702   stress tolerance or strategy of the species (Larcher, 2003), suggesting that further model
703   developments should focus on this aspect.

704   Other discrepancies affecting other sites could probably be reduced with a site-specific
705   parameterization.

706   *2.   Does the model reproduce the observed inter-monthly and inter-annual GPP*
707   *variability?*

708   Overall, the distribution of the modelled inter-monthly variability was sufficiently consistent
709   with the observed one. The model, however, showed reduced variability in the distribution for
710   both conifers and deciduous species. The model's ability in better representing higher rather
711   than lower anomalies suggests that it may still be less sensitive to some drivers of variability.
712   In this context, the phenological cycle may have an important role, since it influences canopy
713   cover and is controlled by environmental drivers (Richardson et al., 2010). According to Suni
714   et al. (2003) and Jeong et al. (2013), spring phenology largely affects the summertime carbon
715   budget. Hence, uncertainties in the growing season start date may affect 3D-CMCC FEM's
716   ability to reproduce IMV. In summer and autumn, petioles loss of turgor, cavitation in xylem
717   vessels and leaf yellowing may have an important role in the GPP variability of temperate
718   forests (Reichstein et al., 2007).

719   Even though evergreen forests do not experience complete dormancy in winter, changes in
720   'greenness' can be attributed to seasonal variation in canopy biochemistry, the production of
721   new foliage by canopy species and, particularly where the overstorey is sparse, the phenology
722   of understory vegetation (Richardson et al., 2010). Leaves of different ages have different

723 efficiency, sensitivity to solar radiation, temperature and water related stresses (Chabot &
724 Hicks, 1982). All these elements may have an important role in affecting GPP dynamics, but
725 are still scarcely or not represented by mechanistic ecosystem or forest models. As a
726 confirmation of these suspects, slight modifications in representing phenology and leaf
727 turnover resulted in general improvement of model consistency with EC data (Marconi,
728 2014).

729 Distribution of IMV values showed specific patterns attributable to the dominant species.
730 Beech forests IMV PDFs were concentrated around the average value and strongly influenced
731 by high biases. This pattern was probably due to the fact that half of the months in one year
732 have no or little photosynthesis (i.e. early spring, fall and winter) and most of the
733 photosynthetic activity occurs in late spring and summer, when carbon assimilation is
734 influenced by temperatures and solar radiation (Mercado, et al.; 2009). Conifers PDFs were
735 usually smoother, non-skewed, with reduced variability and fitted by a statistical normal
736 curve. The model showed an average NRMSE for IMV of 1.22 but still captured about two
737 thirds of the annual anomalies sign (a little bit more than the fifty percent that represents a
738 simple causality).

739 The results for IAV (see Figure 9) are quite contrasting and largely depend on the site and the
740 number of annual-by-annual comparisons. The recent modelling studies, that we are aware,
741 show unanimously the difficulties of models to explain the large interannual variability in
742 cases where no obvious triggers like management or climatic extreme are at work (e.g.
743 Keenan et al., 2012; Wu et al., 2013). In 3D-CMCC FEM better results have been obtained
744 for FI-Hyy and FR-Pue, so there is no apparent correlation with latitudes and forest species.
745 Interestingly, the performance of a DGVM for IAV in FR-Pue is also higher than other sites
746 (Zhao et al., 2012), indicating the main determinant factor for GPP simulation in this
747 Mediterranean site may not come from the treatment of canopy representation. However, the
748 advantage of a 3D canopy representation needs to be revalued in the future. Similarly, worse
749 results are reported for IT-Ren, IT-Cpz and BE-Bra where the number of annual correlations
750 are lower than the other sites. The magnitude of differences in the standard deviation
751 generally follows the same tendency, particularly for BE-Bra, IT-Ren and IT-Cpz. These
752 results confirm the model's limited ability to represents the inter-annual variability in these
753 specific sites rather than in these ecosystems.

The comparison between modelled and observed data at the inter-annual time scale shows the model to be sufficiently able to reproduce the sign of variability through the years including the extreme events (heat wave combined to drought) during the summer 2003 (Ciais et al., 2005; Vetter et al., 2008) and, for some sites, the anomalous carbon uptake during the warm spring of 2007 described by Del Pierre et al. (2009). Potentially negative effects from the anomalous 2003 were modelled into negative GPP anomaly at DK-Sor and IT-Cpz due to model simulation of summer drought stress, while such anomalies are not evident from measurements for DK-Sor (Pilegaard et al., 2011) and IT-Cpz. This could be due to the more maritime climate for DK-Sor and the presence of shallow groundwater for IT-Cpz that weakened the effects in the first part of the summer. In both sites, and included DE-Tha, the effects during July to September were captured by the model (data not shown). As reported by Ciais et al. (2005), Mediterranean sites showed a smaller degree in carbon fluxes, largely dominated by less respiration. It is noteworthy that IT-Col, differently from other european beech stands, does not seems to have suffered from this anomalous heat wave in 2003 (G. Matteucci, personal communication). Both simulated and observed data showed a positive GPP anomaly, demonstrating that this beech forest benefited by moderate higher temperature values and consequently had "extra" days for assimilation and growth (see also Churkina et al., 2002; Richardson et al., 2010). A similar behaviour was reported also by Jolly et al. (2005) for the Swiss Alps, especially between March and July. This pattern seems to be mostly related to an untimely beginning of the growing season (see Piao et al., 2006), to a reduction in plant transpiration that causes an increase in plant water use efficiency throught the partial closure of stomata (Warren et al., 2011) and to high fluxes related to forest floor vegetation.

It is also noticeable that in FR-Hes during the summer of 2004 a negative anomaly occurred, larger than in 2003; and while its sign was captured by the model, its magnitude was not. This can be explained by the modelled postponed effects of a low NSC allocation during the year 2003 to the subsequent periods (Granier et al., 2007; Gough et al., 2009). These results highlight that model has a sort of "memory" linked to short-term events (e.g. drought stress) and that these events affect the long-term processes.

Quantitatively, modelled inter-annual anomalies show a very large spread across the sites. Correlations vary widely, without any apparent relation with latitude and/or species. If modelled anomaly signs are potentially agreeing with the observed ones most of the time,

786 their magnitude was not. This behaviour seems to be related to several aspects, mainly to an

787 over/under estimation of the causes that reproduce anomalies, e.g. processes simulated linked

788 to the type of climate anomaly, mismatches in phenology or to a missed representation of

789 other processes (e.g. mast years, disturbances, shallow water). Keenan et al. (2012) asserts

790 that a lack in phenological variability and in canopy and soil dynamics are the main culprits of

791 these mismatches but also that flux measurements are affected by random errors especially

792 when fluxes are higher. Poulter et al. (2009) found a similar magnitude of errors with models

793 that were driven by remote-sensing data. Open questions remain as to the proportion of

794 interannual variability in land-atmosphere carbon exchange that is directly explainable by

795 variability in climate (Hui et al., 2003; Richardson et al., 2007)

796 *3.   Is the model generic enough that a single set of species-specific parameterization*

797 *allows reproducing GPP behaviour across different ecosystems without further need of a*

798 *site-related calibration?*

799 Overall, the model showed good flexibility although the sites showed a pronounced spatial

800 and temporal heterogeneity (i.e. a variable number of forest layers, different cohorts and

801 species). The model was able to reliably represent the ecophysiology of beech and spruce

802 species at different latitudes, without modifying or tuning the parameterization sets. However,

803 annual and seasonal performance indices, calculated exploiting daily and monthly series,

804 evidenced different performances between the two northern beech sites and the two southern

805 ones. Tables S1 and S2 show a systematic difference in all the statistics used, suggesting the

806 presence of a latitudinal gradient in 3D-CMCC FEM's ability to represent beech forest

807 processes. This gradient could be explained by how the model represents the different limiting

808 factors and their impacts on GPP. For example, we expect low temperatures to be the most

809 important limiting factor at higher latitudes, compared to soil water availability at lower

810 latitudes (Chapin et al., 2002).

811 We obtained similar results for the two spruce sites. The model showed better performance at

812 higher latitudes. While phenotypic plasticity, and thus the parameter set, may influence the

813 model results, it is noteworthy that the IT-Ren site has different topographic and climatic

814 conditions. Lower average temperatures, higher slopes, and non-negligible encroachment of

815 different species in a more complex canopy, may negatively influence the model performance

816 in IT-Ren with respect to DE-Tha. Since the model showed unrealistic results for the two

817 Mediterranean forests, we think it is not easy to determine if and how differences in

818 performances are related to the generality of the model rather than to bad assumptions behind

819 the simulated processes. From our findings, we conclude that for non-water limited conditions

820 it is possible to yield satisfying results with general parameter sets.

821 ***4.   Do the model's results improve when considering a complex 3D canopy structure?***

822 We evaluated possible improvements that could be made if a more accurate model

823 representation at a higher rate of heterogeneity of: forest structure, differences in ages and

824 species composition and their linked structural-ecophysiological processes, are assumed.

825 These analyses helped us to understand the importance of each process within the represented

826 combination (i.e. light competition, age related decline and the specific differences in

827 ecophysiology) on modelled GPP. Doubtless, a direct comparison between modelled and

828 observed GPP data is not possible due to the lack of partitioned measurements of GPP across

829 different layers, cohorts and species. However, in situations where the different

830 ecophysiological behaviours express themselves in the species specific canopy responses

831 during certain periods of the seasonal cycle, the test of a mixed forest tree model with flux

832 measurements is possible, as the results by Oltchev et al. (2002) showed using the model

833 MixFor-SVAT.

834 This preliminary analysis can be considered as a sensitivity analysis in terms of processes

835 explicitly simulated instead of lumped parameterisation. As a whole, model results using

836 different initialization data are within the observed GPP uncertainties but a quantitative

837 assessment for two sites, BE-Bra and IT-Ren showed the potential to increase the model's

838 ability in simulating fluxes, while for DE-Tha there is no evidence that model performances

839 could benefit of these efforts. For BE-Bra, taking into account two species (that differ

840 especially for their phenological traits) was beneficial in terms of model performances, the

841 same occurred for different layers (with the exception of BE-Bra P_Q-3L vs. BE-Bra P_Q-2L

842 whose results were similar) and different cohorts. Better performances, in terms of seasonal

843 GPP representations, were obtained when each of the above mentioned characteristics was

844 accounted for by the model. For IT-Ren, similar results were obtained, although no

845 differences were found in the simulation of phenological patterns in daily and monthly results.

846 Differently, for DE-Tha a differentiation between the two evergreen coniferous species did

847 not cause marked differences in model results, due to low differences in species

848 ecophysiological traits, justifying in these cases the use of a Plant Functional Type (PFT)

849 level of parameterization instead species level (Poulter et al., 2015).

5 Conclusions

This study aimed at evaluating the performances of the updated version of 3D-CMCC FEM compared to nearly 10x10 sites x years GPP data across eddy-covariance European forest sites. Although the sites showed high spatial and temporal environmental heterogeneity the model appears able to reproduce trends in all of the ten sites. Different performance indexes showed that daily and monthly level model results match well, both for the annual and seasonal scale, against observed data, with some exceptions. Mediterranean sites (IT-Cpz and FR-Pue) showed to be the most problematic in reproducing carbon fluxes. This is likely due to their specific ecosystem peculiarity, e.g. shallow groundwater for IT-Cpz and, for both sites, a low pronounced seasonality. In these two sites, the model showed less generalisation unless additional processes were included. Differently from other models, 3D-CMCC FEM, both for daily and monthly simulations and for both X and Y datasets, performs better for deciduous species rather than for evergreen, although deciduous species have a more complex phenology and a more pronounced seasonality. Some mismatches in the simulation over the seasons and over the sites still remain, especially during winter and summer. The first reason for these low agreements in winter can be also attributable to errors during the estimation of GPP from NEE and Ecosystem Respiration values from measurements data. The second can be related to the model's lack or simplicity in representation of snow pack dynamics as reported by Krishnan et al. (2008; 2009), especially for evergreen sites (Keenan et al., 2012). Disagreements in summer could be related to model simplicity in simulating soil drought and, using the Monteith approach (Monteith, 1977), to the strong nonlinearity at the daily scale of GPP and PAR, and to the lack of representation of the light saturation processes. In addition, as reported by Keenan et al. (2012), the apparent high variability in the data during the summer season could therefore be due to random errors in the flux measurements, generating larger variability and then lower correlations against modelled data.

No marked differences were found in simulations across different latitudes, so model parameterizations for the different tree species could be useful over Europe with quite a high rate of confidence, with the exception of specific cases in Mediterranean forests.

As for other models, 3D-CMCC FEM showed to have the potential to correctly reproduce the signs of interannual variability, like the 2003 heat wave and drought extreme and the anomalous carbon uptake during the warm spring of 2007 and their instantaneous biological

881 response to these events. Significant disagreements were, however, found in reproducing the
882 magnitude of these anomalies.

883 The consideration of stand hetereogeneity, when possible or existing (i.e. layers, cohorts and
884 mixed composition), led the model to improve its results in two of the three sites compared to
885 generalized simulations of forest attributes. This plasticity makes the model able to be used in
886 a wider range of forest ecosystems.

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Table captions

Table 1 Main characteristics of the study sites. Sites were classified according to the IGBP
(International Geosphere Biosphere Program) legend as in the FLUXNET database:
MF=mixed forest; DBF=deciduous broadleaf forest; EBF=evergreen broadleaf forest;
ENF=evergreen needle leaf forest. Year of simulation starting and ending depend on available
time series of observed data.

Table 2 IMV and IAV NRMSE for the analyzed sites. Each specific IMV distribution was
tested for normality goodness of fit (N = normal distribution, P = non normal distribution). A
test for equivalence of central tendency was performed between IMV_{MD} and IMV_{EC} values.
(na) refers to the case of sites with inconsistent distributions (one normally, one not normally
distributed). (*) marks refer to the acceptance of the null hypothesis that the two distributions
are equivalent for the specific statistic ($\alpha=0.05$). ECT stands for "Equivalence for Central
Tendency"; EV for "Equivalence for Variance".

Table 3 Performance statistics (r, NRMSE, MEF, MABstd) are reported as derived from daily
and monthly series of GPP_{EC} and GPP_{MD} values over long-term annual scale, for the different
forest structure simulations. The (*) refers to p-value < 0.0001 in correlation between GPP_{EC}
and GPP_{MD} data. In addition, long term average of annual GPP_{MD} and GPP_{EC} values (gC m^{-2}
yr^{-1}) for the different forest structures are shown.

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Figure captions

Figure 1 3D-CMCC FEM performance indices at different time scales; daily (Figure 1-a) and daily aggregated to month (Figure 1-b) for X dataset. Figure 1-c and 1-d refer to Y daily and Y monthly dataset following decomposition technique proposed in Zhao et al. (2012). DE-Tha refers to the 1S simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L simulation (see text).

Figure 2 Taylor diagrams for daily (a) and daily aggregated to month (b) GPP evaluated representing: the deviation of model results from observations in terms of normalized standard deviation of observations, represented by the distance from the site point to the point on the x-axis identified as reference (REF); the difference of model normalized standard deviation from that of observations, represented by the distance of the site point with respect to the quarter arc crossing REF; and the correlation, given by the azimuthal position of the site point to the x-axis. The sites are numbered in ascending order as follows: (1) DE-Hai, (2) DK-Sor, (3) FR-Hes, (4) IT-Col, (5) FR-Pue, (6) IT-Cpz, (7) DE-Tha, (8) FI-Hyy, (9) IT-Ren, (10) BE-Bra. Colors refer to different IGBP vegetation classes: DBF (yellow), EBF (orange), ENF (light-blue), MF (green).

Figure 3 Distributions of annual GPP (gC m^{-2} yr^{-1}). MD (red) are model results, EC (blue) measured by eddy covariance. The vertical bars represent $\pm$ 1 standard deviation. DE-Tha refers to the 1S simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L simulation (see text).

Figure 4 3D-CMCC FEM performances indices of daily GPP at different seasons. DE-Tha refers to the 1S simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L simulation (see text).

Figure 5 3D-CMCC FEM performances indices of daily GPP aggregated to months at different seasons. DE-Tha refers to the 1S simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L simulation (see text).

Figure 6 Comparison between GPP$_{MD}$ and GPP$_{EC}$ data. The top plots show the average GPP$_{EC}$:GPP$_{MD}$ correlation for (left) monthly (gC m^{-2} month^{-1}) and (right) daily (gC m^{-2}d^{-1}) data. The bottom plots show absolute difference range between GPP$_{MD}$ and GPP$_{EC}$ while increasing GPP$_{EC}$ values. Negative values are excluded because of model assumptions. DE-

975 Tha refers to the 1S simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L
976 simulation (see text).

977 **Figure 7** Seasonal (monthly) cycle of GPP across the ten sites. The grey line and margins of
978 the grey area represent long-term average of monthly GPP_{EC} ($gCm^{-2}month^{-1}$) and its ± 1
979 standard deviation, respectively. The green and red dashed lines represent the long-term
980 average of monthly GPP_{MD} ($gCm^{-2}month^{-1}$) and its ± 1 standard deviation, respectively. DE-
981 Tha refers to the 1S simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L
982 simulation (see text).

983 **Figure 8** Distribution of the magnitude for the inter-monthly variability values (IMVs, $gC\ m^{-2}d^{-1}$) for each specific site, resulted by standard kernel density estimation. The vertical red line
984 $^{2}d^{-1}$) for each specific site, resulted by standard kernel density estimation. The vertical red line
985 is the media, the box plot limit the 25th and 75th percentiles, the dashed black bars represent
986 the rest of the distribution range excluding outliers (red crosses) DE-Tha refers to the 1S
987 simulation, IT-Ren to the 2L_2C simulation, BE-Bra to the P_Q-3L simulation (see text).

988 **Figure 9** Inter-Annual Variability (IAV) based on Keenan et al. (2012). Red and blue bars
989 indicate the observed and modelled IAV values, respectively; *r* values refer to correlation
990 between observed and modelled variations. DE-Tha refers to the 1S simulation, IT-Ren to the
991 2L_2C simulation, BE-Bra to the P_Q-3L simulation (see text).

1 Table 1.

Site Name (Site code)	Lat (°) / Lon (°)	IGBP	Simulation year (Starting - Ending)	Mean Annual Temperature (°C)	Annual Precipitation Amount (mm yr^{-1})	Elevation (m a.s.l.)	Main species and forest description	Main references
Hainich (DE-Hai)	51.08 / 10.45	DBF	2000 – 2007	8.3	720	445	Uneven-aged, unmanaged multi-layered forest of beech (*Fagus sylvatica*, 250 years, mean DBH 30.8 cm, mean tree height 23.1 m, stand density 334 trees/ha)	Knohl et al., 2003 + BADM files
Sorø (DK-Sor)	55.49 / 11.64	DBF	2001 – 2009	8.2	660	40	Beech (*Fagus sylvatica*, averagely 80 years, mean DBH 36.13 cm, mean tree height 25 m, stand density 283 trees/ha)	Pilegaard et al., 2003 + BADM files
Hesse (FR-Hes)	48.67 / 7.07	DBF	2001 – 2007	9.2	820	300	Beech (*Fagus sylvatica*, averagely 35 years, mean DBH 8.19 cm, mean tree height 13 m, stand density 3384 trees/ha)	Granier et al., 2000 + BADM files
Collelongo (IT-Col)	41.85 /13.59	DBF	1997 – 2012	6.3	1180	1550	Beech (*Fagus sylvatica*, averagely 100 years, mean DBH 20.2 cm, mean tree height 19.8 m, stand density 900 trees/ha)	Scartazza et al., 2013 + BADM files
Puechabon (FR-Pue)	43.74 /3.60	EBF	2000 – 2011	13.5	883	270	Holm oak (*Quercus ilex*, averagely 59 years, mean DBH 7 cm, mean tree height 6 m, stand density 8500 trees/ha)	Loustau et al., 2005 + BADM files
Castelporziano (IT-Cpz)	41.71 /12.38	EBF	2000 – 2008	15.6	780	3	Holm oak (*Quercus ilex*, averagely 45 years, mean DBH 16 cm, average tree height 12.5 m, stand density 458 trees/ha)	Vitale et al., 2003 + BADM files
Tharandt (DE-Tha)	50.96/ 13.57	ENF	2000 – 2010	7.7	820	380	Mixed Norway spruce (*Picea abies*, averagely 113 years, mean DBH 33 cm, tree height 26, density 396 trees/ha) and Scots Pine (*Pinus sylvestris*, averagely 113 years, mean DBH 33.1 cm, tree height 26.1 m, density 81 trees/ha)	Grünwald & Bernhofer, 2007 + BADM files
Hyytiälä (FI-Hyy)	61.85 / 24.29	ENF	2001 – 2011	3.8	709	170	Scots pine (*Pinus sylvestris*, 39 years, mean DBH 30.8 cm, mean tree height 23.1 m, stand density 334 trees/ha)	Suni, et al., 2003 + BADM files

Renon (IT-Ren)	46.59 / 11.43	ENF	2006 - 2010	4.7	809	1735	Uneven-aged multi-layered forest of Norway spruce (*Picea abies* averagely, 190 and 30 years, average DBH 30.8 cm, average tree height 23.1m, stand density 334 trees/ha)	Montagnani et al.(2009) + BADM files
Brasschaat (BE-Bra)	51.30/4.52	MF	2001 - 2010	9.8	750	16	Mixed, uneven-aged multi-layered forest of Scots pine (*Pinus sylvestris*, averagely 72 years) and Pedunculate oak (*Quercus robur*, averagely 65 years)	Gielen et al., 2013 + BADM files

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Table 2

		DE-Hai	DK-Sor	FR-Hes	IT-Col	FR-Pue	IT-Cpz	DE-Tha (1S)	FI-Hyy	IT-Ren (2L-2C)	BE-Bra (P_Q-3L)
NRMSE	IAVs	2.4	1.8	1.3	0.3	0.6	1.1	1.0	2.7	1.3	0.9
NRMSE	IMVs	1.7	2.7	1.1	0.6	1.1	1.2	1.1	1.2	1.0	0.5
ECT	p-value	1.00*[N]	0.12*[N]	0.54*[N]	0.00 [N]	0.15*[N]	1.00*[na]	1.00*[P]	0.04 [N]	0.88*[P]	0.85*[N]
EV	p-value	0.53*[N]	0.00 [N]	0.00 [N]	0.46*[N]	0.00 [N]	0.02 [na]	0.78*[P]	0.00 [N]	0.27*[P]	0.01 [N]

Table 3.

Site	Model set-up code	Daily				Monthly				Yearly	
		r	NRMSE	MEF	MABstd	r	NRMSE	MEF	MABstd	GPP$_{MD}$ gC m^{-2} yr^{-1}	GPP$_{EC}$ gC m^{-2} yr^{-1}
BE-Bra	P	0.72*	0.73	0.47	0.51	0.86*	0.55	0.70	0.39	1003	
	Q_3L	0.76*	0.91	0.18	0.67	0.84*	0.71	0.49	0.52	1105	
	Q_2L	0.74*	0.89	0.21	0.66	0.86*	0.74	0.45	0.55	1179	
	Q_1L	0.75*	0.95	0.01	0.70	0.86*	0.68	0.53	0.50	1147	
	P_Q-3L	0.77*	0.65	0.57	0.46	0.93*	0.39	0.84	0.28	1141	1193
	P_Q-2L	0.75*	0.67	0.55	0.46	0.91*	0.44	0.81	0.30	1037	
	P_Q-1L	0.75*	0.66	0.56	0.46	0.91*	0.68	0.53	0.50	1056	
IT-Ren	**2L_2C**	0.82*	0.62	0.61	0.44	0.95*	0.30	0.91	0.23	1349	1362
	1L_1C	0.83*	0.85	0.27	0.61	0.96*	0.61	0.62	0.45	1950	
DE-Tha	**1S**	0.90*	0.46	0.79	0.31	0.96*	0.27	0.93	0.19	1840	1869
	2S	0.89*	0.48	0.80	0.31	0.95*	0.29	0.91	0.19	1898	

a   X dataset daily

b   X dataset monthly

c   Y dataset daily

d   Y dataset monthly

Legend (each panel): ◆ r ▲ MEF ☐ NRMSE ✕ MABstd

Sites (x-axis): DE-Hai, DK-Sor, FR-Hes, IT-Col, FR-Pue, IT-Cpz, DE-Tha, FI-Hyy, IT-Ren, BE-Bra
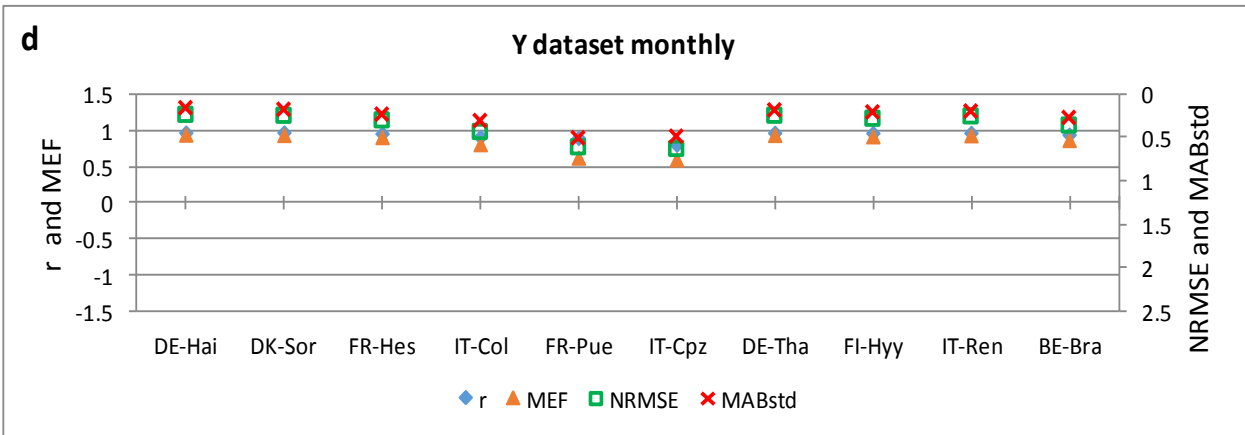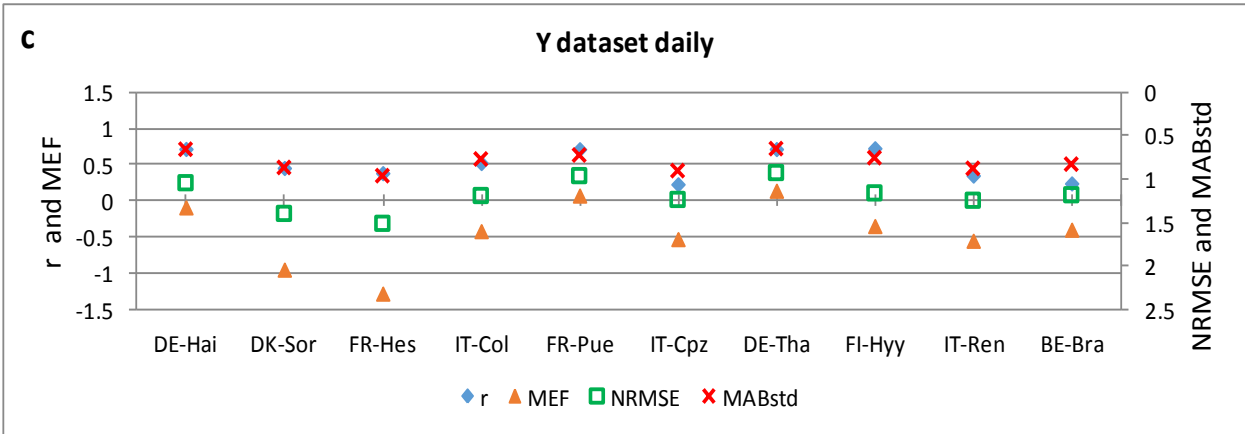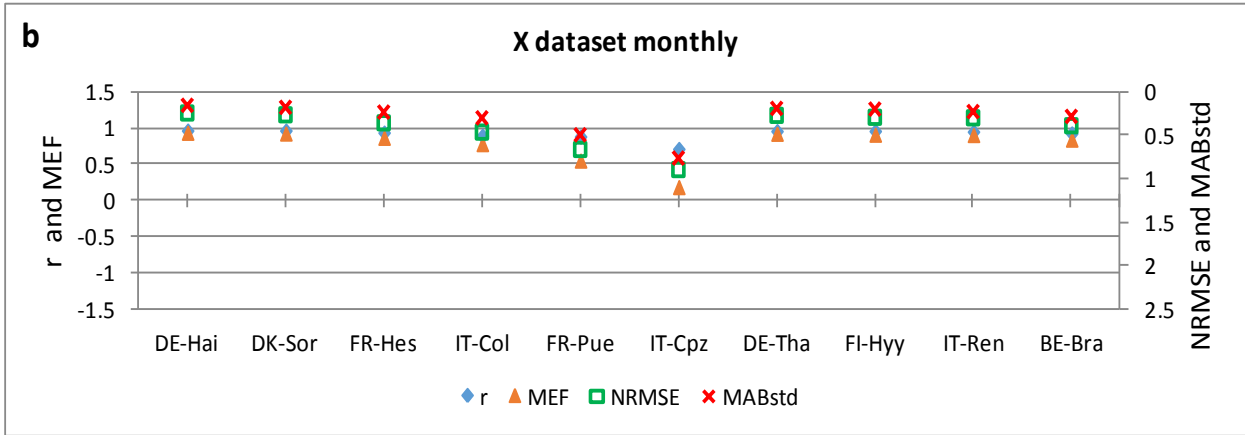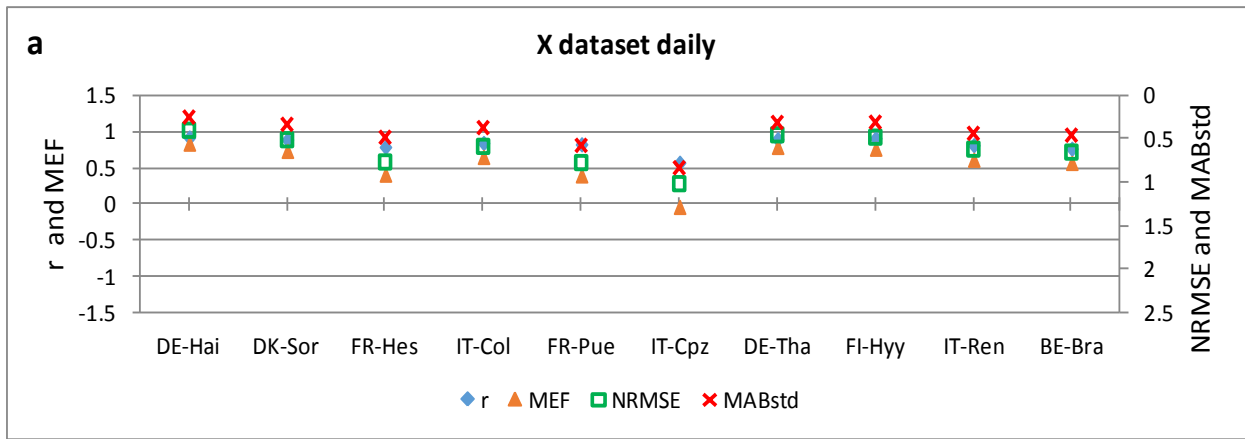
Figure 1

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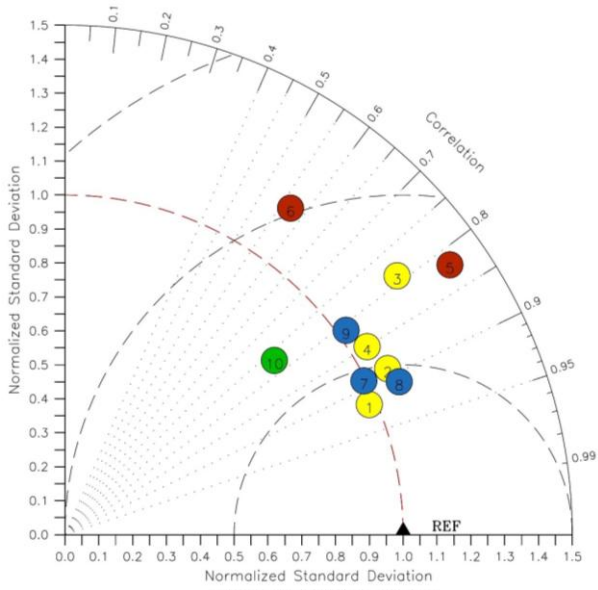
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MEAN MONTHLY CYCLE
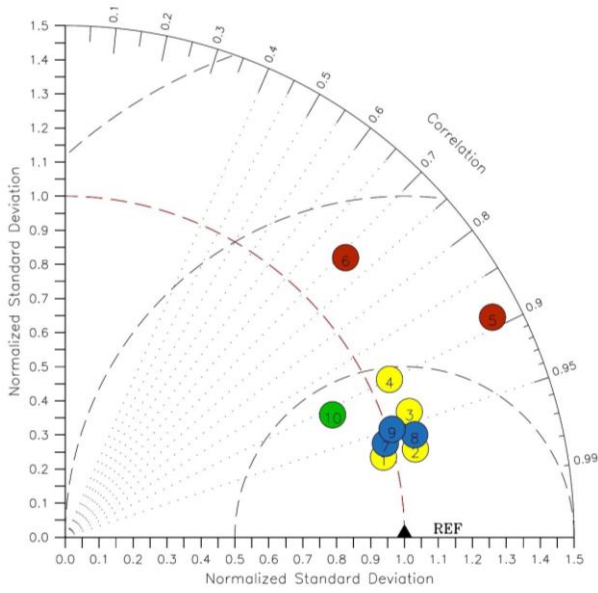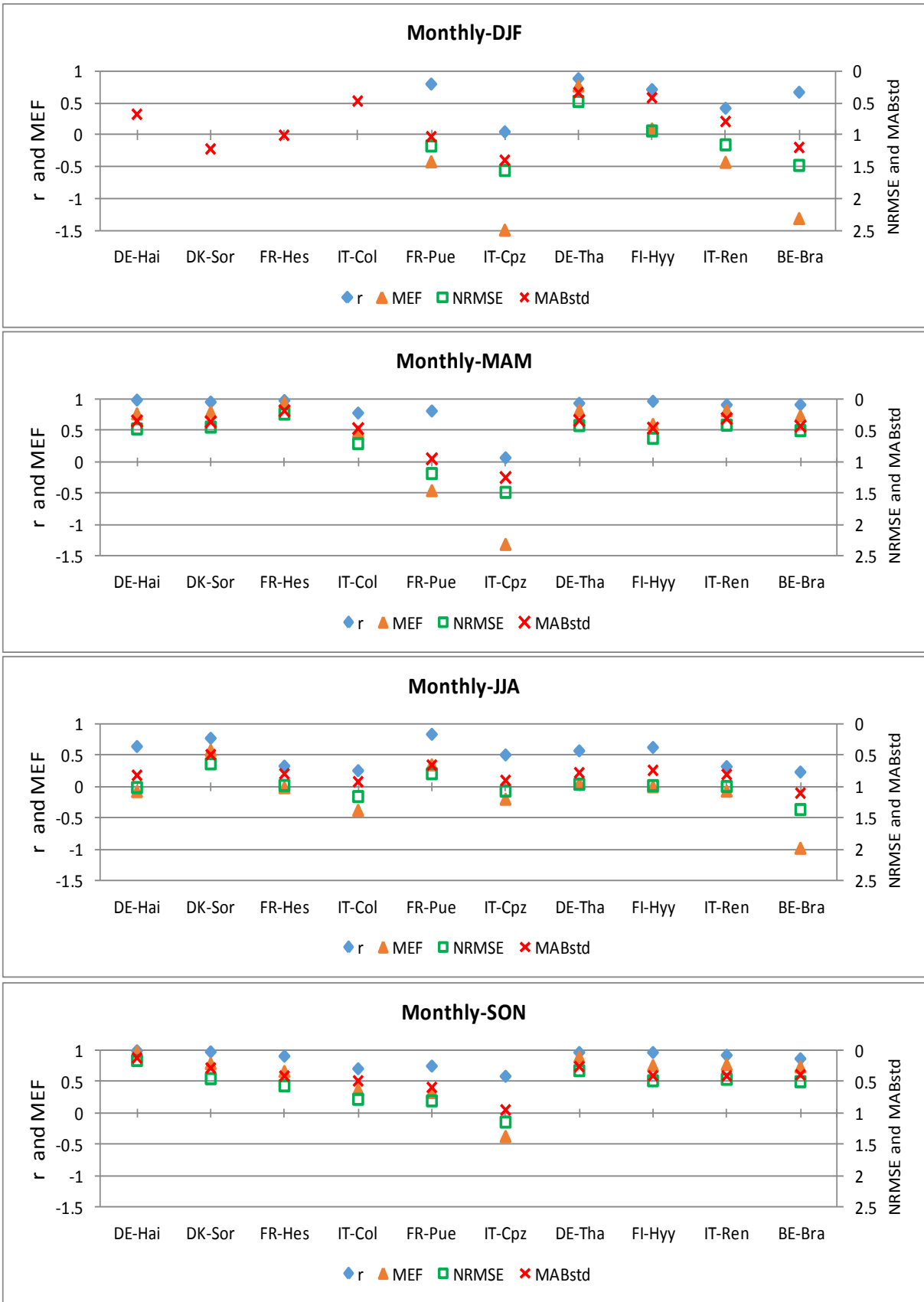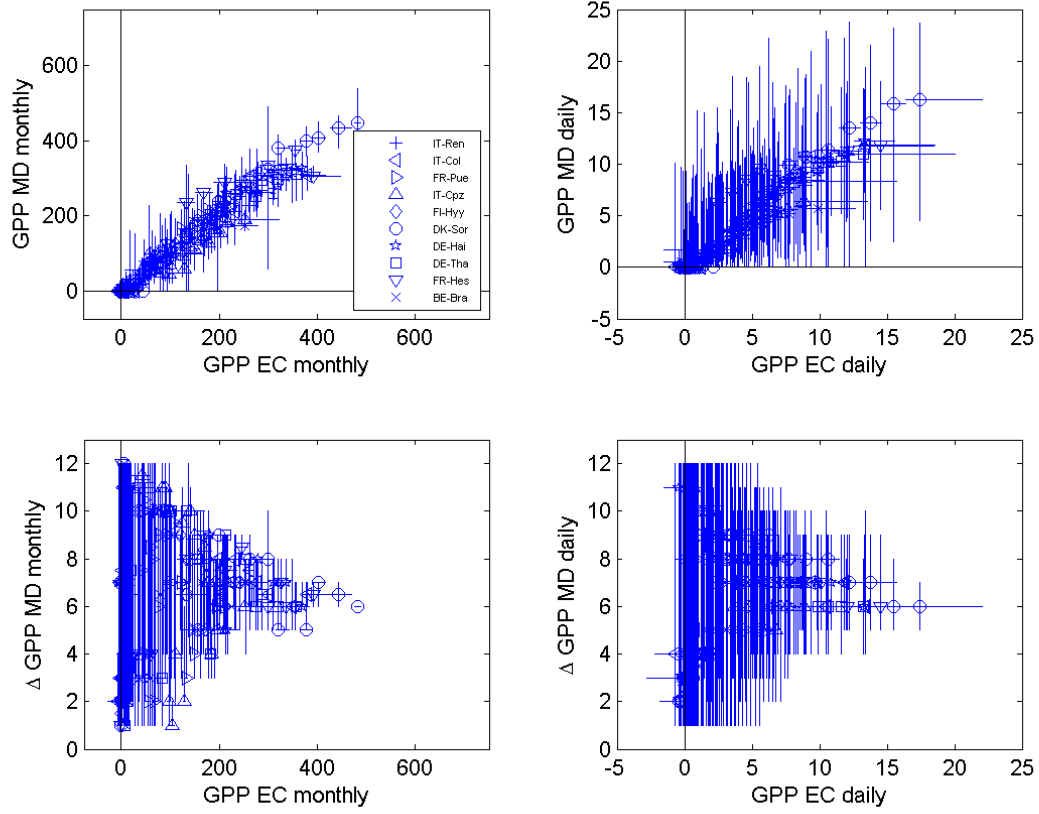

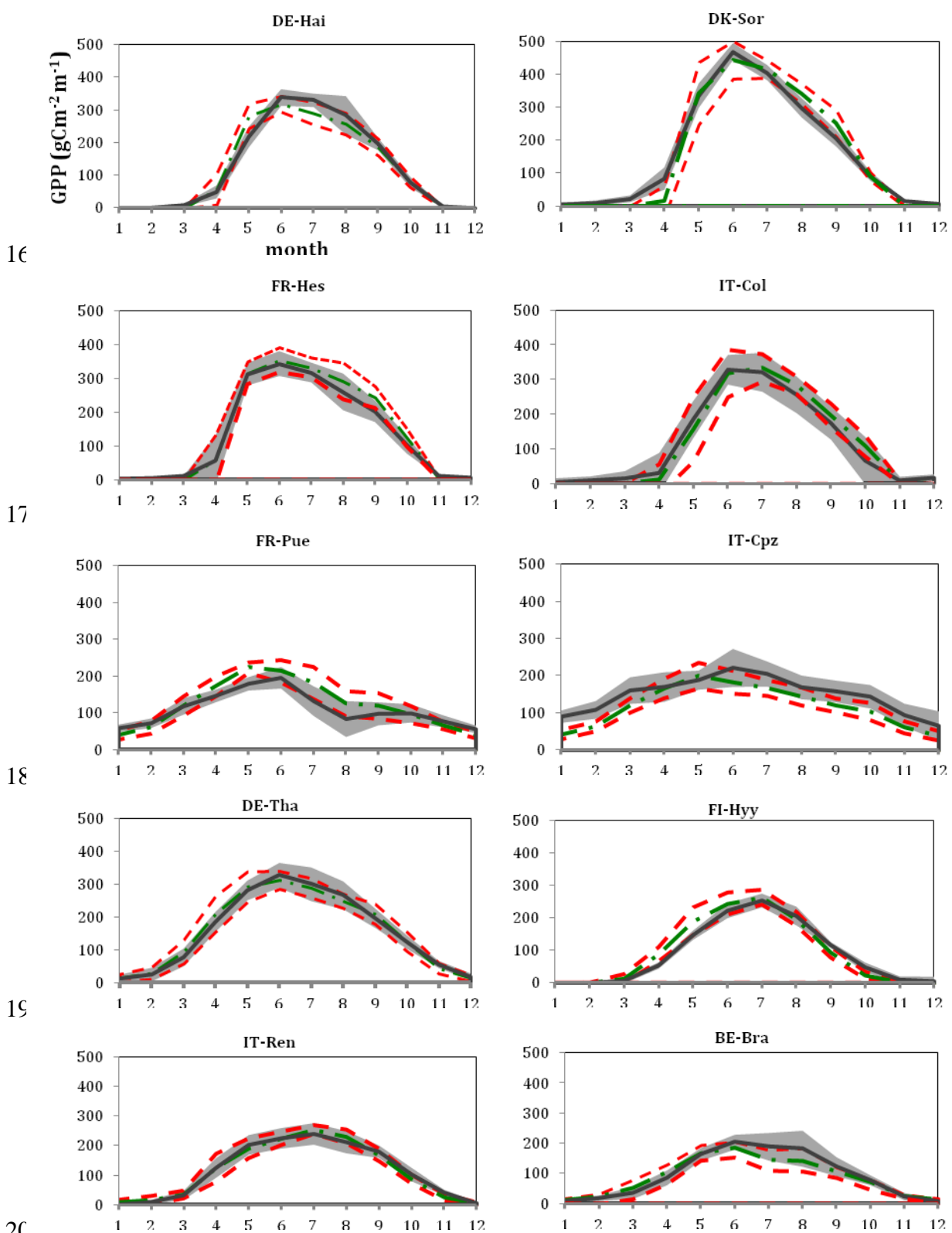6

7   *Figure 2*
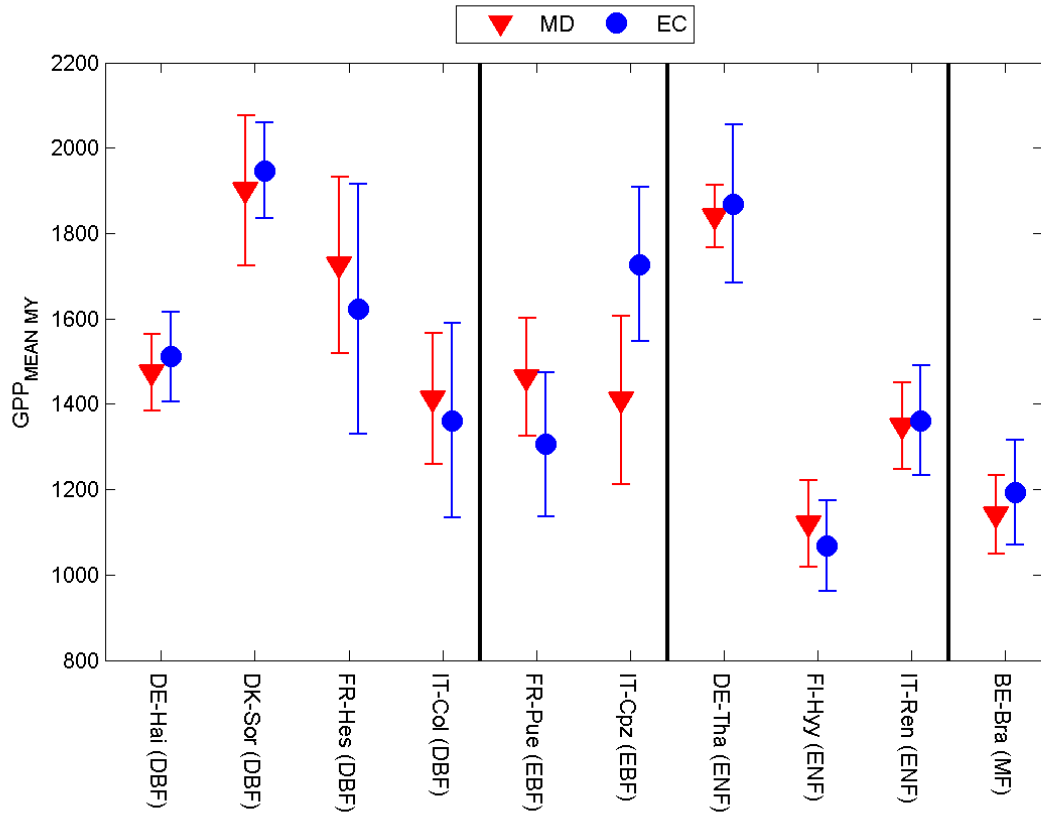
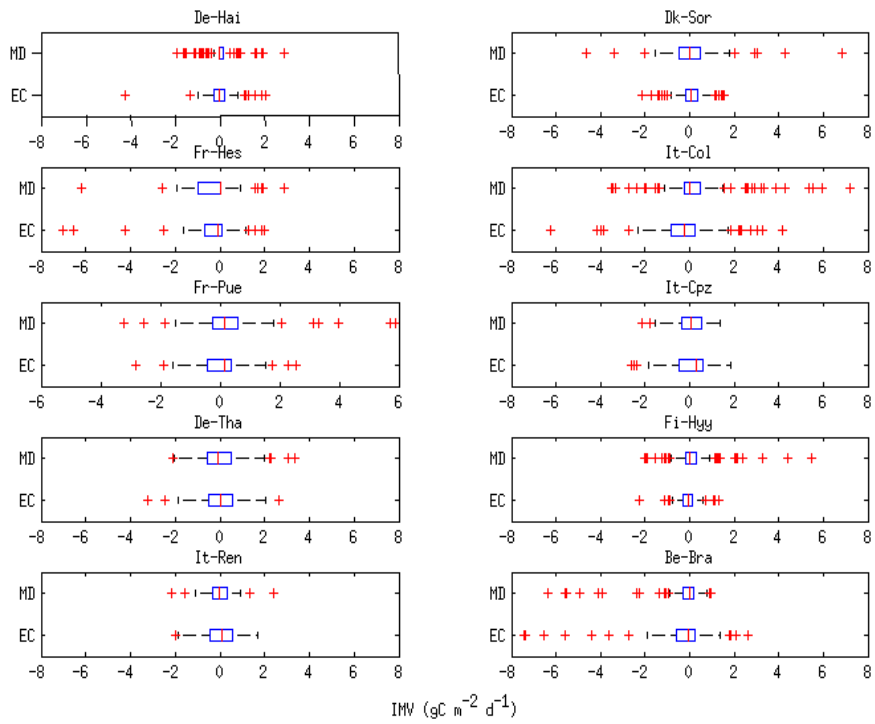*Figure 3*

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Figure 4

Figure 5
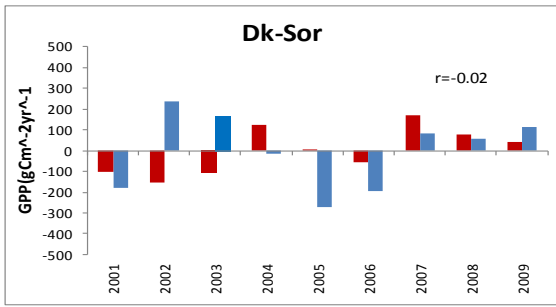
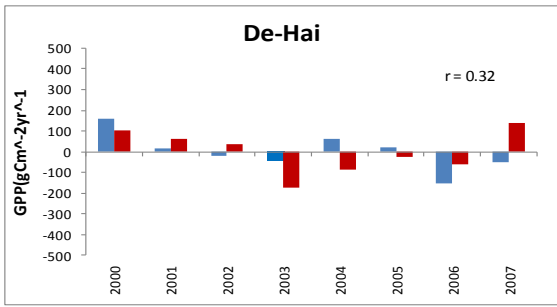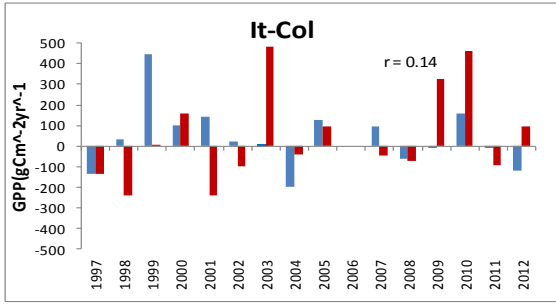12
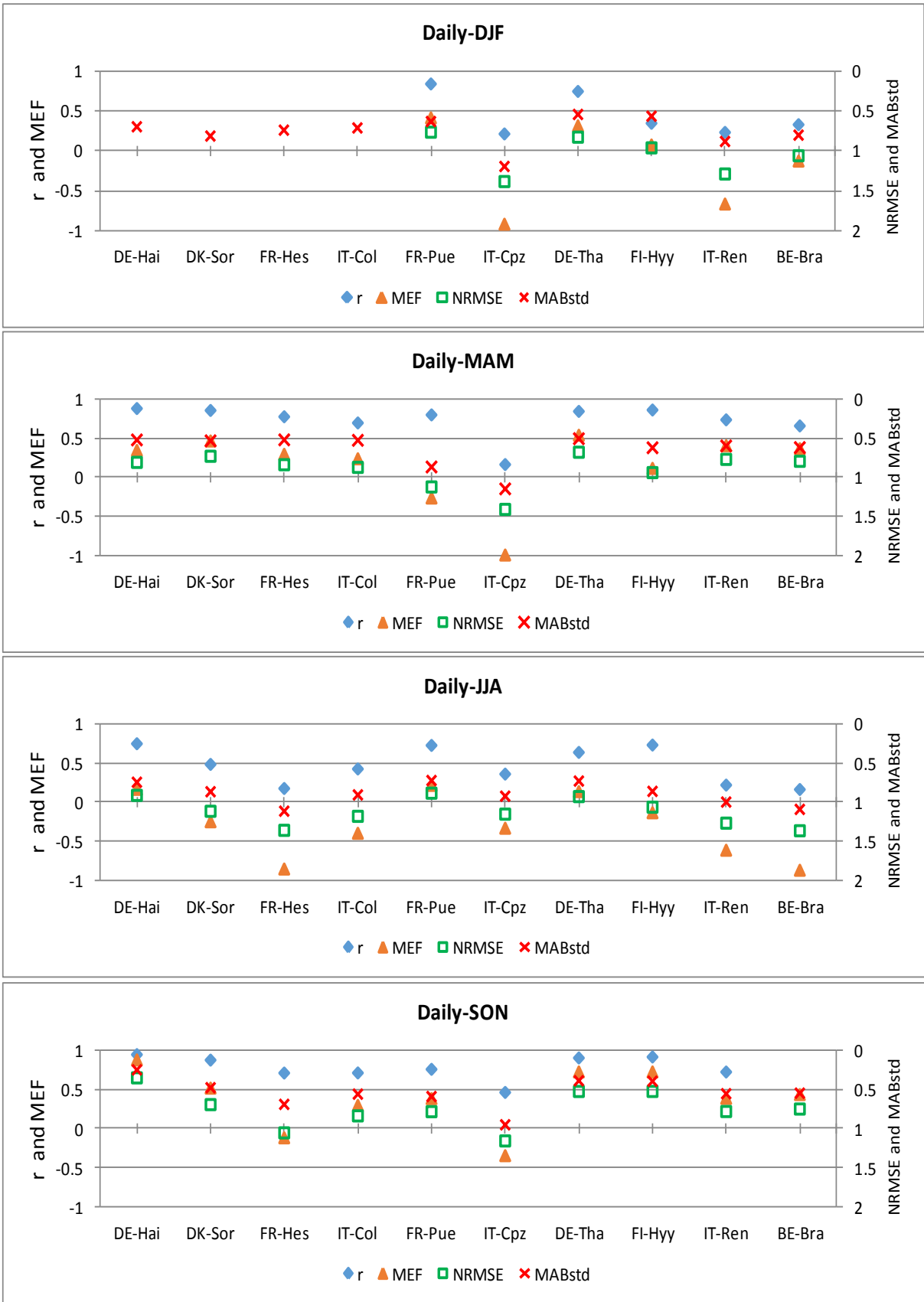
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14   *Figure 6*

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Figure 9

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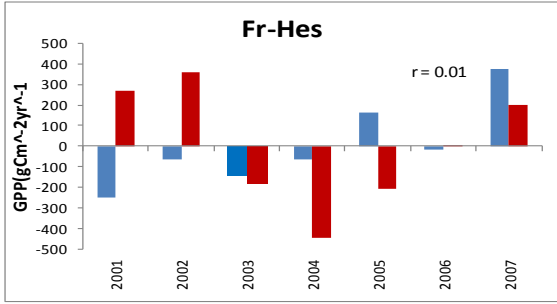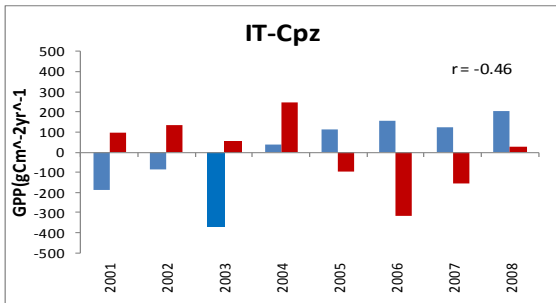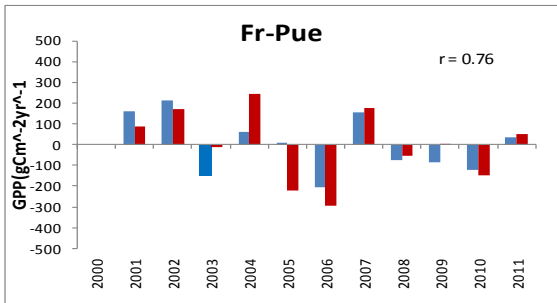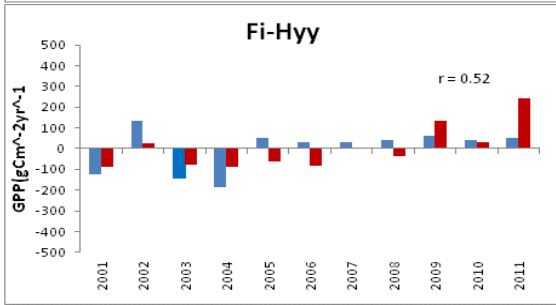
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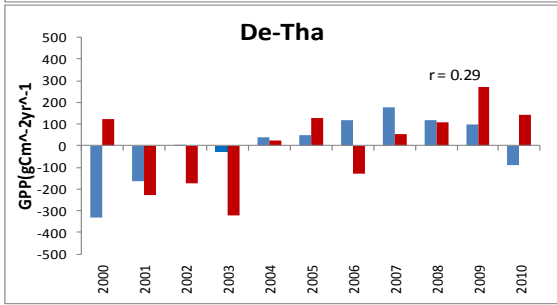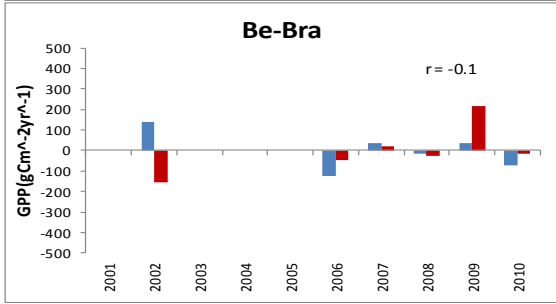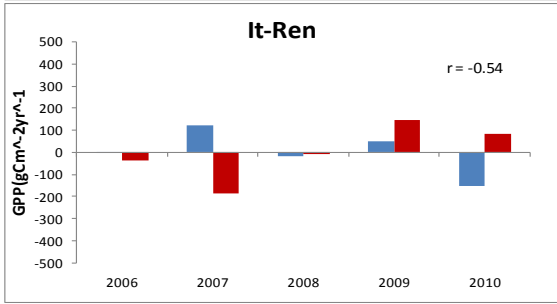Arneth, A., Sitch, S., Bondeau, A., Butterbach-Bahl, K., Forestr, P., Gedney, N., et al. (2010). From biota to chemistry and climate: towards a comprehensive description of trace gas exchange between the biosphere and atmosphere. *BioGeosciences* , 7, 121-149.

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