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Key Points:

- GPP and NEP simulations of Mediterranean forest ecosystems are tested
- Modified C-Fix and BIOME-BGC are applied on annual and daily bases
- The results obtained confirm the validity of the modeling approach

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Estimating daily forest carbon fluxes using a combination of ground and remotely sensed data

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Abstract Several studies have demonstrated that Monteith's approach can efficiently predict forest gross primary production (GPP), while the modeling of net ecosystem production (NEP) is more critical, requiring the additional simulation of forest respirations. The NEP of different forest ecosystems in Italy was currently simulated by the use of a remote sensing driven parametric model (modified C-Fix) and a biogeochemical model (BIOME-BGC). The outputs of the two models, which simulate forests in quasi-equilibrium conditions, are combined to estimate the carbon fluxes of actual conditions using information regarding the existing woody biomass. The estimates derived from the methodology have been tested against daily reference GPP and NEP data collected through the eddy correlation technique at five study sites in Italy. The first test concerned the theoretical validity of the simulation approach at both annual and daily time scales and was performed using optimal model drivers (i.e., collected or calibrated over the site measurements). Next, the test was repeated to assess the operational applicability of the methodology, which was driven by spatially extended data sets (i.e., data derived from existing wall-to-wall digital maps). A good estimation accuracy was generally obtained for GPP and NEP when using optimal model drivers. The use of spatially extended data sets worsens the accuracy to a varying degree, which is properly characterized. The model drivers with the most influence on the flux modeling strategy are, in increasing order of importance, forest type, soil features, meteorology, and forest woody biomass (growing stock volume).

1. Introduction

Forests play an important role within the global carbon cycle by acting as sinks [*Intergovernmental Panel on Climate Change,* 2007]. Therefore, quantifying the amount of carbon stored within forests has become an important task in view of global climate changes [*Kolström et al.*, 2011] and under the broader perspective of ecosystem service assessments [*Corona et al.*, 2011]. Among the methodologies proposed to obtain these quantifications (e.g., eddy covariance techniques, remote sensing, and biogeochemical models), the methods based on the integrated use of ecosystem process models and remotely sensed data are among the most promising [*Waring and Running*, 2007]. These methods, in fact, offer the possibility of simulating ecosystem processes based on the knowledge of the investigated forest species and of the environmental conditions under which these species are grown. Simultaneously, these techniques provide information for large areas and with high temporal frequency.

In particular, several investigations have shown that Monteith's approach is suited to simulate the gross primary production (GPP) of forest ecosystems [e.g., *Veroustraete et al.*, 2002; *Gilabert et al.*, 2015]. This approach, which combines remotely sensed estimates of the fraction of photosynthetically active radiation absorbed by vegetation (fAPAR) with meteorological data, provides the theoretical foundation for the most widely used methods for predicting GPP, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) GPP algorithm [*Heinsch et al.*, 2003]. The modeling of forest net ecosystem production (NEP) is, instead, a much more critical issue, requiring the additional simulation of both autotrophic and heterotrophic respiration rates. Such simulation is theoretically and practically complex, since these rates are nonlinearly dependent on several environmental factors which are spatially variable and difficult to assess over wide areas (forest type, density, age, etc.) [*Waring and Running*, 2007].

Previous methodological work has shown the potential for employing an integrated methodology based on two models, C-Fix and BIOME-BGC (BioGeochemical Cycles), to predict the gross and net carbon fluxes of forest ecosystems. C-Fix is a Monteith-type model that combines meteorological and Normalized Difference Vegetation Index (NDVI) data to predict forest production [*Veroustraete et al.*, 2002]; this model has been recently modified for the improved simulation of water-limited environments [*Maselli et al.*, 2009a]. BIOME-BGC is a biogeochemical model that is capable of estimating photosynthesis, respiration, and allocations of all the main terrestrial ecosystems. The outputs of these two models are finally combined using the strategy proposed by *Maselli et al.* [2009b].

The general validity of this modeling approach has been demonstrated against forest production data aggregated over space (i.e., regional net primary productivity (NPP) measurements collected for a national inventory) [*Maselli et al.*, 2010; *Chirici et al.*, 2015] and over time (i.e., monthly GPP and NEP data collected by the eddy correlation technique) [*Maselli et al.*, 2009b; *Chiesi et al.*, 2011]. These tests were generally successful but did not specifically address the validation of the model accounting for the effect of forest disturbance, which provides the basis for predicting net forest carbon fluxes. The combination strategy applied, in fact, uses a proxy of ecosystem distance from *equilibrium* condition to estimate the ratio between respiration and photosynthesis and consequently that between NEP and GPP. The NEP estimation accuracy of the method is therefore dependent on this critical step, concerning both the annual mean values and the seasonal evolution.

The current study addresses this issue by analyzing the flux measurements collected at five eddy covariance sites representative of various Italian forest ecosystems. In particular, the primary objective involved testing the theoretical validity of the modeling approach, which was accomplished by applying the integrated method using optimal driving variables (i.e., collected or calibrated at the sites). According to what mentioned above, this validation was performed both on annual and daily bases. A secondary objective was to assess the applicability of the approach at the national scale using available spatially explicit auxiliary data sets, i.e., wall-to-wall maps of forest and soil features and meteorological variables.

The paper is organized into six sections. The first section briefly describes the modeling strategy with a specific focus on the adopted models. This section is followed by a description of (i) the study area and data utilized, (ii) the processing steps applied, primarily focusing on the validation against independent data sets of GPP and NEP, and (iii) the results obtained. The problems encountered in applying the modeling strategy are then discussed with a particular focus on the effects of using spatially explicit input data. Relevant conclusions are drawn in the last section.

2. Modeling Strategy

The simulation of forest carbon fluxes is based on the integrated use of the C-Fix and BIOME-BGC models. This approach combines the advantages of the former, which is capable of directly estimating photosynthesis based on remotely sensed data, with those of the latter, capable of simulating all other processes needed to retrieve net carbon fluxes (i.e., respirations and allocations). A recombination of the two model outputs is finally required to take into account the effects of the occurred ecosystem disturbances (see *Maselli et al.* [2009b] for details). The main characteristics of the two models and the integration of their outputs within the modeling strategy are summarized in the following paragraphs.

2.1. Modified C-Fix

C-Fix is a Monteith-type model driven by temperature, radiation, and fAPAR, which is quantified through its generalized relationship with NDVI [*Veroustraete et al.*, 2002, 2004]. *Maselli et al.* [2009a] proposed a modification of C-Fix aimed at improving the model performance when vegetation growth is limited by water availability [*Bolle et al.*, 2006]. This version (modified C-Fix) includes an additional water stress factor (Cws), which is computed using meteorological data and limits photosynthesis in cases of short-term water stress [*Maselli et al.*, 2009a]. Modified C-Fix, therefore, predicts the forest GPP of day *i* (GPP_i) as:

$$\mathrm{GPP}_i = \varepsilon \cdot \mathrm{Tcor}_i \cdot \mathrm{Cws}_i \cdot \mathrm{fAPAR}_i \cdot \mathrm{PAR}_i, \tag{1}$$

where ε is the maximum radiation use efficiency (1.2 g C MJ^{-1} absorbed photosynthetically active radiation); and all for day *i*, Tcor_i is the MODIS temperature correction factor of each biome type [*Heinsch et al.*, 2003];

Cws_i is the water stress factor; $fAPAR_i$ is the fraction of absorbed photosynthetically active radiation (PAR); PAR_i is the solar incident PAR. fAPAR is derived from the NDVI by using the generalized linear equation proposed by *Myneni and Williams* [1994].

2.2. BIOME-BGC

BIOME-BGC is a biogeochemical model that estimates the storage and fluxes of water, carbon, and nitrogen within terrestrial ecosystems [*Running and Hunt*, 1993]. This model requires daily climate data, general environmental information (i.e., soil, vegetation, and site conditions), and parameters describing the ecophysiological characteristics of the vegetation [*White et al*., 2000]. BIOME-BGC is capable of finding a quasi-climax equilibrium (sensu *Odum* [1971]) for the local ecoclimatic conditions through a spin-up phase, the aim of which is the quantification of the initial amounts of all carbon and nitrogen pools. Next, the model proceeds with a normal simulation that estimates all respiration and allocation processes corresponding to the requested study years [*Churkina et al*., 2003].

The modeling of the quasi-climax condition has important consequences on the simulated carbon budget. The sum of all the simulated respiration processes becomes, in fact, nearly equivalent to GPP, which makes the annual NPP approximate to the heterotrophic respiration (Rh), and the NEP move toward zero. Additionally, this modeling approach produces GPP estimates that are practically similar to the results produced by modified C-Fix, which are descriptive of all ecosystem components [*Maselli et al*., 2009b].

The version of the model employed (BIOME-BGC 4.2) includes complete parameter settings for six main biome types [*White et al*., 2000]. These settings have been modified to adapt to Mediterranean ecosystems, which exhibit ecoclimatic features that are markedly different from those for which the model was originally developed [*Chiesi et al*., 2007; *Maselli et al*., 2009a]. Following an autoecological criterion, Italian forests were grouped into seven ecosystem types (including macchia), for which the optimal BIOME-BGC settings were identified using the procedure described in *Chiesi et al*. [2007, 2010].

2.3. Simulation of Actual Forest Conditions

As stated above, both modified C-Fix and BIOME-BGC compute forest GPP as an expression of total, or potential, ecosystem production. This enables the integration of BIOME-BGC respirations with the more accurate GPP estimates of C-Fix [*Maselli et al*., 2009b]. Finally GPP, respirations and allocation estimates obtained from the two models must be transformed into estimates of actual forest conditions, which generally differ from the equilibrium condition because of natural and/or human-induced disturbances [*Liu et al*., 2011]. According to *Maselli et al*. [2009b], an indicator of the distance from equilibrium is given by the ratio between the actual growing stock volume (which is measured in the field or derived from maps) and the potential growing stock volume which might be sustained by the environment in equilibrium with local ecoclimatic conditions. Therefore, this ratio can be used to correct the photosynthesis and respiration estimates obtained by the previous model simulations. According to this strategy, the actual forest NEP, NEP_A, is approximated as

$$\mathrm{NEP}_A = \mathrm{GPP}\cdot \mathrm{FC}_A - R_{\mathrm{gr}}\cdot \mathrm{FC}_A - R_{\mathrm{mn}}\cdot \mathrm{NV}_A - R_h\cdot \mathrm{NV}_A, \quad (2)$$

where R_{gr}, R_{mn}, and R_h represent the BIOME-BGC estimates of the growth, maintenance, and heterotrophic respiration rates, and the two terms FC_A (actual forest cover) and NV_A (actual normalized volume) describe the ecosystem proximity to the equilibrium condition [*Maselli et al*., 2009b]. In particular, NV_A is the ratio between the actual and potential growing stock volume, and FC_A represents the fraction of photosynthetic radiation that is usable by the tree canopy, which is obtained by combining NV_A and the leaf area index following Beer's law. This makes simulated NPP and NEP increase with NV_A up to a certain level (usually 30–40% of potential growing stock). Next, NPP and NEP decrease as NV_A approaches one (i.e., fully stocked equilibrium condition), and, in particular, both tend to BIOME-BGC simulations (i.e., to equal heterotrophic respiration and zero, respectively) [*Maselli et al*., 2009b].

In light of the previously described functional equivalence of the C-Fix and BIOME-BGC estimates of GPP, the outputs from the two models can be combined by multiplying the BIOME-BGC respiration estimates by a ratio between C-Fix and BIOME-BGC GPP. This step is necessary to render the respiration estimates of the biogeochemical model consistent with C-Fix GPP. A detailed description of the entire strategy is reported in *Maselli et al*. [2009b] in addition to all assumptions and approximations required for its application.

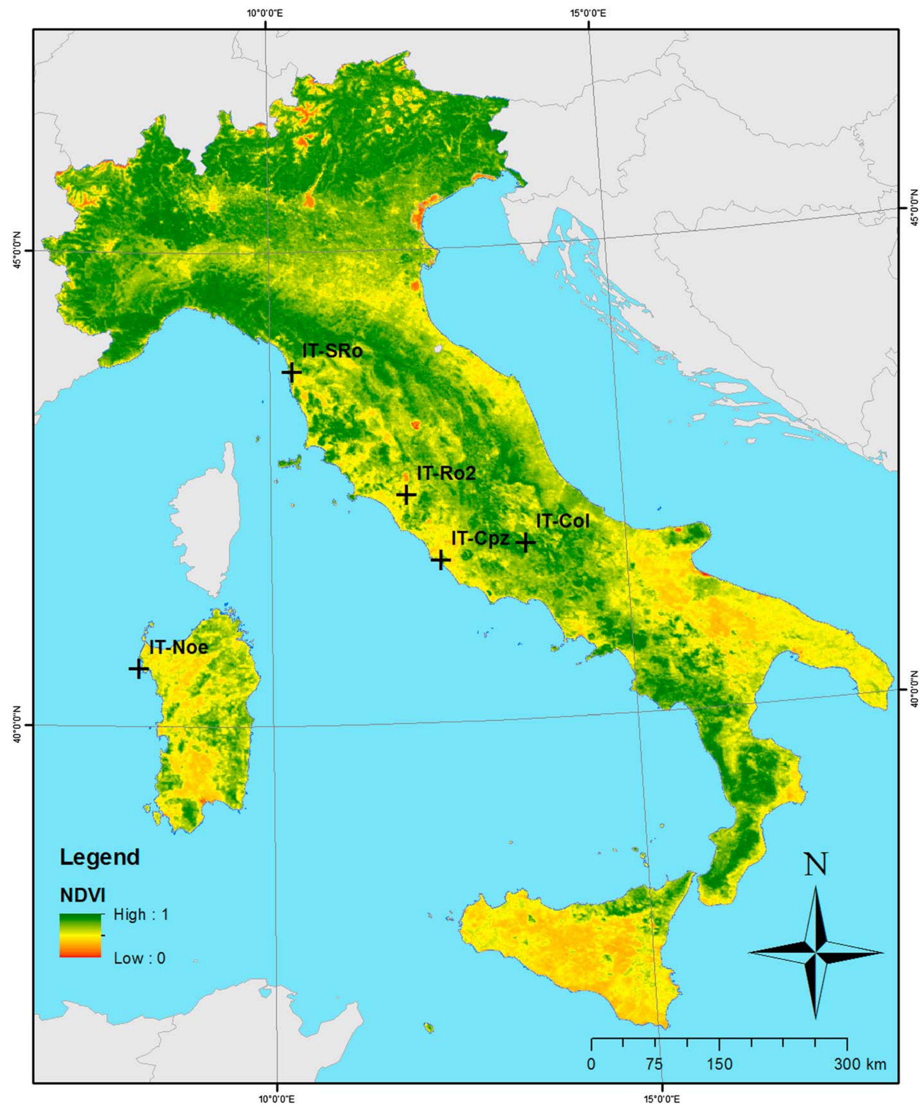

Figure 1. Spot-VGT NDVI image of August 2009 with the locations of the five eddy covariance sites considered.

3. Study Area

Italy is geographically situated between 36° and 47°30′ North latitude and between 5°30′ and 18°30′ East longitude (Figure 1), and its orography is complex because of the presence of two main mountain chains, the Alps in the North and the Apennines in the Center-South. The Italian climate is highly variable following the latitudinal and altitudinal gradients and the distance from the sea and generally ranges from Mediterranean warm to temperate cool.

According to the Italian National Forest Inventory (www.infc.it), which bases the data on the Food and Agriculture Organization forest definition, the forests in Italy cover an area of approximately 87,600 km^2. Overall, 32% of the forest formations are included in the Alpine biogeographical region, 16% in the Continental region, and 52% in the Mediterranean region (sensu the Habitat Directive of the European Commission 43/92). The most widespread forest formations are dominated by various oak species (*Quercus* spp.) and beech (*Fagus sylvatica* L.). A large portion of the area of broadleaved forests is managed as coppices [*Ciancio et al*., 2006]. Among conifers, the most abundant forest formations are dominated by Norway spruce (*Picea abies*), followed by mountain pines (e.g., *Pinus sylvestris* and *P. nigra*) and Mediterranean pines (*P. halepensis*, *P. pinaster*, and *P. pinea*).

4. Data Used

4.1. Ancillary Data

The digital elevation model (DEM) of Italy used in this work has a pixel size of 1 km^2. This DEM is projected in the UTM-32 North reference system, which is employed as a standard for the processing of all other information layers.

A soil map of Italy was recently produced by the CARBOITALY project with a spatial resolution of 1 km [*Valentini and Miglietta*, 2015]. The map is composed of four information layers that are descriptive of soil depth and texture (i.e., percentage of sand, silt, and clay).

A forest map was derived from the Co-ORdinated INformation on the Environment (CORINE) Land Cover 2006 map of Italy [*Istituto Superiore per la Protezione e la Ricerca Ambientale*, 2010]. The original CORINE data set of Europe classifies forests, at the 1:100,000 scale (minimum mapping size of 25 ha), into the following three general classes: broadleaf, coniferous, and mixed. Instead, the available forest map classifies forests and other wooded lands into 26 types on the basis of the dominant tree species, maintaining geometric and thematic congruency with the original CORINE data set. The forest map of Italy was produced by the manual photointerpretation of Landsat imagery supported by several ancillary sources of information. For a previous study, the original vector data set had already been rasterized at the available DEM resolution (1 km), grouping the original classes into seven forest types with expected uniform NDVI evolution [*Maselli et al*., 2014].

Information regarding the growing stock volume was derived from another 1 km resolution map which was obtained by *Maselli et al*. [2014] combining ground measurements of regional forest inventories with the CORINE land cover map of Italy and the global Geoscience Laser Altimeter System (GLAS)/MODIS canopy height map.

4.2. Meteorological Data

Maps of daily meteorological variables (minimum and maximum temperature and precipitation) for the Italian national territory were derived from the E-OBS data set [*Haylock et al*., 2008; *van den Besselaar et al*., 2011]. This data set was designed for use in a wide range of applications, has a grid spacing of 0.25°, and covers the time period from 1950 to the present. The data set has been downscaled to 1 km resolution for the years 2000–2009 [*Maselli et al*., 2012]. The same study demonstrated that the accuracy of the downscaled data set is high for daily temperatures (particularly maximum) but lower for rainfall.

4.3. Satellite Data

NDVI images taken by the Spot-VEGETATION sensor were obtained from the archive of Flemish Institute for Technological Research (VITO) (http://free.vgt.vito.be), which has freely distributed preprocessed maximum value composite (MVC) images for the entire globe since April 1998. The applied preprocessing procedure comprises the radiometric calibration of the original channels and their geometric and atmospheric corrections [*Maisongrande et al*., 2004]. The final product of this procedure is a collection of 10 day NDVI MVC images with a pixel size of approximately 1 km^2. Ten day MVC images of Europe were downloaded from 2000 to 2009 and a window over Italy was selected for further processing.

4.4. Flux Tower Data

The Italian eddy covariance flux tower network comprises approximately 45 flux towers located in various ecosystems ranging from forests (about half of them) to grasslands and croplands and includes a number of climatic conditions (http://www.europe-fluxdata.eu). The collected flux data are all available in a standardized format and quality checked using state of the art methodologies [*Aubinet et al*., 2012], including gap filling and the partitioning of the net flux into its two components (i.e., GPP and ecosystem respiration).

The tower sites may be subject to errors in the data acquisition that deteriorate the overall data quality, to disturbances or management events, or to other CO_2 sources that affect the partitioning methodologies [e.g., *Rey et al*., 2014]. Moreover, the data obtained from most of the Italian towers have been collected for brief and/or discontinuous time periods which are unsuitable for the testing of a multiyear monitoring procedure. For these reasons only a reduced number of effective forest reference sites were considered in the current investigation, selected by using the following two criteria:

1. NEP/GPP ratios lower than 0.5 on an annual basis, which are indicative of not anomalous C flux observations [see *Waring and Running*, 2007].

Table 1. Main Characteristics of the Five Study Sites Selected for Testing the Current Modeling Strategy (See the FLUXNET Website for Further Detail)

ID	Position (Lat. N, Long. E)	Altitude (m asl)	Mean Annual Temperature (°C)	Mean Annual Rainfall (mm)	Soil	Ecosystem Type	References	Period Considered
IT-SRo	43.73°, 10.28°	1	14.8	900	Albic arenosol	Pine forest	*D.R.E.Am* [2003] and *Chiesi et al.* [2005]	2001–2005
IT-Cpz	41.71°, 12.38°	14	15.3	740	Haplic arenosol	Holm oak forest	*Chiti et al.* [2010]	2000–2008
IT-Ro2	42.39°, 11.92°	162	14.4	900	Cambisol, sandy-clay	Turkey oak forest	*Rey et al.* [2002]	2004–2008 (no 2006)
IT-Col	41.55°, 13.59°	1579	10.0	1000	Humic alisol	Beech forest	*Kramer et al.* [2002]	2000–2008
IT-Noe	40.6°, 8.15°	57	15.9	588	Lithic xerorthent	Mediterranean macchia	*Beier et al.* [2009]	2004–2009

2. The availability of a minimum number of quasi-complete years during the study period (i.e., at least 3 years with 10 months per year from 2000 to 2009), which are necessary to reconstruct representative annual profiles.

The application of these two criteria led to the identification of the five tower sites listed in Table 1. This table also summarizes the main features of each site and provides references where additional information can be found. A brief description of the five tower sites is reported in the following paragraphs.

San Rossore (IT-SRo) is a coastal area characterized by Mediterranean subhumid climate [*Rapetti and Vittorini*, 1995]. The area is mostly covered by a large and homogeneous Mediterranean pine forest (both *Pinus pinaster* Ait. and *Pinus pinea* L.) [*Chiesi et al.*, 2005]. The forest around the flux tower is dominated by the former species and has a mean height around 20 m.

Castelporziano (IT-Cpz) extends over a plain coastal area with a Mediterranean climate. The area is characterized by the presence of a holm oak (*Quercus ilex* L.) forest that is distributed along the typical sea-inland belt and has access to the ground water table. This forest is an old coppice that has been unmanaged for a long time and has now an average height of approximately 10 m.

Roccarespampani 2 (IT-Ro2) is a hilly area characterized by a typical Mediterranean climate and by the presence of *Quercus cerris* L. The forest surrounding the flux tower is managed as a coppice of about 25 years.

Collelongo (IT-Col) is a mountain area having a Mediterranean mountain climate and is dominated by the presence of beech (*Fagus sylvatica* L.). The beech forest surrounding the flux tower has a basal area of approximately 32 m^2 ha^{-1} and a mean height of 22 m [*Kramer et al.*, 2002].

Arca di Noè (IT-Noe) is located in the Sardinia island and is characterized by a Mediterranean dry climate. The typical vegetation is Mediterranean macchia, with a mean height ranging between 0.9 and 1.8 m and a ground cover varying between 45% and 95%.

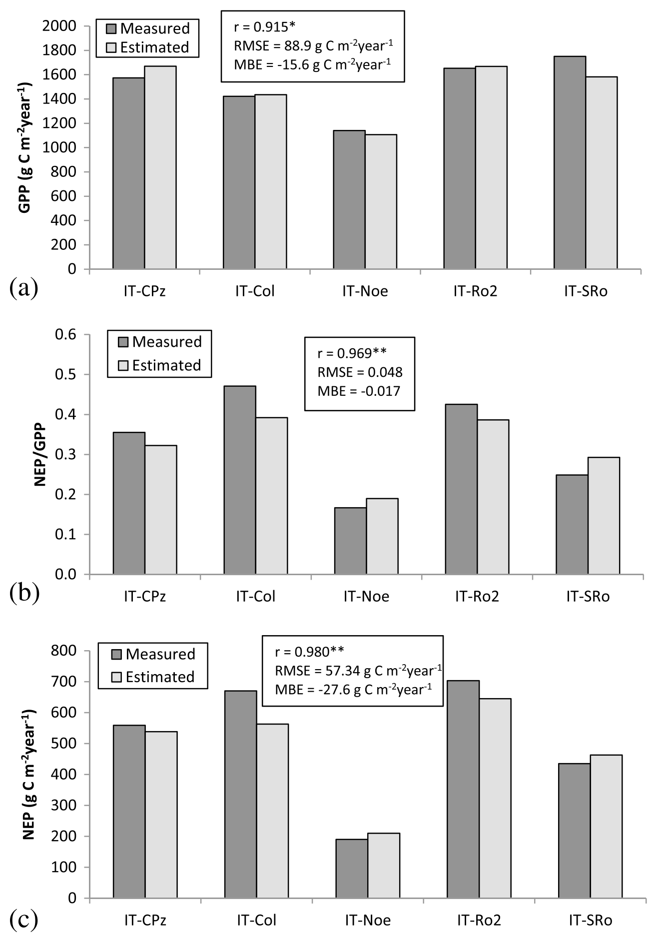

Figure 2. (a–c) Measured and estimated annual averages of the five study towers: (a) GPP, (b) NEP/GPP, and (c) NEP (* = significant correlation, $P < 0.05$; ** = highly significant correlation, $P < 0.01$).

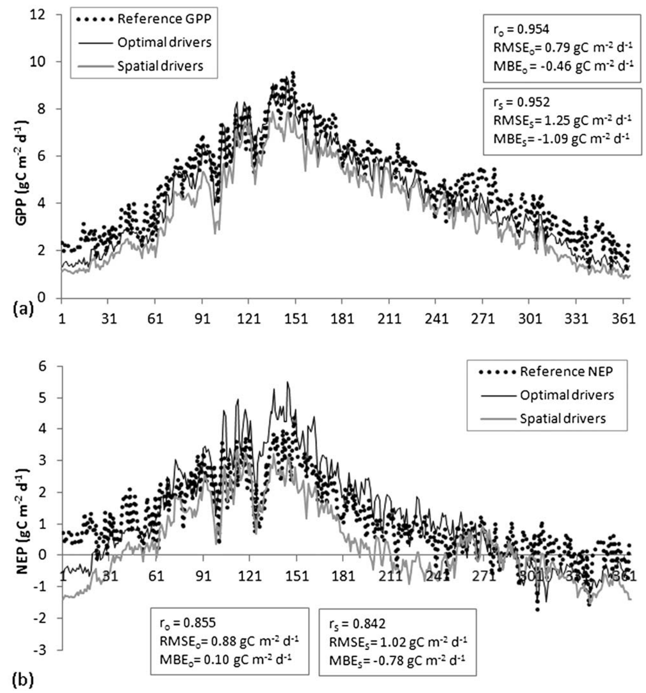

Figure 3. IT-SRo: mean daily (a) GPP and (b) NEP profiles measured and estimated using optimal model drivers (site meteorological data, soil depth and texture, forest type, and forest standing volume, O) and model drivers derived from spatially explicit maps (S) (all correlations are highly significant, $P < 0.01$).

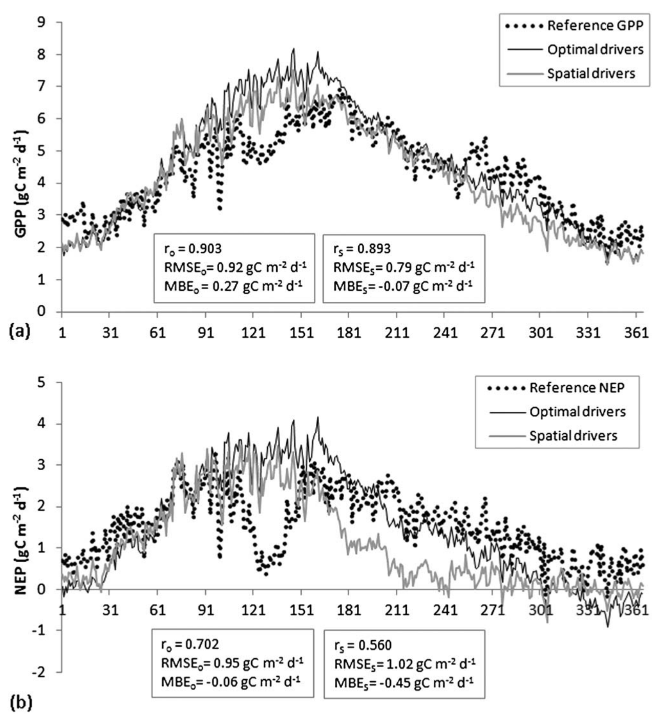

Figure 4. IT-Cpz: mean daily (a) GPP and (b) NEP profiles measured and estimated using optimal model drivers (site meteorological data, soil depth and texture, forest type, and forest standing volume, O) and model drivers derived from spatially explicit maps (S) (all correlations are highly significant, $P < 0.01$).

5. Data Processing

The assessment of the theoretical validity of the modeling approach was performed by driving the simulations with the most accurate available inputs. Unfortunately, the meteorological data series measured at the tower sites were incomplete and discontinuous and did not allow the correct application of BIOME-BGC. Thus, the 1 km daily meteorological data sets were corrected by applying different methods for air temperatures and precipitation. In the former case, the data were corrected through linear regressions developed versus the available measurements of the flux towers. In the case of rainfall, a ratio correction was applied obtained by the same comparison. The corrected meteorological variables were then elaborated by the MT-CLIM algorithm [*Thornton et al.*, 2000; *Chiesi et al.*, 2010 for more details] to obtain the global radiation solar, which was converted into PAR using a coefficient equal to 0.464 [*Iqbal*, 1983].

The calibrated meteorological data of each study site were supplied as input to modified C-Fix for the computation of relevant GPP estimates. The NDVI values of the five sites were extracted from the Spot-VGT imagery using the methodology by *Maselli* [2001], which is capable of estimating spatially variable NDVI values of pure classes by relying on a higher spatial resolution land cover map (in this case, the forest type map of CORINE Land Cover). A small modification was applied to the MODIS temperature correction factor (Tcor) to account for the high capacity of Mediterranean species to photosynthesize at low temperatures [*Scarascia-Mugnozza et al.*, 2000], and specifically, the $Tcor_{min}$ values of all the ecosystem types were lowered by 3–4°C (from 7.9–9.1°C to 5.0°C).

Next, BIOME-BGC was applied in a spin-up and go mode to estimate the forest GPP, respiration rates, and allocation rates. In addition to the

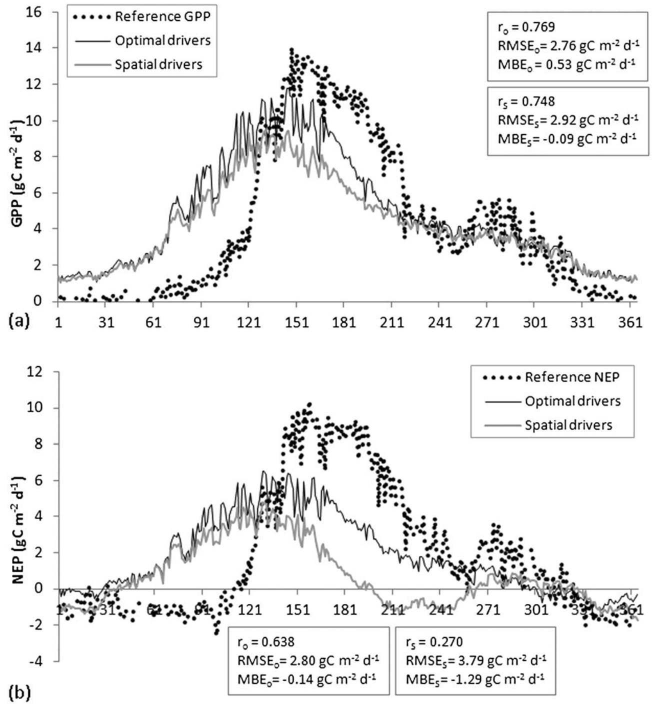

Figure 5. IT-Ro2: mean daily (a) GPP and (b) NEP profiles measured and estimated using optimal model drivers (site meteorological data, soil depth and texture, forest type, and forest standing volume, O) and model drivers derived from spatially explicit maps (S) (all correlations are highly significant, $P < 0.01$).

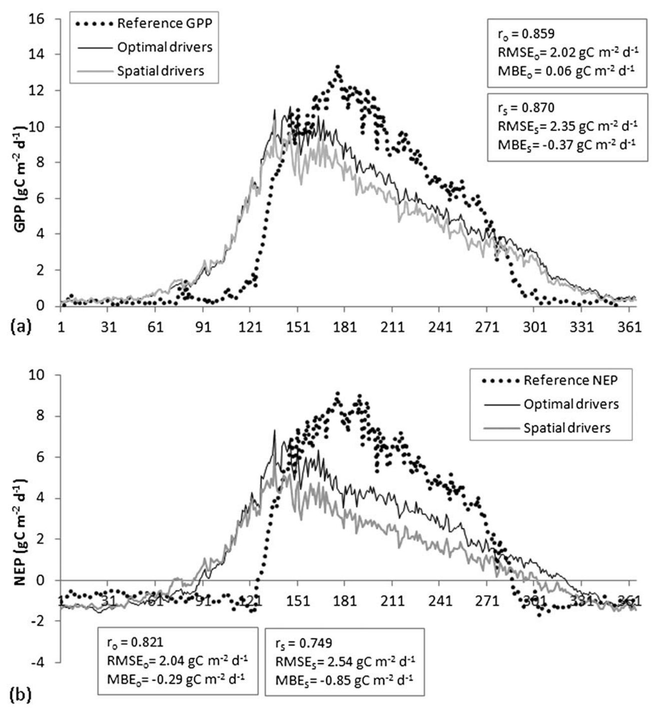

Figure 6. IT-Col: mean daily (a) GPP and (b) NEP profiles measured and estimated using optimal model drivers (site meteorological data, soil depth and texture, forest type, and forest standing volume, O) and model drivers derived from spatially explicit maps (S) (all correlations are highly significant, $P < 0.01$).

described daily meteorological data, the model requires information on the dominant forest type and on soil characteristics (depth and texture), which were both derived from the tower descriptions. BIOME-BGC was also run to produce photosynthesis and respiration estimates of herbaceous vegetation, which served to complement the forest estimates in cases of incomplete tree canopy cover [*Maselli et al.*, 2009b]. In this case, the model ecophysiological parameters were those reported for C3 grasses by *Maselli et al.* [2013].

The final estimates for each pixel were obtained by combining the contributions of trees and grasses weighed by FC_A and 1-FC_A, respectively [*Maselli et al.*, 2010]. Concerning the portion of each study site covered by forest, equation (2) was applied to correct the BIOME-BGC outputs and obtain relevant NEP_A estimates. The actual forest growing stock volumes required for this operation were derived from the tower descriptions. Next, C-Fix GPP estimates were used to rescale the BIOME-BGC respiration estimates and to compute the integrated NEP_A [*Maselli et al.*, 2009b].

Finally, the daily GPP and NEP estimates for each study site were compared to the daily eddy covariance measurements of NEP and derived GPP. For this operation only the most reliable flux tower data were selected, i.e., those with a quality flag higher than 0.8. The comparisons were performed for both the mean annual profiles and the entire data series. The results were summarized by calculating common accuracy statistics as follows: correlation coefficient (r), root mean square error (RMSE), and mean bias error (MBE).

The tests were repeated using the uncorrected meteorological data sets and the forest information derived from the available 1 km maps (i.e., uncalibrated E-OBS data and the

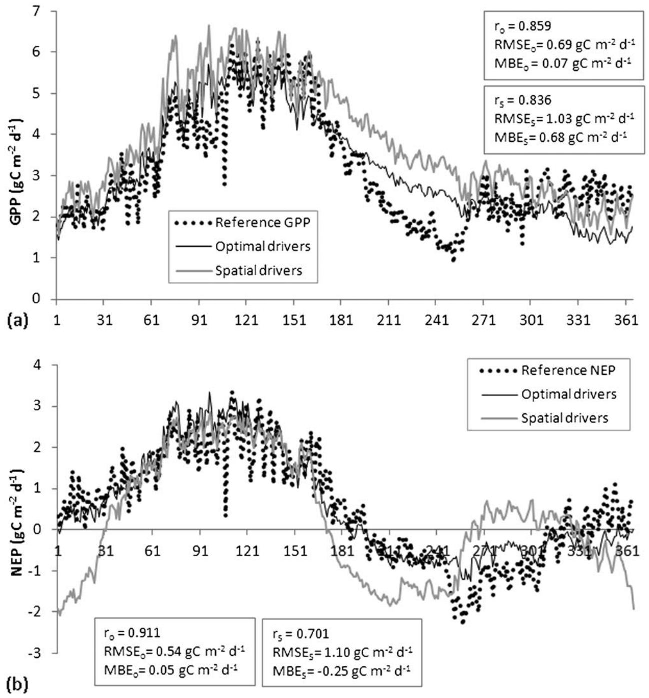

Figure 7. IT-Noe: mean daily (a) GPP and (b) NEP profiles measured and estimated using optimal model drivers (site meteorological data, soil depth and texture, forest type, and forest standing volume, O) and model drivers derived from spatially explicit maps (S) (all correlations are highly significant, $P < 0.01$).

CORINE land cover, soil and growing stock volume maps). The same statistics as listed above were used for the final accuracy assessment of the mean annual profiles.

6. Results

6.1. Estimates Obtained Using Optimal Model Drivers

The results obtained by initializing modified C-Fix and BIOME-BGC using the optimal model drivers were generally satisfactory, indicating the capability of the method for estimating both the gross and the net forest carbon fluxes. The first analysis concerned the mean annual totals of GPP simulated by equation (1) using the optimal model drivers. The histogram of Figure 2a shows that the estimated annual GPP averages of the five towers were in very good and significant agreement with the measured values, with only a marginal tendency to underestimation. As previously noted, the simulation of NEP through equation (2) was based on a proxy of ecosystem distance from equilibrium, NV_A, which determines the ratio between the simulated ecosystem respiration and photosynthesis. Figure 2b shows the ratios between the mean annual NEP and GPP totals obtained from the measured and estimated data, the latter derived from the following NV_A values: IT-Cpz = 0.234, IT-Col = 0.247, IT-Noe = 0.794, IT-Ro2 = 0.236, and IT-SRo = 0.225. The accordance between the two ratio series was very high, and the relative errors were low. Consequently, the mean NEP totals of the five towers were also estimated accurately (Figure 2c).

The next step concerned the validation of the daily carbon flux estimates. Figures 3a–3b present the measured and simulated mean annual profiles of both GPP and NEP for IT-SRo (coastal plain pine forest). The accuracy achieved was sufficient, and the annual development was well captured. The GPP observed for IT-Cpz (coastal plain holm oak forest) was also well reproduced, with the exception of an overestimation in early spring (Figure 4a). The same pattern was observed for NEP; however, the degree of spring overestimation was higher (Figure 4b). The annual GPP trend of IT-Ro2 (hilly Turkey oak forest) was not well reproduced (Figure 5a), and the beginning of the season was anticipated by the model. The peak was underestimated, and the same trend was even more evident for NEP (Figure 5b). For IT-Col (mountain beech forest), the seasonal GPP and NEP patterns were well reproduced, except for the annual peak, which was lower and earlier than the reference values

Table 2. Accuracy Statistics Obtained on a Daily Basis for All Test Sites Using Optimal Model Drivers (All Correlations Are Highly Significant, $P < 0.01$)

	GPP			NEP		
ID	r	RMSE (g C m^{-2} day^{-1})	MBE (g C m^{-2} day^{-1})	r	RMSE (g C m^{-2} day^{-1})	MBE (g C m^{-2} day^{-1})
IT-SRo	0.777	1.62	−0.47	0.614	1.56	0.08
IT-Cpz	0.624	1.81	0.30	0.454	1.59	−0.02
IT-Ro2	0.636	3.54	0.38	0.568	3.23	0.00
IT-Col	0.793	2.74	−0.04	0.715	2.58	−0.28
IT-Noe	0.708	1.25	0.08	0.767	1.08	0.06

Table 3. Summary of the Information Used to Drive the Proposed Modeling Approach as Derived From Site Measurements (Optimal Model Drivers) and Spatially Explicit Sources (CORINE Land Cover 2006 Map, Downscaled E-OBS Data Set, Soil and Growing Stock Maps): (a) Data Used to Drive C-Fix and (b) Additional Data Used to Simulate NEP by the Integrated Approach (C-Fix Plus BIOME-BGC)[a]

(*a*)

	Ecosystem Type		T_{AV} (°C)		PREC (mm yr^{-1})	
ID	Real	Map	Real	E-OBS	Real	E-OBS
IT-SRo	Pine	Pine	15.4	15.6	**976**	**745**
IT-Cpz	Holm oak	Holm oak	14.8	16.7	**754**	**517**
IT-Ro2	Turkey oak	Turkey oak	15.3	15.7	**849**	**420**
IT-Col	Beech	Beech	7.7	9.1	844	701
IT-Noe	**Mediterranean macchia**	**Pine**	16.6	16.9	366	333

(*b*)

	Soil Depth (cm)		Soil Texture (% sand, % silt, % clay)		Growing Stock Volume (m^3 ha^{-1})	
ID	Rea	Map	Real	Map	Real	Map
IT-SRo	100	127	**94, 3, 3**	**45, 20, 35**	**240**	**88**
IT-Cpz	100	162	**89, 5, 6**	**30, 30, 40**	**220**	**82**
IT-Ro2	100	82	50, 15, 35	55, 20, 25	**200**	**83**
IT-Col	**80**	**37**	30, 40, 30	10, 60, 30	325	278
IT-Noe	**40**	**66**	30, 30, 40	30, 30, 40	**20**	**96**

[a]The names/numbers in bold represent the difference between the real and mapped values that can be considered relevant for model computations (i.e., differences in ecosystem or soil types and differences greater than 2°C for temperature and 20% for precipitation, soil depth, soil texture, and growing stock volume; soil depths greater than 1 m are ineffective on BIOME-BGC functions).

(Figures 6a–6b). Concerning IT-Noe (Mediterranean macchia), the phenological development was well reproduced; however, a slight overestimation of GPP during the summer months occurred (Figure 7a), and this trend was not evident for NEP (Figure 7b).

The same accuracy statistics are shown for the entire data series in Table 2. The global agreement was always lower than that achieved in the case of the annual mean, and the statistics related to daily NEP were clearly worse for three out of five sites, especially in terms of temporal accordance.

6.2. Estimates Obtained Using Spatially Explicit Data Sets

The driving variables extracted from the spatially explicit data sets presented different levels of inaccuracy for the five study sites (Table 3). The ecosystem type was almost always correctly assessed by the CORINE map (4 cases out of 5). The accuracy was even better for the 1 km E-OBS mean daily temperatures, which were all within 2°C from the corresponding tower values. In contrast, the 1 km E-OBS annual rainfalls exhibited varying degrees of underestimation, which were higher than 20% in three cases. The available soil maps correctly reproduced the depth and texture for three cases. Finally, the extended forest growing stock volume was highly underestimated in three cases and overestimated in one case.

These patterns affected the outputs of the two models and of the integration strategy in varying ways. The mean annual profiles obtained by this strategy are again presented in Figures 3–7, and in all cases the accuracies of the model estimates were lower than those previously shown.

The C-Fix GPP estimates of IT-SRo were marginally influenced by the small rainfall underestimation, which markedly affected only the GPP predictions of BIOME-BGC. The effect on GPP on the integrated NEP estimates was obvious; however, these impacts were, in general, lessened by the underestimation of the growing stock volume. Similar results were obtained for IT-Cpz, for which only the rainfall and the growing stock were underestimated. The effect of these errors on the GPP and NEP was not particularly marked, and the biggest difference was associated with the presence of spring decreases in the measurements that were not well reproduced by the modeling approach. The worst case involved IT-Ro2, in which rainfall was strongly underestimated (by greater than 50%), and the same was true for the growing stock volume (83 m^3 ha^{-1} against 200 m^3 ha^{-1}). The use of the spatially explicit input data reinforced the previously mentioned suboptimal reproduction of the annual profile, which added to the overestimated water stress (caused by the low annual rainfall) and, concerning NEE, to the incorrect annual pattern (because of the low growing stock volume) and brought to a strong reduction of accuracy. Good results were obtained for IT-Col, where almost all the extended driving variables were quite accurate, even if the mean annual pattern was slightly shifted. Finally, good results were also obtained for IT-Noe, where the ecosystem type error was associated to a corresponding growing stock error, and, together, they had a marginal effect.

7. Discussion

The current paper presents the testing of an integrated modeling strategy against data collected from five Italian sites representative of various forest ecosystems (deciduous and evergreen forests and Mediterranean macchia). The testing relies on the use of daily eddy covariance carbon flux data, which are, however, also affected by various sources of uncertainty. These data, in fact, can be discontinuous and incomplete; therefore, the application of gap filling and partitioning algorithms is fundamental to reconstructing reliable data sets and obtaining GPP [*Aubinet et al*., 2012]. In addition, in a number of instances, the data collection is performed in locations that are suboptimal for the application of the eddy covariance technique (e.g., areas that are heterogeneous in terms of topography and/or vegetation type). Consequently, the dimensions of the fetch (the area contributing to the fluxes) may strongly vary in time and/or space [*Hollinger and Richardson*, 2005]. In the current study, the use of problematic reference data was avoided by adopting very restrictive criteria for the selection of the flux towers to consider.

The results obtained when applying the modeling strategy using optimal drivers (i.e., using measured or calibrated data) support the validity of the basic theoretical foundation. Good results are produced for all of the considered sites, particularly for GPP, which is easier to predict than NEP because of the complexity in simulating the respiration and allocation processes [*Maselli et al*., 2009b]. This result is in agreement with the results of previous investigations in which the monthly C-Fix GPP estimates were successfully verified against independent data [e.g., *Maselli et al*., 2009a; *Moreno et al*., 2014]. In the current case, the greater problems are associated with the inaccurate definition of forest phenology and, in particular, of the start and the peak of the growing season (e.g., IT-Ro2 and, to a lesser extent, IT-Col). These inaccuracies are likely associated with the presence of mixed and fragmented vegetation cover, which may affect the NDVI/fAPAR values at the examined 1 km spatial resolution. In fact, the applied NDVI end-member identification method can only approximate the real NDVI value of relatively small forest stands [*Maselli*, 2001]. This problem, however, could not be fully characterized because of a lack of available ground fAPAR measurements.

The current results also confirm the findings of previous investigations [*Maselli et al*., 2009b; *Chiesi et al*., 2011], concerning the potential of the integration method to predict net carbon fluxes. In particular, the capacity of C-Fix to estimate daily GPP is crucial for predicting NEP. C-Fix GPP estimates, in fact, are capable of correcting major BIOME-BGC outputs (e.g., photosynthesis and respiration rates), which are abnormally reduced in cases of severe thermal or water limitation (i.e., for IT-Col and IT-Noe respectively, data not shown). Another fundamental modeling step is represented by the correct simulation of the NEP/GPP ratios, which is demonstrated by the analyses of the mean annual totals. This last finding supports the validity of the modeling theory proposed in *Maselli et al*. [2009b], which relies on the identification of the ecosystem distance from equilibrium conditions.

As expected, the use of spatially explicit model drivers resulted in a general decrease in the estimation accuracy, which, again, is particularly evident for NEP. The study analyzed the relevance of the following major model drivers:

1. Forest type map. Errors in identifying the correct forest cover are not very frequent and only partially influential. The effects of these errors, in fact, are essentially related to the BIOME-BGC simulations of the respiration and allocation functions, which are different for deciduous/evergreen and broadleaf/needleleaf species [*White et al*., 2000].
2. Soil map. As expected, because of the local inaccuracy of most low-resolution soil maps, erroneous identifications of soil depth and texture are quite common. This problem, however, is also only partially influential because of the previously noted stabilization achieved using the C-Fix GPP estimates.
3. Meteorological data. The downscaled E-OBS data layers are associated with varying levels of accuracy. Daily temperatures are estimated quite accurately, while this is not the case for rainfall, which is often underestimated [*Maselli et al*., 2012]. These patterns usually result in an overestimation of water stress,

which reduces the summer estimates of both GPP and NEP. This common phenomenon is generally proportional to the underestimation of local rainfall but is again attenuated by the aforementioned stabilization achieved by C-Fix.

4. Map of growing stock volume. This map was obtained from the combination of field inventory data and the GLAS/MODIS canopy height map and is significantly more accurate than the corresponding pan-European map by *Gallaun et al*. [2010]. However, the current map still contains variable uncertainty at the local scale because of the intrinsic spatial variability of growing stock within 1 km pixels. In particular, the underestimation of growing stock occurs for most sites (four out of five) and can be partially attributed to the preferred selection of mature and undisturbed forest plots for tower positioning; in these cases, in fact, the biomass measured at the towers is likely higher than that within the corresponding 1 km pixels. Growing stock errors have a direct effect on the identification of the correct forest development phase (i.e., distance from ecosystem equilibrium, see discussion above), which is critical for obtaining accurate NEP predictions.

Regarding the comparison of the current results with the findings of previous studies, several investigations have been performed to test the accuracy of the MODIS GPP product across the globe. For example, *Heinsch et al*. [2006] tested the MODIS GPP algorithm against reference data collected from 15 flux tower sites in the United States, and the results indicated that the algorithm has a tendency to overestimate the GPP. In addition, the possible causes of this overestimation are identified in the input data. *Wang et al*. [2011] assessed the potential of using an integrated model (GLOPEM-CEVSA) to predict both the gross and net carbon fluxes of three forest sites in China and USA. A good estimation accuracy was obtained for GPP, while the NEP estimates reproduced the seasonal evolution of the tower measurements but showed substantial biases. As regards Mediterranean environments, only a few studies have been conducted to assess the capacity of similar modeling approaches on a daily time step. Among these approaches, *Nolè et al*. [2013] applied a modified version of the 3-PGS model to the IT-Cpz and IT-Noe sites, and the accuracy achieved is comparable to that obtained in this study.

8. Conclusions

The use of remote sensing data is particularly suited to estimating forest ecosystem GPP on a large scale [*Veroustraete et al*., 2002; *Heinsch et al*., 2006]. In particular, several investigations have shown that the NDVI-driven C-Fix model is capable of accurately reproducing the monthly GPP of Italian forests at a 1 km resolution [*Maselli et al*., 2006, 2009a; *Chiesi et al*., 2011]. The current study indicates that when applying this model on a daily time step, a major source of uncertainty is the erroneous definition of NDVI and fAPAR, which is fundamental for the assessment of vegetation phenology. However, in general, the use of remotely sensed fAPAR estimates tends to improve the prediction of photosynthesis, reducing its sensitivity to the inaccurate assessment of local meteorological features.

This study also confirms that the modeling strategy based on the integrated use of C-Fix and BIOME-BGC is capable of providing reliable daily estimates of NEP at the examined 1 km spatial resolution. This capacity can be attributed to the general applicability of the biogeochemical model for the majority of environmental situations, which is currently reinforced by the aforementioned capacity of C-Fix to stabilize all of the final estimates. Another fundamental modeling step is the correct reproduction of the NEP/GPP ratio, which is achieved by an ecophysiologically sound simulation of the ecosystem trophic condition.

When driving the models with spatially explicit data sets, the accuracy of these estimates is affected by the correct definition of the following parameters (in increasing order of importance): the ecosystem type and soil features (which guide the BIOME-BGC functions, but the effect of which can be reduced by the integration with C-Fix outputs); the site climatology and, particularly, the precipitation regime (which directly affect both the C-Fix water stress factor and the BIOME-BGC water budget); and the growing stock volume at the site level (which defines the biomass quantity and the proximity of the ecosystem to equilibrium).

The results of this study encourage the application of the proposed modeling strategy over large areas (e.g., at national and continental scales) wherever appropriate input data sets are available. In particular, the modeling performance could be improved by including higher accuracy data layers that describe the meteorology (particularly rainfall) and the growing stock and by using NDVI data sets with enhanced spatial and temporal features derived by suitable data integration strategies [*Maselli and Chiesi*, 2006; *Rao et al*., 2015] or foreseen satellite missions (e.g., Sentinel-2 and Sentinel-3).

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