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ORIGINAL PAPER

Prediction of forest NPP in Italy by the combination of ground and remote sensing data

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Abstract Our research group has recently proposed a strategy to simulate net forest carbon fluxes based on the coupling of a NDVI-driven parametric model, Modified C-Fix, and of a biogeochemical model, BIOME-BGC. The outputs of the two models are combined through the use of a proxy of ecosystem distance from equilibrium condition which accounts for the occurred disturbances. This modeling strategy is currently applied to all Italian forest areas using an available set of NDVI images and ancillary data descriptive of an 8-year period (1999–2006). The obtained estimates of forest net primary production (NPP) are first analyzed in order to assess the importance of the main model drivers on relevant spatial variability. This analysis indicates that growing stock is the most influential model driver, followed by forest type and meteorological variables. In particular, the positive influence of growing stock on NPP can be constrained by thermal and water limitations, which are most evident in the upper mountain and most southern zones, respectively. Next, the NPP estimates, aggregated over seven main forest types and twenty administrative regions in Italy, are converted into current annual increment of standing volume (CAI) by specific coefficients. The accuracy of these CAI estimates is finally assessed by comparison with the ground data collected during a recent national forest inventory. The results obtained indicate that the modeling approach tends to overestimate the ground CAI for most forest types. In particular, the overestimation is notable for forest types which are mostly managed as coppice, while it is negligible for high forests. The possible origins of these phenomena are investigated by examining the main model drivers together with the results of previous studies and of older forest inventories. The implications of using different NPP estimation methods are finally discussed in view of assessing the forest carbon budget on a national basis.

Keywords Modified C-Fix · BIOME-BGC · Forest inventory · Current annual increment · Regional estimates · Italy

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Introduction

The assessment of forest production is a central issue in applied ecology and is becoming increasingly important for evaluating the role of forest ecosystems as possible carbon sink (Hagedorn et al. 2001; Waring and Running 2007; Kolström et al. 2011). Information on forest production has been traditionally collected through user-driven national forest inventories (Corona and Marchetti 2007; Corona et al. 2011). In Italy, a national forest inventory (INFC) was recently completed (Gasparini et al. 2009a). One of the main objectives of this inventory is to provide an updated national estimate of forest growing stock (i.e., carbon net primary productivity, C-NPP), which can be derived from wood volume increment statistics through the use of biomass expansion factors (BEFs) (Evrendilek 2004; Federici et al. 2008). Such statistics are presently published at regional level, together with other information on main forest features (type, basal area, volume, etc.). The NPP estimates derived from INFC, however, are only partially in agreement with those derived from other data sources (e.g., Arrigoni et al. 1998; Chirici et al. 2007; Valentini et al. 2014). This indicates the existence of a challenging framework, where uncertainties are rather high.

Recent investigations conducted in other countries have confirmed that the modeling of forest production over large European areas is complex due to its high spatial and temporal variability and requires the application of sophisticated modeling strategies difficult to be generalized for large areas (Osborne et al. 2000; Pietsch and Hasenauer 2006; Chirici et al. 2007). One of these strategies has been recently developed and applied by our research group to obtain spatial production estimates for the main Italian forest categories (Maselli et al. 2006, 2009a). The method is based on the use of a NDVI-driven parametric model, Modified C-Fix, to calibrate and stabilize the functions of a biogeochemical model, BIOME-BGC (Maselli et al. 2009a). This approach can efficiently predict monthly and annual gross primary production (GPP) of all Italian forests at a spatial scale of about 1 km^2.

The conversion of GPP into NPP estimates is, however, a non-trivial issue. The two variables, in fact, are only partially interrelated when forest resources are strongly influenced by management practices or other disturbing factors (wildfires, pests and diseases). As noted by Maselli et al. (2009b), forest GPP is an expression of total ecosystem productivity, which includes the contribution of both trees and understory vegetation (brushes and grasses). The latter component can even prevail when tree density is low due to the effect of heavy disturbances, which is relatively frequent in Italy as well as in most other European and North American countries (FRA 2010). In contrast, the forest NPP which can be derived from tree increments is completely related to the accumulation of woody biomass, which is obviously limited in case of low tree density. This can give rise to a substantial uncoupling between forest GPP and NPP, which can be further complicated by the effects of variable tree aging and stand development phases (Gower et al. 1996; Song and Woodcock 2003). These factors, which are also influenced by the mentioned disturbances, affect the respiration and allocation patterns of forest ecosystems and alter the relationship between GPP and NPP (Thornton et al. 2002; Van Tuyl et al. 2005; Petritsch et al. 2007; Bergeron et al. 2008; Chiesi et al. 2012).

To address this issue, Maselli et al. (2009a) introduced the concept of ecosystem distance from the quasi-equilibrium condition (sensu Odum 1971), which is aimed at describing the actual status of forests consequent on biomass reduction. Such conditions are simulated by the use of BIOME-BGC and are then converted into the conditions of real ecosystems through a proxy variable given by the ratio of real over potential tree volumes. The approach is generally applicable on a regional scale, with implications and limitations which are fully discussed in the same paper.

The current investigation aims at testing the applicability of this approach to assess forest NPP on a national scale in Italy. In particular, the modeling approach is applied over the Italian territory at the spatial resolution of 1 km^2 using consistent spatially distributed input data layers (terrain morphology, meteorology, forest type and growing stock, etc.). The NPP estimates obtained are first analyzed in order to assess the importance of the main model drivers on relevant spatial variability. These estimates, aggregated over seven main forest types and twenty administrative regions, are then converted into current annual increment of standing wood volume (CAI) by the use of BEFs and validated through comparison with INFC data.

The paper is organized as follows. The main features of Italian forests are first described together with those of the ground and remote sensing data utilized. The modeling strategy is then introduced, followed by the main steps used for applying it on the national territory, performing a sensitivity analysis and validating the NPP estimates against INFC increment data. Next, the results are described and discussed, with distinctive reference to the examination of the main sources of uncertainty in the evaluation of NPP. The paper is concluded by a section which highlights the potential contribution of the approach for the assessment of forest carbon budget on a national scale.

Study area and data

Main features of Italian forests

Italy is geographically situated between 36° and 47°30′ north latitude and between 5°30′ and 18°30′ east longitude. Its orography is complex due to the presence of two main mountain chains, the Alps in the north and the Apennines in the centre south. Italian climate is also very variable following the latitudinal and altitudinal gradients and the distance from the sea. In general, it ranges from Mediterranean warm to temperate cool. The country is administratively divided into 20 regions (Fig. 1).

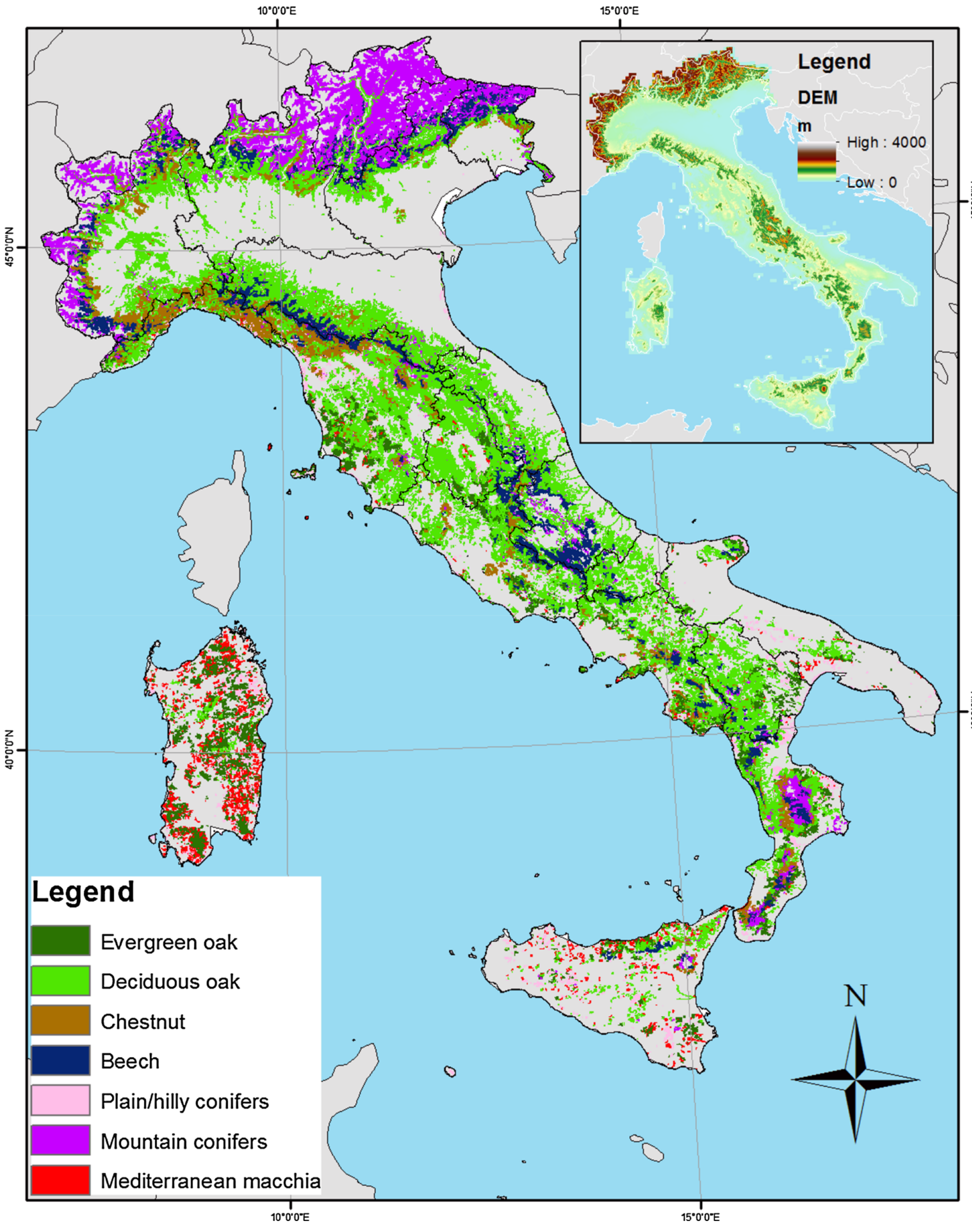

Fig. 1 Distribution of the seven forest types listed in Table 1 as derived from the CORINE Land Cover 2006 map of Italy with superimposed boundaries of the twenty administrative regions in Italy. The *upper-right window* shows the DEM of Italy

According to the CORINE Land Cover 2006 map (ISPRA 2010), forest land (including bushland) covers nearly 92,000 km^2 in Italy. INFC (see www.infc.it), whose data are based on the FAO (2010) forest definition, reports a total extent of forest areas equal to 87,600 km^2. Thirty-two percent of the forest formations is included in the Alpine biogeographical region, 16 % in the Continental region and 52 % in the Mediterranean region (sensu Habitat Directive of the European Commission 43/92). According to INFC, the most widespread forest formations are dominated by various oak species (*Quercus* spp.), a fourth of which is characterized by the prevalence of evergreen oaks, and beech (*Fagus sylvatica*). Large part of broadleaved forests are managed as coppices (Ciancio et al. 2006; Gasparini et al. 2009a). Among conifers, the most abundant forest formations are dominated by Norway spruce (*Picea abies*), followed by mountain pines (*Pinus sylvestris*, *P. nigra*) and Mediterranean pines (*P. halepensis*, *P. pinaster*, *P. pinea*). The main eco-climatic characteristics of these forests are summarized in Table 1, while their spatial distribution is shown in Fig. 1. Table 2 reports relevant growing stock and CAI averages drawn from INFC.

Data used

The digital elevation model (DEM) of Italy used for the current study has a pixel size of 1 km^2 and was derived

Table 1 Definition and main features of the seven forest types (FTs) considered and the corresponding CORINE cover classes

FT	Dominant forest species	CORINE class definition	Mean elevation (m)	Mean temperature (°C)	Mean rainfall (mm)
1	Evergreen oak	Holm oak	428	15.3	577
2	Deciduous oak	Mediterranean broadleaves	518	13.4	757
3	Chestnut	Chestnut	623	12.4	925
4	Beech	Beech	1,220	9.2	956
5	Plain/hilly conifers	Mediterranean pines	349	15.5	605
6	Mountain conifers	White fir/Norway spruce	1,418	6.7	894
7	Mediterranean macchia	High maquis	348	16.1	502

The main eco-climatic features of the FTs were derived from the available ancillary data (DEM, meteorological dataset, see text for details)

Table 2 Average growing stock and CAI of six forest types (FTs) obtained from the indicated sources (see text for details)

FT	Average INFC growing stock ($m^3 ha^{-1}$)	Average INFC CAI (m^3 ha^{-1} $year^{-1}$)	Average growing stock from Maselli et al. (2014) (m^3 ha^{-1})	Average CAI from current simulation (m^3 ha^{-1} $year^{-1}$)
1	72	2.44	78	2.3
2	97	2.86	123	4.9
3	176	6.48	225	10.3
4	231	5.19	256	6.8
5	131	3.57	111	2.1
6	379	7.69	386	9.1

from the EU-DEM dataset carried within the framework of the Global Monitoring for Environment and Security (GMES) project (more info at http://www.eea.europa.eu/data-and-maps/data/eu-dem). This DEM is projected in the UTM-32 North reference system, which is taken as a standard for the processing of all other information layers.

Basic daily weather variables (minimum and maximum temperature and precipitation) for the Italian national territory were derived from the E-OBS dataset (Haylock et al. 2008; van den Besselaar et al. 2011). This is a dataset designed for use in a wide range of applications, which has a grid spacing of 0.25° and a time-period coverage from 1950 to present. The dataset has been recently downscaled to 1-km resolution by the use of a DEM (Maselli et al. 2012). The same study shows that the accuracy of the downscaled dataset is high for daily temperatures (particularly maximum), and lower for rainfall. In the current case, daily data of 8 years were considered (from 1999 to 2006), which approximately corresponded to the period immediately preceding and contemporaneous to that of INFC data collection (from 2003 to 2006, see below).

A forest-type map was derived from the CORINE Land Cover 2006 map of Italy (ISPRA 2010). The original CORINE dataset of Europe classifies forests at 1:1,00,000 scale (minimum mapping size of 25 ha) in three general classes: broadleaved, coniferous and mixed (EEA 2002). The available forest map instead classifies forests and other wooded lands in 26 types on the basis of the dominant tree species, maintaining the geometric and thematic congruency with the original CORINE dataset. The forest map of Italy was produced by manual photointerpretation of Landsat imagery supported by several ancillary information (ISPRA 2010). In a previous work (Maselli et al. 2006), the original vector dataset was rasterized at the available DEM resolution (1 km^2) grouping the original classes into twelve main forest types (FTs). Among these forest types, the seven, which are most widespread and representative over the Italian territory, were selected in conformity with what already done by Chiesi et al. (2007) for Tuscany (Central Italy).

A 1-km map of forest growing stock has been recently produced for the Italian national territory through the combination of ground and satellite data (Maselli et al. 2014). More particularly, growing stock data from regional inventories have been combined with optical and LiDAR imagery acquired from satellite platforms to yield the map shown in Fig. 2. The reliability of this map, assessed at regional scale through comparison with INFC data, is decidedly high (root mean square error, RMSE = 48 m^3 ha^{-1}; mean bias error, MBE = 11 m^3 ha^{-1}).

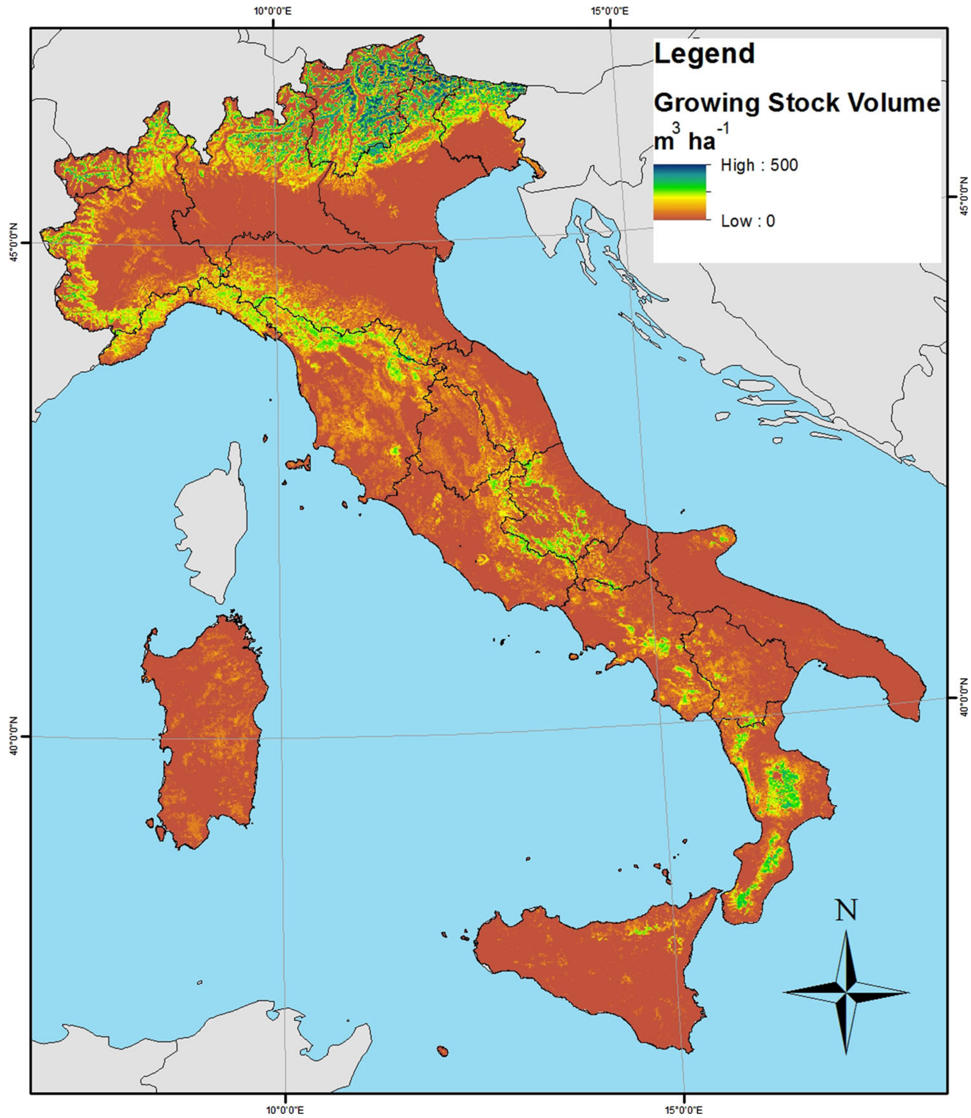

Fig. 2 Map of growing stock produced by the combination of regional inventory and satellite data (see Maselli et al. 2014 for details)

Normalized difference vegetation index (NDVI) images taken by the Spot-Vegetation (VGT) sensor were obtained from the archive of VITO (http://free.vgt.vito.be), which freely distributes preprocessed 10-day maximum value composite (MVC) images for the entire globe since April 1998. The applied preprocessing steps comprise the radiometric calibration of the original channels and their geometric and atmospheric corrections (Maisongrande et al. 2004). The final product of these steps is 10-day NDVI MVC images having a pixel size of about 1 km^2. All 10-day images of Europe were downloaded for the same period mentioned above (January 1999–December 2006). From these images, a window over Italy was selected, preprocessed as described in Maselli et al. (2006) and further composited over monthly periods (e.g., Fig. 3).

The assessment of the model outputs was based on reference forest data derived from the standing volumes and the CAIs measured by the INFC (Gasparini et al. 2009a, b). This inventory comprised a three-phase sampling (Fattorini et al. 2006). The first two phases were aimed at estimating the forest area and its distribution into different classes according to qualitative attributes (e.g., ownership, management issues, vegetation structure and conditions, site features). The third phase was aimed at collecting quantitative measurements of tree and stand attributes by means of ground surveys carried out on about 7,000 plots. During this last phase, which was carried out from 2003 to 2006, several forest variables (tree stem diameter, tree height, tree stem diameter increment, etc.) were collected on a plot basis. Statistics from these mea-

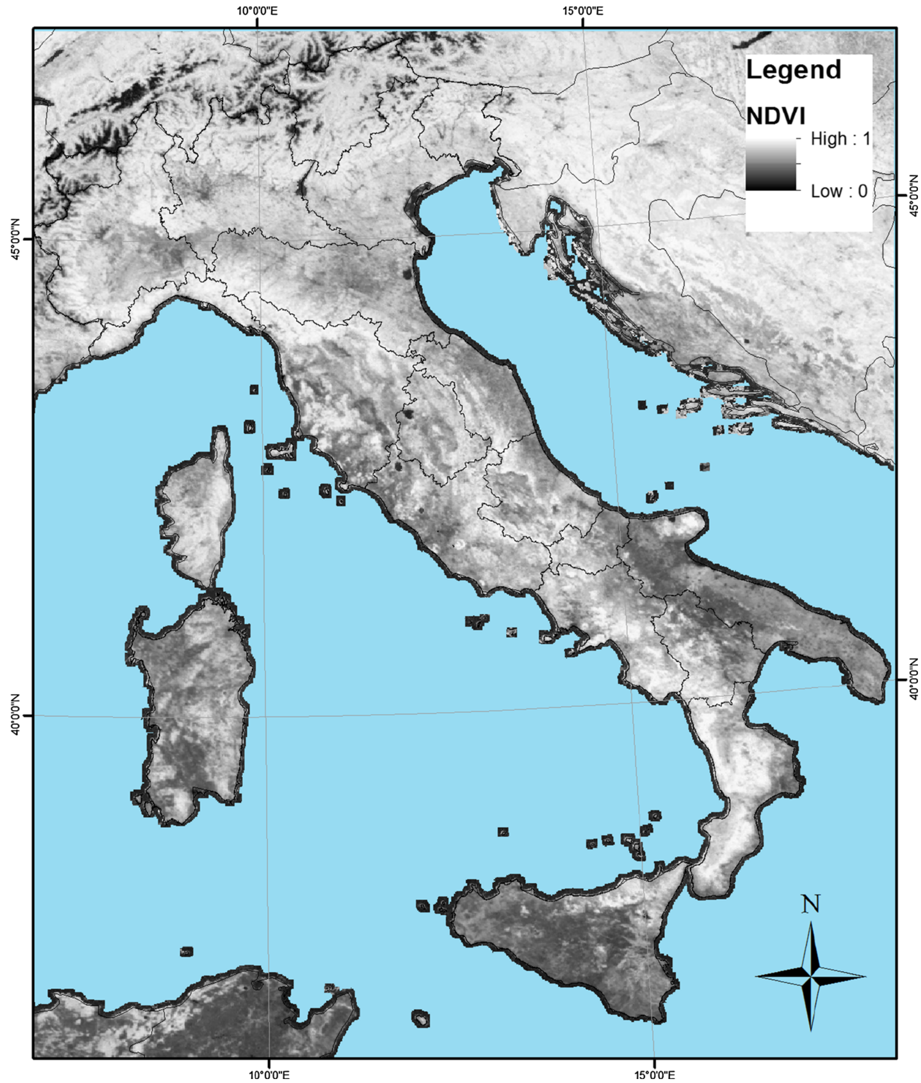

Fig. 3 Spot-VGT NDVI image of August 2006, corrected as described in Maselli et al. (2006)

surements are provided only in an aggregated form for all Italian administrative regions. For more information and for accessing online to the full-descriptive statistics produced by the Italian NFI, we refer to www.infc.it.

Modeling strategy

Modified C-Fix

C-Fix is a Monteith-type parametric model driven by temperature, radiation and the fraction of absorbed photosynthetically active radiation (fAPAR), quantified through its generalized relationship with the NDVI (Veroustraete et al. 2002, 2004). NDVI, which is mathematically defined as NDVI = [NIR − R]/[NIR + R] where NIR stands for near-infrared reflectance (0.7–1.1 µm wavelength) and R stands for red reflectance (0.6–0.7 µm wavelength), is an indicator of plant photosynthetic activity, and particularly of fAPAR (Baret and Guyot 1991; Bannari et al. 1995).

C-Fix combines NDVI-derived fAPAR with field-based estimates of incoming solar radiation and air temperature in order to simulate total photosynthesis (Veroustraete et al. 2004). The model is conceptually simple and generally applicable, and can use inputs averaged over different time periods (most commonly 10 days to monthly). Maselli et al. (2009b) proposed a modification of C-Fix aimed at improving the model performance in Mediterranean areas, which are characterized by a long summer dry season during which vegetation growth is limited by water availability (Bolle et al. 2006). Modified C-Fix includes an additional water stress factor, Cws, that is obtained from a simplified site water balance and limits photosynthesis in case of short-term water stress. Accordingly, the annual GPP (g C m^{-2} $year^{-1}$) of a forest ecosystem can be computed as:

$$\mathrm{GPP} = \varepsilon \sum_{i=1}^{12} T_{\mathrm{cor}i} \mathrm{Cws}_i \mathrm{fAPAR}_i \mathrm{Rad}_i \quad (1)$$

where ε is the radiation use efficiency, $T_{\mathrm{cor}\ i}$ is a factor accounting for the dependence of photosynthesis on air temperature, Cws_i is the water stress factor, fAPAR_i is the fraction of absorbed PAR, and Rad_i is the solar incident PAR, all referred to month i. In the current case, ε is equal to 1.2 g C MJ^{-1} APAR (Maselli et al. 2010), T_{cor} is the MODIS temperature correction factor (Heinsch et al. 2003), Cws is computed as the ratio between precipitation and potential evapo-transpiration as described in Maselli et al. (2009b), and fAPAR is derived from the top of canopy NDVI according to the linear equation proposed by Myneni and Williams (1994).

BIOME-BGC

BIOME-BGC is a biogeochemical model developed at the University of Montana to estimate the storage and fluxes of water, carbon and nitrogen within all terrestrial ecosystems (Running and Hunt 1993). It requires daily climate data, information on the general environment (i.e., soil, vegetation and site conditions) and parameters describing the eco-physiological characteristics of vegetation. The model uses a "big-leaf" approach, meaning that vegetation canopy is treated as a unique transpiring and photosynthesizing entity which is characterized by its leaf area index (LAI) (Running and Hunt 1993). BIOME-BGC is capable of finding a quasi-climax equilibrium with local eco-climatic conditions through the spin-up phase, whose aim is to quantify the initial amount of all carbon and nitrogen pools; after that, it proceeds with a normal simulation which estimates all respiration and allocation processes corresponding to the requested study years (White et al. 2000; Churkina et al. 2003).

The modeling of quasi-climax condition has important consequences on the simulated carbon budget. The sum of all simulated respirations becomes in fact nearly equivalent to GPP, which makes that annual NPP approaches heterotrophic respiration (Rh) and net ecosystem exchange (NEE) tends to zero. Also, such modeling renders the obtained GPP estimates similar to those produced by C-Fix, which are descriptive of all the ecosystem components (Maselli et al. 2009a).

The version of the model currently used (BIOME-BGC 4.2) includes complete parameter settings for six main biome types (White et al. 2000). Previous methodological works concerned the modification of these settings to adapt to Mediterranean ecosystems, which show eco-climatic features markedly different from those for which the model was originally developed (see Chiesi et al. 2007; Maselli et al. 2009a). In particular, the vegetation parameters of BIOME-BGC were calibrated for the seven FTs of Table 1 by the use of GPP estimates derived from C-Fix. The calibration consisted of slightly modifying the BIOME-BGC eco-physiological parameters related to stomata conductance, which control all the main transpiration and production processes (Chiesi et al. 2010).

Correction for actual forest conditions

The strategy proposed by Maselli et al. (2009a) to address the mentioned uncoupling between ecosystem GPP and woody NPP is based on the integration of the outputs of C-Fix with those of BIOME-BGC. The respiration and allocation estimates obtained in the previous steps must in fact be transformed into estimates of real forest ecosystems, which are generally far from equilibrium conditions due to the occurred disturbances. The modeling strategy considers the ratio between actual and potential stem volume (or growing stock) as an indicator of ecosystem proximity to climax. This ratio can therefore be used to correct the photosynthesis and respiration estimates obtained by the previous model simulations. According to this strategy, actual forest NPP, $\mathrm{NPP_A}$, is approximated as:

$$\mathrm{NPP_A} = \mathrm{GPP} \cdot \mathrm{FC_A} - R_{\mathrm{gr}} \cdot \mathrm{FC_A} - R_{\mathrm{mn}} \cdot \mathrm{NV_A} \quad (2)$$

where GPP, R_{gr}, and R_{mn} correspond to the GPP, growth and maintenance respirations estimated by BIOME-BGC, and the two terms $\mathrm{FC_A}$ (actual forest cover) and $\mathrm{NV_A}$ (actual normalized volume) describe the ecosystem proximity to equilibrium conditions (Maselli et al. 2009a). In particular, $\mathrm{NV_A}$ is the ratio between actual (measured or estimated) and potential (simulated by BIOME-BGC) growing stock, and $\mathrm{FC_A}$ represents the fraction of forest canopy cover, which is obtained by combining $\mathrm{NV_A}$ and BIOME-BGC maximum LAI following Beer's law. In this way, net carbon flux predictions change nonlinearly as the ecosystem approaches equilibrium conditions.

Due to the previously described functional equivalence of C-Fix and BIOME-BGC GPP estimates, the outputs from the two models can be combined by multiplying BIOME-BGC photosynthesis and respiration estimates for a ratio between C-Fix and BIOME-BGC GPP (Maselli et al. 2008). A detailed description of the entire strategy is reported in Maselli et al. (2009a), along with all the assumptions and the approximations for its application.

Data processing

Application of the modeling strategy

The described modeling strategy was applied to all Italian forests over the 8 study years at spatial and temporal scales, which represent a novelty with respect to previous investigations (Maselli et al. 2009a, 2010). In those cases, in fact, the strategy was applied on aggregated spatial and/or temporal scales, while in the current simulation all model runs were carried out at 1-km-pixel resolution and daily time step.

First, Modified C-Fix was driven by the downscaled E-OBS dataset and the Spot-VGT imagery. To this aim, daily solar radiation was derived from 1-km temperature and rainfall estimates by the use of MT-CLIM (Thornton et al. 2000); it was then converted into PAR applying a coefficient equal to 0.464 (Iqbal 1983). The CORINE land cover map reclassified into seven main forest types was transformed into relevant abundance images. Using these images, monthly spatially variable multi-temporal NDVI profiles of each forest type were then extracted from the Spot-VGT MVC imagery using the methodology of Maselli (2001). This methodology is capable of estimating spatially variable NDVI end-members of pure classes relying on the higher spatial resolution land cover map. The monthly NDVI values of the seven FTs were linearly interpolated on a daily basis and recombined with the meteorological data through Eq. (1) to predict the GPP for each FT. The recombination of these estimates with the CORINE abundance images yielded corresponding GPP maps for the entire Italian territory.

Next, BIOME-BGC was fed with the same meteorological dataset and CORINE map, using the parameter settings identified as optimum for each FT. Daily estimates of GPP and respirations were thus obtained, together with annual values of stem carbon and LAI. All these data were aggregated on an annual basis, averaged over the whole study period and combined through Eq. (2) with the actual per-pixel growing stock estimates derived from the available map in order to produce a mean forest NPP map.

Sensitivity analysis and accuracy assessment

A sensitivity analysis was first conducted to quantify the importance of the main model drivers in determining the spatial variability of the obtained NPP estimates on the national territory. This was carried out by computing the percentage of spatial NPP variance explained by each main model driver, i.e., mean annual temperature, mean annual rainfall, mean annual NDVI, forest type and growing stock. The same analysis was repeated considering separately broadleaved (i.e., FT1, FT2, FT3, FT4 and FT7) and coniferous (i.e., FT5 and FT6) forests. Next, attention was focused on the most important model driver, investigating the spatial variability of its influence on NPP by means of spatially (or geographically) weighted variance analysis (Brunsdon et al. 1996; Maselli 2002).

The accuracy assessment was carried out using the regional INFC data. Specifically, regional mean values were extracted from the NPP map produced by the modeling strategy for the seven forest types considering the administrative regions where the presence of each forest type was significant (at least 10 1-km^2 pixels). These values were transformed into CAI estimates through the formula:

$$\mathrm{CAI} = \mathrm{NPP_A} * \mathrm{SCA}/\mathrm{BEF}/\mathrm{BWD} * 2 * 100 \qquad (3)$$

where SCA is the Stem C allocation ratio, BEF is the volume of aboveground biomass/standing volume biomass expansion factor (both dimensionless), and BWD is the basic wood density (Mg m^{-3}). The SCAs of the seven forest types are those of BIOME-BGC, while BEFs and BWDs are taken from Federici et al. (2008) and Maselli et al. (2010). The multiplication by two accounts for the transformation from carbon to dry matter, and multiplication by 100 for the change in magnitude from g m^{-2} to Mg ha^{-1}. The modeled CAI values were finally validated versus the INFC CAIs. The accuracy assessment was summarized using the coefficient of determination (r^2), the RMSE and the MBE.

Results

The seven FTs considered are mostly distributed over hilly and mountain zones (Table 1; Fig. 1). The climatic features of these zones range from Mediterranean dry (FT7, FT1 and FT5) to Mediterranean temperate (FT2 and FT3) and temperate humid (FT4 and FT6) following both latitudinal and altitudinal gradients. Broadleaved species are found along the whole climatic range (from FT7 to FT4), while conifers are mostly found in the driest (FT5) and wettest (FT6) areas. Mean growing stocks derived from both INFC and the map of Maselli et al. (2014) generally follow the main eco-climatic gradient, increasing from the driest to the most humid ecosystems (Table 2; Fig. 2). The same gradient is followed by INFC CAI averages (Table 2).

The mean annual forest GPP simulated over the study period mostly ranges from 700 to 1800 g C m^{-2}year^{-1}. In general, Mediterranean forest types (FT1 among broadleaved, and FT5 among needleleaves) show the highest GPP levels. These forests grow in temperate areas, and their photosynthetic activity is limited mainly by water availability during the dry season. Mountain ecosystems (FT4 and FT6), which are limited by the thermal factor during most of the year, show the lowest GPP levels. Overall, the prevalence of thermal limitation determines decreasing trends of GPP from Southern, plain areas to northern mountain zones, following the main latitudinal and altitudinal gradients. These trends are complicated by the previously mentioned occurrence of summer water stress in the most arid areas of central-southern Italy.

The NPP map produced by the modeling strategy is shown in Fig. 4. NPP follows both GPP gradients and the distribution of growing stock. NPP, in fact, generally follows growing stock variability with two exceptions: Forest production decreases on the upper mountain zones (over 1,500 m, mainly on the Alps and, secondarily, on the Central Apennines) due to thermal limitation and, less evidently, in southern Italy (particularly in the two main islands, Sicily and Sardinia) due to water stress. The highest NPP values (around 800–900 g C m^{-2} $year^{-1}$) are therefore reached at intermediate altitudes on the Alps and Apennines.

The results of the sensitivity analysis are summarized in Fig. 5. Out of the meteorological factors, mean temperature and rainfall explain a similar percentage of NPP variance (around 45 %). A lower percentage of NPP variance is explained by NDVI (9 %), which drives only C-Fix functioning. Forest type determines almost 50 % of NPP variance. Growing stock is by far the most influential model driver, explaining over 60 % of NPP variance. The sum of all explained variances is obviously higher than 100 %, due to the strong intercorrelations among the drivers, which all follow the previously mentioned main eco-climatic gradients related to latitude and altitude. When considering separately broadleaved and coniferous forests, the importance of mean temperature is higher for the latter, while the opposite is true for rainfall. The influence of NDVI is quite low and slightly higher for conifers, while that of FT and, above all, growing stock is much higher for broadleaves.

Following these results, spatially weighted variance analysis was focused on growing stock; the spatial variability of this analysis was regulated by means of a

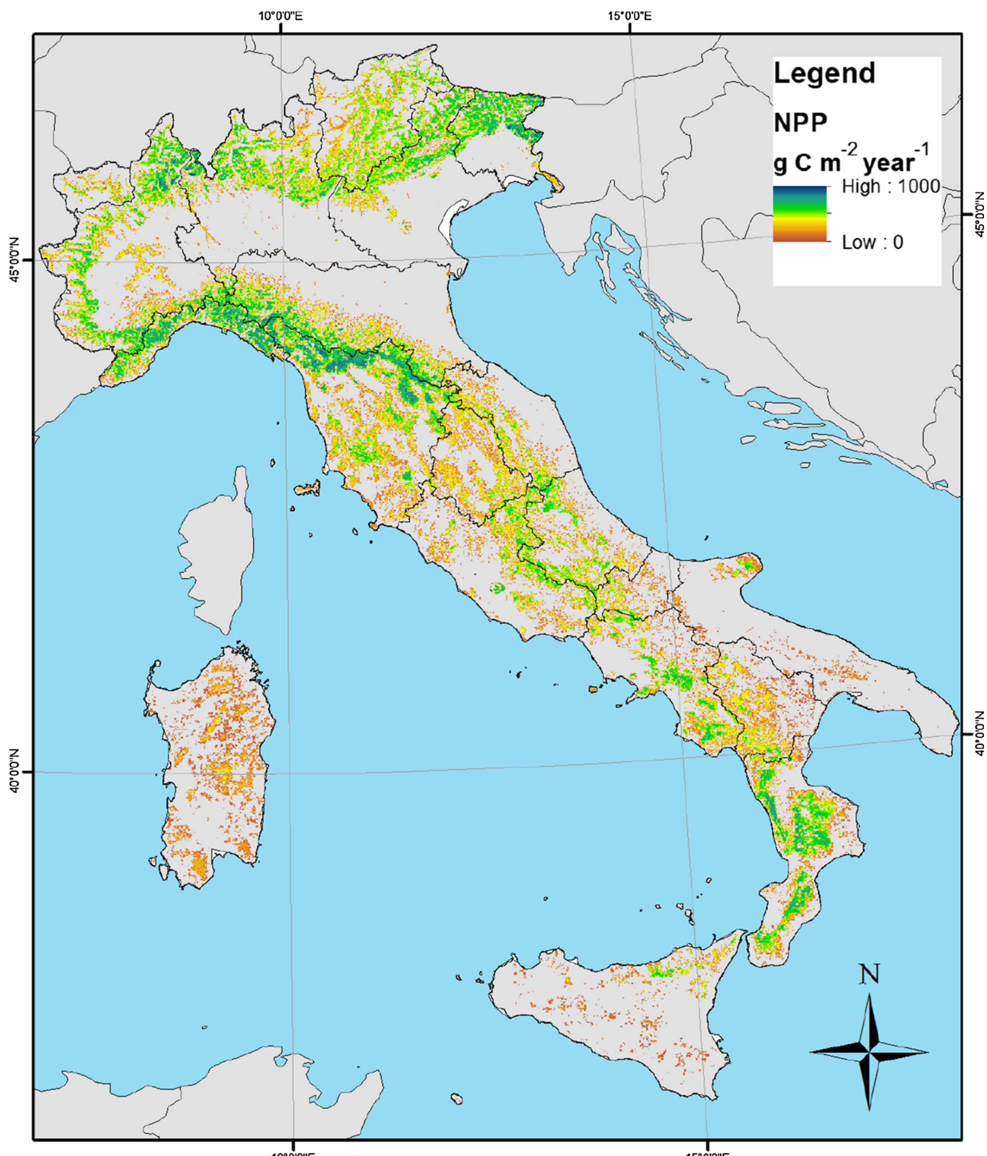

Fig. 4 Map of mean annual forest NPP computed by the modeling strategy here proposed over the period 1999–2006

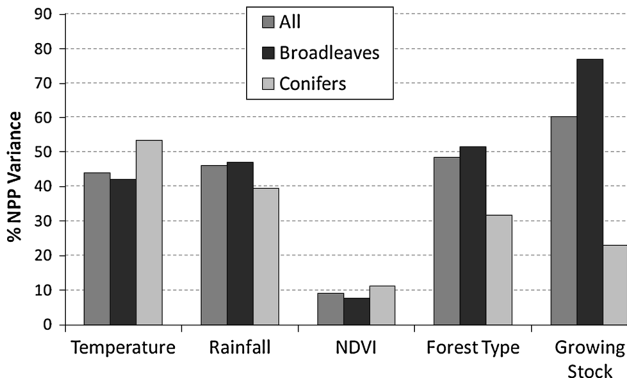

Fig. 5 Results of the sensitivity analysis; percentage of NPP variance explained by the main model drivers over the entire Italian national territory for all, broadleaved and coniferous species

negative exponential weighting function having a distance range of 33 km. The resulting spatially weighted percentage of NPP variance explained by growing stock is shown in Fig. 6. This variance is very high over most of the Italian territory, with major reductions on the highest Alpine mountains and, to a lower degree, the Central Apennines. Minor reductions in NPP variance are found in Sicily and Sardinia.

The comparisons between measured (INFC) and modeled CAI values yield the results summarized in Table 3 and in Fig. 7. The reported accuracy statistics are computed for reduced numbers of points due to the absence, or marginal presence, of some forest types in some regions. The overall accuracy for each forest type is from low to moderate, with significant overestimation for FT2, FT4 and, above all, FT3. As regards the global comparison of Fig. 7, the agreement between the two data series is good both in terms of correlation and errors, with a moderate tendency to overestimation which mostly derives from similar errors found for the three deciduous broadleaf forest types.

Discussion

The application of Modified C-Fix and BIOME-BGC on a national scale relies on the consolidated capacity of these models to correctly predict the annual GPP of Mediterranean forests at 1-km^2 spatial resolution (Maselli et al. 2009a). Distinctively, Modified C-Fix, being driven by a direct estimate of fAPAR, is usually more accurate than BIOME-BGC and less sensitive to possible errors in the conventional model drivers (meteorological data, site information, etc.) (Maselli et al. 2009b). In contrast, the latter biogeochemical model allows a complete simulation of all main forest processes (photosynthesis, respirations, allocations, etc.). Combining the outputs of the two models therefore permits the optimal exploitation of the respective potentials (Turner et al. 2004).

The ability of the two models to predict the main forest processes is not sufficient to guarantee the correct estimation of NPP, due to the complexity of the relationships which link total ecosystem production to woody biomass accumulation. Both forest GPP and NPP predicted by Monteith's approaches and those simulated by BIOME-BGC are, in fact, descriptive of fully stocked, quasi-equilibrium forest ecosystems (Maselli et al. 2009a; Hasenauer et al. 2012). In reality, this NPP can be significantly reduced by various kinds of forest disturbances (e.g., thinning and cutting operations, wildfires), which limit the woody biomass that actually grows. This situation prevents the application of simple estimation methods which consider woody NPP as a constant ratio of GPP (Waring et al. 1998). In the current case, the constant ratio approach provides CAI estimates which are almost two times higher than those from INFC (data not shown). A similar overestimation is obtained when directly using the NPP/GPP fractions simulated by BIOME-BGC, which are still descriptive of forest ecosystems at equilibrium conditions.

The modeling strategy of Maselli et al. (2009a) was specifically developed to account for the effects of intense forest disturbances. The current application of this strategy yields regional CAI estimates which are globally in good agreement with the INFC estimates, but are still higher than those. Part of this discrepancy is due to the intrinsic and mostly unavoidable inaccuracy of the modeling approach applied and of the data layers used. Among these, the meteorological drivers affect the functions of both basic models used; as a consequence, the modeling approach is similarly sensitive to temperature and precipitation. Temperature is more influential on coniferous species, which are almost all evergreen, and the opposite is true for rainfall. These last patterns can be explained considering the greater role exerted by water limitation for deciduous species (Turner et al. 2004), which in our case correspond mostly to broadleaves.

The sensitivity of NPP to NDVI is quite low and slightly higher for coniferous species, which are prevalently distributed on the highest Alpine zones where vegetation phenology is constrained by the thermal factor. This C-Fix driver, in fact, is important to determine the temporal GPP evolution of forest ecosystems and, additionally, stabilize relevant model functions. In particular, the results obtained by Chiesi et al. (2007) indicate that the integration of C-Fix and BIOME-BGC outputs notably reduces the negative effects of inaccurate ground data thanks to the information provided by NDVI-derived fAPAR estimates. The accuracy of the currently used NDVI dataset is enhanced by the extraction method applied, which is effective in reducing local errors and noise (Maselli 2002).

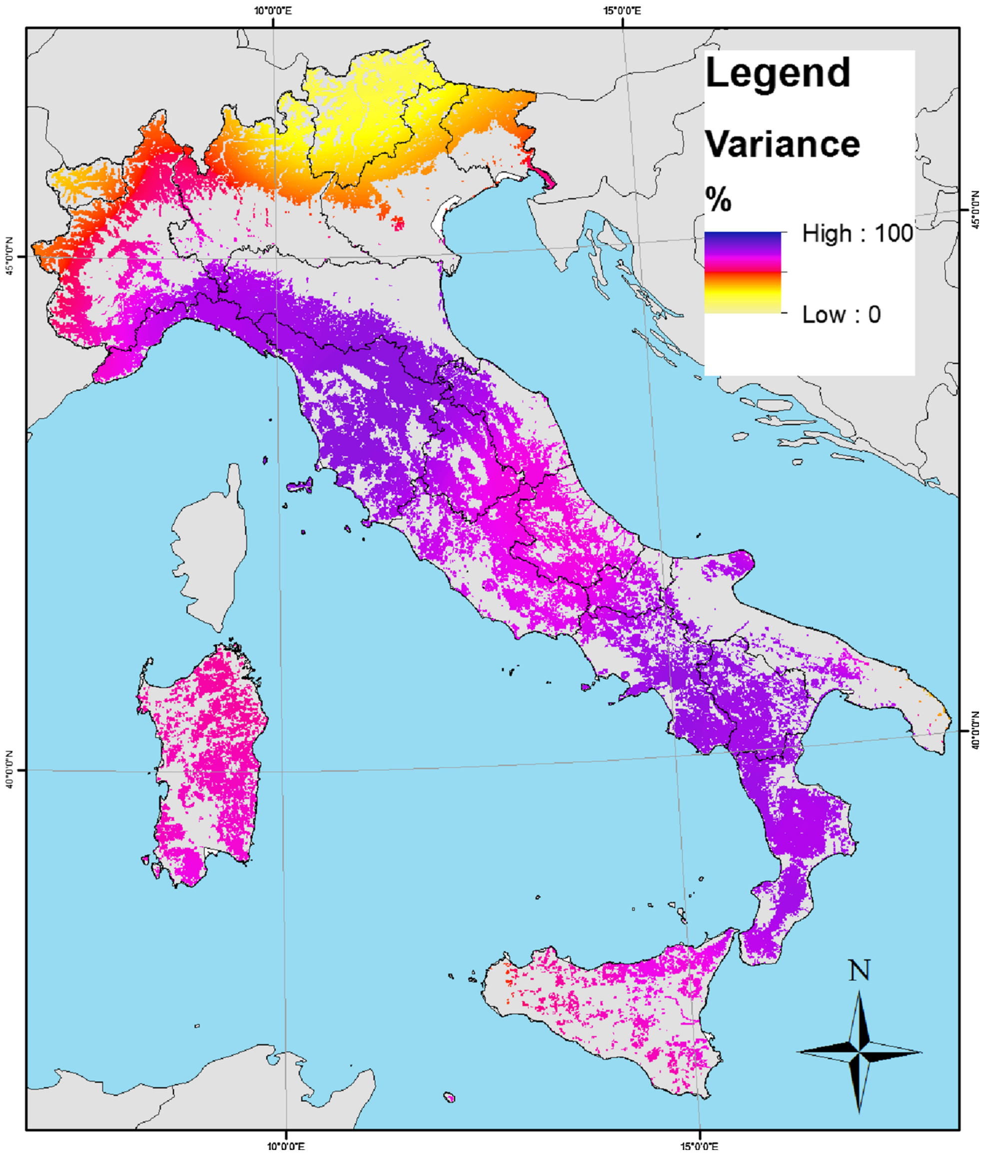

Fig. 6 Spatially weighted percentage of NPP variance explained by growing stock over the entire Italian national territory (see text for details)

Table 3 Accuracy of CAI estimates obtained by the modeling strategy here proposed versus the regional estimates reported by INFC

FT	No. regions	r	RMSE ($m^3\ ha^{-1}$)	MBE ($m^3\ ha^{-1}$)
1	9	0.470	0.57	−0.11
2	15	0.469	2.08	2.11
3	10	0.156	4.04	3.85
4	17	0.560*	1.75	1.47
5	8	0.665	1.62	−1.31
6	8	0.813*	1.83	0.91

* Significant correlation, $P < 0.05$

In addition to meteorological and remotely sensed data, the current modeling of forest NPP and CAI utilizes spatially distributed estimates of FT and growing stock. FT determines all BIOME-BGC eco-physiological parameters and is therefore important in differentiating the relevant processes (i.e., photosynthesis, respirations, allocations). These processes mostly differ between evergreen and deciduous forests, which are both present among broadleaves. This explains the highest importance of FT for this functional group. The FT estimates currently used are derived from the CORINE land cover map of Italy, which is surely accurate at the considered spatial scale but could be replaced by any other information layer descriptive of forest cover.

Growing stock is the main driver of the whole modeling approach, due to the importance of initial carbon pools in determining woody biomass accumulation (Turner et al. 2004, Maselli et al. 2009a). This is particularly the case for broadleaved forests, while the impact of growing stock is

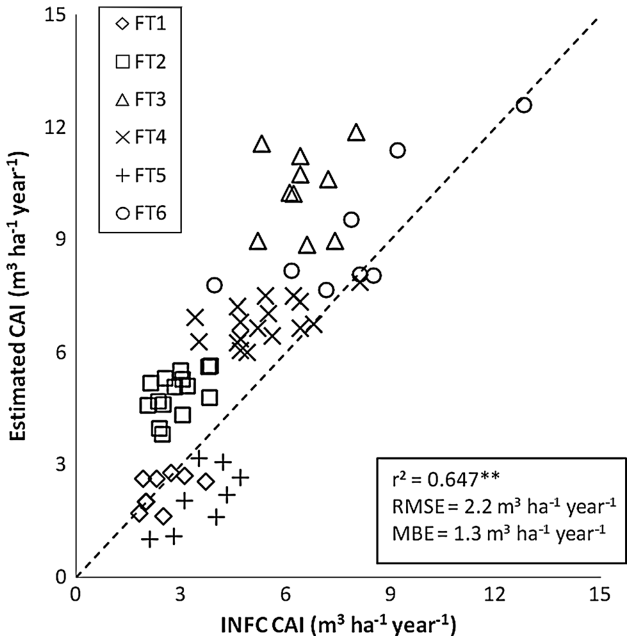

Fig. 7 Comparison between the regional estimates of CAI provided by INFC and those estimated by the modeling strategy here proposed (n = 67, **highly significant correlation, $P < 0.01$)

minor for conifers. Such behavior can be attributed to the contrasting effects of thermal and water limitations on coniferous forests, which are widespread in both coldest (highest) and driest (most southern) areas. This is confirmed by the spatially weighted variance analysis, which shows that major minima of growing stock influence on NPP exist in the highest Alpine and, to a lesser degree, Apennine zones. These minima are evidently due to the thermal limitation of forest growth, which weakens the positive relationship between woody biomass and NPP. Similarly, secondary minima of growing stock influence are found in the most southern, driest regions, where the same relationship is constrained by water stress. The map of growing stock produced by Maselli et al. (2014) represents an improvement with respect to previous Pan-European products (e.g., Gallaun et al. 2010), but still shows minor systematic errors for some FTs: the growing stock of FT5 is, in fact, underestimated, while that of all other FTs is variably overestimated. This is directly reflected on the CAI values obtained by the current method, which are similarly overestimated or underestimated (Table 2), confirming the relevance of growing stock as model driver.

The general CAI overestimation currently found is similar to that obtained by Maselli et al. (2010) and is likely related not only to the modeling approach applied but also to the reference data used. The disagreement between measured and estimated CAI values, in fact, could be affected by the measurement protocol applied in the collection of the ground data. According to that protocol, not all the field plots where conventional forest attributes are measured (number of trees, basal area, standing volume, etc.) are surveyed to derive the increment statistics, due to the complexity which is inherent in the collection and analysis of tree cores (Gasparini et al. 2009a). For the same reason, within each selected plot the cores are taken only from a limited number of tree stems (from four to ten), which mostly coincide with the biggest (oldest) plants. The mean relative CAI of these trees (i.e., CAI/growing stock) is then extrapolated to predict the total growing stock of the plot. Since relative CAI generally tends to decrease with tree size (age), such a procedure likely brings to CAI underestimation. This hypothesis is supported by Marziliano et al. (2012), who have theoretically stressed that the INFC protocol applied for estimating increments invariably leads to underestimation in the case of mature even-aged stands.

Simulation analyses carried out using growing stock and CAI data taken in various study sites (Chiesi et al. 2012, 2014) indicate that within-plot tree heterogeneity can reduce the CAI determined through the INFC protocol particularly for coppice forests, where few dominant plants are intermingled with many smaller trees. Such a hypothesis is supported by further statistical analysis of the data shown in Fig. 7, whose results are summarized in Table 4. In spite of the notable CAI overestimation (MBE = 1.3 m^3 ha^{-1} $year^{-1}$), the intercept and slope of the regression equation defined considering all data points are not significantly different from 0 and 1, respectively. The same is the case considering only points of species which are

Table 4 Statistics obtained by linearly regressing the CAI estimated by the modeling strategy here proposed (dependent variable) on INFC CAI estimates (independent variable)

Data points considered (number)	r	Intercept (m^3 ha^{-1} $year^{-1}$)	Slope (dimensionless)
All species (67)	0.804**	0.90	1.10
High forest species (25)	0.916**	−0.72	1.12
Coppice species (42)	0.797**	2.21**	1.01

First, all data points of Fig. 5 are considered; next, these points are split into species which are managed as high forest and species which are prevalently managed as coppice

** Correlation and intercept significantly different from 0, $P < 0.01$

managed as high forests, for which CAI is marginally underestimated (MBE = -0.2 m^3 ha^{-1} year^{-1}). In contrast, a notable overestimation (MBE = 2.2 m^3 ha^{-1} year^{-1}) and an intercept significantly higher than 0 (2.2 m^3 ha^{-1} year^{-1}, $P < 0.01$) are obtained when considering only points of species mostly managed as coppice. This indicates that the modeling strategy here proposed overestimates CAI, with respect to the INFC estimates, mostly for these forests, where intra-plot tree size heterogeneity is usually maximum. Such an explanation is in agreement with Maselli et al. (2010), who has evidenced that the CAI statistics of the forest inventory carried out by the Tuscany regional administration are consistently higher than the corresponding values provided by INFC for the same region.

All these considerations confirm the existence of the problematic framework mentioned in the introduction. As a matter of fact, the disagreements from the various inventories as well as the overestimation of our modeling approach with respect to INFC data are likely originated by a number of causes. In addition to the mentioned application of different data collection and elaboration protocols, a major problem could be finally related to the use of different definitions of forest area and forest classes (Tosi and Monteccone 2004). This is a well-known source of uncertainty in the collection of forest statistics, since categorical definitions are generally variable depending on the context and objectives of the inventory (Vidal et al. 2009). Indeed, the need for harmonizing forest inventory protocols is a current topic issue (McRoberts et al. 2009).

Conclusions

The modeling strategy applied was specifically developed to account for the state of forests which are kept far from equilibrium conditions by a long and intense disturbance history. The application of this strategy requires, in addition to the data needed to feed the two basic models (Modified C-Fix and BIOME-BGC), spatially extended estimates of forest standing volume, which were presently derived from a recent data integration effort. All data layers currently used are obviously affected by errors and uncertainty, which negatively influence the final accuracy of the model outputs. Moreover, the analysis conducted by Maselli et al. (2010) indicated that also the reference CAI measurements are affected by intrinsic uncertainty.

As a consequence, the CAI values obtained by the modeling approach are only in moderate agreement with INFC data and show a tendency to overestimation which is more evident for forest stands managed as coppices. This tendency can be attributed to both the most influential driver used, growing stock, and the protocol applied for collecting and elaborating the ground measurements. This confirms the critical nature of this subject area and can have important consequences on the regional-scale assessment of carbon accumulation in forest ecosystems. The use of estimation methods based on the integration of multisource ground and remote sensing data (Chirici et al. 2012) is proposed as a possible means to explore and, if possible, reduce such uncertainty with limited labor and cost expenses additional to those of the ground data collection and elaboration.

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