Simulation of olive grove gross primary production by the combination of ground and multi-sensor satellite data

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A B S T R A C T

We developed and tested a methodology to estimate olive (Olea europaea L.) gross primary production (GPP) combining ground and multi-sensor satellite data. An eddy-covariance station placed in an olive grove in central Italy provided carbon and water fluxes over two years (2010–2011), which were used as reference to evaluate the performance of a GPP estimation methodology based on a Monteith type model (modified C-Fix) and driven by meteorological and satellite (NDVI) data. A major issue was related to the consideration of the two main olive grove components, i.e. olive trees and inter-tree ground vegetation: this issue was addressed by the separate simulation of carbon fluxes within the two ecosystem layers, followed by their recombination. In this way the eddy covariance GPP measurements were successfully reproduced, with the exception of two periods that followed tillage operations. For these periods measured GPP could be approximated by considering synthetic NDVI values which simulated the expected response of inter-tree ground vegetation to tillages.

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1. Introduction

Olive (Olea europaea L.) is one of the most ancient cultivated fruit trees in the Mediterranean basin (Zohary and Spiegel Roy, 1975; Moriondo et al., 2008; Villalobos et al., 2012) where it plays a fundamental role by integrating agriculture, environment and landscape into a complex system. Although in recent years olive trees have been cultivated successfully in countries such as California, Australia, Argentina and South Africa (De Graaff and Eppink, 1999), olive is mainly grown in the Mediterranean area and dominates its rural landscape (Lounou and Giourga, 2003). This region includes about 700 million olive trees over 9 Mha, representing about 96% of areas cultivated worldwide (Vossen, 2007).

In addition to the agronomic and economic value, olive cultivation systems (agro-forestry stands, traditional groves and new intensive orchards) provide additional ecosystem services on local to regional scales by improving soil conservation and allowing high carbon sequestration (Sofot et al., 2005; Lounou and Giourga, 2003). Olive trees can also play a fundamental role on a global scale, given their long-term carbon storage capacity (Nieto et al., 2010). Consequently, the contribution that these ecosystems give to the global carbon cycle should not be neglected, especially considering that the Mediterranean basin is one of the regions most exposed to the risk of climate change (IPCC, 2007).

Gross primary production (GPP), defined as the overall carbon fixation rate through the process of photosynthesis, is a fundamental parameter for both local scale ecosystem monitoring and global scale carbon cycle and climate change research. Approximately, half of this amount is incorporated into new plant tissues such as leaves, roots and wood, and the other half is released back into the atmosphere through autotrophic respiration (Kotchenova et al., 2004).

The need for assessing ecosystem production over large areas has recently promoted the development of new strategies and techniques. Among these, one of the most widely applied is the Eddy Covariance method. This micrometeorological technique allows to measure turbulent fluxes (e.g. CO₂, H₂O, sensible heat) that are exchanged between vegetation canopy and the atmosphere (Baldocchi and Meyers, 1988; Stull, 1988; Baldocchi et al., 1996). Starting from the measurement of CO₂ net ecosystem exchange (NEE), a partitioning algorithm can be used to calculate GPP at ecosystem scale according to the equation: NEE = ecosystem respiration (Reco) – GPP. However, eddy covariance systems provide integrated CO₂ flux measurements over limited footprint areas, with sizes and shapes that vary with tower height, canopy physical characteristics and wind speed, and therefore do not allow observations over large areas (Osmond et al., 2004).

The lack of spatially extensive flux tower observations over large areas can be overcome through the combination of ground and
remotely sensed data. Remote sensing provides information on photosynthetic processes of plants on several spatial and temporal scales (Veroustraete et al., 2002; Prince, 1990; Kumar and Monteith, 1981). In recent years the use of remote sensing allowed systematic observations to be made of vegetation and relevant ecosystem parameters, becoming a fundamental instrument for the characterization of vegetation structure and for estimating GPP at a broad scale (Keenan et al., 2012; Xiao et al., 2010; Yang et al., 2007; Behrenfeld et al., 2001; Running, 1999). In particular, many studies have shown that tree production can be efficiently simulated by Monteith’s approach (Monteith, 1972), which combines measurements of incoming radiation and ecosystem radiation use efficiency with remotely sensed estimates of the fraction of absorbed photosynthetically active radiation (FAPAR). This approach has obtained great benefit from the recent availability of MODIS images, which presently represent the best descriptor of vegetation properties with moderate spatial resolution (250 m) and high temporal frequency (8–16 days) (Maselli et al., 2012).

The application of Monteith’s approach to estimate olive grove GPP, however, involves particular complications due to the multi-layered nature of this ecosystem type. Olive groves are composed of trees and inter-tree ground vegetation which, showing different eco-physiological constraints to the photosynthetic process, must be treated separately in the simulation of ecosystem GPP.

In the light of these considerations, the current paper aims at developing and testing a new multi-step methodology capable of estimating olive grove GPP. The major novelty of the study is the modeling of GPP within a complex multi-layer agricultural ecosystem, which is obtained by simulating separately the behavior of the two main ecosystem components (ground vegetation and olive trees). In particular, a modified version of the parametric C-Fix model, which is driven by normalized difference vegetation index (NDVI) data (Veroustraete et al., 2004; Maselli et al., 2009), was applied to simulate the GPP of these two components. The modeling performances were assessed against GPP data derived from eddy covariance measurements taken in an olive grove in South Tuscany (Follonica, Central Italy) during the period 2010–2011.

2. Study area

The study was conducted on an olive grove situated in an agricultural area near Follonica (Gr), Tuscany (Central Italy, 42°56′ N, 10°46′ E). In Tuscany olive groves cover an area of 96,828 ha with a total production of 117,482 t (http://www.istat.it/it/). Around 49,300 farmers grow olives, representing 62% of Tuscan farms. Olive trees have a strong effect on the Tuscan landscape and land use, occupying about 11% of the regional utilized agricultural area (UAA). Olive tree cultivation contributes about 95 M€ to the value of regional agricultural production, which is approximately 4% of the total value of agricultural gross domestic product (GDP) (IRPET, 2011). Olive groves are mostly situated on plains and in hilly areas. However, given the heterogeneity of climatic and soil conditions in Tuscany, the distribution of olive groves varies in each administrative province (Maselli et al., forthcoming).

The experimental site at Follonica (Fig. 1) lies about 41 m above sea level, has a regular morphology and a southerly exposure and covers an area of about 6 ha. This olive grove dates back to 1993 and contains around 1500 trees of about 4 m in height. Olive canopy cover is about 25%, and inter-tree areas are covered by several herbaceous native species (Cynodon dactylon, Trifolium campestr, Medicago polymorpha, Picris hieracioides, Geranium sp., Convolvulus arvensis, Anagallis arvensis, Calendula arvensis, Rumex acetosella, Eruca sativa, Linula viscosa, Ordeum murino, Daucus carota, Bromus sp.). Cropping management follows the typical tradition of the area, with no irrigation and superficial plowing (disc harrowing). During the study period, the site was plowed twice: the first time in late April 2010, the second in February 2011. The site was treated with inorganic fertilizer in spring 2010 and February 2011. Olive production in 2010 and 2011 was 3.1 t ha⁻¹ and 4.1 t ha⁻¹, respectively.

The soil belongs to the clay-loam textural class, with 40% silt and 38% clay. Soil texture and depth were obtained from the soil map produced by the Tuscany Region (http://sit.lamma.rete.toscana.it/websoili/). According to the classification of Thornthwaite (1948), the climate of the area can be described as mesothermic, between dry subhumid and semiarid, with the high summer temperatures and mild winters that are typical of the Mediterranean climate (Table 1). Meteorological conditions differed in the two study years as shown in Fig. 2. The first year (2010) was markedly wetter than the second (2011).
with intense rainfall events concentrated in spring (i.e. May) and late autumn (i.e. November), as is typical for the Mediterranean climate. The second year was much drier, especially in spring (42.8 mm compared to 170 mm in spring 2010). Moreover, the dry period during the first year continued for about 4 months, whilst in 2011 it lasted from April to September with only a short break in July.

3. Study data

3.1. Ancillary data

Daily temperatures and precipitation for the years 2010–2011 were derived from ancillary sensors linked to the eddy covariance station and collected at half-hour time scale. To check the data quality a double control was done by comparing these meteorological data to those collected by a close meteorological station.

Information on soil water content and soil temperature was obtained using a TDR sensor and two thermocouples. Also these data were collected at half-hour time scale. In addition, information about soil organic carbon (SOC) concentration, clay content and bulk density was obtained by field analysis.

3.2. Satellite data

The estimation of NDVI values for the two olive grove components required the combined processing of three satellite data types, which are more fully described in Maselli et al. (2012). First, several pan-sharpened color IKONOS images were downloaded from Google Earth. These images have 1 m spatial resolution, which allows the easy identification of olive trees over relatively small areas.

A Landsat ETM+ scene collected on July 12, 2002 was used to cover all Tuscany olive groves. This image was selected because it was completely free of atmospheric disturbances, such as clouds or fog. In addition, the image acquisition time coincided with maximum solar illumination, which minimized the effects of tree shadows and enhanced the spectral contrast between tree crowns and understory.

Multitemporal NDVI values of the study area were derived from MODIS images having 250 m spatial resolution and composed over 16-day time periods. All MODIS NDVI images covering Central Italy were downloaded from the USGS database (https://lpdaac.usgs.gov) for the years 2010–2011.

3.3. Eddy covariance data

Eddy covariance measurements at the study site were recorded for almost two years, from February 2010 to December 2011. The tower mast was placed 6.5 m above ground and 1.9 m above the canopy top, in the center of the olive grove, and was equipped with a Metek USA 1 triaxial sonic anemometer in conjunction with an open path infra-red CO$_2$–H$_2$O analyzer (Liric 7500) (high frequency sensors). Ancillary slow sensors included: 2 soil temperature profiles from 5 to 20 cm (thermocouples J and T types), global and net radiation (NR LITE Kipp & Zonen CMP3), air temperature and humidity (HMP45 Vaisala), rain gauge (Davis 7852). High frequency (20 Hz) data were stored on a PC, while slow frequency data were stored on a data-logger (CR10, Campbell Scientific). Fluxes of sensible heat, latent heat, momentum and CO$_2$ (Net Ecosystem Exchange, NEE) were derived at half-hourly time resolution (Aubinet et al., 2000). Density corrections were applied according to Webb et al. (1980). Data quality was assessed and quality flags created using the methods of Foken and Wichura (1996). Filtering for low turbulence conditions was applied by investigating the dependence of friction velocity ($u^*$) with night time CO$_2$ flux, and a threshold of 0.17 m s$^{-1}$ was derived. Data were then gap-filled and flux-partitioned using the methodology of Reichstein et al. (2005), whose final products are continuous datasets of NEE, GPP and ecosystem respiration ( Reco). This type of flux partitioning procedure is based on using night time turbulent flux data to constrain the temperature dependence of ecosystem respiration, and then applying such dependence on the whole dataset. GPP was then calculated as the difference between Reco and NEE.

Footprint analysis, aimed at estimating the extent of the area surrounding the tower generating the observed fluxes, was made using an analytical footprint model (Hsieh et al., 2000), calculating footprint distances as a function of wind speed and direction, atmospheric stability, measurement height and surface roughness. The footprint area, expressed as the area containing 90% of the observed flux, was computed at an average of 108 ± 16 m around the observation point, that is almost entirely contained within the olive orchard limits, extending 152 ± 26 m in the various directions (Fig. 1).

4. Data processing

As previously mentioned, the olive grove soil was covered, in addition to olive trees, by a significant proportion of inter-tree ground vegetation, which contributed to total olive grove GPP. Since the two components showed different eco-physiological features, the prediction of GPP by a Monteith model was performed separately. More specifically, two modified versions of C-Fix were concurrently applied for olive trees and ground vegetation, which were fed by respective fAPAR estimates.

MODIS spatial resolution (250 m) obviously did not allow the identification of individual olive trees. Consequently, the contribution of tree canopies and ground vegetation to MODIS NDVI had to be estimated by a statistical procedure which utilizes the information contained in relatively large image portions covering olive groves. This operation had to account for the fact that the fraction of olive tree canopy within each olive grove varies depending on local management practices and the size of the trees. This fraction was predicted by the procedure described in Maselli et al. (2012). In summary, olive canopy cover fraction was first assessed over a limited number of small areas by applying a semiautomatic olive tree identification method to the IKONOS imagery. Next, the olive canopy cover fractions of these sites were extended over all Tuscany olive groves through the application of locally calibrated regression to the Landsat ETM+ image of July 2002 (Maselli, 2001). The olive canopy cover fraction map produced in this way was finally used to extract the olive tree NDVI values of the study olive grove by using the method proposed by Maselli (2001). This method, which is capable of estimating spatially variable NDVI values of pure cover classes (endmembers), currently predicted the 16-day olive tree canopy NDVI values of the study site for the two years examined.

These NDVI values were transformed into daily values by linear interpolation and converted into fAPAR by the generalized equation of Myneni and Williams (1994). The NDVI values of inter-tree ground vegetation were linearly extrapolated using the extracted endmembers and the original values of the olive grove, and were converted into fAPAR by the same equation applied above.

The two fAPAR series were then used to drive two versions of C-Fix. For olive trees, GPP was predicted by modified C-Fix as (Maselli et al., 2012):

$$GPP_i = s \cdot T_{cor} \cdot C_{sv} \cdot f_{APAR,Rad}$$

where $s$ is the maximum radiation use efficiency (1.2 g C MJ) APAR (Maselli et al., 2012), $T_{cor}$ is the MODIS temperature correction factor for evergreen broadleaves, $C_{sv}$ is the water stress factor for Mediterranean trees, $f_{APAR}$ is the fraction of absorbed PAR, and $Rad$ is the solar incident PAR, all referred to day $i$. All
meteoro\-logical driving variables (i.e. daily temperatures, rainfall and solar radiation) were estimated through the sequential application of the DAYMET and MT-Clim procedures, as fully described in Chiesi et al. (2011).

For inter-tree ground vegetation, GPP was predicted by applying a similar equation but considering different factors (Maselli et al., forthcoming). In particular, ε was set to 1.65 g C/MJ APAR, Tcor was the MODIS temperature correction factor for C3 grasses and Cws was derived from a water balance computed over one month instead of the original two months (Maselli et al., forthcoming). As fully explained in Maselli et al. (forthcoming), these modifications take into account the generally lower green biomass of ground vegetation with respect to trees, as well as their different capacity to respond to thermal and water limitations.

The daily GPP estimates of olive trees and inter-tree ground vegetation were finally combined to produce relevant photosynthesis estimates for the entire olive grove examined (Fig. 3). Specifically, daily GPP estimates for the whole olive grove were obtained by summing the contribution of olive trees and inter-tree vegetation weighted for the respective cover fractions. These estimates were validated by comparison with the GPP measurements of the tower using the correlation coefficient (R), the mean bias error (MBE) and the root mean square error (RMSE) as accuracy statistics.

5. Results

5.1. Estimation of NDVI profiles

During the two study years the NDVI profile of olive trees and ground vegetation showed notable inter- and intra-year variations (Fig. 4). The NDVI profile of olive trees was uniformly high, around a value of 0.8. In the first year it showed a unique minimum (0.75) in mid-spring and a unique maximum (0.94) in winter, with a steady increase that indicated the absence of a long summer dry period or decrease in water soil content. In the second year, the NDVI olive profile showed more xerophic features, with a primary peak in early summer, a secondary peak in fall, and two minima in winter and summer.

The NDVI profile of ground vegetation was markedly lower than that of olive trees. In the first year the maximum value (0.54) was found in winter, while the minimum value (0.25) was in summer. In the second year, the profile showed many intra-year variations, with two minima in spring and late summer typical of arid conditions. Generally, NDVI was maximum in late winter and minimum in summer. The greatest inter-year differences were in late winter and early spring, when the index was markedly lower in 2011.

5.2. Analysis of simulated GPP profiles

The simulated GPP profiles of olive trees and ground vegetation are reported in Fig. 5. The simulated profile of olive trees was typical of Mediterranean woody vegetation. The active growing phase started in March and reached its peak in late spring/early summer, then it decreased progressively, at first due to water stress (i.e. summer months) and then to leaf senescence and low temperature (i.e. fall and winter months). The main differences in GPP profiles between the two years were recorded during late spring/early summer (14–13 g C·m⁻²·d⁻¹ in 2010 vs. 8–9 g C·m⁻²·d⁻¹ in 2011).

The simulated GPP profiles of ground vegetation followed that of olive trees, but with significantly lower GPP values (i.e. maximum GPP: 7–8 g C·m⁻²·d⁻¹ in 2010 vs. 4–5 g C·m⁻²·d⁻¹ in 2011). Also for ground vegetation the main differences in simulated GPP between the two years were recorded in late spring/early summer.

The more extreme meteorological conditions recorded in 2011 determined a reduction in annual GPP, which was markedly lower in 2011 (976.8 g C·m⁻²·d⁻¹) than in 2010 (1227.33 g C·m⁻²·d⁻¹).

5.3. Comparison of observed and simulated olive grove GPP

During the two study years (730 days) some problems due to power supply did not allow a complete data acquisition. In particular, 134 days mainly concentrated in early 2010 were missed. During the remaining days (596), the eddy covariance tower collected a

![Fig. 4. NDVI profiles of olive trees and ground vegetation during 2010 and 2011. Filled line = olive; dotted line = ground vegetation.](image-url)
Table 2
Number of half-hourly data measured by eddy covariance station in 2010 and 2011. Num. tot. val. indicates all the measured data; Num. orig. val. indicates all the measured data used to obtain observed daily GPP data; Num. gaps indicates the measured data that cannot be directly used to obtain observed daily GPP data. For these half-hourly data GPP data were reconstructed using the gap-filling procedure. The quality classification scheme for gap-filled values is: A: best; B: acceptable; C: dubious.

<table>
<thead>
<tr>
<th></th>
<th>2010</th>
<th>%</th>
<th>2011</th>
<th>%</th>
<th>2010–2011</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. tot. val.</td>
<td>13,936</td>
<td>100</td>
<td>14,688</td>
<td>100</td>
<td>28,624</td>
<td>100</td>
</tr>
<tr>
<td>Num. orig. val.</td>
<td>11,191</td>
<td>80.3</td>
<td>11,286</td>
<td>78.44</td>
<td>22,477</td>
<td>78.57</td>
</tr>
<tr>
<td>Num. gaps</td>
<td>2,745</td>
<td>19.7</td>
<td>3,402</td>
<td>23.16</td>
<td>6,147</td>
<td>21.43</td>
</tr>
<tr>
<td>Category: A</td>
<td>2,532</td>
<td>18.17</td>
<td>1,623</td>
<td>11.05</td>
<td>4,155</td>
<td>14.61</td>
</tr>
<tr>
<td>Category: B</td>
<td>201</td>
<td>1.44</td>
<td>679</td>
<td>4.62</td>
<td>880</td>
<td>3.03</td>
</tr>
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<td>Category: C</td>
<td>12</td>
<td>0.09</td>
<td>1,100</td>
<td>7.49</td>
<td>1,112</td>
<td>3.79</td>
</tr>
</tbody>
</table>

Fig. 6. Daily values of GPP estimated by C-Fix model (dotted line) and reconstructed from eddy covariance measurements (filled line). The two black bars on the x-axis indicate the periods likely affected by the tillages (see text for details).

Fig. 7. Daily values of GPP estimated by C-Fix model (dotted line) and reconstructed from eddy covariance measurements (filled line). The GPP after the two tillages has been estimated by considering simulated ground vegetation NDVI values (see text for details).

total of 28,624 values (100%) of CO2 fluxes (i.e. NEE) at half-hourly time resolution. Among these 22,477 (78.57%) were good while the remaining (21.43%) did not satisfy QA/QC quality criteria for eddy covariance measurements. The gap-filling procedure was applied to obtain a continuous dataset, by filling missing or QA/QC-flagged data using an average window mobile. This procedure considered both the co-variation of fluxes with meteorological variables and the temporal auto-correlation of the fluxes (Reichstein et al., 2005). Filled data were conventionally classified into three categories (A–C) corresponding to best, acceptable and dubious, respectively. According to this quality classification, the majority of these data were classified as best (14.61%) (Table 2).

The observed and estimated GPP data series were generally similar, with the exception of two periods in spring 2010 and late-winter early-spring 2011 (Fig. 6). These periods coincided with those subsequent to tillages. The presence of these periods significantly reduced the correlation between measured and estimated GPP ($R = 0.462$ and RMSE = 1.88 g C m$^{-2}$ d$^{-1}$) (Table 3).

This was confirmed by the comparison of observed and estimated GPP after the removal of data subsequent to tillages, i.e. for 32 days in 2010 (from May 6th to June 5th) and 69 days in 2011 (from March 19th to May 26th). The different number of daily data removed in the two years was due to the season when tillage occurred and the different meteorological conditions recorded in these periods (see Section 6). After removing these periods the correlation between the two data series (observed and estimated) was substantially higher ($R = 0.662$ and RMSE = 1.31 g C m$^{-2}$ d$^{-1}$). The two tillages were expected to affect almost exclusively the GPP of the ground vegetation layer; in particular, they likely caused an abrupt reduction of fAPAR due to ground vegetation removal, followed by a slow recovery during subsequent weeks. In an attempt to simulate this effect, the NDVI values of ground vegetation used to drive C-Fix were replaced by synthetic values. More precisely, synthetic NDVI dropped to 0.15 just after the tillage, remained unvaried for about half of the above-mentioned periods and then linearly recovered to the original values (Fig. 7). This reconstruction significantly improved the correlation between observed and estimated GPP ($R = 0.582$ and RMSE = 1.45 g C m$^{-2}$ d$^{-1}$, Table 3).

Table 3
Accuracy of GPP estimates obtained applying C-Fix model for different time intervals (see text for details on $R$, RMSE and MBE).

<table>
<thead>
<tr>
<th>GPP</th>
<th>Time interval</th>
<th>$R$</th>
<th>RMSE (g C m$^{-2}$ d$^{-1}$)</th>
<th>MBE (g C m$^{-2}$ d$^{-1}$)</th>
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<tbody>
<tr>
<td>All data</td>
<td>Daily</td>
<td>0.462</td>
<td>1.88</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>10-days</td>
<td>0.604</td>
<td>1.51</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>Monthly</td>
<td>0.657</td>
<td>0.66</td>
<td>0.61</td>
</tr>
<tr>
<td>Post-tillage removed</td>
<td>Daily</td>
<td>0.662</td>
<td>1.31</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>10-days</td>
<td>0.844</td>
<td>0.83</td>
<td>0.16</td>
</tr>
<tr>
<td></td>
<td>Monthly</td>
<td>0.815</td>
<td>0.81</td>
<td>0.17</td>
</tr>
<tr>
<td>Post-tillage simulated</td>
<td>Daily</td>
<td>0.581</td>
<td>1.45</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>10-days</td>
<td>0.771</td>
<td>0.98</td>
<td>0.34</td>
</tr>
<tr>
<td></td>
<td>Monthly</td>
<td>0.817</td>
<td>0.82</td>
<td>0.33</td>
</tr>
</tbody>
</table>
6. Discussion

6.1. Flux tower data

The GPP of the studied olive grove was determined by the seasonal growth of olive trees and inter-tree ground vegetation. In particular, the intensity of ground vegetation growth varies during the growing season. Several studies have indicated a spring peak production mainly caused by the behavior of the herbaceous species, where their reproductive phase of growth is much faster than the vegetative stage (Cavalleri and Ciotti, 1991; Parsons, 1988). The best growing season for the majority of herbaceous species in the Mediterranean environment is during spring, while they can suffer from water shortage in summer months (De Marco et al., 2008; Xu et al., 2004). Both patterns, and particularly the latter, may be influenced by agricultural practices.

In the current case, two main tillages were done in spring 2010 and 2011. Tillage can affect the GPP estimates by removing ground vegetation cover, causing reduction in GPP and consequently changes in its daily trend. In the first study year (2010), tillage was done in spring (May 5th), which is usually the period of maximum vegetative activity and greater biomass amount. As a consequence, tillage may have caused a removal of herbaceous biomass and consequently a strong reduction in ecosystem GPP. On the other hand, tillage was done in a period with high temperatures and intense rainfall, which may have ensured an increase in soil water content. In the semi-arid climates that characterize most of the Mediterranean basin, successful germination and subsequent plant establishment is mostly determined by rainfall amount and soil moisture availability (Veenendaal et al., 1996), while temperature mainly influences the rate at which leaves expand and the frequency at which they appear (Peacock, 1976). After these tillages, the soil was almost bare, but some herbaceous species within the olive grove are characterized by fast growth and development. Indeed, direct visual observations showed that two weeks after tillage, some plants (especially dicotyledons) started to regrow from those parts of roots that had been pulled out above the soil level, as confirmed by Janicka (2005).

In 2011, tillage was done in late winter–early spring (March 19th) in a period with sparse herbaceous cover and low biomass amount. As a consequence, tillage may have removed less herbaceous biomass than in the previous year, with consequent lower effect on ecosystem GPP. Visual observations showed that the regrowth of the herbaceous cover after tillage was slower in 2011, with a longer period of bare soil (about four weeks), probably due to lower temperatures. This condition, added to the dryness of the 2011 growing season, may have caused a reduction in soil water content and consequently water stress. Several studies have indicated that individual plants are often water-limited during the growing season, in regions with dry summers, and water competition is frequent between species (Vignolio et al., 2002; Dyer and Rice, 1999). Globally, this situation may have slowed down ground vegetation development in the second study year.

The eddy covariance flux partitioning procedure was also likely affected by tillage practices. In fact, the procedure is based on both a seasonal long-term window, and a short-term running temporal window of 15 days, which is considered representative of the characteristic temporal length scale of an ecosystem dynamic (Reichstein et al., 2005). In the case of tillage, as well as other management or natural actions that act as a temporal discontinuity by instantaneously changing some of the system properties, it is likely that the flux partition procedure may be biased in the first period after the discontinuity, while it recovers to proper values after the transient situation is stabilized. Tillages can affect GPP by removing the vegetation from the soil and, in turn, can also result in reduced carbon sequestration (Baker and Griffis, 2005).

In addition, tillage in different climatic conditions can influence soil respiration: in periods with high temperatures and high water soil content tillage can induce large carbon loss due to increased bacterial growth in the short-term (Reicosky, 1997). The higher bacterial activity increases oxidation of soil organic matter causing a loss of soil carbon and consequently a higher ecosystem respiration (USDA-NRCS, 2004). On the other hand, when tillages are done in periods with low temperature, their influence on ecosystem respiration and maximum microbial activity is reduced. The increase of soil respiration within the system led to higher CO2 soil emissions. The eddy covariance technique is not able to discern CO2 fluxes coming from soil from those of vegetation component, and consequently measured an overall C sequestration reduction. Given that GPP estimates derive from a partitioning algorithm which is based on NEE measurements, GPP decreases when NEE increases. Therefore, in our study tillages events in the warm season may have suddenly removed biomass and at the same time increased the ecosystem respiration, resulting in NEE increase. This has induced an under-estimation of GPP until new higher respiration rates were observed over a multiple day time scale.

6.2. C-Fix GPP estimated data

The current application of C-Fix had to overcome particular problems linked to the peculiar composition of olive grove ecosystems. These ecosystems, in fact, are composed of a variable mixture of olive trees and inter-tree ground vegetation, which obviously show different eco-physiological properties that must be taken into account in the modeling operation. This issue was addressed by the separate application of C-Fix for the tree and herbaceous components, which was made possible by the preliminary estimation of olive tree canopy cover based on the use of very high spatial resolution satellite data. Two versions of C-Fix were then applied, tuned in previous research conducted in Central Italy (Maselli et al., 2009, 2012, forthcoming).

The whole approach relies on the correct definition of the olive grove fractions covered by tree canopies and inter-tree ground vegetation. This is a non-trivial issue, due to the difficulty in obtaining correct area estimates of different cover types from satellite imagery (Conese and Maselli, 1992). In the current case, the use of very high spatial resolution Ikonos imagery to obtain site cover fraction estimates is complicated by the effects of tree shadows and of varying canopy and ground vegetation densities. These problems are exacerbated by the use of lower spatial resolution ETM+ images to extend the estimates over larger areas. These issues have been addressed by the sequential application of a semi-automatic procedure to Ikonos imagery and of locally calibrated regressions to ETM+ images, which should guarantee a substantial reduction in bias of the final estimates (Maselli et al., 2012). This is confirmed by the accuracy assessment performed over the studied olive grove, which shows a substantial agreement between the olive tree cover fraction defined visually and estimated automatically.

The correct estimation of olive tree and ground vegetation cover fractions has allowed the prediction of the different temporal NDVI profiles that are necessary to drive relevant C-Fix versions. In this regard, the use of the current MODIS NDVI data posed some theoretical and practical problems concerning the spatial and temporal resolutions of the investigation. In fact, the spatial resolution of these data (250 m) is not sufficient to detect subtle changes in vegetation cover due to the application of management practices over small areas (2–3 ha) (Sing, 2011; Lamb, 1998; Fitzpatrick et al., 1990). In particular, this resolution is not sufficient to distinguish the different NDVI values of inter-tree ground vegetation subsequent to the tillage, especially in 2011, when the ground vegetation cover was sparse and low before plowing. As a consequence,
this limitation could lead to overestimate the ground vegetation biomass, increasing the ecosystem GPP.

Considering all these possible error sources, the C-Fix GPP estimates are in reasonable agreement with the GPP data derived from the eddy covariance tower. The results obtained indicate that C-Fix can reproduce the observed GPP values with the exception of the periods following tillage. During the days following plowing in 2010 the observed GPP significantly goes down, while the estimated GPP increases. Maximum disagreement is reached at the end of May, where the model shows the annual peak of production. The GPP data series again shows good agreement at the end of spring, when the observed GPP increases, probably due to the reduction of tillage effects. There is a similar trend in 2011, where observed GPP decreases during the days following plowing, which was done in late winter.

The accuracy of the daily GPP values predicted by the model was confirmed by a simulation that considered the NDVI values after the tillages (for 15 and 30 days in 2010 and 2011, respectively) to be equal to 0.15, followed by a slow linear recovery. In this way the observed and simulated GPP daily values for the two study years are moderately correlated ($R = 0.581$ and RMSE = 1.455), and have more similar bi-annual totals (1480 g C m$^{-2}$ year and 1693 g C m$^{-2}$ year, respectively). In this regard it should be kept in mind that in the post-tillage transient period the model GPP overestimation could be partly due to the previously mentioned problems in the correct application of the eddy covariance partitioning methods.

7. Conclusions

Carbon exchange data taken in agro-ecosystems provide the fundamental basis for developing and validating simulation models to monitor gross/net primary production over wide areas and lengthy time periods (i.e. Joseph et al., 2012; Suyker et al., 2005; Xiao et al., 2004; Gitelson et al., 2003; Ruimy and Saugier, 1994). Such models may have a different level of complexity and simulate processes such as whole-plant photosynthesis and heterotrophic/autotrophic respiration. In this work, we presented a modified version of a simple parametric model, C-Fix, to estimate daily GPP of an olive grove by separating the contribution of the autotrophic components dominating this ecosystem, i.e. olive trees and ground vegetation. The daily GPP values estimated by C-Fix were compared against GPP daily data obtained from eddy covariance flux measurements taken for two years in an olive grove located in South Tuscany, Italy.

The method applied was generally successful in simulating daily olive grove GPP for most of the two study years. Relevant discrepancies between observed and estimated GPP were found for two post-tillage periods (i.e. the model overestimated the olive grove photosynthesis). This is due to the low spatial resolution of the used MODIS imagery, which does not allow a proper detection of the post-tillage NDVI drops of ground vegetation. This problem could therefore be at least partly overcome by the future availability of high spatial resolution satellite data.

Most of the discrepancies found were accounted for by properly simulating NDVI variations of ground vegetation during the post-tillage periods. The length of post-tillage periods and the consequent model GPP overestimation were strongly linked to weather conditions, which determined the re-growth of the herbaceous component. These results confirm that the Monteith type parametric model C-Fix, properly tuned for the two components, can be used to simulate total olive grove GPP based on the main driving factors of solar radiation, thermal and water stresses and fAPAR.

In general, however, the current approach is likely suboptimal to fully simulate the effects of tillage or other management operations, which could be more efficiently carried out using more sophisticated ecosystem modeling strategies based on specific soil modeling (i.e. DayCent, DNDC). Given the impact that crop management (i.e. tillage) may have on the carbon cycle and the scarce knowledge on carbon fluxes dynamics in agro-ecosystems such as olive groves, studies should be conducted to assess the possibility of further improving the model performances by including a management parameterization in the ecosystem simulation framework.

In particular, studies should be conducted in olive groves characterized by the same climatic conditions but different agronomic practices (i.e. tillage types and times or no tillage), with the aim of assessing the accuracy of the method under different management practices.

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