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Modeling primary production using a 1 km daily meteorological data set

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ABSTRACT: The availability of daily meteorological data extended over wide areas is a common requirement for modeling vegetation processes on regional scales. The present paper investigates the applicability of a pan-European data set of daily minimum and maximum temperatures and precipitation, E-OBS, to drive models of ecosystem processes over Italy. Daily meteorological data from a 10 yr period (2000 to 2009) were first downscaled to 1 km spatial resolution by applying locally calibrated regressions to a digital elevation model. The original and downscaled E-OBS maps were compared with meteorological data collected at 10 ground stations representative of different eco-climatic conditions. Additional tests were performed for the same sites to evaluate the effects of driving a model of vegetation processes, BIOME-BGC, with measured and estimated weather data. The tests were carried out using 10 BIOME-BGC versions characteristic for local vegetation types (Holm oak, other oaks, chestnut, beech, plain/hilly conifers, mountain conifers, Mediterranean macchia, olive trees, and C3 and C4 grasses). The experimental results indicate that the applied downscaling performs best for maximum temperatures, which is the most decisive factor for driving BIOME-BGC simulation of vegetation production. The downscaled data set is particularly suitable for the modeling of forest ecosystem processes, which could be further improved by the use of information obtained from remote sensing imagery.

KEY WORDS: Meteorological data set · E-OBS data set · Locally calibrated regression · BIOME-BGC model · Gross primary production modeling · Italy

1. INTRODUCTION

Gross primary production (GPP) corresponds to the amount of carbon fixed by vegetation through photosynthesis and is a key component of ecosystem carbon fluxes. It is therefore a fundamental variable for studying the effects of global climate change on terrestrial ecosystems (Waring & Running 2007). GPP is traditionally measured in the field by portable instruments (e.g. CIRAS-1, see www.ppsystems.com), which can only provide instantaneous and point measurements. At the ecosystem level, the eddy-correlation technique is applied to collect continuous measurements of net carbon fluxes (Aubinet et al. 2000) and indirectly estimate GPP by flux partitioning (Reichstein et al. 2005). Eddy covariance towers, however, perform local measurements that are related to the so-called footprint area, an area extending upwind of the observation point as a function of atmospheric stability, wind speed, and surface properties (Vesala et al. 2008). The footprint distance can extend up to few hundred meters, but the measured fluxes cannot be directly attributed to wider areas.

The estimation of GPP on a regional scale therefore requires the use of different instruments and methodologies, such as those based on remotely sensed data and biogeochemical models (e.g. Prince 1991, Veroustraete et al. 2002). In all cases, meteorological

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data extended over wide land surfaces must be combined with other ground or remotely sensed information to drive the modeling approaches. More specifically, numerous models (e.g. ORCHIDEE, Krinner et al. 2005; LPJ, Sitch et al. 2003) require the use of daily meteorological inputs having a spatial resolution suitable to describe the ecosystems examined (Nungesser et al. 1999). This is also the case for the well-known biogeochemical model BIOME-BGC, which has been widely applied to simulate the processes of a variety of vegetation types all over the world (Running & Hunt 1993, Thornton et al. 2002, Churkina et al. 2003, Hlásny et al. 2011). In most cases, the model simulations were performed at a spatial resolution of about 1 km, which approximately corresponds to the footprint of many eddy covariance flux towers (Baldocchi 2003, Mu et al. 2007).

Various sets of daily meteorological data have been produced for the North American and European continents (van der Goot 1997, Higgins et al. 2000). As regards Europe, a land-only high-resolution gridded data set has been recently released for precipitation, sea level pressure, and minimum and maximum temperature: the E-OBS data set version 4.0 (hereinafter called E-OBS) (Haylock et al. 2008, van den Besselaar et al. 2011). It consists of a joint effort by the EU-FP6 project E-OBS (http://www.ecad.eu/download/ensembles/ensembles.php) and the European Climate Assessment & Dataset (ECA&D) project (Klein Tank et al. 2002, http://eca.knmi.nl). The data set, with a spatial resolution of 0.25°, has been designed for use in a wide range of applications, from monitoring of climate anomalies to analysis of climate variability, and from validation of numerical models to evaluation of impact models.

The main objective of the present study is to evaluate the usability of the E-OBS data set to drive the modeling of vegetation processes at 1 km resolution over Italy. Daily temperature and rainfall E-OBS data were first downscaled to 1 km resolution by applying locally calibrated regression procedures. The accuracy of the downscaled products was then evaluated against independent meteorological data collected at 10 ground stations representative of different eco-climatic conditions. The same 10 sites were used to evaluate the effects of driving BIOME-BGC versions of typical ecosystem types with measured and estimated data. In particular, the differences in simulating vegetation GPP using the original and downscaled E-OBS data series were assessed. Conclusions were drawn on the possible utilization of the data set produced for the operational monitoring of vegetation processes.

2. STUDY AREA

Italy is situated between 36° and 47° 30′ N and between 5° 30′ and 18° 30′ E. The latitudinal extent of the Italian peninsula, the presence of 2 main mountain chains (the Alps in the north and the Apennines in the center-south), and the proximity of the African and Eurasian continental masses generate a great variety of climatic regions, bioclimates, and climate types, depending on whether tropical or mid-European influences predominate. Climate therefore ranges from Mediterranean warm to temperate cool and, with the influence of edaphic and human-induced factors, leads to a great variety of biogeographic regions (Blasi & Michetti 2007).

Due to such a pronounced biogeographical variability, semi-natural vegetation is very heterogeneous and is represented by forests (nearly 30% of the total land), shrubs, and pasture formations (Marchetti & Barbati 2007). Some 95% of forest land is on hills and mountains. Of the forest formations, 32% are 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, http://ec.europa.eu/environment/nature/legislation/habitatsdirective/index_en.htm). Agricultural lands are mostly in plain or hilly areas. Olive trees are grown under different management practices throughout the central south. C3 grasses are generally concentrated in the temperate regions, where temperature and water regimes are suitable for production; C4 species are found in more arid environments typical of the central-southern regions.

3. STUDY DATA

3.1. Ancillary data

A digital elevation model (DEM) of Italy with a pixel size of 1 km^2 was derived from Blasi (2005). This DEM was projected in the reference system UTM-32 North with WGS84 datum, which was taken as standard for processing all other information layers.

A digital vegetation map was derived from the CORINE Land Cover 2000 map of Italy (Maricchiolo et al. 2004). This map was produced by manual photo-interpretation of Landsat imagery supported by ancillary information (Bologna et al. 2004). The map classifies forests, agricultural lands, and other cover types at a nominal scale of 1:100 000. Using this information, 10 biome types representative of the most important Italian ecosystems were identified (Table 1).

Table 1. The 10 selected meteorological stations (see Fig. 1) with their relative biome type. a.s.l.: above sea level; T_{max} and T_{min}: maximum and minimum temperature respectively

Stn no.	Stn name	Biome type	Latitude N (°)	Longitude E (°)	Altitude (m a.s.l.)	Annual T_{max} (°C)	Annual T_{min} (°C)	Annual precipitation (mm yr^{-1})
1	Sibari	Holm oak	39.74	16.45	10	22.8	11.0	612
2	Santa Fista	Other oaks	43.52	12.13	311	19.7	6.2	796
3	Carpeneto	Chestnut	44.68	8.62	230	17.5	8.6	821
4	Castel di Sangro	Beech	41.75	14.10	810	17.4	2.7	914
5	San Piero a Grado	Plain/hilly conifers	43.67	10.35	3	20.6	8.6	827
6	Moena	Mountain conifers	46.38	11.66	1205	14.2	0.2	915
7	Chilivani	Mediterranean macchia	40.62	8.94	216	22.5	8.0	491
8	Turi	Olive	40.92	17.01	230	20.8	10.1	652
9	Piubega	C3 grass	45.21	10.51	38	19.1	7.9	708
10	Santo Pietro	C4 grass	37.12	14.53	313	22.4	11.9	574

3.2. E-OBS data set

The E-OBS data set was designed as a best estimate of grid box average instead of being representative of point-value time series and is therefore suitable for applications defined on regular grid domains and for evaluation studies of numerical model outputs (Klein Tank et al. 2002, Haylock et al. 2008, van den Besselaar et al. 2011). Its time period coverage extends from 1950 to the present, and new data are released on a monthly basis with a 1 mo delay. The data set was generated by applying a 3-step procedure (similar to universal kriging) to observed data, with a single variogram for all days and a search radius of 450 km for precipitation and 500 km for temperature. For both temperature and precipitation, a high-resolution elevation field at 0.1° by 0.1° was used as a covariate in the interpolation of the 'master' gridded field (Haylock et al. 2008). From any 'master' field, a final gridded data set is computed at 2 lower grid spacings: 0.25° and 0.50°. The Italian peninsula is represented within the data sets by 324 observed time series, not covering all interpolated fields. The spatial distribution of the stations is denser in the northern than the southern part, with a consequent increase in the relative errors associated with the daily gridded data values.

3.3. Ground meteorological data

Independent ground data of temperature and precipitation were used to both evaluate the E-OBS data set and drive reference runs of BIOME-BGC. These meteorological data could not be derived from the existing network of flux tower stations, which show short and incomplete daily measurement series not suitable to drive BIOME-BGC (see http://fluxnet.ornl.gov). Consequently, reference daily data were obtained from 10 meteorological stations selected among those that had not contributed to the E-OBS project following criteria: (1) completeness of the daily meteorological records for the whole study period (2000–2009), with particular attention paid to precipitation, which is the most difficult variable to interpolate. Thus, only stations with <5% of missing daily rainfall were selected (183 d over the 10 yr). (2) Selected stations should present the maximum possible representativeness for the different climatic situations in Italy, with particular reference to gradients of latitude, altitude, and distance from the sea. (3) The stations should be as close as possible to areas covered by the 10 biome types representative of Italian ecosystems. The application of these 3 criteria led to the identification of 9 stations from the CRA-CMA data set and 1 station from the MeteoTrentino data set (Table 1, Fig. 1). The last station was needed to cover the upper mountain Alpine zone, that has ecologically and economically important evergreen coniferous forests. The daily minimum and maximum temperature and rainfall data of these stations were freely downloaded from www.cra-cma.it and www.meteotrentino.it.

Additional meteorological data were collected from other networks for a flat area surrounding Pisa (central Italy). More specifically, minimum daily temperatures from 1999 were taken from the urban weather station of Pisa Facoltà di Agraria (43.71° N, 10.41° E) and from the eddy covariance flux tower of the San Rossore pine forest (43.73° N, 10.28° E).

4. DATA PROCESSING

4.1. Downscaling of E-OBS meteorological data

The downscaling of E-OBS daily weather variables (minimum and maximum temperatures and precipitation) was carried out by applying a modified ver-

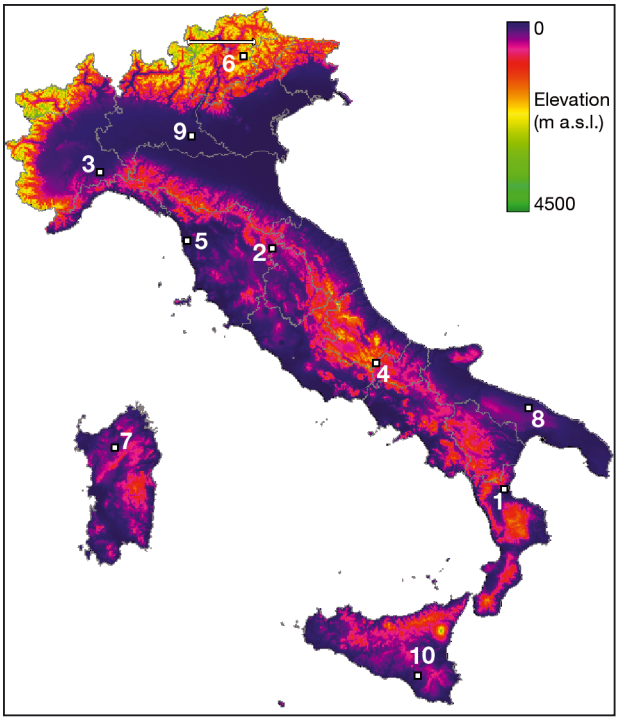

Fig. 1.Digital elevation model (1 km resolution) of Italy with indication of the 10 reference meteorological stations (see Table 1). Grey lines indicate the administrative boundaries of the 20 Italian regions. The transect in northern Italy (over Stn 6) is used for analysis of spatially explicit flux fields (see Section 4.2). a.s.l.: above sea level

sion of locally calibrated regression. The general principles of locally calibrated (or weighted) regressions were put forward by Cleveland & Devlin (1988) and developed by Brunsdon et al. (1996). Mathematically, they consist of computing a regression model for each estimation point by weighting the values of the reference points according to the relevant distances. Locally calibrated regressions can, therefore, be easily applied to image analysis, where regularly distributed measurements of land spectral properties (pixels) are available (Maselli 2002). In this case, different statistics can be computed for each image pixel by using weights that give preferential consideration to the nearest reference pixels.

A locally calibrated regression model can be written in the form:

$$Y_{Lest} = A^{\star} + B^{\star}{}_{j}\, X_j + \ldots + B^{\star}{}_{nb}\, X_{nb} \qquad (1)$$

where Y_{Lest} is the estimated value of the dependent variable, nb is the number of independent variables, $A^{\star}$ is the locally calibrated intercept, and $B^{\star}{}_{j\ldots nb}$ and $X_{j\ldots nb}$ are the locally calibrated regression coefficients and the values of the independent variables, respectively. The coefficients, $A^{\star}$ and $B^{\star}{}_{j\ldots nb}$ are derived for each image pixel from relevant statistics (mean vectors and variance-covariance matrices) computed by giving different weights to the N reference pixels. Thus, a fundamental step for the application of locally calibrated regressions is the definition of a suitable function to compute these weights. Among the different options, an efficient way is a negative exponential function of the Euclidean distance, which is regulated by the distance range (Maselli 2002).

The computation of local statistics allows the consideration of spatially variable relationships between the independent and dependent variables. This enhances the flexibility of locally calibrated regressions and encourages their application to cases where the spatial nonstationarity of the considered relationships reduces the efficiency of conventional regression methods (Brunsdon et al. 1996, Maselli 2002). This is relevant to the present application, since the altitudinal gradients of temperatures and precipitation are affected by several factors, such as distance from the sea, latitude, prevalent air flows, etc. (Lookingbill & Urban 2003). Locally calibrated regressions can account for this spatial variability by allowing the per-pixel derivation of different gradients from the low spatial-resolution data set and the subsequent application of these gradients to the higher-resolution elevation grid.

In the present case, locally calibrated regressions were trained on the gridded values of each daily E-OBS variable (minimum and maximum temperature and precipitation) and elevation, the latter degraded to the same resolution of the E-OBS data (i.e. to a pixel size of 0.25°). For each variable and day, the optimal distance range to compute the regression weights was found by a leave-one-out cross-validation strategy (Maselli 2002). Using these weights, a locally calibrated regression model was developed and applied for each 1 km pixel of the elevation grid, thus obtaining final estimates with this resolution. No further physically based calibration, such as lapse rate correction, was applied during the downscaling process. Such fine-tuning correction, often applied for gridding observed surface data or for reducing bias in numerical modeling estimates near the surface, requires an independent and accurate knowledge of the atmospheric boundary stability, which is limited over a wide area such as the study domain (Sheridan et al. 2010).

The accuracy of the original and downscaled E-OBS meteorological data was assessed by the use of daily data collected at the 10 independent weather stations. For all these stations, the temperature series

were first completed using data extrapolated from adjacent stations, while missing precipitation values were set to 0. Since only stations with <5% of missing daily rainfall data were selected, the application of this criterion should reduce the errors of the ground references to a level that is acceptable, though not possible to accurately define. Estimated values of the 10 stations were extracted from corresponding points of the original E-OBS grids and single pixels of the downscaled gridded fields. The comparisons between measured and estimated data were summarized using the correlation coefficient (r), root mean square error (RMSE), and mean bias error (MBE) as accuracy statistics. These statistics, which are robust to the presence of non-normal statistical distributions, were also computed for rainfall, following similar evaluation exercises (Ebert et al. 2007); in this case, MBE was expressed as a percentage (%MBE), which is indicative of relative errors.

4.2. Application of BIOME-BGC for 10 vegetation types

The measured and estimated daily meteorological data were used to drive BIOME-BGC modeling of ecosystem GPP (Running & Hunt 1993). BIOME-BGC was developed at the University of Montana and is capable of simulating all vegetation processes related to water, carbon, and nitrogen cycles. The model requires daily meteorological data (minimum and maximum temperature, precipitation, and solar radiation), information about the local environment (i.e. soil depth and texture, vegetation, and site conditions) and parameters describing the ecophysiological characteristics of vegetation (White et al. 2000). BIOME-BGC works by identifying a quasi-equilibrium condition with local climatic and edaphic factors through the spin-up phase; this corresponds to quantifying the initial amount of all carbon and nitrogen pools from which the real simulation starts.

For each site and corresponding biome type, 3 simulations were performed driven by daily meteorological data measured and estimated at the original (0.25°) and downscaled (1 km) resolutions. In all cases, vapor pressure deficit and solar radiation were first obtained from daily temperatures and precipitation using the MT-CLIM algorithm (Thornton et al. 2000). Next, BIOME-BGC was applied in a spin-up and go mode using daily meteorological data for the period 2000–2009 and parameter settings appropriate for the 10 vegetation types considered. In particular, the parameter settings of 8 biome types (6 forest types, macchia, and olive) were taken from recent calibration exercises (Chiesi et al. 2007, 2012, Maselli et al. 2012). The original settings proposed by White et al. (2000) were instead used for C3 and C4 grasses (Table 2), which are representative of herbaceous ecosystems not subjected to agricultural activities. The effect of driving the model with measured or estimated meteorological data was assessed by intercomparing the 2 daily GPP data series obtained for each site. The results obtained for both the original and downscaled estimates were summarized by the same accuracy statistics used in Section 4.1.

A further assessment of the downscaling procedure was performed through the analysis of spatially explicit flux fields. To this aim, a transect of 100 pixels of 1 km each was defined in a highly rugged mountain area of northern Italy (Trentino), and the relevant temperature and rainfall data series were extracted from both the original and downscaled E-OBS data sets. The 2 meteorological data series, completed by MT-CLIM, were then used to drive the BIOME-BGC version of mountain conifers. This simulation was restricted to the pixels where this biome type is actually prevalent (i.e. those where the relevant CORINE cover fraction is >0.8) placed at an altitude suitable for proper model functioning (i.e. from 800 to 1600 m above sea level [a.s.l.], see Chiesi et al. 2007). The mean annual GPP outputs obtained over

Table 2. Maximum stomatal conductance and fraction of leaf nitrogen (N) in Rubisco used within BIOME-BGC for the 10 biome types

Biome type	Maximum stomatal conductance ($m\ s^{-1}$)	Fraction of leaf N in Rubisco
Holm oak[a]	0.0016	0.029
Other oaks[a]	0.0020	0.09
Chestnut[a]	0.0023	0.078
Beech[a]	0.0045	0.09
Plain/hilly conifers[a]	0.0024	0.022
Mountain conifers[a]	0.0032	0.027
Mediterranean macchia[b]	0.0018	0.021
Olive[c]	0.0012	0.04
C3 grass[d]	0.005	0.15
C4 grass[d]	0.005	0.15

[a]Biome types for which the model was calibrated in Chiesi et al. (2007)
[b]Biome type for which the model was calibrated in Chiesi et al. (2012)
[c]Biome type for which the model was calibrated in Maselli et al. (2012)
[d]Original versions of BIOME-BGC reported by White et al. (2000) were used

the study period from the 2 data series were analyzed also in comparison with those obtained by an independent model, modified C-Fix. C-Fix is a parametric model that uses the normalized difference vegetation index (NDVI) and meteorological data to assess forest GPP (Veroustraete et al. 2002), and it was adapted and successfully tested in Italy by Maselli et al. (2009). In the present study, the model was applied over the selected 1 km transect pixels using completely independent drivers of the same study period, i.e. monthly NDVI data from pure mountain conifers and monthly weather data extrapolated from the CRA-CMA network for the years 2000–2009.

5. RESULTS

5.1. E-OBS meteorological estimates

The main climatic patterns of the 10 stations used for accuracy assessment are reported in Table 1. These stations cover most climatic variability of the Italian territory, with the exception of the highest mountain zones (above 1300 m), for which reference data with the mentioned characteristics could not be found. The average temperatures of the 10 sites range from the coolest mountain areas of Castel di Sangro and Moena (on the Apennine and Alps chains, respectively) to the warmest zones of Santo Pietro and Sibari (in Sicily and south Italy, respectively). Rainfall is also very variable, generally decreasing moving from north to south.

The results of the accuracy assessment for the original E-OBS data are summarized in Table 3. Regarding minimum temperature, the correlation coefficient is always >0.9, except in the case of Castel di Sangro (r = 0.877). Estimated temperatures were always higher than measured temperatures, with mean differences between 0.6 and 6.6°C. The greatest negative errors were found for Castel di Sangro and Chilivani. The accordance between measured and estimated maximum temperatures is better (Table 3). All correlation coefficients are >0.92, and there is only a slight tendency to underestimation, which is notable for the station of Moena (–6.0°C). Regarding precipitation, the correlation coefficients between measured and estimated values are moderate, varying from 0.41 to 0.79 (Table 3). The estimates tend to be slightly lower than the ground measurements. The greatest relative differences are found for Santa Fista (+39%) and Castel di Sangro (–28%).

The optimal distance ranges found for the application of

Table 3. Accuracy statistics obtained by comparing measured and estimated daily minimum and maximum temperature and precipitation for the 10 reference stations. All data refer to the period 2000 to 2009. RMSE: root mean square error (°C for temperature, mm for precipitation); MBE: mean bias error (°C for temperature, % for precipitation)

Stn	Original E-OBS			Downscaled E-OBS		
	r	RMSE	MBE	r	RMSE	MBE
Minimum temperature						
Sibari	0.946	3.12	2.34	0.948	3.97	3.41
Santa Fista	0.926	3.45	2.40	0.940	4.18	3.57
Carpeneto	0.975	2.12	1.45	0.974	2.21	1.54
Castel di Sangro	0.877	7.27	6.58	0.860	6.97	6.20
San Piero a Grado	0.950	2.81	2.03	0.947	2.98	2.23
Moena	0.906	3.10	0.91	0.908	4.95	4.00
Chilivani	0.914	4.19	3.45	0.923	4.41	3.79
Turi	0.959	2.39	1.58	0.958	2.51	1.75
Piubega	0.981	2.26	1.68	0.976	2.54	1.94
Santo Pietro	0.966	1.63	0.58	0.966	1.97	1.26
Maximum temperature						
Sibari	0.962	3.26	–2.33	0.962	2.41	–0.74
Santa Fista	0.956	3.42	–2.15	0.977	1.91	–0.09
Carpeneto	0.978	2.14	0.48	0.980	2.08	0.78
Castel di Sangro	0.985	1.48	–0.50	0.985	2.03	–1.44
San Piero a Grado	0.979	1.58	–0.33	0.979	1.58	–0.06
Moena	0.925	6.77	–5.98	0.931	3.64	–1.96
Chilivani	0.975	3.42	–2.50	0.977	3.04	–1.91
Turi	0.965	2.51	–1.07	0.965	2.42	–0.85
Piubega	0.991	1.36	0.45	0.991	1.33	0.38
Santo Pietro	0.972	2.38	–1.43	0.972	2.08	–0.75
Precipitation						
Sibari	0.538	6.3	2.86	0.533	6.2	–8.61
Santa Fista	0.409	4.2	38.60	0.548	4.0	–14.97
Carpeneto	0.670	5.1	12.12	0.670	5.0	3.85
Castel di Sangro	0.656	7.2	–28.47	0.660	5.2	–31.84
San Piero a Grado	0.702	5.2	0.18	0.700	5.2	–5.73
Moena	0.788	4.5	–15.17	0.778	4.5	–32.50
Chilivani	0.580	5.2	11.54	0.583	5.2	4.66
Turi	0.674	5.1	–23.11	0.670	4.9	–27.48
Piubega	0.662	3.8	–20.86	0.706	3.7	–16.20
Santo Pietro	0.573	4.0	–4.48	0.581	4.3	–7.88

locally calibrated regressions are mostly between 10 and 20 km for both temperatures and precipitation. The use of these ranges permits us to capture most of the spatial variability of altitudinal gradients contained in the original E-OBS data. The high-resolution daily temperature and precipitation maps obtained generally reproduce the main climatic gradients of Italy. A negative altitudinal gradient is evident for both minimum and maximum temperatures, but is more evident for the latter. Concerning precipitation, the gradient with altitude is usually positive but very variable and heterogeneous dependending on local topography and daily meteorological conditions. These spatial patterns are evident in the example maps shown in Fig. 2 for relevant periods of 2009. The minimum temperature map for 20 January shows values between −6 and 10°C, with the lowest temperatures in the Alps and in the center of the Apennines. A clear difference is evident between the northern flat area of the Po Valley and the plains south of the Apennines, where the mean temperatures are around 1 and 8°C, respectively. The maximum temperature map refers to 15 August, a typical sunny day during the summer season; the altitudinal gradient is more pronounced with respect to that of minimum temperature. The precipitation map for 30 November corresponds to a day of intense rainfall over the Alps and part of the Italian peninsula. The heterogeneous distribution of precipitation is here more evident, with the estimates affected by the regular grid of the original E-OBS data.

These observations are mostly confirmed by the examination of example seasonal maps of temperature and precipitation. Fig. 3 shows the daylight mean temperature and the total rainfall computed for spring 2002 and 2003, which represents a relevant period for Mediterranean vegetation growth in 2 years with opposite meteorology, the first cold and humid and the second warm and dry. Daylight mean temperature was computed following Hungerford et al. (1989) as the temperature that is most influential on terrestrial photosynthetic processes and is a major driver of BIOME-BGC (see Section 6.2). The 4 maps in Fig. 3 highlight the different features of the 2 seasons, and particularly the extremely warm and dry spring 2003, which coincided with the beginning of an exceptional heat wave (Reichstein et al. 2007).

The accuracy statistics for the downscaled E-OBS data are given in Table 3. In general, these statistics are similar to those found for the original data, but with some relevant differences. As regards minimum temperature, the original tendency to overestimation is slightly increased, while the correlations are practically unvaried. For maximum temperature, the tendency to underestimation is clearly reduced, and the correlations are marginally increased. For precipitation, the mean errors maintain the same absolute magnitude, but the tendency to underestimation is slightly accentuated; most of the correlations remain constant, and are increased for 2 stations (Santa Fista and Piubega).

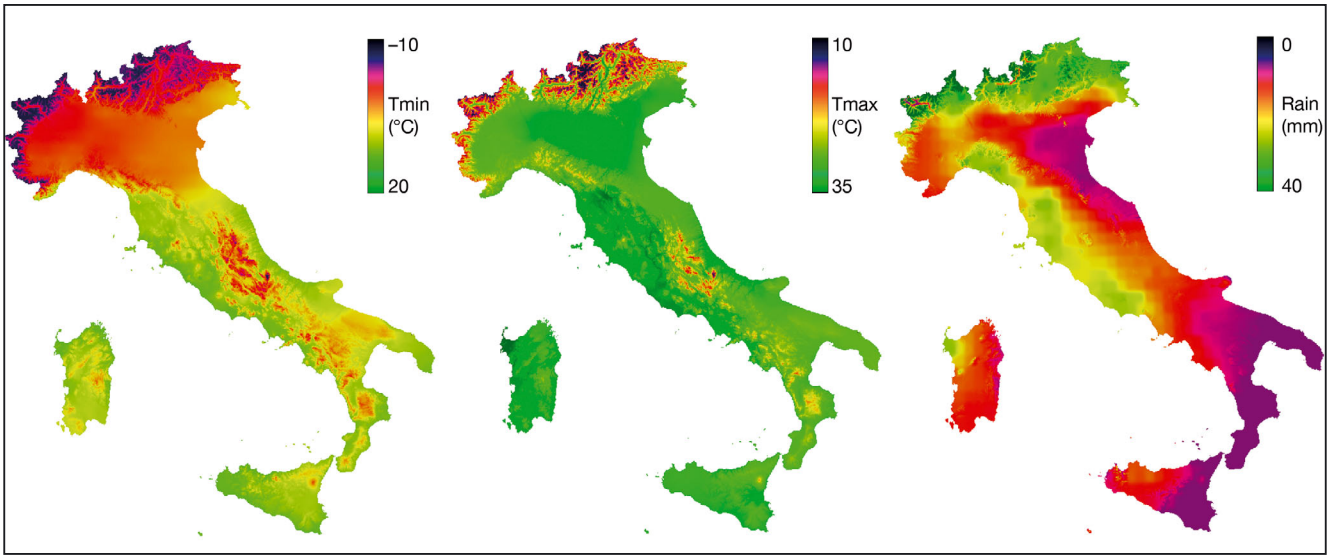

Fig. 2. Example maps of (A) daily minimum temperature (20 Jan 2009), (B) maximum temperature (15 Aug 2009), and (C) precipitation (30 Nov 2009) obtained by applying locally calibrated regression procedures

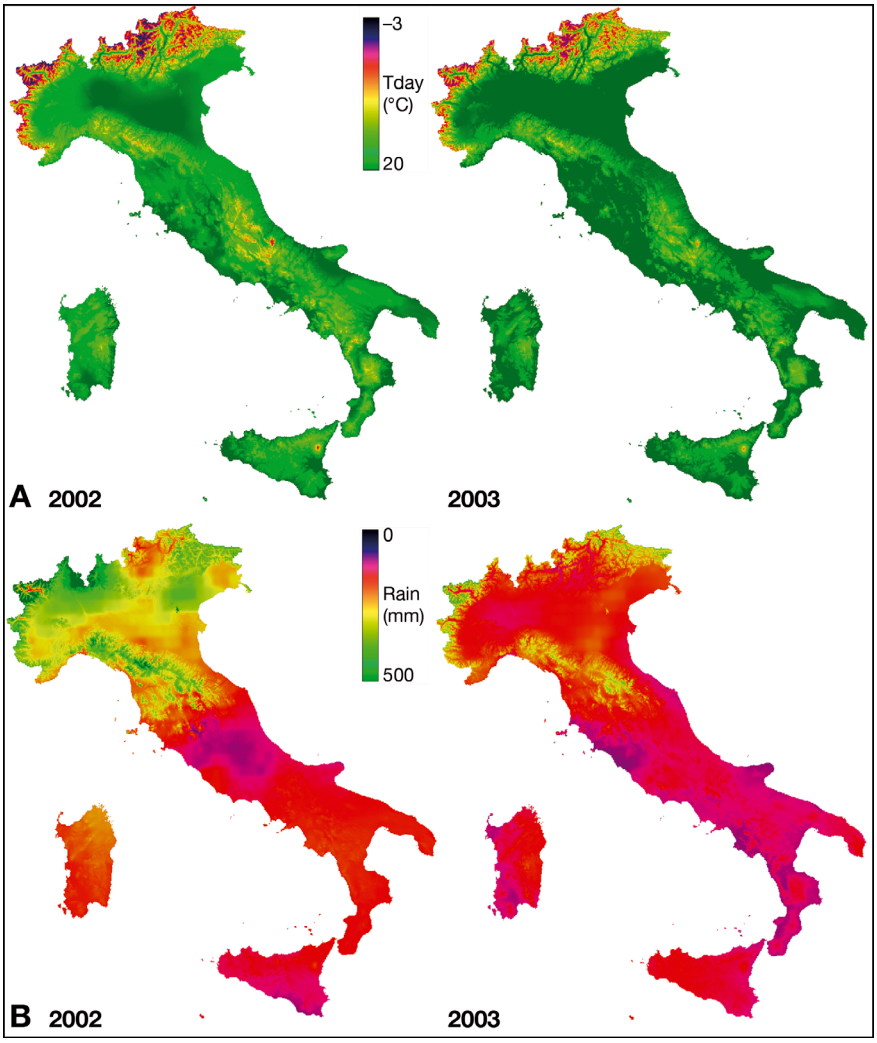

Fig. 3. Example maps of (A) mean daylight temperature and (B) total rainfall derived from the 1 km daily maps for spring 2002 (left panels) and 2003 (right panels)

5.2. BIOME-BGC simulations

Fig. 4 shows the annual GPP averages obtained by BIOME-BGC driven by weather data measured and estimated at the original and downscaled spatial resolutions (0.25° and 1 km). The annual GPP values obained with measured data vary from about 700 g C m^{-2} yr^{-1} for herbaceous species to about 1700 g C m^{-2} yr^{-1} for the most productive biome types (other oaks, chestnut, and olive). The mean GPP values obtained driving BIOME-BGC with original E-OBS data reproduce the previous GPP patterns, with the exception of 2 cases. The GPP of mountain conifers is dramatically decreased, while that of Mediterranean macchia is notably increased. Almost all GPP values simulated with downscaled E-OBS data are more similar to those simulated with measured data. This is particularly evident for mountain conifers, while olive represents the only exception.

These patterns are mostly confirmed by the examination of seasonal and interannual GPP variations. Examples of GPP series simulated by BIOME-BGC driven by the measured and by the original and downscaled E-OBS data sets are shown in Fig. 5 for Castel di Sangro and Piubega. These examples are representative of deciduous forests (beech) located on low mountains and of C3 grasses in plain areas. In general, the seasonal GPP evolution of the deciduous forest follows a bimodal pattern, with a primary maximum in spring–early summer and a secondary maximum in late summer. This evolution is typical of the Mediterranean climate in central-southern Italy, where summer aridity also affects forests found at medium altitudes. The perennial C3 grass site in the Po Valley (northern Italy) shows lower GPP levels and a reduced inactive period in winter. As regards interannual GPP variations, the lowest values are generally simulated for 2003 and 2007, which were warm and dry, while higher productions are simulated for the more humid 2002.

In almost all cases, the GPP profiles obtained from E-OBS data closely follow those simulated by the use of ground measurements. The correlation coefficients between the data series simulated using weather data measured and estimated at the 2 resolutions are mostly high and similar (Table 4), with the exception of olive, for which the original data are more efficient, and mountain conifers, which show the opposite behavior. These last patterns are even more evident when considering mean errors; the RMSE of mountain conifers, in particular, is dramatically decreased by the use of downscaled data.

Fig. 6 shows the mean annual GPP series simulated using the different models and data sets over the 20

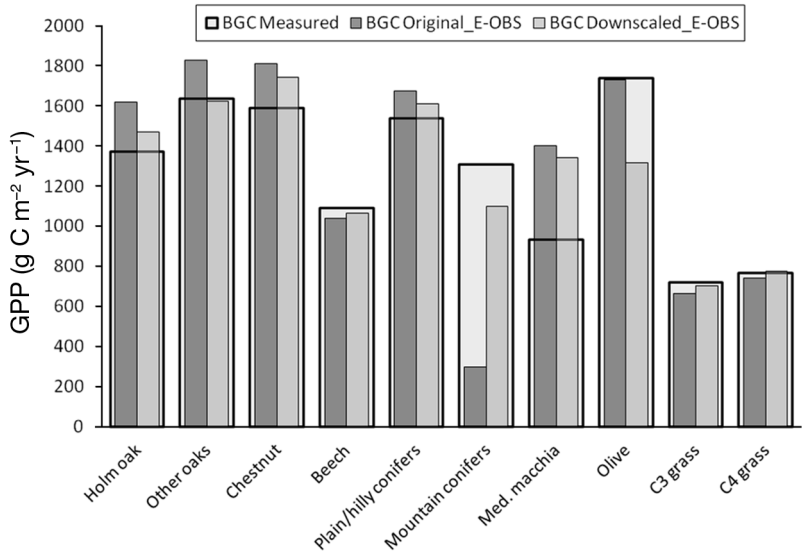

Fig. 4. Annual gross primary production (GPP) averages obtained by driving BIOME-BGC with daily meteorological data measured and estimated from original and downscaled E-OBS data

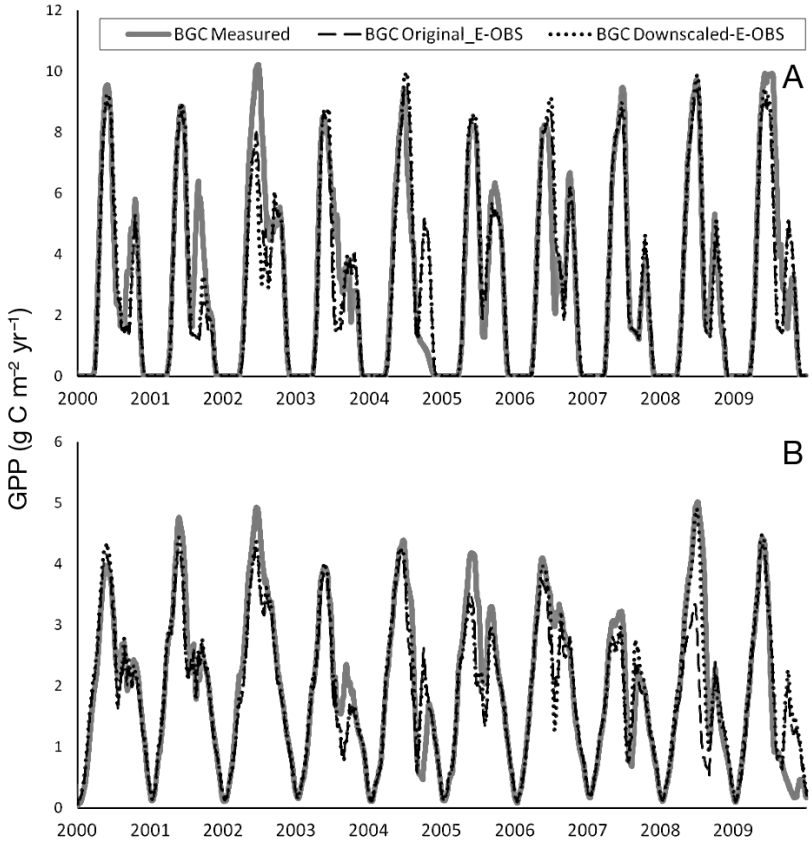

Fig. 5. Daily gross primary production (GPP) series simulated by BIOME-BGC driven by the measured (CRA-CMA) and by the original and downscaled E-OBS meteorological data sets, for (A) beech at Castel di Sangro and (B) C3 grass at Piubega. The irregularities of all series have been smoothed by means of a mean filtering with a 31 d moving window

transect pixels identified by the previously described criteria (i.e. actual prevalence of mountain conifers and suitable altitudinal range; see Section 4.2). These pixels fall in 5 grid points of the original E-OBS data set, whose elevations (black bars in Fig. 6) are generally higher than those derived from the 1 km DEM (grey bars in Fig. 6). The annual GPP computed by modified C-Fix is strictly dependent on the latter ($r = -0.951$), due to the strong altitudinal gradients that characterize both NDVI and meteorological data in this rugged mountain area. BIOME-BGC driven by the original E-OBS data is incapable of correctly following these altitudinal gradients and reproducing the spatial GPP variability of C-Fix. More precisely, most transect pixels (15) fall in the first 2 original E-OBS grid points, which have a mean altitude >1800 m a.s.l. In these cases, BIOME-BGC cannot simulate GPP, due to extremely low temperatures (annual averages <3°C). In contrast, the downscaled E-OBS data set reproduces the altitudinal gradients, providing plausible temperatures for all transect points (annual mean temperatures between 5.5 and 9.5°C). BIOME-BGC driven by these data yields a GPP transect that follows these gradients, and is similar to that of modified C-Fix ($r = 0.847$, RMSE = 141.8 g C m^{-2} yr^{-1}, and %MBE = −13).

6. DISCUSSION

6.1. E-OBS meteorological estimates

The E-OBS data set is known to be affected by several error sources related to both the intrinsic inaccuracy of the original observations and to the methods applied for interpolating the data over the 0.25° grid (Haylock et al. 2008). In the present study, the clear overestimation of minimum temperature and slight underestima-

Table 4. Correlation coefficients and root mean square errors (RMSE) between daily gross primary production obtained by driving BIOME-BGC with meteorological data measured and estimated from original and downscaled E-OBS data

Biome type	BGC_Original E-OBS r	RMSE (g C m^{-2} d^{-1})	BGC_Downscaled E-OBS r	RMSE (g C m^{-2} d^{-1})
Holm oak	0.740	1.48	0.748	1.23
Other oaks	0.943	1.44	0.924	1.49
Chestnut	0.928	1.76	0.929	1.67
Beech	0.899	1.51	0.890	1.58
Plain/hilly conifers	0.926	1.06	0.926	0.97
Mountain conifers	0.805	3.49	0.899	1.34
Mediterranean macchia	0.717	1.76	0.702	1.61
Olive	0.861	1.08	0.751	1.76
C3 grass	0.878	0.68	0.909	0.58
C4 grass	0.985	0.21	0.969	0.28

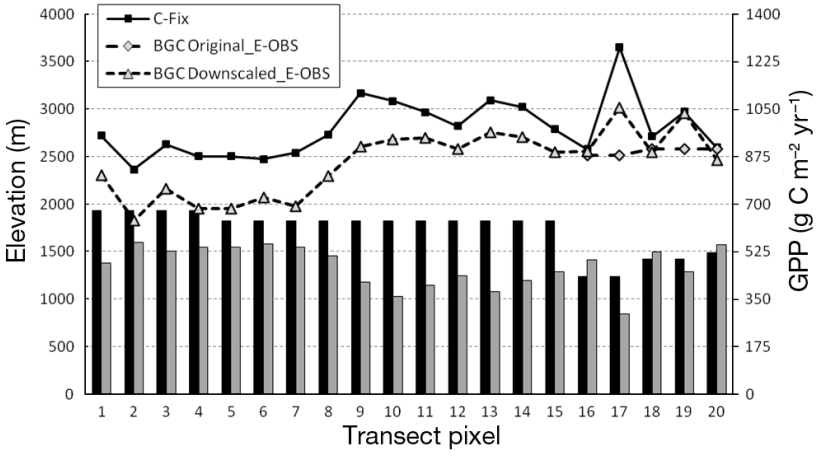

Fig. 6. Altitude (left axis) and simulated gross primary production (GPP) (right axis) found over the 20 transect pixels of Fig. 1 selected by the described criteria. Altitudes are provided for both the original E-OBS (black bars) and 1 km (grey bars) grids. GPP estimated by BIOME-BGC at the 2 spatial resolutions is contrasted with GPP simulated by the C-Fix model driven by the normalized difference vegetation index at 1 km resolution (see Maselli et al. 2009 for details). Most BIOME-BGC runs (15 points) at the original resolution gave null GPP estimates due to excessively low input temperatures (see Section 5.2). In contrast, the accordance between the GPP simulated by C-Fix and BIOME-BGC fed by downscaled data is high and highly significant (r = 0.847, root mean square error (RMSE) = 141.8 g C m^{-2} yr^{-1}, and mean bias error as a percentage (%MBE) = −13)

tion of maximum temperature and precipitation are quite consistent throughout the test stations, and can be mostly attributed to intrinsic differences between the CRA-CMA/MeteoTrentino and E-OBS data sets.

The stations of both the CRA-CMA and MeteoTrentino networks are in ideal conditions for meteorological measurements, as they are placed in open fields only marginally affected by the influence of other land cover types (see www.cra-cma.it and www.meteotrentino.it). This is not the case for the stations used to create the E-OBS data set. The superposition of these stations on the CORINE land cover map of Italy reveals that about 25% of them are placed within urban areas. This figure is likely underestimated, since it comprises all stations used for rainfall measurement, which are about 3 times as many as those used for temperature. Since the latter are mostly placed in proximity to urban centers, which also have the most complete data sets, the actual percentage of E-OBS temperature measurements coming from urban stations is likely >40%. The weather data taken at these stations are expected to be influenced by the heat island effect, which increases minimum temperature, slightly reduces maximum temperature, and has a controversial effect on rainfall (Oke 1982). These patterns would therefore explain most of the discrepancies found, particularly for minimum temperature.

The issue can be investigated using the 2 additional stations placed in the proximity of San Piero a Grado (Fig. 1). This is a flat coastal area in central Italy where the CRA-CMA station is relatively close (10 to 12 km) to a station placed within the town of Pisa and to an eddy covariance flux tower located in the pine-wood of San Rossore (Chiesi et al. 2005). This provides an opportunity to estimate the effect of 3 cover types (grass, urban, and forest) on minimum temperature. Such an operation, however, must refer to different periods, since data from only 1 year (1999) are available for the 2 stations of Pisa and San Rossore. The temperature averages reported in Table 5 confirm the previously seen E-OBS overestimation of minimum temperature at San Piero a Grado (about 2°C). This pattern, however, is reverted not only for the urban area (Pisa), but also for the forest area (San Rossore). Both E-OBS temperatures are slightly lower (0.5 and 1.1°C, respectively) than those measured during a corresponding year. This supports the hypothesis that E-OBS data are partly representative of urban meteorological conditions, which are quite similar to those within closed forests.

Table 5. Minimum temperature (T) averages measured and estimated from the original E-OBS data set for 3 adjacent sites over the years indicated

Stn	Measurement period	$T_{measured}$ (°C)	$T_{original\ E\text{-}OBS}$ (°C)
San Piero a Grado	2000–2009	8.6	10.6
Pisa	1999	10.5	10.0
San Rossore	1999	11.1	10.0

Another characteristic of the original E-OBS stations is their non-uniform distribution in Italy. Most stations (about 80%) are concentrated in 2 regions (Emilia Romagna and Trentino), both located in northern Italy. This is the likely cause for a substantial undersampling of weather spatial variability in the other regions, especially in central-southern Italy.

This problem can be particularly deleterious for the subsequent downscaling of the E-OBS data set to 1 km resolution. Locally calibrated regressions are a nearly unbiased estimator, but may suffer from the locally erroneous characterization of the relationships between independent and dependent variables (Maselli 2002, Maselli & Chiesi 2006). This drawback is evident when the density of the measurement network (in the present study: the original E-OBS stations) is insufficient to characterize the spatial nonstationarity of the relationships examined (Brunsdon et al. 1996). As a consequence, the estimation of altitudinal gradients from the E-OBS data set may be inaccurate, particularly in southern Italian regions, where the original E-OBS stations are rarer. Among the 3 weather variables, this problem is more serious for minimum temperature and above all rainfall, which show a weaker and more irregular dependence on elevation. In all cases, the inaccurate estimation of altitudinal gradients may be amplified by the application of the regression models found to 1 km pixels.

These considerations provide a reasonable explanation for the more irregular and sometimes higher errors found when using downscaled minimum temperature and rainfall estimates instead of the original E-OBS data. These error patterns can be attributed to the ineffectiveness of the applied regression procedures to properly characterize relevant altitudinal gradients. This problem is particularly evident for the 2 mountain stations of Moena (Alps) and Castel di Sangro (Apennines). In the latter case, the problematic definition of the altitudinal gradients is likely exacerbated by the low density of E-OBS stations in central-southern Italy. The same considerations explain the improvements obtained by applying the downscaling procedure to maximum temperature, whose altitudinal gradients are generally stronger and easier to capture. This is evident for the most elevated study station (Moena), where the consideration of constant elevation within a 0.25° E-OBS grid point leads to a dramatic maximum temperature error, which is alleviated by the applied downscaling.

6.2. BIOME-BGC simulations

Recent evaluation exercises have shown that BIOME-BGC is capable of reproducing both timing and amplitude of annual GPP variations for several Italian forest ecosystems (Chiesi et al. 2007, 2011, Maselli et al. 2010). The present study generally supports the previous findings. The annual GPP values simulated using ground meteorological data are similar to the measurements taken by flux towers in corresponding ecosystems. This is particularly the case for the biome types for which BIOME-BGC was recently calibrated. The present study's estimate of Holm oak GPP is around 1400 g C m^{-2} yr^{-1}, which is in the range of values given by the flux towers of Castelporziano and Lecceto (around 1600 and 1300 g C m^{-2} yr^{-1} respectively) (Nolé et al. 2009, Chiesi et al. 2011). The average simulated GPP of deciduous oaks is about 1600 g C m^{-2} yr^{-1}, which is slightly higher than the value observed for the 2 Roccarespampani towers (1400 to 1500 g C m^{-2} yr^{-1}) (Desai et al. 2008). For beech, the average estimate of about 1100 g C m^{-2} yr^{-1} is slightly lower than the measurement at Collelongo (about 1300 g C m^{-2} yr^{-1}) (Nolé et al. 2009). As regards plain/hilly conifers, the estimated value of 1580 g C m^{-2} yr^{-1} is very close to the value measured for the San Rossore pine forest (about 1600 g C m^{-2} yr^{-1}) (Maselli et al. 2009). For mountain conifers, the flux tower measurements of Renon indicate a GPP of about 900 g C m^{-2} yr^{-1} (Nolé et al. 2009), while BIOME-BGC simulates a GPP of 1300 g C m^{-2} yr^{-1}. The difference can be partly explained considering that the flux tower is placed in a forest at 1750 m a.s.l., while the weather station of Moena is at about 1200 m a.s.l. The present study's annual GPP estimate of Mediterranean macchia (around 950 g C m^{-2} yr^{-1}) is slightly lower than the measurements collected for this biome type on the 2 islands of Sardinia and Pianosa (1000 to 1100 g C m^{-2} yr^{-1}, Chiesi et al. 2012). Finally, the annual GPP simulated for olive in Southern Italy (about 1700 g C m^{-2} yr^{-1}) is slightly higher than the value reported by Maselli et al. (2012) for a dense olive grove in the more temperate Tuscany re-

gion (about 1600 g C m^{-2} yr^{-1}). Concerning the 2 grass types, no reference GPP measurement can be cited, due to the lack of flux towers placed in low-altitude semi-natural grasslands in Italy (see http://fluxnet.ornl.gov).

These indirect evaluations could be completed by comparing BIOME-BGC GPP estimates driven by different weather data sets to the measurements of eddy covariance flux towers. As mentioned in Section 3.3, however, such accuracy assessment is complicated by the difficulty of obtaining sufficiently long and reliable daily weather and GPP data series from Italian flux towers, which are mostly placed over fragmented and environmentally irregular areas (Maselli et al. 2009). The lack of a full validation of BIOME-BGC estimates against eddy covariance GPP data is a main limitation of the present study, which should be overcome by additional investigations. Some of these are in progress for specific flux tower sites in collaboration with the relevant scientists. The first results obtained indicate that BIOME-BGC driven by downscaled E-OBS data is able to simulate daily GPP of both forests (Chiesi et al. 2012, Chirici et al. 2012) and grasslands (Maselli et al. unpubl.). More particularly, the modeling approach shows a variable tendency to underestimate forest GPP, which can be mostly attributed to the previously seen E-OBS underestimation of rainfall.

With the exception of a few cases, the differences found between GPP simulations performed using measured and estimated meteorological data are relatively limited. These good model performances can be explained by a combination of factors. First, BIOME-BGC is mostly driven by daylight average temperature, which is computed by giving a higher weight (0.725) to maximum temperature (Hungerford et al. 1989, Thornton et al. 2002). This enhances the influence of this variable, which is the most accurately estimated from the E-OBS data set, while reducing the relevance of minimum temperature, whose estimation accuracy is generally lower. As regards precipitation, its influence on GPP simulation is marginal in most temperate-humid mountain zones, whereas it may be important in the driest Mediterranean areas, where vegetation growth is mostly limited by summer water availability.

These considerations explain the great dependence of BIOME-BGC simulations on the original E-OBS maximum temperature estimates. This is particularly evident for mountain areas, where vegetation growth is mostly temperature-limited. In the case of mountain conifers, the underestimation of maximum temperature is clearly reflected in a GPP decrease. Daylight temperatures are also important in Mediterranean areas, where they mainly affect the summer water requirement. This explains the behavior of Mediterranean macchia, for which a small daylight temperature underestimation (−0.9°C) along with a slight rainfall overestimation (11.5%) leads to a clear GPP increase.

The same considerations help to interpret the effects of passing from the use of original to that of downscaled E-OBS data. This process implies an evident increase in the estimation accuracy of maximum temperature, which is accompanied by more irregular changes in the accuracy of minimum temperature and rainfall. As a consequence, enhanced GPP modeling performances are generally obtained. The mean GPP differences from the simulations with the original E-OBS data are small (<10%) for half of the study stations. This number rises to 7 stations out of 10 when using the downscaled E-OBS estimates. In particular, this use leads to a strong reduction of the dramatic GPP difference found for mountain conifers with the original E-OBS data. A similar but less evident pattern is visible for most of the other biome types. The only exception concerns olive, for which the use of downscaled E-OBS data results in a significant GPP decrement with respect to the simulation driven by ground data. This decrement is due to a combination of increased temperature overestimation and rainfall underestimation (Table 3), which leads to a significant rise in summer water stress. The sensitivity of olive to this stress could be overestimated, since the BIOME-BCC version of this vegetation type was calibrated in Tuscany, where the climate is more humid than that of Turi (southern Italy).

The test performed over the transect in northern Italy confirms the capacity of the downscaling procedure to capture the altitudinal gradients of temperature and precipitation in elevated mountain areas. Since in these areas, forests are mostly placed in the valleys, the use of the original E-OBS data set leads to a general overestimation of elevation, with a consequent underestimation of temperatures. This is reflected in a problematic application of BIOME-BGC, which is mostly corrected by the use of downscaled weather data. The GPP underestimation obtained from BIOME-BGC with respect to C-Fix (about 12%) can be ascribed to the diverse functioning of the 2 models and to the use of different drivers. The reliance of C-Fix on remotely sensed data renders this model more stable and less sensitive to the meteorological anomalies that may negatively affect BIOME-BGC performances (Chiesi et al. 2011).

This last observation supports the possibility of integrating ground and remote sensing data for improving the simulation of ecosystem processes. Previous studies suggest that the GPP modeling inaccuracy caused by meteorological data can be strongly alleviated by the use of remote sensing estimates of the fraction of photosynthetically active radiation absorbed by vegetation (Chiesi et al. 2011). In the present study, this hypothesis was tested by applying modified C-Fix to the Mediterranean macchia of Chilivani, which shows the highest relative GPP bias from the use of downscaled E-OBS data (Fig. 4). The model, driven by observed and estimated weather data and a constant NDVI value typical for evergreen macchia (0.7), yields a mean GPP difference lower than 9%, which represents a dramatic reduction with respect to the BIOME-BGC simulation (38%).

7. CONCLUSIONS

The 1 km daily maps of Italy obtained from the E-OBS data set are, on the whole, relatively accurate in describing the spatial and temporal variability of the ground stations' weather data. The downscaled data overestimate minimum temperature rather uniformly and underestimate rainfall in a variable way. The first pattern is mostly related to the heat island effect that affects the original E-OBS meteorological stations. The second pattern is likely due to an incorrect reproduction of rainfall altitudinal gradients, which may be exacerbated by the low density of the original E-OBS stations in some Italian regions.

The effects of these problems, however, are generally limited on BIOME-BGC modeling of vegetation production. This model is mainly driven by maximum daily temperatures, which are most accurately reproduced by the applied downscaling. The effects of precipitation on GPP simulations are mostly confined to the driest Mediterranean areas, where the inaccurate estimation of rainfall altitudinal gradients has minor importance.

The present study also indicates that the GPP differences currently obtained from the use of ground and E-OBS data are an upper bound for forest ecosystems. In these cases, the temperatures estimated by E-OBS are likely much closer to the ground observations than what was assessed here, due to the similar effect of forest and urban areas in mitigating daily temperature ranges. It can therefore be concluded that the 1 km data set produced is particularly suited to drive BIOME-BGC modeling of forest ecosystem processes all over Italy. This is especially relevant for the model's application in highly rugged mountain areas, where the use of the original E-OBS data set can lead to dramatic inaccuracy in GPP simulation.

Similar evaluation exercises could be conducted to assess the performances of other ecosystem simulation models driven by the original and downscaled E-OBS data sets. For example, LPJ or ORCHIDEE could be applied to study the interaction between atmosphere and biosphere on various spatial and temporal scales (Sitch et al. 2003, Krinner et al. 2005). In general, these experiments should be preceded by proper tuning and testing phases aimed at guaranteeing the model's capacity to cope with the complexity and irregularity of Italian environments.

A final simulation test confirmed the previously found possibility of using remotely sensed data to further attenuate the negative effects of erroneous meteorological estimates on GPP modeling. This is particularly the case for ecosystems affected by summer water limitation, such as those that cover most peninsular and insular Italian regions.

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