Modeling Pasture Dynamics in a Mediterranean Environment: Case Study in Sardinia, Italy

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Introduction

Pastures and grasslands, with their 50 million km^2, represent two-fifths of the emerged lands, support most part of the over 3 billion pet ruminants and constitute, besides forests, a main carbon storage worldwide (Scurlock and Hall 1998; Scott et al. 1999; da Silva et al. 2004). These grasslands are located mostly in steep, semiarid marginal areas, less suitable for agriculture. Interest towards these areas grew recently, particularly focusing upon the effects of (over)grazing (Senft et al. 1984), potentially changing soil properties, and pasture patterns (Fiedler et al. 2002). This phenomenon, besides spoiling the land from a chemical and physical point of view, prevents the natural renovation of forests by reducing soil fertility. Assessment of forage biomass and nutritional quality is essential for evaluating pasture productivity and functioning. The quantity and quality of available forage, for example, influence grazing distribution patterns of livestock (Bailey et al. 1996) and affect animal performance (Ball et al. 2001). Therefore, their accurate assessment and prediction is required for a rational management of livestock distribution and for monitoring the state of the pasture (Hunt et al. 2003). Pasture yield could, in turn, have significant implications on land use planning and local policymaking (e.g., allocation of subsidies, early measures to tackle drought crises, and so on), particularly in Mediterranean areas, where overgrazing and management practices are key factors in land degradation processes (e.g., Badini et al. 2007; Fava et al. 2009). Pastures and their dynamics are tremendously important for sustainable breeding of livestock within a number of areas worldwide [e.g., central Asia (Liu et al. 2005), South America (Numata et al. 2007), West Africa (Badini et al. 2007), Middle East (Husain et al. 2009), and Australia (Cullen et al. 2009), among others], and also in Italy (Confalonieri and Bechini 2004; Colombo et al. 2009). Pasture growth is tightly linked to climate, most notably to precipitation and temperature. Therefore, potential modification of these climatic variables, namely under global warming conditions, may result into modified (possibly worse) pasture conditions, especially as an outcome of extreme events (Tubiello et al. 2007; Cullen et al. 2009), as also expected for crop systems (Soussana et al. 2010; Bocchiola et al. 2013). As such, researchers need to develop modeling tools, able to accurately mimic pasture production under specific climate conditions (Confalonieri and Bechini 2004), and water availability (e.g., De Silva et al. 2008; Snyder et al. 2008), that can be later used to (1) evaluate potential for pasture production, and (2) assess potential effect of climate variations [Tubiello et al. (2007) provides a review of potential effect of climate change upon crops and pastures]. A number of models have been developed to simulate pasture growth [Confalonieri and Bechini (2004), for example, is a review, specifically focusing upon alfalfa, *Medicago Sativa L.*]. Growth models, along with pasture yield, may provide a number of parameters related to pasture production and water usage, including leaf area index (LAI), soil moisture, and evapotranspiration, necessary for a number of conjectures, including about water needs for pasture and fodder. Several scientists studied pasture productivity using ground-based data from field campaigns, and satellite data (Gianelle and Vescovo 2007; Boschetti et al. 2007; Cho et al. 2007;

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Note. This manuscript was submitted on November 22, 2013; approved on August 19, 2014; published online on October 10, 2014. Discussion period open until March 10, 2015; separate discussions must be submitted for individual papers.

Fava et al. 2009). In turn, before models can be credibly used for conjectures on pasture dynamics, their outputs need to be validated against others, independently gathered measurements, or estimates of (some of) the output variables (e.g., Confalonieri et al. 2009). In this paper, it was developed and tested a simple, hydrologically based, spatially distributed multiyear daily pasture model, called Poly-Pasture PP (developed in Matlab(R) environment, release R2013a), for the purpose of reproducing the spatially distributed dynamics of pasture systems under given climate conditions. *Poly-Pasture PP* is based upon the inclusion of a pasture-growth module within a spatially distributed hydrological model already developed and used by the writers (Groppelli et al. 2011; Bocchiola et al. 2011) to mimic the joint dynamics of water budget and runoff production within hydrological catchments, and pasture (and crop) production upon vegetated or cultivated areas therein. The *Poly-Pasture PP* module has been already used and validated, also in spatially distributed mode, to mimic pasture and, with proper modifications for crops, productivity (e.g., Nana et al. 2013, 2014). *Poly-Pasture PP* model can be used to obtain pasture biomass estimates starting from physically based information, i.e., meteorological data, topographic characteristics, and physiological behavior of pasture grasses. In this paper, the *Poly-Pasture PP* model is presented, and its performance is assessed in a case study area in Italy, displaying a Mediterranean climate. In this paper, there are available estimates and measures of pasture biomass from a previous study (Colombo et al. 2009) in the area of Marghine Goceano (Sardinia; Fig. 1) that could be used to benchmark the model's results. In that study average annual productivity (biomass, in units of tons per hectare) estimates during 2001–2006 have been delivered using a model, validated against pointwise ground measurement carried out during 2004. First, pasture grass growth for those 6 years (2001–2006) was simulated in the research reported in this paper, and yearly average biomass yield (in units of tons per hectare) was compared against the estimates from that previous study. Then, intraseasonal biomass dynamics was evaluated during year 2004 and compared against the pointwise ground measurements. Also, LAI estimates as derived from *Poly-Pasture PP* model were benchmarked against satellite-derived LAI maps (Zhu et al. 2013), during 2005–2006. Specifically, the comparison focused upon (1) space and time patterns of LAI during growth season, to assess general model performance; and (2) LAI at peak, to evaluate the model capability to estimate maximum potential yield of pastures. Objective indicators of model performance are reported, and the results commented. Limitations of the *Poly-Pasture PP* model are then discussed, and prospective future developments sketched.

Case Study

The case study area is the macroarea Marghine Goceano, located in the northwest Sardinia, Italy. It covers about 780 km^2, and it is morphologically characterized by wide valleys and moderate elevations, reaching 1,200 metres above sea level (MASL).

This area is considered representative of the marginal agropastoral zones of the main Italian islands, and of the Mediterranean pasture typology, deriving from the particular climate of the Mediterranean regions. The Mediterranean climate can be interpreted as a transition system between the temperate and the tropical/arid climates (Peel et al. 2007). It is characterized by mainly winter precipitation, mild winters, and hot and dry summers, with high variability of annual precipitations, however low (with an annual average of 500–600 mm). Snowfall is very rare. The vegetative season starts in the end of September and reaches June, with a winter stop, due to low temperatures and a vegetative recovery in March. Vegetation is heterogeneous, with a strong presence of leathery leaf

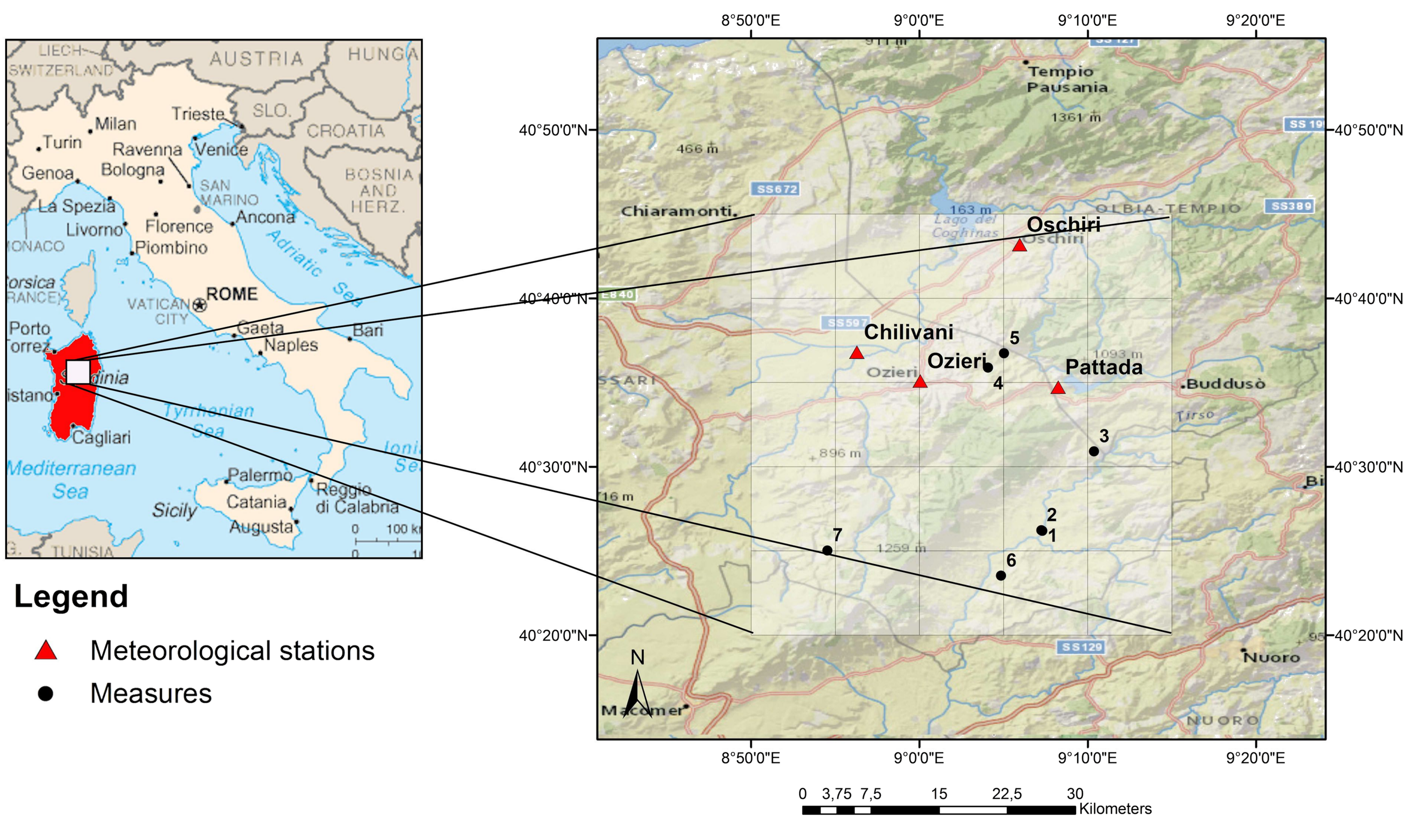

Fig. 1. Study area, cell partitioning, meteorological stations, and biomass measures (field data from Colombo et al. 2009)

Table 1. Meteorological Stations Used in This Paper

Station	Longitude	Latitude	Elevation (MASL)	Average yearly precipitation (mm)	Average yearly temperature (°C)
Chilivani	8°54′26″E	40°36′53″N	220	585	16.2
Oschiri	9°5′59″E	40°43′9″N	202	579	16.8
Ozieri	40°35′4″N	9°0′13″E	390	505	15
Pattada	40°34′59″N	9°4′56″E	674	644	14.7

shrub formations (*sclerofille*), able to develop strategies for surviving summer aridity (Cervelli 2005). Other than shrubs, some evergreen forests dominated by oaks (*Quercus ilex*) are seen. Pastures are considered within this system as a result of progressive degradation, bringing from evergreen forest to simpler vegetative associations and, finally, to steppe (Cervelli 2005). Pastureland covers ca. 550 km^2, ranging from 270 to 850 MASL ca. Pasture cover is mixed (Pulina et al. 2009), with sole grassland, mixed grass and shrubs, and sparse broad-leaved trees, and needle-leaved trees, in the 700–1,200 MASL belt.

Database

Meteorological Data

Daily series of precipitation, and maximum and minimum temperature delivered from meteorological stations belonging to Regional Environmental Protection Agency (ARPA) of Sardinia, were used in the research reported in this paper. Namely, four meteorological stations were considered, i.e., (1) Ozieri, (2) Pattada, (3) Chilivani, and (4) Oschiri, providing measures during 2001–2006 (Fig. 1; Table 1). Whenever the measured data were missing or incomplete, they were integrated with the interpolated meteorological data from the Crop Growth Monitoring System (CGMS), developed by Monitoring Agricultural Resources (MARS) unit of Joint Research Center (JRC). Global radiation series were also retrieved from CGMS.

Table 2. *Poly-Pasture PP* Model Soil Hydraulic Parameters in the Area of Marghine Goceano

Parameters	Loam	Sandy loam
$\theta_w(\cdot)$	0.12	0.09
$\theta_l(\cdot)$	0.26	0.19
$\theta_s(\cdot)$	0.47	0.41
$K(\mathrm{mm\,h^{-1}})$	8.70	27.20

Hydraulic Parameters

Other than the latitude and elevation of the meteorological stations and the average height of each cells, the *Poly-Pasture PP* model requires the hydraulic properties of soil. These properties, namely wilting point θ_w, field capacity θ_l, saturation θ_s, and hydraulic conductivity K, were obtained here starting from soil texture (Saxton et al. 1986), while depth of the soil layer was assigned as per each cell. Texture class was obtained from JRC European texture map (Hiederer 2012), giving mainly loam and sandy-loam substrate (Table 2).

Then, the *Poly-Pasture PP* model requires some agronomic parameters, concerning the phenology of pasture, in analogy with crop models (Moreira et al. 2000; Stöckle and Nelson 2003; Confalonieri et al. 2009; Lacovara 2006; Gusmeroli 2012). These parameters and their chosen values are summarized (Table 3), together with their unit of measurement and range of values. While for crops and agricultural species numerous studies exist, providing the evaluation of base and optimal temperatures (e.g., Angus et al. 1981); for wild grasses these parameters are less largely available. Also, as reported pasture is classified in this paper as a mixture of different species, so that average values for the Mediterranean pastures were retrieved and used in the research reported in this paper (Angus et al. l981; Cervelli 2005; Gusmeroli et al. 2005; Colombo et al. 2009). A degree day factor is used to characterize every growth stage within *Poly-Pasture PP* model. In this paper, degree day was obtained in accordance with an empirical method (e.g., Stöckle et al. 2003). This consists in two steps, namely (1) identifying the time when the species reaches each growth stage (choosing from the available literature base and cutoff temperatures fitting that particular species), and (2) calculating the number of degree days gathered starting from the vegetative recovery and linking the degree days to the highlighted dates.

Leaf Area Index Satellite Maps

The LAI estimates during 2005–2006 could be retrieved (Zhu et al. 2013), derived from AVHRR NDVI3 g data, available at the National Aeronautics and Space Administration (NASA) Earth

Table 3. Input Phenologic Parameters Required by the *Poly-Pasture PP* Model

Parameter	Definition	Range	Value
T_{base} (°C)	Base temperature	0–15	2
T_{cutoff} (°C)	Cutoff temperature	0–45	42
T_{opt} (°C)	Optimal temperature for growth	T_{base}–T_{cutoff}	25
$R_{d,\max}$ (m)	Maximum root depth	0.1–3.0	0.3
DD_{emerg} (°C day)	Degree days at emergence	0–500	50
DD_{mat} (°C day)	Degree days at physiological maturity	1,000–2,500	2,000
DD_{flow} (°C day)	Degree days at flowering	DD_{emerg}–1,500	730
$K_{c0}(\cdot)$	Parameter for crop coefficient	0.1–1.6	0.85
$k(\cdot)$	Extinction coefficient for solar radiation	0.3–0.8	0.5
L_{tbc} (g/MJ	Radiation conversion factor	1–5	2.5
$WU_{\max}$ (mm/day)	Maximum daily water uptake	5–15	13
$\Psi_{l,sc}$ (J/kg)	Critical leaf water potential	−2000 to −500	−1,200
Ψ_{wilt} (J/kg)	Wilting leaf water potential	−3,000 to −1,100	−1,500
BTR (kPa kg/m^3)	Above ground biomass-transpiration	3.5–6	5
SLA (m^2/kg)	Specific leaf area	15–25	25
LS$(\cdot)$	Leaf/stem partition	1.5–4.0	3

Exchange website. These data contain Level 3 information (Hagolle et al. 2004) and are already processed to remove cloud disturbance. These data are gridded at a 1/12-degree spatial resolution, and are available with a 15-day temporal frequency.

Biomass Data

Colombo et al. (2009) developed a method for the estimation of pasture productivity by way of a growth model driven using MODerate resolution Imaging Spectroradiometer (MODIS) remote sensing estimates of the normalized difference vegetation index (NDVI). The writers studied the area of Marghine Goceano, and provided (1) sparse pointwise biomass measurements during 2004, and (2) average annual productivity estimates during 2001–2006 using their validated model (Table 3). These data were also used to validate *Poly-Pasture PP* model.

Materials and Methods

Poly-Pasture Model

The spatially semidistributed *Poly-Pasture PP* model was used in the research reported in this paper. The *Poly-Pasture PP* model was obtained by including a vegetation growth module within a spatially distributed hydrological model already developed and used by the Politecnico di Milano staff (Groppelli et al. 2011; Bocchiola et al. 2011; Confortola et al. 2013). The vegetation growth model was developed with the aim of providing a simplified version of a crop growth model, such as *Cropsyst* model (Stöckle et al. 2003). The hydrological model, through a water budget scheme, provides soil water content, which is then used by the vegetation module to simulate pasture growth. In turn, the vegetation growth model provides daily values of LAI, used by the hydrological model to calculate the transpiration and fraction of vegetated soil, and modified soil water content through vegetation water use. Both modules work at a daily scale upon a grid cells scheme, with side size defined by the user. Each cell has its own topography, vegetation, meteorological inputs variables, and soil properties. At present, every cell is considered independent from the others, neglecting the lateral flows. Such approximation is valid for large cells, and flat areas, with little lateral redistribution, as expected in the research reported in this paper. Only one soil layer is considered, given the limited root depth of pasture grasses. Preliminary testing indicated that the *Poly-Pasture PP* model provides acceptable results in vegetation and crop modeling, when compared against state of the art crop models (e.g., *Cropsyst*; Addimando 2013; Nana et al. 2013, 2014). The hydrological model is based upon a simplified daily step water budget equation

$$S^{t+\Delta t} = S^t + P + M_s - \mathrm{ET} - Q_g - Q_s \quad (1)$$

where S = soil water content; P = rainfall; M_s = snow melting (not applicable in this paper); ET = actual evapotranspiration; Q_g = groundwater discharge; and Q_s = overland superficial flow, all expressed in units of millimeters. Use of actual ET is to stress the difference against potential evapotranspiration ET_p, calculated in this paper using Hargreaves' method. This is to keep into account water stress as resulting by limited precipitation and large temperatures. Measured values of evapotranspiration were not available in the research reported in this paper. Q_s is proportional to soil water content and soil permeability. Interaction of underground flow Q_s with water table is not explicitly considered, given the lack of information about the latter. The vegetation growth model estimates daily biomass as the minimum value between a water dependent growth G_{TR} and a solar radiation dependent growth G_R

$$G_{\mathrm{TR}} = T_{\mathrm{eff}} \mathrm{BTR}/\mathrm{VPD} \quad (2a)$$

$$G_R = L_{\mathrm{tbc}} \cdot \mathrm{PAR} \cdot f_{\mathrm{PAR}} \cdot T_{\mathrm{lim}} \quad (2b)$$

with G_{TR} (kg m^{-2} day^{-1}) = transpiration-dependent biomass growth; T_{eff} (m day^{-1}) = effective actual transpiration; VPD (kPa) = average vapor pressure deficit; BTR (kPa kg m^{-3}) is the biomass transpiration coefficient; G_R (kg m^{-2} day^{-1}) = radiation-dependent biomass growth; L_{tbc} (kg MJ^{-1}) = light-to-biomass conversion coefficient; PAR (MJ m^{-2} day^{-1}) = photosyntetically active radiation; $f_{\mathrm{PAR}}(.)$ = fraction of incident PAR intercepted by canopy; and T_{lim} is the temperature limitation factor$(\cdot)$. The writers assumed full availability of soil nutrients. Such assumption is not generally true since pasture, albeit subject in some cases to natural fertilizing processes through animal feces, does not generally undergo fertilization (or irrigation). Biomass estimates are in this sense potential, with respect to the actual availability of nutrients. Vegetation growth stages are based on the accumulation of thermal time (or degree days) during the growth season. Every species reaches the next growth stage when the necessary thermal time has been cumulated. Below a base temperature the thermal time is not cumulated (Stöckle and Nelson 2003). In the presence of vegetation biomass, the fraction of incident photosynthetically active raiation, f_{PAR}, depends upon the LAI, which is iteratively calculated for each day of the simulation

$$f_{\mathrm{PAR}} = 1 - \exp(-k\mathrm{LAI}) \quad (3)$$

where $k[\cdot]$ = extinction coefficient for solar radiation. The effective transpiration depends upon soil water content and plant vegetative stage (Stöckle et al. 1994)

$$T_{\mathrm{eff}} = 86{,}400C/[1.5(\Psi_s - \Psi_x)] \quad (4)$$

where C (kg s m^{-4}) = root conductance; Ψ_s = soil water potential (J kg^{-1}) depending upon soil water content; Ψ_x (J kg^{-1}) = leaf water potential depending upon plant roots development; 86,400 is the number of seconds per day; and 1.5 is a factor converting root conductance into hydraulic conductance.

Cells Size and Influence Area

Cell size is in this paper taken based upon the resolution of the satellite maps used in the comparison. Namely, the writers used 25 square cells sized 1/12-degree (9.3 km). So doing, the spatial resolution is low, the computational burden is reduced, and the writers can directly compare the model simulated LAI maps against those from the satellite. To provide precipitation input in each cell, Thiessen polygons were created for the four available rain gages. A linear temperature-altitude gradient is estimated from data and adopted to extrapolate temperature in each cell.

Results and Discussion

First, *Poly-Pasture PP* yearly average biomass yield estimates were compared against those derived by Colombo et al. (2009) using NDVI from MODIS (Fig. 2). The productivity is calculated by multiplying biomass by an index, generally 0.5 (Pona et al. 2002), to evaluate the effective amount of biomass in the final product. The indices of agreement reported [Table 4, which gives root-mean square error (RMSE); percentage RMSE, and coefficient of residual mass (CRM); see e.g., Confalonieri et al. (2009)] show that the model can in general reproduce the annual average produc-tivity (RMSE $= 0.46$ t ha^{-1}, RMSE$_{\%} = 12\%$, CRM $= 0.003$, and $R^2 = 0.69$). To obtain a comparison against measured data, the pointwise ground measures of Colombo et al. (2009) have been

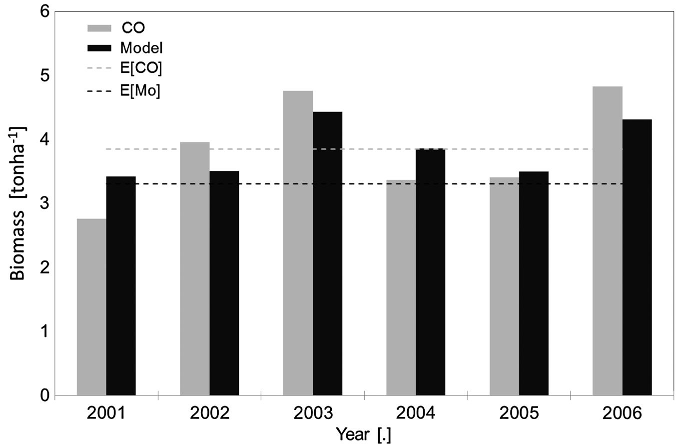

Fig. 2. Comparison of yearly peak biomass from PP model and control values from Colombo et al. (2009) during 2001–2006

Table 4. Agreement between *Poly-Pasture PP* Estimates and Independent Estimates

Statistic	Model, Colombo et al. (2009)[a]	Measurements, pointwise, Colombo et al. (2009)[b]
RMSE (t/ha)	0.46	0.95
$RMSE_{\%}$ (%)	11.97	25.03
CRM($\cdot$)	0.003	0.108
$R^2(\cdot)$	0.69	0.35

[a] *Poly-Pasture PP* biomass against the biomass estimated by Colombo et al. (2009) during 2001–2006.

[b] *Poly-Pasture PP* biomass and the biomass measured pointwise by Colombo et al. (2009) during 2004.

compared to the model estimates of biomass in the cells related to the sampling sites (Fig. 3; Table 4).

From Fig. 3 the model underestimates the biomass values initially (i.e., in April 2004). This may be due to some mismatch concerning onset of the growing season. Moving forward in time, however, the model estimates get closer to the observed values, reaching with good accuracy the biomass amount at the end of the flowering stage. The corresponding statistics on the whole period are RMSE $= 0.95$ t ha^{-1}, $RMSE_{\%} = 25\%$, CRM $= 0.11$, and $R^2 = 0.35$). In spite of the low R^2, calculated over the whole period, the *Poly-Pasture PP* model may provide reasonable esti-mates of pasture productivity at peak.

The LAI values from *Poly-Pasture PP* model were then compared against their satellite-derived counterparts (Fig. 4). The satellite-derived LAI is somewhat high outside the growing season. The satellite estimates of LAI mirror the condition of vegetation by representing the whole panorama of the species in the area, the latter having different growing seasons and flowering times. Thus, researchers may assume that errors in depicting LAI sooner or later than the growing season may indeed be given by the presence of different vegetation species, not simulated by the model. Fig. 4 shows that during the growing season the modeled LAI is in better agreement with the satellite derived LAI during years 2005–2006. The pasture grasses object of this paper reach the flowering stage within the second half of May and the first days of June, corresponding to LAI peaks derived from satellite in late spring. After reaching the peak, the modeled LAI decreases, enter-ing a dormant phase until the next year, but other Mediterranean species reach the flowering stage, so that the satellite LAI moves to higher values. In Fig. 5 the scatter plot of satellite LAI is reported against LAI from *Poly-Pasture PP*, calculated during growth sea-son (five dates), and at peak. A spatial comparison of modeled LAI distribution (at peak) against its satellite-derived counterpart during 2005–2006 is shown (Fig. 6). In Table 5 they are reported measures of agreement between the spatially distributed LAI during the vegetative period (25 cells, five dates around peak, years 2005–2006, 250 points; Figs. 4 and 5), and the spatially distributed LAI at peak dates (25 cells, one peak date, years 2005–2006, 50 points; Fig. 6). The indices for spatially distributed LAI at peak are RMSE $= 0.54$ and 0.52 t ha^{-1}, $RMSE_{\%} = 19$ and 19%, and CRM $= -0.05$ and -0.02, during 2005–2006, while for spatially distributed LAI during grow season (five dates) they are RMSE $= 0.82$ and 0.67 t ha^{-1}, $RMSE_{\%} = 41$ and 38%, and CRM $= -0.08$ and -0.04, during 2005–2006. The R^2 was not reported for this data. Given the low spatial variability (i.e., SD) of the observed LAI from satellite images (SD nearby 0.4 in both cases of peak date, and five dates), the estimation error (RMSE in Table 5, in the order of 0.5, and up to 0.8 for five dates) would be larger than process variability. Thus, R^2 would be negative. However, the large

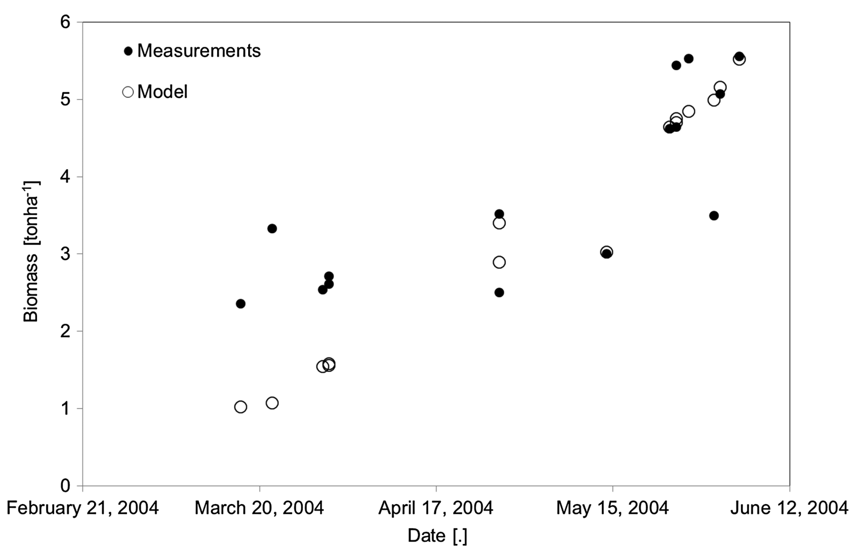

Fig. 3. Comparison between the point wise ground measurements by Colombo et al. (2009), and *Poly-Pasture PP* model estimates

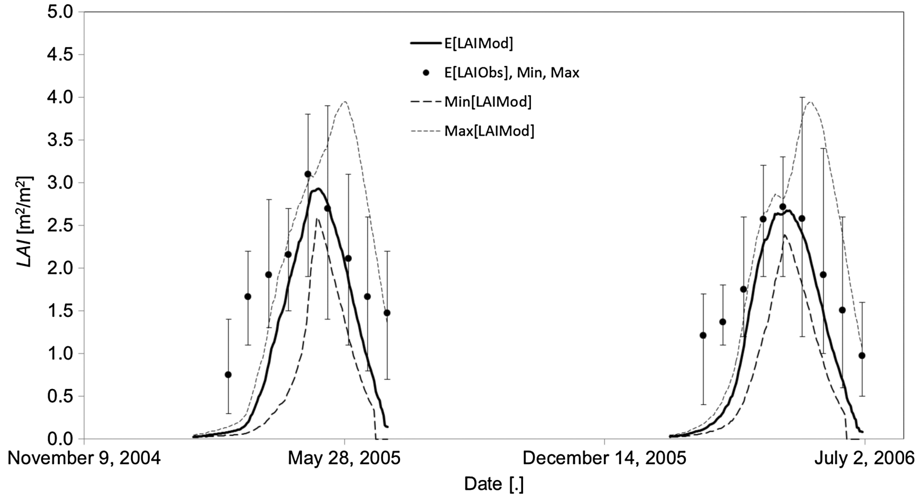

Fig. 4. *Poly-Pasture PP* and satellite LAI evolution during 2005–2006; spatially averaged LAI, together with least (mnimum) and greatest (maximum) value in the grid is reported

homogeneity (i.e., low SD) of LAI at peak may be an artifact of satellite estimation, and further some uncertainty may be entailed in LAI estimates from satellites, so use of R^2 seems less suitable for this data. In this context, other indices were provided, such as CRM, which depicts a first-order (i.e., on average) assessment of the model capability of representing pasture growth, and RMSE, which depicts the average error in each single cell when calculating LAI. The comparison made for peak date only, and for five dates, demonstrates that at peak the performance of *Poly-Pasture PP* model tends to improve, especially on average (i.e., lower CRM), and the model can be somewhat useful for assessment of average pasture productivity, in spite of more variable accuracy in space.

From the results, researchers may state that the objective of the paper seems reasonably well-reached. The *Poly-Pasture PP* model, despite being simple enough, can reproduce acceptably biomass and LAI evolution in time. Inaccuracies ($RMSE_{\%}$) nearby 20% or so seem commonly accepted in crop growth simulation (Cho et al. 2007; Colombo et al. 2009), and the model of the research

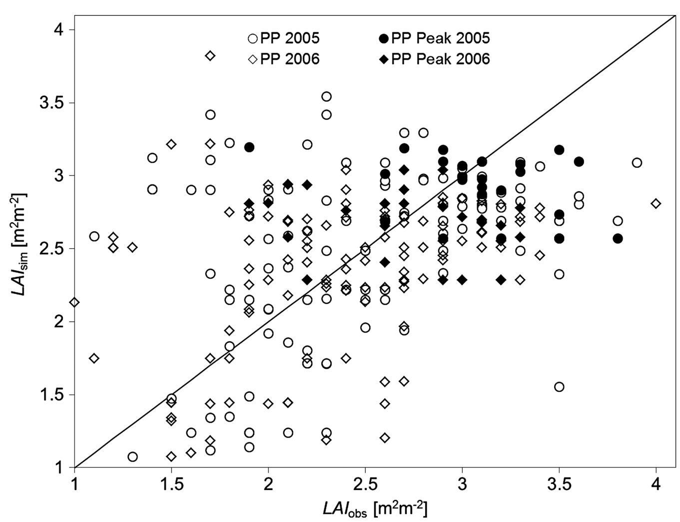

Fig. 5. Scatter plot of satellite LAI, and *Poly-Pasture PP* LAI calculated during growth season (five dates), and at peak

reported in this paper seems able to perform within this range at peak dates. Both pasture biomass estimates from another model and pasture biomass measurements from the field are acceptably reproduced by *Poly-Pasture PP*. The comparison against the satellite-derived LAI series seemingly produced positive outcomes. In the simulated 2 years, and in all of the model's grid cells, the modeled values of LAI during the growing seasons display a range of variations fully comparable with those provided as derived from MODIS data, average error (CRM) is low, and the cellwise agreement seems acceptable, also considering potential noise within LAI estimates from MODIS. Most importantly, at peak dates *Poly-Pasture PP* seems to represent reasonably well the spatial patterns of LAI, thus indicating an acceptable capability in depicting the greatest (yield) pasture biomass in a spatially distributed fashion. Some limits to usage of satellite data to obtain biomass estimates are likely highlighted in this paper. Satellite images may not discern between the different species on the ground. Whenever different species would possess different growing seasons, and/or flowering times with respect to the target one (or ones, i.e., those simulated by the model), superposition of signals from different species may occur, and use of satellite LAI would be taken with care. Satellite-derived LAI can be considered representative of pastures during specific periods, depending on the area of study, so that preliminary investigation about such periods is warranted. From the spatial point of view, the model considers the evolution of a single, either real or representative species, and thus provides LAI values as if the species entirely occupied each single cell, which may not generally be true, especially using large-dimension cells. Unexpected LAI values in the maps may therefore regard cells with different prevalent species besides pasture grasses. The LAI estimates from AVHRR NDVI3 g could not be validated, given that lack of LAI data from the ground. The LAI estimates may display some noise, changing with vegetation type, and geographic area (Zhu et al. 2013). In this paper, satellite estimates of LAI were used as a proxy for ground truth for a first-order assessment of *Poly-Pasture PP* model performance. In the future, the uncertainty of satellite estimates will be explicitly accounted for.

The *Poly-Pasture PP* model makes a number of simplifying assumptions. Full availability of nutritive substances in the soil is hypothesized, which is not granted. The acceptable results seen in the case of Marghine Goceano seem to suggest that no strong lack of nutrients is seen in the research reported in this paper,

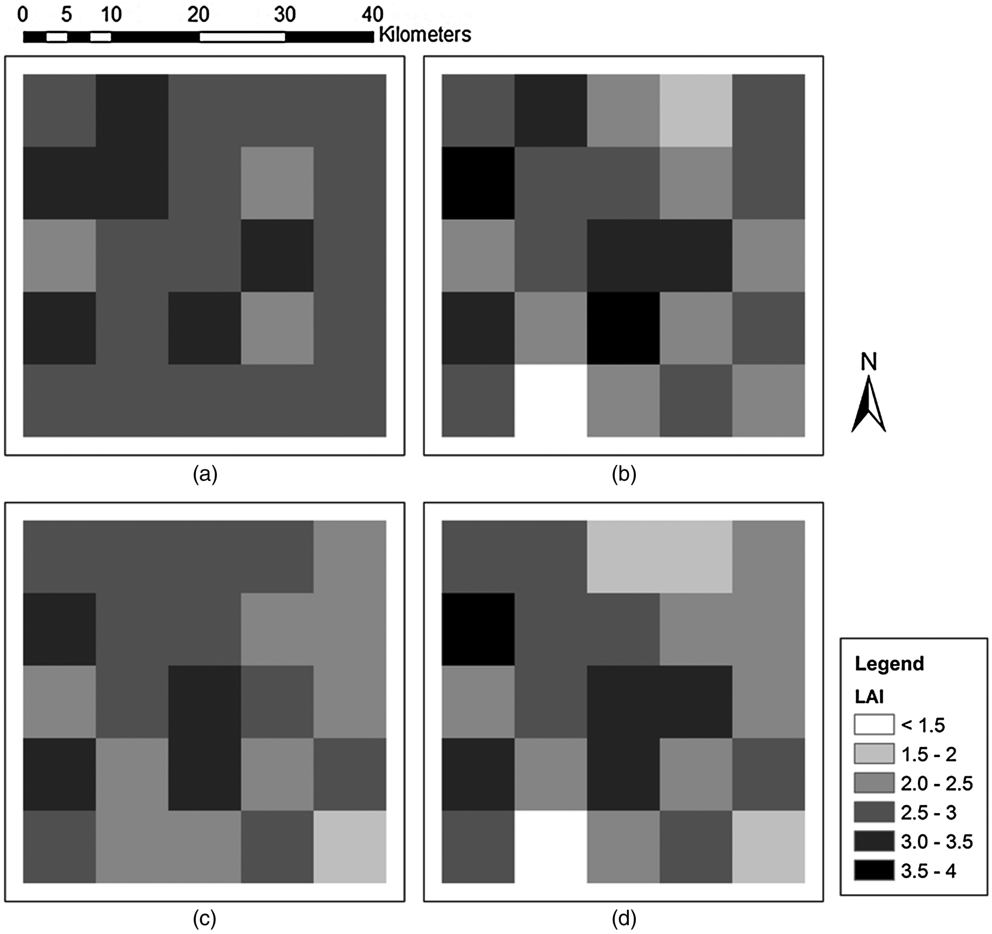

Fig. 6. Leaf area index maps at peak: (a) year 2005, LAI modeled by *Poly-Pasture PP*; (b) year 2005, LAI derived by AVHRR satellite; (c) year 2006, LAI modeled by *Poly-Pasture PP*; (d) year 2006, LAI derived by AVHRR satellite

and possibly grazing livestock provide for land fertilization. This may be true in places where pastures are controlled and restoration periods of natural species are respected, while this may not be true within overexploited (overgrazed) areas, where degradation of soil nutritive properties may be larger. Future developments of the model should therefore include nutrient cycle dynamics, and thereby assessment of the positive (e.g., fertilization) and negative (e.g., overgrazing) effects of nutrient budget. With the caveats and needs for future deepening as previously mentioned, the *Poly-Pasture PP* model displays some potential for application. The *Poly-Pasture PP* model is mounted as reported upon a fully spatially distributed hydrologically based model, so it may be used to investigate hydrology of catchments, including in presence of specific crop/pasture species. Generally speaking, hydrological models include rough representation of vegetation processes, mostly devoted to assess evapotranspiration. However, evapotranspiration patterns are tightly linked to vegetation dynamics and accurate depiction of the latter would lead to accurate assessment of the former. Evapotranspiration carries a large share of the hydrological budget, and increasingly so under transient global warming (e.g., Groppelli et al. 2011), and it requires duly investigation. Recent studies (Nana et al. 2013, 2014) demonstrate that *Poly-Pasture PP* model can acceptably depict not only crop yield and LAI as in this paper, but even soil moisture and evapotranspiration, against observed data, so likely providing a chance for accurate closure of water budget in hydrological models including depiction of pasture/crop dynamics.

Table 5. Agreement between Satellite-Derived and Model-Estimated LAI Maps

Period	RMSE ($m^2\ m^{-2}$)	RMSE (%)	CRM($\cdot$)
Peak[a]			
2005	0.54	19.4	−0.05
2006	0.52	9.8	−0.02
Season, five dates[b]			
2005	0.82	41	−0.08
2006	0.67	37.8	−0.04

[a]Spatially distributed LAI at peak dates (25 cells, years 2005–2006, 50 points).
[b]Spatially distributed LAI during vegetative period (five dates, 25 cells, years 2005–2006, 250 points).

Conclusion

In this paper, it was presented a *Poly-Pasture PP* model, able to obtain pasture biomass estimates from physically based information related to the growth and the development of the vegetation, e.g., meteorological data, topographic characteristics, and phenological behavior of pasture grasses. Model performances have been evaluated in an Italian Mediterranean case study area, where estimates and measures of pasture biomass were available from a previous study in the area of Marghine Goceano (Sardinia), and where LAI estimates from MODIS data could be used.

The *Poly-Pasture PP* model has provided acceptable results herein this paper, and even considering the necessity of some refining as outlined, it displays some potential when it comes to studying future coupled hydrological and phenological dynamics of catchments under prospective climate change. Dependence upon meteorological conditions makes pastures very vulnerable ecosystems under climate change scenarios, especially where increasing temperatures and decreasing precipitation are expected, like in Sardinia in the research reported in this paper, and the writers anticipate that the *Poly-Pasture PP* model may turn to be useful for simulation of pasture fate under climate change.

Acknowledgments

The CGMS developed by MARS unit of JRC is acknowledged for sharing their maps of climate variables. Dr. Zhu at Boston University and Beijing Normal University is acknowledged for sharing LAI maps from AVHRR satellite. Eng. Ester Nana acknowledges support from the SHARE-Stelvio project funded by Lombardia Region. Eng. Daniele Bocchiola acknowledges support from 5xMille:I-CARE project funded by Politecnico di Milano. Eng. Andrea Soncini and Gabriele Confortola at Politecnico di Milano are kindly acknowledged for their help with geographic information system (GIS) processing.

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