Can a simple model implemented with satellite data be used for modelling the vegetation dynamics and water cycle in water-controlled environments?

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ABSTRACT

Vegetation plays a key role in catchment's water balance, particularly in semi-arid regions that are generally water-controlled ecosystems. Nowadays, many of the available dynamic vegetation models are quite complex and they have high parametrical requirements. However, in operational applications the available information is quite limited. Therefore parsimonious models together with available satellite information can be valuable tools to predict vegetation dynamics. In this work, we focus on a parsimonious model aimed to simulate vegetation and hydrological dynamics, using both field measurements and satellite information to implement it. The results suggest that the model is able to adequately reproduce the dynamics of vegetation as well as the soil moisture variations. In other words, it has been shown that a parsimonious model with simple equations can achieve good results in general terms and it is possible to assimilate satellite and field observations for the model implementation.

KEY WORDS: satellite data; parsimonious; dynamic vegetation model; semi-arid; water fluxes

1. Introduction

A better understanding of the components of catchments' water balance has traditionally been one of the main objectives of the hydrological community (Gerten *et al.,* 2004). To this end, it is certainly well-known that the vegetation plays a key role in a catchment's water balance particularly in semi-arid regions (Laio *et al.,* 2001). In these water-controlled ecosystems, the vegetation controls the hydrological processes through its influence on interception, infiltration, evapotranspiration, surface runoff and, consequently, groundwater recharge (Rodriguez-Iturbe *et al.,* 2001). The vegetation key role on controlling the hydrological cycle is such that the actual evapotranspiration may account for more than 90% of the precipitation (Pilgrim *et al.,* 1988; Huxman *et al.,* 2005). From here that reliable estimates of spatial and temporal variations of actual evapotranspiration as well as precipitation are vital to obtain reliable estimates of the available water resources (Andersen, 2008). In spite of this, traditionally, very few hydrological models had incorporated the vegetation dynamic as a state variable, neglecting in this way most of the interactions with vegetation and vegetation dynamics themselves (Lee and Pielke, 1992; Parlange and Katul, 1992; Walker and Langridge, 1996; Alvenäs and Jansson, 1997; Snyder *et al.,* 2000; Aydin *et al.,* 2005). In fact, most of them are able to represent fairly well the observed discharge at the catchment outlet, but usually including the vegetation as a static parameter (Quevedo and Francés, 2008).

In the last decades, the number of hydrological models which explicitly take into account the vegetation development as a state variable has increased substantially and considerable efforts have been made to understand and reproduce adequately the interactions between the vegetation and the water cycle. However, most of the time, these models are difficult to constrain because of the high number of parameters that are required to be estimated (Quevedo and Francés, 2008). This represents a particularly challenging task, especially considering that in operational applications the available information is frequently quite limited, in particular for arid and semi-arid regions which often in some respects could be categorized as ungauged basins (Andersen, 2008).

Therefore parsimonious models, together with available remote sensing information, can be valuable tools to predict vegetation dynamics. For this reason, we have focused on the use of the parsimonious and dynamic vegetation LUE-model proposed by Pasquato *et al.* (2014).Briefly, the parsimonious LUE-model simulates gross primary production (GPP) as a function of absorbed photosynthetically active radiation (APAR) and the vegetation light use efficiency (LUE). Net primary production (NPP) is then calculated taking into account maintenance respiration. This model is focused particularly on simulating foliar biomass, which is obtained from NPP through an allocation equation based on the maximum LAI sustainable by the system (Pasquato *et al.*, 2014).

However, since LUE is a parsimonious and conceptual model, some vegetation processes have been neglected. It is important to check that the most relevant processes are being captured by the model. For this reason, the present study compares the capability of this parsimonious model against a physically-based model in reproducing the interaction between vegetation and water. The selected physically-based model was the well-known Biome-BGC (Thornton *et al.,* 2002). The models were applied in a semi-arid forest experimental plot (East of Spain) and their performances were analyzed against field data (daily soil water content and transpiration). The parsimonious LUE-Model was calibrated using remote sensing data and validated using the field observations, while the BIOME-BGC model was implemented only using the field measurements.

In this way, we want to know if the use of a parsimonious model together with remote sensing data is an option comparable to the use of a physically-based model together with field observations. This question is very interesting in those cases in which there are not field measurements. Zhang *et al.* (2011) showed how model's predictions can be improved using satellite imagery combined with field data. However, there are still many open questions regarding the remote sensing's applicability and robustness. Pasquato *et al.* (2014) highlighted the importance to evaluate firstly the remote sensing data to be used in order to ascertain the value of the information that can be extrapolated from them, taking into account the fact that external conditions and the structure of vegetation canopy can alter the computed vegetation indices values (Jackson and Huete, 1991).

In most of the applications, satellite data is used combined with field data. But, actually, it will be rare to have field measurements for model implementation in practical applications. Therefore, in this paper we address the following two questions: (1) is the proposed parsimonious model capable to satisfactory simulate vegetation and hydrological dynamics or a more complex model is needed? and, (2) can satellite products be used to implement a dynamic vegetation model or are field measurements totally necessary?

2. Study area

The study site is an experimental plot located in the Public Forest *Monte de la Hunde y Palomeras* in the East part of Spain (Figure 1). The sandy-silty loam soils predominate with high concentration of carbonate (16-38%, pH 7.7-8.2). Soil thickness ranges between 50 and 60 cm. The climate is Mediterranean with a mean annual rainfall of 466 mm and a mean annual temperature of 13.7 ºC (1960-2007). The mean annual reference evapotranspiration is 749 mm. Using the Köppen climate classification, the climate of this area is classified as semiarid (González-Sanchis *et al.*, 2015).

The vegetation in the experimental plot is characterized by an homogeneous Aleppo pine (*Pinus halepensis*) plantation of high tree density with scant presence of other tree species either in forest gaps or as understory species (e.g., *Quercus ilex* sbsp. *ballota, Pinus pinaster*) (Molina and del Campo, 2012). This place has been previously studied and modeled. Information about the results of the previous studies can be found at González-Sanchis *et al.* (2015), Molina and del Campo (2012) and, del Campo *et al.* (2014).

Figure 1. Location of the experimental plot study site. Detailed view of the 60 years old aleppo pine plantation, control plot, used for this work.

3. Field measurements

Measurements of Soil Water Content (SWC) and transpiration were carried out in an experimental plot of 30x30 m (Del Campo *et al.,* 2014). Transpiration was measured in 4 trees by considering the diametrical distribution (<20.5 cm low, 20.5-26.5 cm medium, >26.5 cm high). Four trees were selected: one of the high, one of the low and two of the medium diameter class. Sap flow velocity was measured through the HRM method (Burgess *et al.,* 2001; Hernandez-Santana *et al.,* 2011; Williams *et al.,* 2004) in all sample trees and programmed to average every hour. In each tree a HRM sap flow sensor (HRM sensor, ICT International, Australia) was placed at 1.3 m height and at the north side.

SWC was measured using 9 FDR sensors (EC-TM, Decagon Devices Inc., Pullman, WA), placed at 30 cm depth and considering either tree influence or not (i.e., under projected crown or not). SWC was continuously measured for the whole period every 20 minutes. Field sensor calibrations were carried out by determining the gravimetric water content in four sampling dates (saturation, field capacity, between field capacity and wilting point and wilting point) to obtain the full range of SWC in the study site (Del Campo *et al.,* 2014). In this way, plant transpiration and soil moisture were obtained in the experimental plot during the observational period from 27/03/2009 to 31/05/2011.

The Leaf Area Index (LAI) was estimated on field using a LAI-2000 sensor (LI-COR, 1991) only once at the beginning of the work. Readings were taken under direct solar radiation (Molina and Del Campo, 2011) with a 270° view cap and with the sensor always shaded to avoid light dispersions affecting sensor readings (LI-COR, 1991). The measured LAI has a value of 2.6.

At the end, we used the following field measurements to carry out the implementation of the complex model: (1) daily transpiration data calculated as an average which takes into account the number of trees included in each diameter class (low, medium and high), and (2) daily SWC data calculated according to the vegetation cover, assuming that the sensors under tree influence (mean value) were representative of the area covered by vegetation and the sensors without tree influence (mean value) were representative of bare soil. The fraction covered by pine in the experimental plot is the 84% with a tree density of 1489 tree/ha.

4. Satellite data

In this work, we analyzed the following satellite products provided by NASA (NASA Land Processes Distributed Active Archive Center (LP DAAC)): the Normalized Difference Vegetation Index (NDVI), included in the MOD13Q1 and

MYD13Q1 products; the Leaf Area Index (LAI), included in the MOD15A2; and the MYD15A2 products and the actual evapotranspiration (ET), included in the product MOD16A2. For the coverage of the study site, the h17v05 tile is required, where h and v denote the horizontal and vertical tile number, respectively. The MODIS vegetation index datasets provided in Hierarchical Data Format (HDF) were imported to GeoTIFF format by MODIS Reprojection Tool (MRT) (software provided by NASA) and reprojected from the Integerized Sinusoidal (ISIN) projection to Universal Transform Mercator projection system.

The NDVI data is provided by NASA every 16 days and with a spatial resolution of 250X250 m. On the other hand, the LAI data is provided every 8 days and with a spatial resolution of 1X1 km. Both MODIS products were analyzed from 18/02/2000 to 02/02/2013. Finally, the ET datasets provided by NASA are evaluated using Mu *et al*.'s algorithm (2011) based on Penman Monteith equation (Monteith, 1965). This algorithm uses the following satellite information to be implemented: land cover classification, albedo, LAI and fPAR (fraction of the photosynthetically active radiation). It is available from 01/01/2000 to 26/12/2012, provided every 8 days and with a spatial resolution of 1X1 km. As the study experimental plot (described above) is only of 30X30 m and it is completely covered by one satellite pixel, we used directly the value of NDVI, LAI and ET from this pixel. In other words, interpolation techniques were not needed.

As a result of the dataset analysis, only NDVI was finally used to calibrate LUE model. Despite the fact that all analyzed satellite products (NDVI, LAI and ET) showed a marked seasonal quasi-sinusoidal behavior as expected (Figure 2), the values of LAI were significantly lower than the one measured in the field. Satellite

LAI values ranged from 0.8 to 1.2, while the measured one was 2.6. This field value is in agreement to values reported in literature (Sabaté *et al*., 2002; Sprintsin *et al*., 2007; Vicente-Serrano *et al.,* 2010) for the same species and under similar climatic conditions. Thus, the use of satellite LAI was finally dismissed. Likewise, as the Mu's algorithm employed to calculate ET uses the MODIS LAI, the use of satellite ET was also rejected. Hence, we used only the NDVI data from 18/02/2000 to 02/02/2013 to carry out the calibration of the LUE model. It should be underline that LAI and ET products are calculated by NASA using models, and at least for this particular pixel, they did not work.

5. Models

5.1. LUE-Model

Hydrological sub-model

The dynamic vegetation model was coupled with a hydrological model based on a tank-based schema (Figure 2). A more detailed description of the hydrological model used can be found in Quevedo and Francés (2008), Pasquato (2013) and Pasquato *et al.* (2014).

Briefly, the first tank represents the amount of water retained by the canopy. This water can only exit from this tank by direct evaporation. On the other hand, the soil depth is divided into two layers: a shallow layer that involves the processes of bare soil evaporation and superficial roots transpiration, and a second underlying layer that provides soil moisture to deeper roots (Figure 2).

Transpiration (both from the shallow layer and from the deeper layer) is calculated according to FAO recommendations (Allen et al., 1998): the transpiration is obtained using the reference evapotranspiration (ET_0) multiplied by a water stress factor (ζ) and by a factor related to the current leaf area index (LAI) simulated by the dynamic vegetation model, as shown in equation 1. Through this factor, the state of vegetation affects the hydrological fluxes and, consequently, the water storage in the different tanks.

$$T_i = (ET_0 - EI) * \min(1, LAI) * \zeta * Z_i \qquad (1)$$

where T_i is the transpiration from the i soil layer, EI is the evaporation of the intercepted water and Z_i is the percentage of roots in the i soil layer. The expression min(1,LAI) is the factor which replaces the crop factor recommended by the FAO 56.

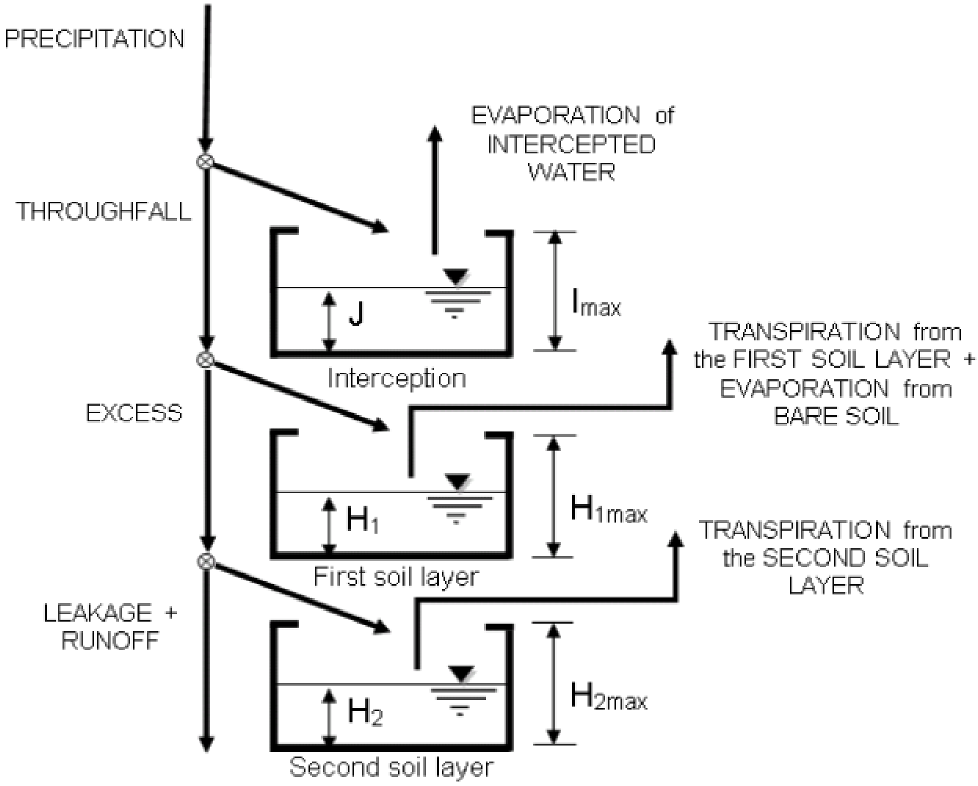

Figure 2. Schema of the hydrological sub-model (Pasquato *et al.*, 2014)

Dynamic Vegetation sub-model

Many approaches for estimating plant biomass production (Field *et al*., 1995; Running *et al.,* 2004; Montaldo *et al.,* 2005; Pasquato *et al.,* 2014) are based on the use of the light use efficiency (LUE) concept. The LUE is the proportionality between plant biomass production by terrestrial vegetation and absorbed photosyntetically active radiation in optimal conditions. However, this efficiency can be affected by stress conditions. The key factors contributing to the variation of this efficiency are: soil moisture content, air temperature (Landsberg and Waring, 1997; Sims *et al*., 2006), and nutrient levels (Gamon *et al.,* 1997; Ollinger *et al.,* 2008).

Our LUE model simulates the leaf biomass (Bl, kg DM m^{-2} ground) as follows (Pasquato *et al.*, 2014:

$$\frac{dB_l}{dt} = (LUE * \varepsilon * PAR * fPAR - Re) * \varphi_l - k_l * B_l \qquad (2)$$

where ε takes into account the reduction in LUE due to stress sources. In this study, as it was applied in a water-controlled catchment, the stress factors considered were only the water stress and the temperature stress. The nutrient levels were not considered, because they are not the dominant stress source in this area. The water stress factor connects the dynamic vegetation model with the hydrological model. Re is the respiration, ϕ_l is the fractional leaf allocation and k_l is the leaf natural decay factor to reproduce the senescence. Finally, PAR and fPAR are the photosyntetically active radiation and the fraction of PAR absorbed by the canopy respectively. More information about these terms can be found in Pasquato (2013).

The daily PAR was obtained from the incident global radiation provided by a nearby meteorological station using a constant ratio of 0.48 MJ (PAR) MJ^{-1} (global radiation) (McCree, 1972). The fPAR was obtained using the Beer-Lambert law:

$$fPAR = 0.95 * \left(1 - e^{-k*LAI}\right) \qquad (3)$$

where k is the light extinction coefficient and LAI is the leaf area index simulated by the model. The LAI is simulated through the specific leaf area (SLA) and the vegetation fractional cover (f_v):

$$LAI = B_l * SLA * f_v \qquad (4)$$

However, Dawson *et al*. (1998) showed that NDVI is influenced by leaf water content. For this reason, some authors (William and Albertson, 2005; Pasquato *et al.,* 2014) recommend the use of a water stress factor to make comparable the LAI with the NDVI as shown in equation 5.

$$LAI_r = LAI * \overline{\zeta_{10}} \tag{5}$$

where the LAI_r is the LAI comparable with NDVI and $\overline{\zeta_{10}}$ is the average plant water stress of the previous 10 days as proposed by William and Albertson (2005).

5.2. Biome-BGC Model

As representative of a complex model, this paper uses the Biome-BGC 4.2 model (Thornton *et al.,* 2002) for two reasons. Firstly, the model is well documented, both technically and in scientific publications; second, the source code of the model is publicly available on the Internet (NTSG 2001). Furthermore, it is also widely used as a benchmark during global change analysis (e.g., Schimel *et al*. 1994). Complete descriptions of the model have been carried out in many studies (Pietsch *et al*., 2003; Tatarinov and Cienciala, 2006; Chiesi *et al.,* 2007; Maselli *et al.,* 2009).

Briefly, the model operates in a 1m^2 scale, with a daily time step and describes the dynamics of energy, water, carbon and nitrogen in a defined type of terrestrial ecosystem (deciduous broadleaf forest, coniferous forest or grassland). The model requires: daily climate data, information of the general environment (soil, vegetation and site conditions) and 34 parameters describing the ecophysiological characteristics of vegetation such as specific leaf area, water interception coefficient or light extinction coefficient. BIOME-BGC is provided with default ecophysiological parameters sets for the major biome types, but these must be modified to adapt to Mediterranean ecosystems (Chiesi *et al.,* 2007). Water cycle calculation includes daily canopy interception, evaporation, transpiration, soil evaporation, soil water potential, soil water content and outflow.

6. Methodology

This paper implements the LUE-Model following two steps: (1) calibration of the model using the satellite NDVI and (2) validation using the available field measurements (transpiration and SWC). The performance of the model is then compared to that of the BIOME-BGC model by comparing the simulation results between them and to the field observations. Thus, the simulated period of both models includes the period with available field data (27/03/2009 to 31/05/2011), as well as two different precipitation scenarios: dry (year 2005) and wet (year 2010). In particular, we computed the amount of 'blue water' (water in liquid form used for the human needs or which flows out the ecosystems) and the amount of 'green water' (water having the vapor for resulting from evaporation and transpiration processes) in order to obtain and compare the blue/green rate (B/G) using both modeling alternatives.

Due to observational and model conceptualization errors and time and space scale effects, any mathematical model must use effective parameters for a better reproduction of reality (Blöschl and Sivalapan, 1995; Francés *et al*., 2007). The main reason of the calibration of a mathematical model is therefore to obtain the effective values of its parameters.

The hydrological sub-model has six parameters to be calibrated: (1) maximum interception storage, (2) the wilting point soil moisture, (3) field capacity soil moisture, (4) optimal point soil moisture, (5) effective depth soil of the first layer and (6) effective depth soil of the second layer. With regards to the dynamic vegetation sub-model, there are seven parameters to be calibrated: (1) LUE, Light Use Efficiency, (2) coverage factor, (3) distribution of roots factor, (4) maximum LAI sustainable by the system, (5) light extinction coefficient, (6) SLA, Specific Leaf Area, and (7) optimal temperature.

To calibrate both sub-models (thirteen parameters) we used the available NDVI data from 18/02/2000 to 02/02/2013. As NDVI is sensitive to green leaf biomass, it can be primarily employed to monitor the photosynthetically active biomass of plant canopies, and the relationships between NDVI and LAI have been strongly demonstrated. For this reason, the selected objective function was the Pearson's correlation coefficient between the simulated LAI_r and the satellite NDVI. Firstly, calibration was carried out using a manual adjustment of parameter's values and using values recommended in literature for each parameter (some sources were: Ceballos and Ruiz de la Torre, 1979; Calatayud *et al*., 2000 and others). Later, a genetic algorithm called Evolver was used to optimize the calibration process. Finally, the model was validated using daily field measurements of SWC and transpiration.

The BIOME-BGC was calibrated and validated using daily field sap flow and soil moisture data. For calibration, the 70% of the field data were used, while the remaining 30% were used to validate the model. Since it is a model which works at 1m^2 scale (individual scale), it was applied in various trees and, later, we calculated an average of these ‘individual’ results. A more detailed description of this process can be found in González-Sanchis *et al*. (2015).

The performance of both models was analyzed comparing the simulation results to the field observations. The selected goodness-of-fit indexes were the Root Mean Square Error (RMSE), the Nash and Sutcliffe efficiency index (E) and the Pearson correlation coefficient (only for the LAI evaluation).

As the main objective of this paper is to know if a simple model implemented only using satellite data can be used as alternative against a well-known physically-based model implemented using field measurements, we ran both models for a long period and, later, we compared the differences between them.

Finally, the B/G water ratio was calculated using the results from each model. In our models, on one hand, the Blue water is the excess water from the upper soil: i.e., surface runoff plus deep percolation. And, on the other hand, the Green water is calculated as the sum of the amount of water transpired by plants, the amount of water evaporated from the bare soil and the amount of water evaporated from the interception.

7. Results

In general, the calibration of the LUE model showed a strong positive relationship between the LAI_r and the NDVI provided by satellite in the entire period (see Figure 3), with a Pearson correlation coefficient of 0.635.

However, during the calibration, despite the fact that generally the simulated peak values of LAIr coincided with those of NDVI, a significant disagreement between both variables was obtained during two specific periods (shaded in Figure 3). During the first period, from July 2004 to December 2005, the LAI_r and the NDVI series were totally uncorrelated, especially during the beginning of this period. Likewise, in the second period, spring 2010, the simulated LAI_r maintained a high value while the NDVI decreased substantially.

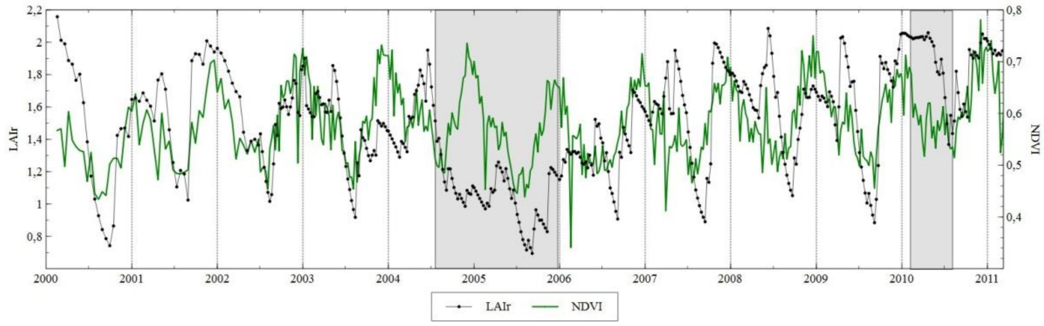

Figure 3. Comparison between LAIr simulated by the model and NDVI from satellite. The shaded areas correspond to the two specific periods with a significant disagreement between simulated LAIr and satellite NDVI.

The validation of the LUE-Model with the field measurements showed a general agreement between the simulated and the measured SWC and transpiration, although the former appears to be more accurately reproduced (see Table II). The major disagreement in the prediction of transpiration values occurred during the spring of 2010, which is the same period where the simulated LAI_r and the NDVI were noticeably uncorrelated.

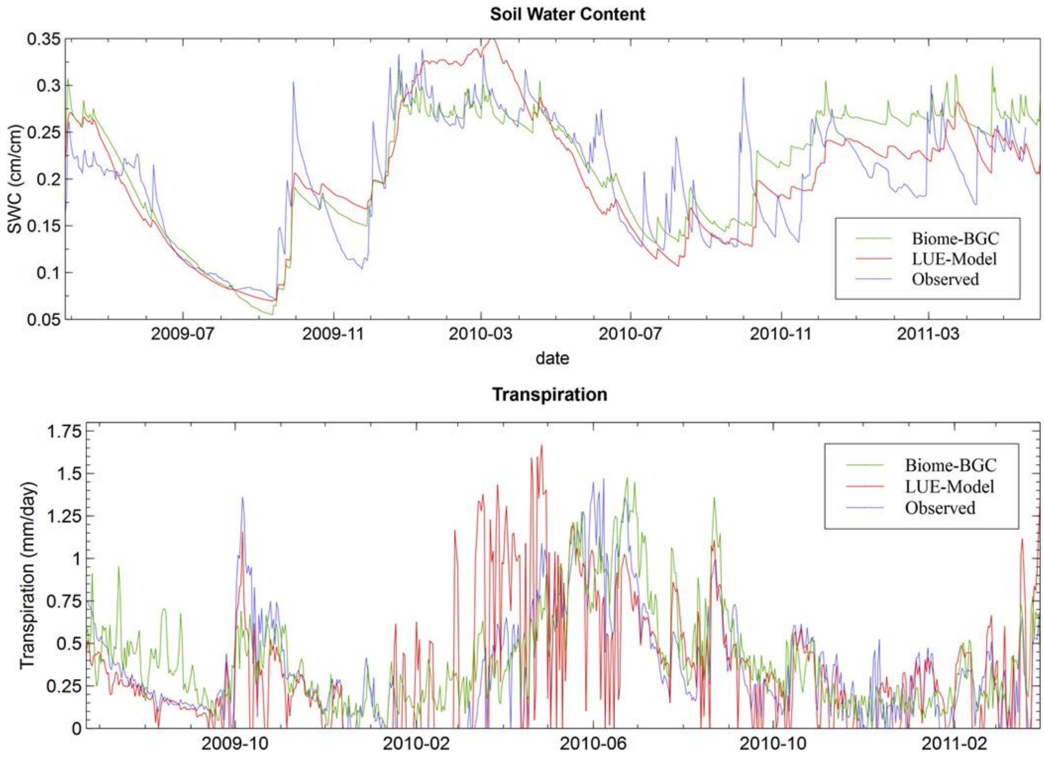

Figure 4. Transpiration and SWC simulated by both models and measured in field

As mentioned before, the calibration and validation of the BIOME-BGC has been previously carried out in González-Sanchis *et al*. (2015) and the results are summarized in Table II. The model predicts accurately SWC and transpiration, although like the LUE model, the BIOME-BGC also reproduces more accurately the dynamics of SWC. The E index is approximately 0.5 in the case of transpiration (0.532 in the calibration and 0.544 in the validation) while the same index in the case of SWC is higher than 0.7 (0.766 in the calibration and 0.715 in the validation). In any case, the obtained results were satisfactory in both, transpiration and SWC.

Therefore, both models reproduce with acceptable accuracy the water dynamics of the study site. In fact, the E indexes in terms of SWC is higher than 0.65 for both models (Table II). However, as it was expected and it is shown by the selected goodness of fit indexes, the BIOME-BGC appears to be more accurate than the LUE-Model (see Figure 4 and Table II).

Table II. Results of the validation using field data for the LUE and Biome-BGC models (observational period 27/03/2008 to 31/05/2011)

	Transpiration		**SWC**	
	LUE-Model	Biome-BGC	LUE-Model	Biome-BGC
E	0.346	0.544	0.65	0.715
RMSE	0.274	0.209	0.051	0.070

Comparing the results of both models in a longer run (from 2004 to 2012 approximately), we can observe that there are not big differences between them (see Figure 5). The agreement between SWC time series is very strong and it is better than the agreement between transpiration time series. But, in general, there are not big differences. In fact, the Pearson correlation coefficient values between them are 0.638 and 0.865 for the transpiration and SWC respectively.

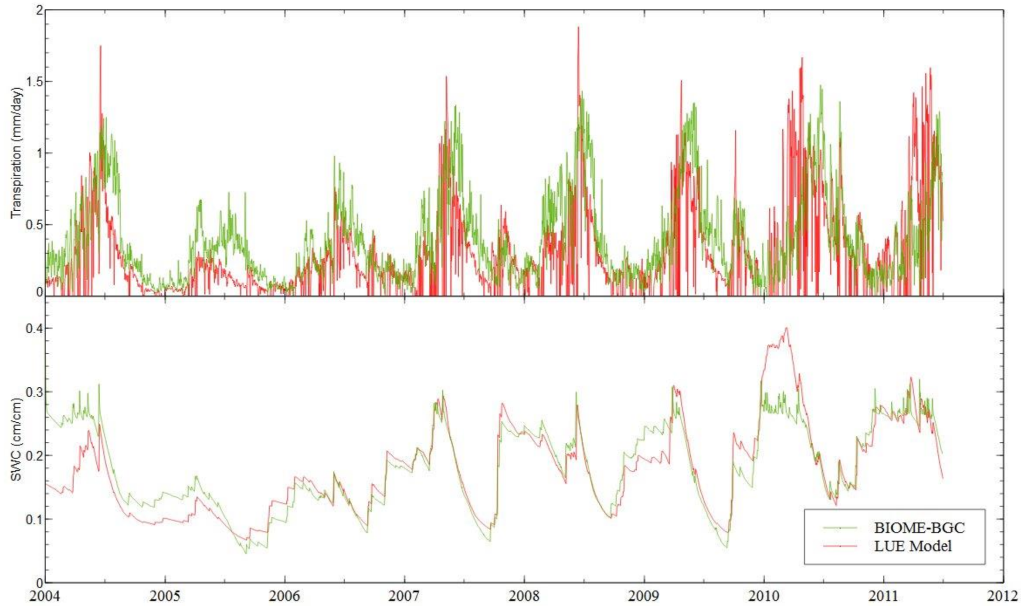

Figure 5. Transpiration and SWC time series simulated by both models (from 2004 to 2012 approximately)

Likewise, when estimating the general B/G rate during the dry and the wet years, the models produce very similar results, with a rate around 0.1 during the dry year and around 0.8 during the wet year (Table III).

Table III. Results of each model in terms of blue (excedence) and green (evapotranspiration) water

	Flows	**Dry year (2005)**	**Wet year (2010)**
LUE-Model	Precipitation (mm)	188	739
	Evapotranspiration (mm)	165.18	431.87
	Excedence (mm)	16.34	326.93
	B/G	0.098	0.757
Biome-BGC	Precipitation (mm)	188	739
	Evapotranspiration (mm)	156.30	408.80
	Excedence (mm)	31.7	330.10
	B/G	0.104	0.807

8. Discussion

In general, LUE and BIOME-BGC reproduced with acceptable accuracy SWC and transpiration values. Both models simulated more accurately SWC than transpiration dynamics, and a disagreement between simulated and observed daily transpiration can be found at certain periods for both models. The disagreement could be due to the fact that 2010 was an abnormally rainy period, and as an outlier, the models might not reproduce it properly. However, since the periods where the models performed with less accuracy were not the same, the high quantity of rain might not be the cause, or at least not the main one. Del Campo *et al* 2014 grouped the simulated period in four spells according to the precipitation and the average daily temperature: Dry Cool (DC), Dry Warm (DW), Wet Cool (WC) and Wet Warm (WW). Analyzing the performance of both models during each spell, it is possible to observe that both models behave different. The LUE model does not reproduce accurately cool spells, either dry or wet, while the BIOME-BGC is slightly less accurate when simulating dry spells, either cool or warm. Analyzing the field data, it is possible to observe a significant linear relationship between transpiration and Vapor Pressure Deficit (VPD) during cool spells, which is stronger during WC spells. Contrarily, during warm spells, the transpiration is significantly correlated to the measured SWC. This behavior describes the general dynamics of the vegetation, where if soil water availability does not limit transpiration, it is expected that transpiration will be affected primarily by atmospheric evaporative demands (Monteith, 1965; Tanner and Fuchs, 1968). Thus, the LUE model appears not to include properly the atmospheric evaporative demands, and its performance during the periods were this demand prevails over SWC is less accurate.

With regards to the lower performance of the BIOME-BGC model when simulating transpiration during dry spells, is probably due to the fact that the model is not originally designed to reproduce arid or semi-arid environments. Indeed the fact that SWC is always accurately simulated indicates that the drought tolerance of semi-arid species might reduce the accuracy of the model at certain periods.

As mentioned previously, when analyzing the performance of the LUE model with satellite information, we observed that the main disagreement between LAIr and NDVI is produced during the period from July 2004 to December 2005, which was an extremely dry period. The precipitation during this period was 188 mm, which is significantly lower than the annual mean precipitation registered in the study site (466 mm). Thus, according to the general dynamics of the vegetation, in this extremely dry period the SWC would be expected to be the main driving factor of transpiration, and therefore, the performance of the LUE model is expected to be more accurate. SWC and LAIr are highly correlated in the LUE model, and a significantly decrease in SWC will also imply a significantly decreasing of LAIr. However, the immediate response of LAIr to SWC variations contrasts to that of NDVI, which appears to be delayed a few months. NDVI values of arid or semiarid areas, as well as those of Mediterranean areas during the dry summer season, have been demonstrated to be strongly dependent on plant water availability in preceding months (Maselli 2004). In particular, inter-year NDVI variations of Mediterranean vegetation cover are mostly controlled by variations in previous plant water stress conditions during the arid season (Caroti *et al*., 1995 and Cannizzaro *et al.,* 2002). Maselli 2004 found a strong dependence of a Mediterranean pine wood summer NDVI values on winter rainfalls and summer NDVI were causally linked; i.e., the first was the main cause for the latter. Besides, as a drought-avoiding species, *Pinus halepensis* has an ability to survive intense and prolonged drought (Maseyk *et al.,* 2008; Schiller and Atzmon 2009) that could delay even more the NDVI response. Thus, the disagreement between LAIr and NDVI found in this study is probably due to the late response of NDVI to a severe drought period. Indeed, after this drought period, NDVI decreases until August 2006, where the regression between LAIr and NDVI, although significant (sig. < 0.05) showed a low regression coefficient of 0.2. Contrarily, from August 2006 onwards, NDVI starts to increase again probably as a response of the rain during the winter of 2006, and the regression coefficient increases to 0.69.

Likewise, the disagreement between LAIr and NDVI during the first half of 2010 can also be due to the late response of NDVI to changes in water availability, although in this case the water availability increases substantially as 2010 was an abnormally rainy period. As a consequence, LAIr increases and remains with high values almost the first half of 2010. On the contrary, the increasing of NDVI is not observed until August, when the regression coefficient between LAIr and NDVI increases from 0.29 to 0.61. However, with these exceptions, the LUE model captures well the dynamic of the vegetation provided by NDVI.

Likewise, the estimation of the general B/G water balance using the LUE and the BIOME-BGC model produced very similar results when simulating both dry and wet years. Both models obtained a B/G water ratio below 1, where more than half of the total annual rainfall would be consumed by the ecosystem and returned to the atmosphere, and a short quantity of water would be able to supply the catchment. The similarity of the results enhances the capability of the parsimonious LUE-Model to distribute water, which is very similar to that of the physically-based Biome-BGC model. A proper distribution of blue and green water is essential for a model as it raises the question of a loss of services that ecosystems provide to human and also the amount of available water to be used by vegetation. Particularly, in Mediterranean ecosystems, where the global climate change scenario predicts an increase in dry years over normal and wet periods (Giorgi and Lionello, 2008), an accurate distribution of the blue and green water is fundamental when designing water management policies.

9. Conclusions

The obtained results in this research suggest that the parsimonious model is able to adequately reproduce the dynamics of vegetation (the correlation coefficient with the satellite and field transpiration data are acceptable), and it also reproduces properly the soil moisture variations. In other words, it has been shown that a parsimonious model with simple equations can achieve good results in general terms, and it is possible to assimilate satellite information for the model implementation. However, it also has been observed that the LUE model's accuracy is worse when the transpiration is limited by the atmospheric demands. It's important to mention that the LUE model uses the reference evapotranspiration during the calculation of the transpiration. As the LUE model implementation represented such situation in which there are not field information, the reference evapotranspiration was calculated by Hargreaves and Samani method (this method only needs information of temperatures and radiation). Maybe the LUE model’s performance can improve if the Penman Monteith method was used to calculate the reference evapotranspiration.

Anyway, the objective of this paper is not to propose a ‘perfect model’. In fact, we want to know if a simple model implemented only using satellite data can be used as alternative against a well-known physically-based model implemented using field measurements. The comparison between both models in a long period shows there are not big differences between them, and the dynamics in both cases (transpiration and SWC) are very similar.

In this research, the satellite data played a key role in the implementation of the model. In fact, the measured transpiration data were available only over less than two years as a field observation of the vegetation state and evolution. In this case, the satellite data was a very useful source of information, and its combination with the parsimonious LUE model has demonstrated to be an accurate tool capable of predict the role of the vegetation in the water cycle with no field data.

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