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IMPLEMENTATION OF EF FROM SEBS IN A LUE MODEL IN A RAPESEED CROPLAND

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ABSTRACT

In assessment of global carbon cycle, evaluation of gross primary production, GPP, of an ecosystem is the main endeavour. The most adequate way to address this study is to apply a Light Use Efficiency, LUE, model in combination with an Eddy Covariance, EC, system.

In this paper, evaporative fraction, EF, from two different databases (ground-based measurements and calculated by the Surface Energy Balance System, SEBS, algorithm developed at ITC) are applied to a LUE model in order to calculate a final ε_0 value which is the maximum PAR conversion efficiency of the cropland.

The LUE model was found to fit properly using both EF databases, with squared correlation coefficients of 0.89 and 0.81 for ground measurements and SEBS results, respectively. Final values for maximum efficiency were of 2.82±0.19 gC MJ^{-1} (measured EF) and 2.59±0.23 gC MJ^{-1} (SEBS). All these results were obtained with FPAR provided by MERIS.

1. INTRODUCTION

Longer temporal series of atmospheric CO_2 concentration have been measured and recorded at Mauna Loa observatory (http://www.cmdl.noaa.gov) showing a continuous increasing trend. At present there is general consensus regarding the influence of GHG (greenhouse gases) on climate change. Increases in surface temperature and sea level are clear indicators of this change [1]. Changes in temperature together with changes in the precipitation pattern can lead to a stomatal closure, which influence the amount of CO_2 sequestered by the ecosystem [2]. This fact can turn an ecosystem from sink to source of carbon. Therefore, knowledge of the behaviour of the different ecosystems is an actual issue widely studied.

Regarding to climate change, assessment of the total amount of CO_2 assimilated by crops, GPP, and Net Ecosystem Exchange, NEE, is a main challenge. Measurements of these variables are usually made using micrometeorological techniques such as EC. Different biomes have been evaluated by installing EC towers, and several networks have been established around the world such as CARBOEUROFLUX, ASIAFLUX or FLUXNET [3]. These networks provide information of these studies, quantifying GPP and NEE for different ecosystems and showing their behaviour as sink or source of carbon. The results obtained evidence the unequal ability to uptake CO_2 in different ecosystems [4].

An alternative for estimating GPP is based on the application of LUE models [5, 6]. In these models EF is used as an important parameter reducing final ε_0 value since low EF values are usually associated to water stress.

In this study, in order to quantify the crop ability as a CO_2 sink, continuous measurements of NEE, latent and sensible heat, LE and H, were made using an EC station. Moreover, a LUE model has been calibrated for a rapeseed crop using MERIS products, EF and meteorological data. EF has been calculated using two separately procedures. Firstly, ground measurements of

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LE and H were used. Secondly, EF results from SEBS algorithm were employed.

This paper presents the results of the GPP 8–d estimated values using a LUE model over a rapeseed crop for the agricultural year using FPAR from MERIS, and calculates the ε_0 value characterizing the studied rapeseed cropland.

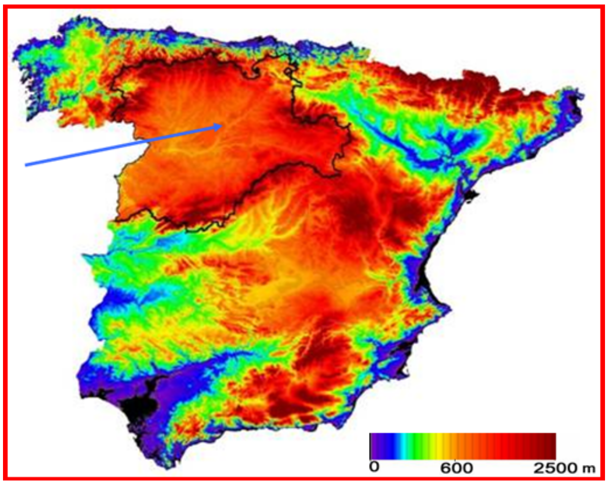

Figure 1. Location of the measuring plot

2. SITE DESCRIPTION

Measurements have been conducted continuously since 2008 in a farmland located about 30 km far from Valladolid in the upper Spanish plateau (Fig. 1). Relief elements are not present and horizontal homogeneity is ensured. This is a required feature when micrometeorological techniques are used to measure ecosystem exchanges. The dominant land use is non–irrigated crops with a rotating scheme including rapeseed, wheat/barley, green peas, rye and sunflower. During the studied period, rapeseed was grown. Rapeseed was sown in September, 2007 and harvested in July, 2008. Measurements started in March–April, 2008. First stages of the crop development were thus missed. However, the period for which the crop presented its full development (April–June), as well as the senescence stages, was covered.

3. METHODOLOGY

3.1 MERIS data

MERIS images were downloaded from the MERCI interface and processed with BEAM VISAT software (version 4.8). The algorithm employed to retrieve biophysical parameters was TOC (Top of Canopy) Vegetation Processor. Detailed information concerning the algorithm can be found in the literature [7, 8].

Values retrieved for LAI and FPAR corresponded to the pixel centred on the measuring plot. Isolated gaps were refilled by linear interpolation between the previous and subsequent data or with the average value calculated for pixels surrounding this central pixel.

MERIS images have a temporal resolution of approximately 3 days and they have been used in Reduced Resolution, RR, covering 1040 m x 1160 m. Biophysical parameters retrieved from the sensor were aggregated into 8–d composites for later calculations.

3.2 Field data

NEE, LE and H were measured using micrometeorological instrumentation by applying the EC technique. This instrumentation consists of an IRGA (InfraRed Gas Analyzer, Li–7500) and a sonic anemometer (USA–1) sampling at a frequency of 10Hz. Instantaneous data were processed each 30min. TK2 software [9] was used to process these 30min averages to ensure the quality of the turbulent fluxes and ecosystem exchanges (water and carbon). The LUE model applied needs of other ancillary data, particularly meteorological measurements. The meteorological instrumentation is placed in a tower located a few meters from the tower housing the micrometeorological instrumentation. This is equipped, among others, with a quantum sensor to measure

Photosynthetically Active Radiation, PAR, and sensors measuring soil and air temperature and moisture. All ground data were aggregated into 8–d composites in the same way than MERIS biophysical parameters.

EF was calculated from LE and H measurements as follows:

$$EF = \frac{LE}{LE+H} \quad (1)$$

GPP, a fundamental parameter to calibrate the LUE model, is indirectly derived by EC measurements as the difference between ecosystem respiration, RE, and NEE as follows:

$$GPP_{obs} = RE - NEE \quad (2)$$

CO_2 total exchange plays a crucial role in the carbon balance, particularly to define the ecosystem behaviour as sink or source of carbon. Therefore, NEE and GPP datasets must be gap-filled in order to quantify the amount of carbon exchanged between the ecosystem and the atmosphere.

RE can be measured experimentally using soil chambers [10] or parameterized from meteorological data. In this study, RE has been parameterized using the soil moisture, SM, and the air temperature, T.
Since photosynthesis only takes place during daytime, GPP takes thus value 0 during nighttime. Hence, RE was determined using the NEE nocturnal data by means of a parameterization using a modified Van't Hoff equation as follows:

$$NEE_{night} = RE_{night} = a \cdot SM \cdot \exp\,(b \cdot T) \quad (3)$$

where the parameters a and b were obtained by a non–linear fit using the Marquardt algorithm. Diurnal RE was then computed using the fitted Eq. 3 together with daytime values of SM and T.
In this paper, NEE gaps during daytime have been filled by fitting a Michaelis–Menten equation relating NEE and PAR [11],

$$NEE = \frac{\alpha \cdot PAR \cdot P_{max}}{\alpha \cdot PAR + P_{max}} + R_{eco} \quad (4)$$

where α is the apparent quantum yield, P_{max} is the maximum photosynthetic assimilation, and R_{eco} is the ecosystem respiration. This equation was fitted for each 15–days period in order to obtain the best results regarding to changes in the crop development.

3.3 SEBS methodology

The single–source SEBS model [12] uses remote sensing products to calculate all energy balance components and EF.
Net radiation, R_N, is calculated as the sum of short and long–wave net radiation by applying the equations:

$$R_N = R_N(SW) + R_N(LW) \quad (5)$$

$$R_N(SW) = (1-\alpha) \cdot R_{SWd} \quad (6)$$

$$R_N(LW) = emis \cdot R_{LWd} - emis \cdot \sigma_{SB} \cdot LST^4 \quad (7)$$

where α and emis are the albedo and emissivity, respectively, LST is the land surface temperature, σ_{SB} is the Stefan–Boltzmann constant, and R_{SWd} and R_{LWd} are downward short and long–wave radiation, respectively. Soil heat flux, G, is calculated from R_N using a non–linear equation [13]:

$$G = R_N \cdot C \cdot \exp\,(-\beta \cdot LAI) \quad (8)$$

where C and β are fitted parameters.
H is calculated iteratively until the lowest error is obtained, taking into account that the values should be

constrained between H values in dry and wet limits, H_{DL} and H_{WL}.

Finally, EF is calculated using relative evaporation, rel_{evap}, and H in the wet limit as follows:

$$EF = rel_{evap} \cdot \frac{(R_N - G - H_{WL})}{(R_N - G)} \quad (9)$$

In this paper, the SEBS algorithm has been modified in order to obtain better results for H and EF. Modification has been applied to the calculation of the roughness for heat transfer, z_{oh}, used in H calculation given by

$$z_{oh} = \frac{z_{0m}}{\exp{(kB^{-1})}} \quad (10)$$

where z_{0m} is the roughness height for momentum transfer and kB^{-1} is a parameter depending on biophysical parameters related to vegetation development retrieved from remote sensing. A scale factor depending on SM has been applied to the calculation of kB^{-1} as described in the literature [14]. A rescaled kB^{-1} parameter is obtained by applying this scale factor, improving results for H and EF.

SM used in the scale factor is retrieved from the AMSR–E sensor onboard Aqua satellite.

Further information concerning the SEBS algorithm [12] and its modification [14] can be found in the literature.

4. LUE MODEL

The LUE model proposed by Monteith is based on the linear relationship between GPP and APAR, where APAR is the product of direct ground PAR measurements and FPAR provided by MERIS.

Different LUE models have been formulated taking into account different vegetation indices [15]. In these models the value for the efficiency has been usually considered constant regardless of the ecosystem studied [6, 15]. However, due to the wide influence of the vegetation features in the efficiency, ε_0 varies greatly as a function of vegetation types, as well as climate conditions.

Previous researches have evaluated how the lack of water and changes in temperature limit the photosynthetic activity of the vegetation [15, 16]. The decrease in the photosynthetic activity and, therefore, changes in the efficiency of the vegetation/ecosystem due to water and temperature stress, are taking into account using a scalar factor varying between 0 and 1. In the model applied in this study temperature stress is dependent on T and water stress is assumed to be equal to EF [16, 17]. Therefore,

$$GPP = \varepsilon_0 \cdot EF \cdot f(T) \cdot PAR \cdot FPAR \quad (11)$$

where ε_0 is the maximum PAR conversion efficiency.

Eq. 11 can be reformulated as

$$GPP_{obs} = \varepsilon_0 \cdot GPP_{MERIS/SEBS} \quad (12)$$

where the subscript MERIS or SEBS indicates if EF from ground or SEBS has been used, respectively, in Eq. 11.

5. RESULTS

Relationship between NEE and PAR is shown in Fig. 2 and also the fit line obtained by applying Eq. 4. As an example, months from April to June are displayed, although in this study all available data for the whole agricultural year are considered. For these months the crop is fully developed and NEE presents its maximum negative values. From this result can be inferred the marked seasonal evolution of NEE and the crop behavior as a CO_2 sink (negative values of NEE), removing carbon from the atmosphere.

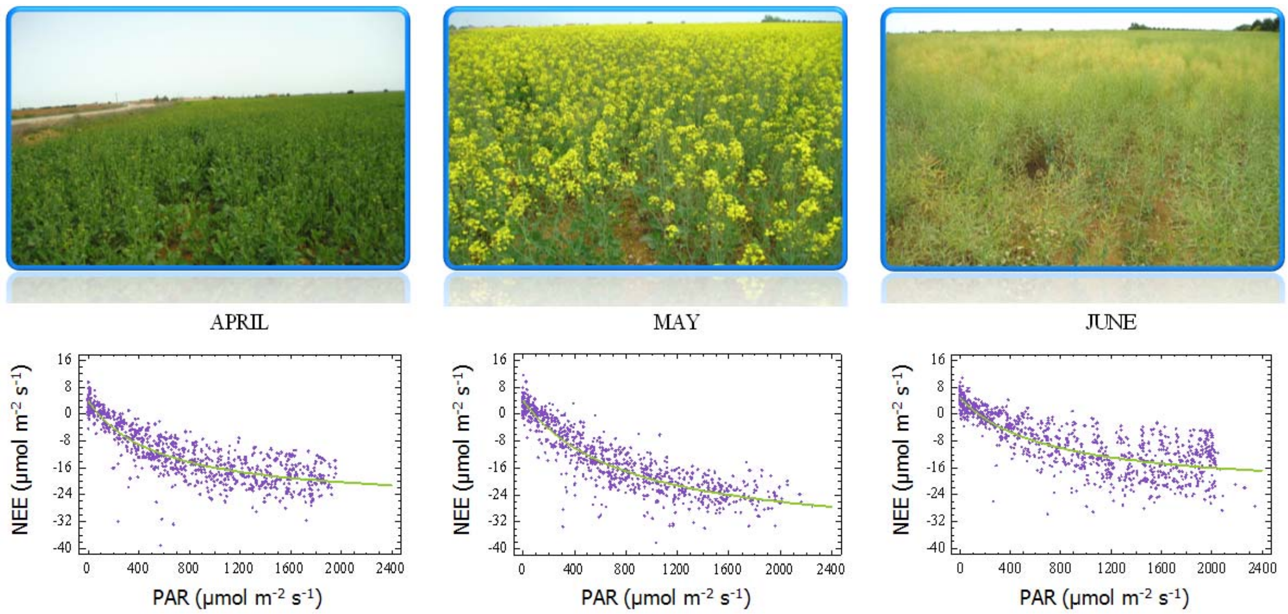

Figure 2. Seasonal evolution of NEE (lower) and crop development (upper)

Maximum peak for CO_2 uptake is found out in May coinciding with the total development of the rapeseed (see picture for May in Fig. 2). In June the crop starts its senescence period and NEE reaches less negative values than in previous months but still behaves as a sink. GPP applied to the LUE model is calculated from these direct measurements of NEE and respiration by Eq. 2, once NEE and RE datasets have been gap-filled using Eq. 3-4.

Since SM retrieved from AMSR–E is used by SEBS, a comparative analysis between those values and ground–measurements is made. Fig. 3 shows the seasonal course followed for both datasets. As derived from this graph, a similar pattern and good agreement (slope = 0.55; R^2 = 0.49) are found. This result probes that SM retrieved from AMSR–E might be representative for the studied plot in spite of the high spatial resolution of AMSR–E (25km).

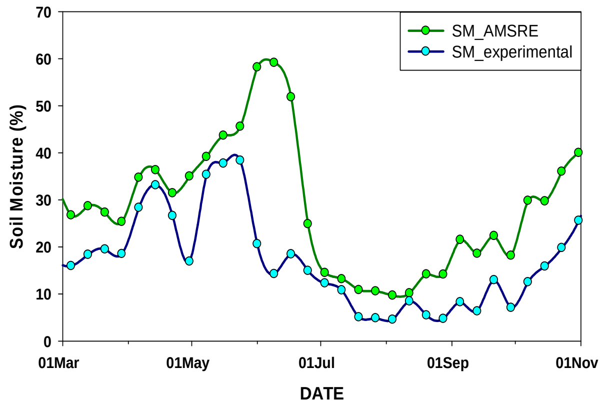

Figure 3. Comparison of the SM retrieved from AMSRE and measured in the studied plot

As stated before, the LUE model uses EF as a factor to take into account water stress into the vegetation. In this paper, this parameter has been calculated using two different approaches. So, two different EF datasets have been obtained. Firstly, EF has been calculated from ground measurements using Eq. 1. Separately, EF has been determined by applying the SEBS model to the studied plot. The comparison of both datasets, depicted in Fig. 4, shows the similarities in the seasonal variation. Despite this general trend, it should be noted that EF retrieved from SEBS tended to overestimating the ground values during the whole year and particularly after July (after the harvest). In summer, EF values was expected to be lower due to the lack of precipitation and vegetation cover. However, EF retrieved from SEBS yielded unrealistic high values, above 0.4 during this period and even higher in autumn.

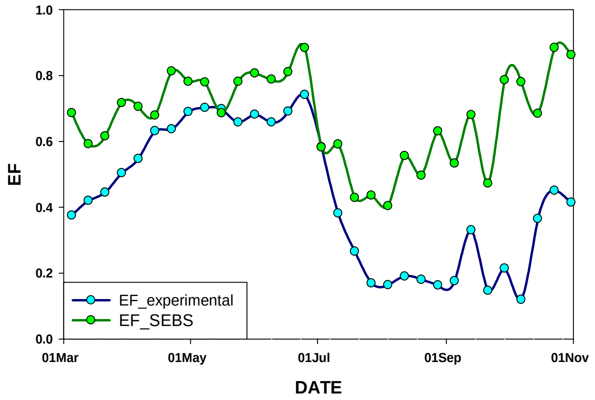

Figure 4. Comparative of the EF calculated from ground measurements and SEBS–retrieved

Finally, ε_0 is inferred through the slope of the linear regression fit given by Eq. 12. GPP observed (GPP_{obs}) is plotted against the GPP modelled ($GPP_{MERIS/SEBS}$) as shown in Figs. 5-6, and the goodness of the fit can be derived. Estimated ε_0 for the rapeseed, given by the slope value, is 2.82 gC MJ^{-1} when EF used in the LUE model is that obtained from ground measurements, and 2.59 gC MJ^{-1} when EF retrieved from SEBS is used. The LUE model fitted properly the GPP estimates using the EF from ground–measurements and that calculated with SEBS with squared correlation coefficient, R^2, of 0.89 and 0.81, respectively.

ε_0 values, independently the source of which EF is retrieved, are slightly higher than other results reported in the literature for crops [11]. The lower ε_0 value obtained when EF from SEBS is used might be attributed to the high EF values during summer, which does not seem to reflect the real lack of water for that period.

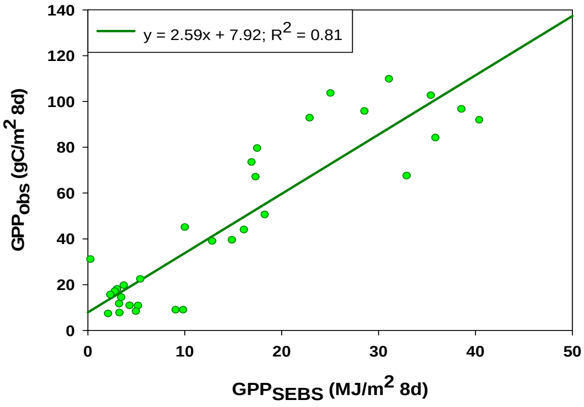

Figure 5. LUE model applying the EF calculated with SEBS model and MERIS data

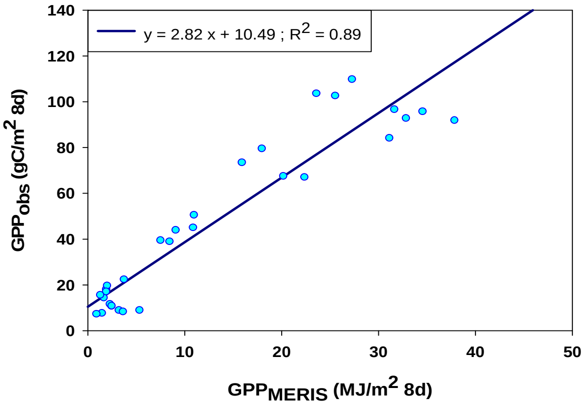

Figure 6. LUE model applying EF calculated from ground measurements and MERIS data

6. CONCLUSIONS

A LUE model based on FPAR measurements retrieved from MERIS and EF has been calibrated over a rapeseed cropland in order to calculate the maximum PAR conversion efficiency of this crop.

Water stress is taken into account in the LUE model through EF values calculated by two methods whilst the rest of the parameters in Eq. 11 have been not modified. Firstly, EF was calculated from ground measurements of LE and H. Secondly, an energy balance model (SEBS) was applied over the studied plot to obtain a new EF dataset. A good agreement has been found between both datasets; however, SEBS tends to overestimate EF values. This overestimation is more marked after the crop is harvested.

The SEBS model applied to calculate EF has been modified by applying a scale factor dependent on SM. An assessment of the SM used by the algorithm has been made and a comparison between these values and those measured is shown in this paper. Similar seasonal pattern is found for the two SM datasets. These results lead to consider SM values retrieved from AMSR–E representative for the studied plot.

Finally, ε_0 is calculated through the calibration of a LUE model over a rapeseed crop. This parameter presents lower differences whether the ground–based or SEBS–based EF is used in the LUE model. Final ε_0 value obtained is slightly higher than the typical values reported in the literature for crops. Besides, it should be mentioned that the rapeseed has not been widely studied and values for the efficiency of this crop are rarely found in the literature. The high efficiency values found in this study evidence the ability of the rapeseed to behave as a CO_2 sink.

7. ACKNOWLEDGEMENTS

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