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# Interactive comment on "Monitoring of carbon dioxide fluxes in a subalpine grassland ecosystem of the Italian Alps using a multispectral sensor" *by* K. Sakowska et al.

**K. Sakowska et al.**

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Dear Reviewer, thank you for the evaluation of the manuscript and constructive comments. We addressed all the issues raised in the review. The reviewer will find below the responses to general and specific comments. We hope that thanks to the comments and suggestions addressed during the reviewing process the scientific value of the article will increase.

General comment:

The work in this paper is very solid and the analysis is good, but the authors do little to expand the science. This work repeats studies done by others without showing us

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anything really new. To me, there are a number of questions that can be addressed by this analysis that would make the paper much more interesting and useful to the community.

Response to the general comment:

In this study we used and tested a 16 band multispectral system which is: 1) not very commonly used in the European proximal sampling and especially in the flux community, 2) relatively low cost (total cost of approximately 4.5 KEUR, including datalogger which is not strictly necessary), 3) commercially available, and 4) easy to configure and use. We believe that the use of such sensors should be encouraged within the EC networks (Fluxnet, ICOS) e.g. to simulate SENTINEL bands and to investigate the ability of the upcoming sensors to provide reliable estimates of biophysical parameters and fluxes across different ecosystems. Also, if it is true that the link between spectral observations and carbon fluxes on grasslands is a well investigated topic, we think that the database of this study (5 years) is very solid and allows us to answer a critical question, regarding the applicability of the simple optical sampling models across different years.

Specific comments:

C1: First, one omission in the methods; there is no description of instrument calibration. Over the long study period, what was done to prevent instrument drift? How stable was the instrument? Is this an issue for anyone else using this type of instrument?

A1: According to the reviewer's question, the following information was added to the manuscript section "Multispectral reflectance and narrow-band vegetation indices" (P7L20):

"Before the beginning of each growing season, the system was calibrated using the method recommended by the manufacturer, based on the use of a white reference panel with known reflectance (http://www.cropscan.com/wsupdn.html).Additionally,

CROPSCAN, Inc. provided cosine response calibration data with each upward facing MSR16 module and temperature sensitivity calibration data. Both cosine and temperature corrections were included in the postprocessing software (POSTPROC program) provided with the MSR system."

C2: In the introduction the light use efficiency equation (LUE) was introduced (Eq 1). However, it is not mentioned again in the paper. Of the four different statistical models, only Model 2 directly relates to the LUE, and Model 2 is stated to do poorly. As the LUE is widely used, what do the results of this study say about its applicability? Is PAR unnecessary in the LUE model? If you do need PAR, why did the statistical models that used PAR in them do poorly? Should there be a direct/diffuse ratio added to the model? These are important questions that fall out of your analysis and should be addressed.

A2: From a remote sensing perspective, a strong argument for the use of the concept of LUE model is that all LUE model input parameters can in principle be derived from remote sensing measurements. Spectral vegetation indices presented in the paper are non-direct measures of fAPAR, which is one of the components of LUE model. In our view, even not using all the components of the LUE model, but only its simplified version, allows for definition of the general idea behind using VIs as a LUE model concept. This will be especially valid in "dynamic" canopies where fAPAR shows high seasonal variations and appears to be the main driver of GEP.

According to the reviewer's comment, the section "Models for GEPm estimation", describing models formulations presented in the paper, was supplemented with clarification that we refer to the LUE model concept (P8L8). Later in the article we refer to terms defined in this section:

"In order to estimate GEPm we used two approaches, one based on linear regression (using the concept of the LUE model) and the other on multiple regression."

Also, we agree with both reviewers that the complex relationship between GEP and

PAR should be further discussed in the paper.

For this reason, in the "Discussion" section we reworded the sentence in P14L19-P14L22 into:

"One of the reasons for this is that sunlight is used by plants more efficiently under cloudy than clear sky conditions due to a more uniform illumination of the canopy, and thus a smaller fraction of the canopy likely to be light saturated (Baldocchi and Amthor, 2001; Chen et al., 2009; Mercado et al., 2009)."

In the same section we added the following paragraph (P15L1):

"A recent study of Peng et al. (2013) confirmed that the use of PAR in the model can introduce noise and unpredictable uncertainties in GEP estimations. As suggested by these authors, the response of productivity to changes in PAR is quite complex and influenced by many variables such as vegetation physiological status, canopy structure and light distribution in the canopy. Some other authors also brought to light some important aspects related to the use of PAR. Sims et al. (2008) showed that the variation in PAR is a more relevant determinant of GEP over very short timescales, and appears to be important for diurnal trends. Gitelson et al. (2012) demonstrated that seasonal variation of PAR potential (defined as the maximal value of incident PAR that may occur when the concentrations of atmospheric gasses and aerosols are minimal) can be used to improve the performance of the models."

Also, we reworded the sentence in P15L1-P15L4 into:

"Therefore, further analyses of the response of different vegetation types to various levels of diffuse radiation are required, and the hypothesis that the DI and PAR potential can improve the performance of the models including radiation as an input parameter needs to be verified."

And the sentence: "Also, the assessment of the influence of radiation quality on canopy reflectance should be further investigated." (P15L4-P15L5) was removed.

C3: The authors suggest that these types of reflectance measurements could be used to determine carbon fluxes and productivity and it would be much cheaper and easier to deploy these optical sensors than flux towers. I wish the authors explored this idea a little farther. How robust are their best models? If the model were parameterized using data from one year, how well would it have performed in the other years?

A3: Considering the long data series presented in the study (characterized by a high variability in both precipitation and air temperature - covering approximately 88% and 54% of the variability observed in a 20 year period for precipitation and temperature, respectively) and the obtained results (robust relationship between GEPm derived from EC measurements and GEPm derived from general model 1, 3 and 4), we see the use of ground spectral measurements for monitoring GEPm in a long-term framework as very promising. However, taking into account the limitation of both methods (EC and optical sampling of vegetation), they cannot be used interchangeably, but only complement each other.

Following the suggestion of both reviewers we performed the validation of the best performing general models (model 1 and 4). Sections "Statistical analysis" (P9L21), "Results" (P13L5) and "Discussion" (P15L21) have been enhanced with the information about the validation procedure and results:

2.5 Statistical analysis:

"Additionally, a validation of the best performing general models (considering all 5 years of observations together) using training/validation splitting approach, in which one year at a time was excluded from the dataset, was conducted. The remaining 4 years subset was used as a training set and the excluded year as the validation set. The model was fitted (calibrated) against each training set and the resulting parameterization was used to predict the GEPm of the excluded year. Validation accuracy was evaluated in terms of RMSE."

3 Results:

"Validation of model 1 based on NDVIred-edge showed that there was no relevant difference in prediction accuracy among validation years (RMSE was varying between 3.12 and 3.85 $\mu$molm$-2$ s$-1$, Figure 2). The general model 4 validation results showed that considering the all 5 validated years RMSE was on average 3.26 $\mu$molm$-2$s$-1$."

4 Discussion:

"The results of the validation of the general model 1 fed with NDVIred-edge showed that RMSE increased, compared to the non-validated general model 1 results, on average (averaging the values obtained from 5 validation years) from 3.41 to 3.48 $\mu$molm$-2$s$-1$. The general model 4 validation results showed that RMSE increased, as regards to the non-validated general model 4 results, on average from 3.06 to 3.26 $\mu$molm$-2$s$-1$. The highest decrease of the GEPm estimation accuracy was noted in the growing season of 2012 (Table 4, Figure 2), which was presumably caused by the unusual drought which occurred just after the cut event. The precipitation to temperature ratio for the period of 15 days after the cut in the growing season of 2012 was more than 10 times lower than in the other years which could have affected GEPm to the higher extend than VIs related to the canopy "greenness". As a consequence, models calibrated with the first four years of the dataset overestimated the GEPm measured in the second part of the growing season of 2012."

C4: Are there particular times or conditions (e.g. rain or very cloudy conditions) where errors in flux estimation are particularly bad?

A4: There are only a few times or conditions under which errors in flux estimation are particularly bad. We are aware of two cases when the data should be discarded from the analysis: 1) when rain was recorded 2 h prior or during the midday averaging period, and 2) when the weather conditions (precipitation) did not allow for the removal of the cut biomass from the footprint of Cropscan system (and EC tower) straight after the cut event. In either case the data were omitted in the deliberation. Also, in order to check the performance of the models in cloudy conditions we established and com-

pared the relationships between EC derived GEPm and NDVIred-edge in the growing season 2012 for: 1) sunny conditions (diffusion index – DI<0.3), 2) cloudy conditions (DI>0.7) and 3) regardless the quality of incoming radiation (DI<0.3 and DI>0.7). The obtained results showed that cloudy conditions did not affect the model performance significantly.

C5: Are the relationships developed during the spring green-up the same as those for the summer green-up after cutting? Can a brief (say, month-long) training dataset provide a good solution for the rest of the season (or other years)?

A5: In order to check the above mentioned possible seasonal effect, we established and compared the relationships between EC derived GEPm and NDVIred-edge measured during the 5 years of observations for: 1) the periods before the cut event, and 2) the periods after the cut event. Slopes and y-intercepts of both linear regressions were statistically indistinguishable (p>0.72) (Figure 1).

C6: If the optical data provide a reliable estimate of GEP, could that then be used to estimate daytime respiration?

A6: In order to answer the reviewer's question, we tested whether our optical data are able to provide reliable estimates of mean midday ecosystem respiration (Reco). The obtained results showed that all our models were performing poorly in Reco predictions. We think that the reason for this is the lack of a direct relationship between reflectance and both, autotrophic and heterotrophic components of the respiration (Wohlfahrt et al., 2010). Moreover, at the Monte Bondone grassland site, temperature plays a major role in affecting both, diurnal and seasonal patterns of ecosystem respiration (Marcolla et al., 2011).

C7: It was also suggested that the optical data could be used to fill in gaps in the flux data. It would be nice to see a test of that idea, by creating gaps of varying sizes at different times of the year and filling them using the optical data. Does a single parameterization work well, or is it better to tune the equations from data surrounding

the gap? Perhaps the authors intend to address these kinds of questions in future papers, but not adding something to the discussion in this paper leaves it with little lasting to say.

A7: Following the reviewer's suggestion we tested the ability of the optical data for GEPm gap-filling.

Accordingly, a new section was added to the manuscript: "2.6 The gap scenarios" (P9L24), and sections "Results" (P13L9) and "Discussion" (P16L21) were extended:

2.6 The gap scenarios:

"In order to evaluate the ability of spectral models to gap-fill flux data, secondary datasets were generated by flagging ∼16 % of the 5 growing seasons data as un-available (artificial gaps constituted 90 observation days out of 573 observation days). The percentage of artificial gaps was chosen due to the fact that during the observation period of the study (May to November, 2008-2012) the presented dataset had an average of 16 % of missing or rejected values of NEE data collected during midday hours. Following Moffat et al. (2007) these artificial gaps were superimposed on the already incomplete data, without regard for the distribution of real gaps in the GEPm data. Three gap length scenarios were considered: gaps of 1 observation day, gaps of 3 observation days and gaps of 5 observation days. The artificial gaps were distributed randomly and each of the three artificial gap length scenarios was permuted 10 times and results were averaged (Moffat et al., 2007). Models used for filling GEPm data were calibrated using secondary datasets with ∼16 % of gaps. The gap-filling statistical metrics (adjR2, RMSE, PRMSE) were calculated using the EC derived GEPm in these artificial gaps to validate the predictions of filling technique."

3 Results:

"The differences in the adjR2 performance of the gap-filling scenarios showed that the accuracy of the gap filling decreased slightly with the gap length. Also, the range of

the goodness of fit statistics (RMSE, PRMSE) increased together with the gap length (Table 6). However, on average, the GEPm gaps were filled with the accuracy of 73% with model 1 fed with NDVIred-edge (RMSE=3.40 $\mu$molm$-2$s$-1$, PRMSE= 16.48 %), and the accuracy of 76% (RMSE=3.14 $\mu$molm$-2$s$-1$, PRMSE= 15.25 %), with the model 4 using reflectance at 681, 720 and 781 nm and PARm data."

4 Discussion:

"The results of a simple gap filling approach presented in this study (based on creating and superimposing randomly distributed artificial gaps of three different lengths on the real dataset and comparing GEPm values derived from EC with GEPm values filled with the best performing spectral models) suggested to hold promise for filling gaps in flux data time series. The spectral based models were able to predict GEPm values with results comparable with others methods with adjR2 ranging from 0.70 (5 days long gap, general model 1) to 0.78 (1 day long gap, general model 4) (Table 6)."

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Additional note:
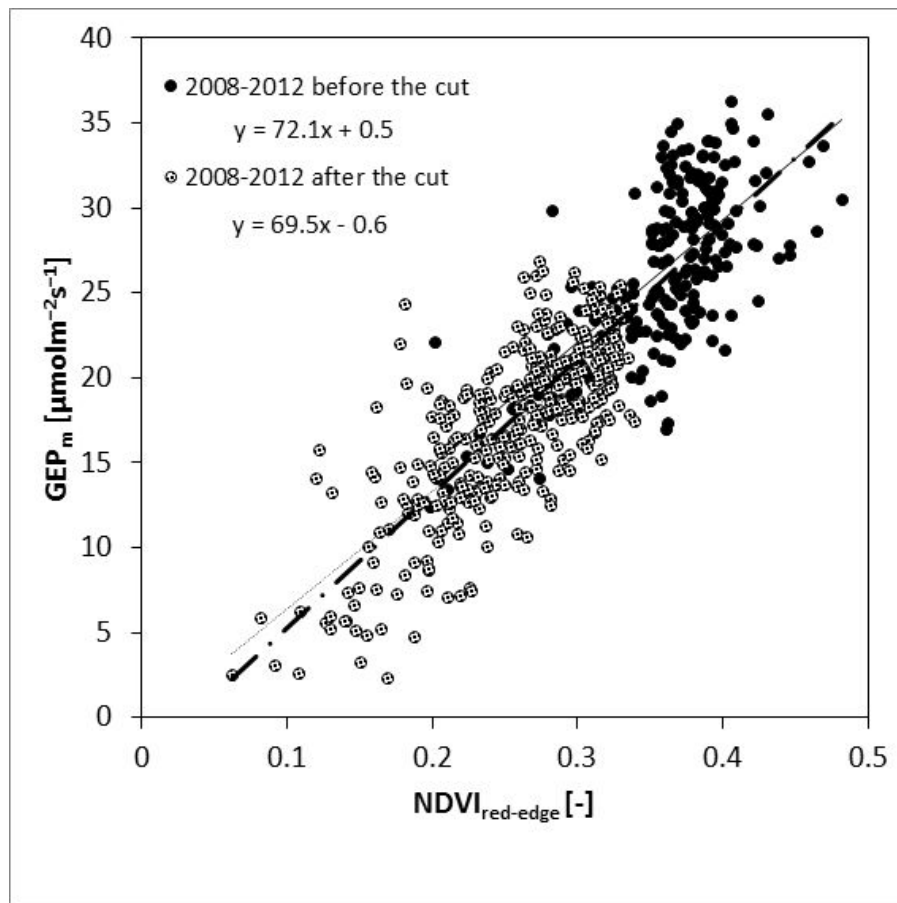
**Fig. 1.** Relationship between the NDVIred-edge and GEPm considering all the 5 years of observations.
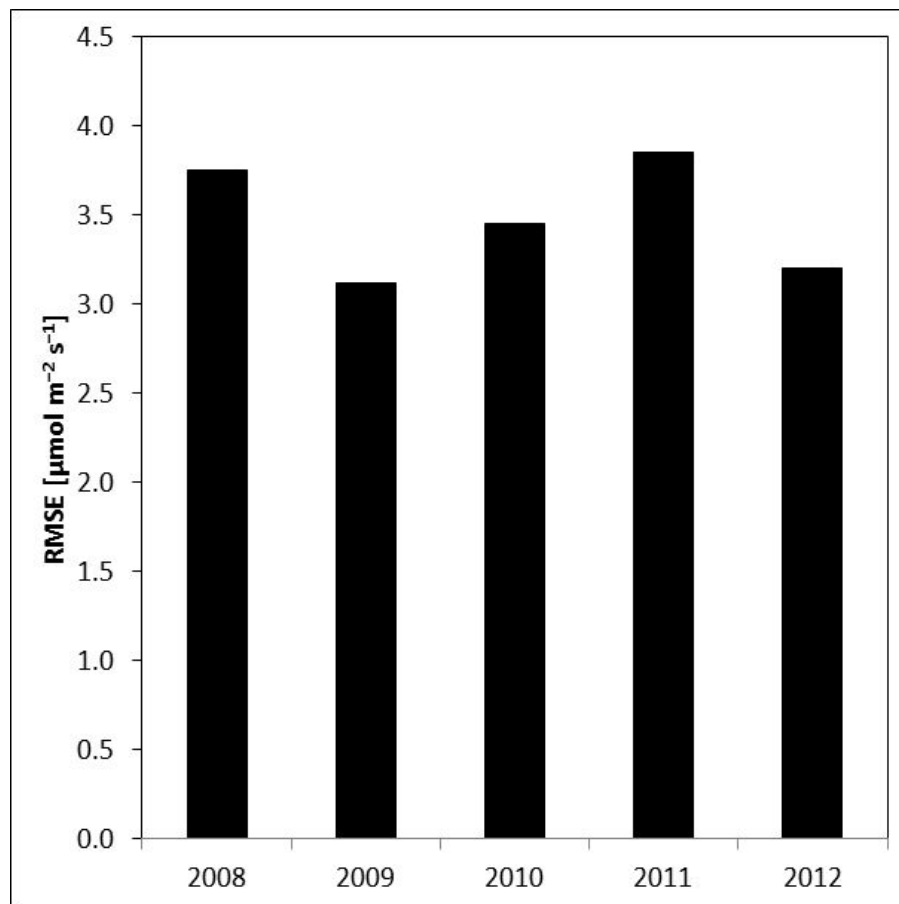
**Fig. 2.** Root mean square error (RMSE) of the validated models based on the NDVIred-edge.

| Model | | Gap length | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 observation day | | | 3 observation days | | | 5 observation days | | |
| | | $adjR^2$ | RMSE | PRMSE | $adjR^2$ | RMSE | PRMSE | $adjR^2$ | RMSE | PRMSE |
| | | - | $\mu mol\, m^{-2} s^{-1}$ | % | - | $\mu mol\, m^{-2} s^{-1}$ | % | - | $\mu mol\, m^{-2} s^{-1}$ | % |
| 1 | mean | 0.76 | 3.41 | 16.45 | 0.72 | 3.43 | 16.71 | 0.70 | 3.34 | 16.28 |
| | range | 0.16 | 0.73 | 3.80 | 0.28 | 1.19 | 5.45 | 0.46 | 0.95 | 6.50 |
| 4 | mean | 0.78 | 3.16 | 15.25 | 0.77 | 3.10 | 15.08 | 0.73 | 3.17 | 15.42 |
| | range | 0.14 | 0.46 | 2.72 | 0.18 | 0.81 | 4.23 | 0.33 | 0.75 | 5.13 |

**Fig. 3.** Table 6. Summary of the statistical metrics of gap filling procedure: adjusted R2 (adjR2), root mean square error (RMSE) and percentage root mean square error (PRMSE).