Interactive comment on "Remote sensing-based estimation of gross primary production in a subalpine grassland" *by* M. Rossini et al.

M. Rossini et al.

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Dear Dr Middleton,

Thank you for the positive evaluation of the manuscript. The manuscript has been revised, according to your comments and suggestions. We have carefully considered each of them and have implemented the corresponding changes in order to improve the manuscript. You will find below the responses to the specific comments (typed in bold characters, while authors' replies are in italics). We are confident to have fully answered all questions and incorporated all the recommendations in the revised paper.

Best regards,

Micol Rossini and co-authors

The Discussion could be compressed somewhat.

According to your suggestions and the indication of referee 1, the discussion has been reworded as:

"Unattended high temporal and spectral resolution canopy spectra coupled with EC data were acquired for two consecutive years on a subalpine grassland to exploit different strategies for evaluating the potential of RS in estimating carbon uptake. Collected data were processed using automatic procedures which took into account a series of quality criteria related to the illumination conditions during the acquisition and the system performances and reliable time series of VIs providing useful information on the time course of different grassland variables have been obtained. In particular, MTCI was the index most related to chlorophyll content and NDVI to $fIPAR_g$ and LAI, confirming previous studies on different ecosystems (Dash and Curran, 2004; Huemmrich et al., 2010; Panigada et al., 2010). PRI indexes based on green reference bands (555 and 551 nm) were instead the indexes most related to LUE_g (Table 2). To our knowledge this is the first study showing the potential of PRI to estimate ε expressed in terms of LUE_g, representing a more physiologically realistic way of quantifying the PAR effectively used for photosynthesis compared to ε more widely computed as GPP/APAR or GPP/incident PAR (see the recent review by Garbulsky et al. (2011)). It is worth noting that, as opposed to $PRI_{555/551}$, PRI computed using a reference band positioned in proximity of the chlorophyll absorption well (645 and 667 nm) were more related to leaf chlorophyll concentration than LUE_g (Table 2). Therefore the choice of the reference band used to compute PRI appears to play a key role in the determination of the sensitivity of this index to photosynthetic efficiency. This result confirmed recent studies by Middleton et al. (2009) and Goerner et al. (2011), although we believe that further studies are needed to explore the best reference band for estimating PRI across vegetation types and temporal scales. Furthermore, the translation of these findings to more complex ecosystems (e.g. forests) is not trivial due to the effects of canopy structure on the relationship between PRI and LUE (Barton and North, 2001; Hilker et al.,

2008a; Cheng et al., 2010, 2011). Most VIs peaked in the first half of July, in correspondence to maximum canopy development, attested by maximum values of LAI and GPP (Figs. 3, 4 and 5). However, due to the different sensitivity of VIs to grassland variables, their minimum and maximum values occurred at different DOYs and their slope changed in time. For example, PRI_{555} and PRI_{551} had a less distinct seasonal course and they reached minimum values about 10–20 days after full canopy development. This time-lag observed between the peak of $PRI_{555/551}$ and indexes using red bands can be explained by considering selective light absorption by photosynthetic pigments. Chlorophyll controls the energy flux that can be transferred to the dark reaction of photosynthesis and, because of the lower chlorophyll absorption of green light (Terashima et al., 2009), indexes based on green wavebands may therefore reach their peak later in the season compared to indexes involving a strong chlorophyll absorption band in the red spectral region. The analysis conducted with LUE models indicated that GPP can be successfully modelled using RS indexes or combining RS indexes with meteorological data. Results of model 1 confirmed that VIs related to canopy greenness, and specifically to chlorophyll content, explained most of the variability in GPP in an ecosystem characterized by a strong seasonality in green-up and senescence such as grasslands and crops (Gitelson et al., 2006; Wu et al., 2009; Peng et al., 2011). MTCI was the best predictor for both GPP_m and GPP_d, confirming its better performances with respect to EVI in estimating GPP in grassland ecosystems (Harris and Dash, 2010). However, as highlighted by Gitelson et al. (2008), this kind of models is not able to describe variations in GPP due to short-term (hours to days) variations of illumination or environmental stresses (such as temperature and water availability). This limitation was overcome by exploiting models 2 and 3, which take into account variations related to changing incident irradiance. Somewhat surprisingly, the inclusion of incident PAR in model formulation did not result in improved estimation of GPP. However, using ln(PAR) instead of PAR in model parameterization, the accuracy of GPP estimation improved. This means that the grassland increases its efficiency at low values of incident PAR while, given its moderate LAI and erectophile leaf angle distribution, it is not able to

fully exploit high radiation loads. This higher efficiency at low PAR can probably result from more diffuse light scattered within the canopy and less photoinhibition on the top of the canopy, which lead to a reduced tendency toward saturation (Chen et al., 2009). Furthermore, in our case, low PAR conditions can probably be associated with precipitation events, associated with high SWC and low temperatures, which are known to stimulate photosynthetic efficiency in alpine plants (Billings and Mooney, 1968; Korner and Diemer, 1987; Polley et al., 2011). To account for stress-induced changes in photosynthetic efficiency, the PRI was also tested to directly infer ε from RS data. The inclusion of PRI in model formulation showed slight improvement in GPP estimation, in particular for GPP_m. Physiologically, this means that in our ecosystem, $APAR_g$ is coupled with ε, and the inclusion of the ε term in the model slightly improves its ability to track seasonal variations. Similar results were obtained by Rossini et al. (2010) and Gitelson et al. (2006) in other ecosystems characterised by strong seasonal variability (crops). Modelling ε as a function of meteorological conditions generally results in lower accuracy in GPP estimation (Table 4). To evaluate the effect of the temporal resolution of VI time series on GPP estimation, 16-day composite time series of MODIS-(i.e. NDVI, EVI and PRI) and MERIS-derived (MTCI) products were then simulated and downscaled to daily frequency and results were compared. Short-term variability (hours to days) in both VIs and flux data is dampened out by averaging data over two weeks, thus leading to good performances when fitting GPP against resampled VIs (Tables 5 and 6). However, when these models are used to simulate annual GPP, they inevitably provide a decrease in the accuracy of total GPP estimation. The results from models driven only by RS and PAR variables were as good as, and in many cases better than, the more complex MOD17 GPP model which requires meteorological and vegetation type data inputs in addition to RS indexes. As with several previous studies on VIs, since the estimation of model coefficients is based on a semiempirical regression technique and is conducted only for a single site, further verification studies should be conducted under other vegetation and climatic conditions and at different sites potentially characterized by a more complex structure to fully explore the efficacy of this

method and make general inferences. This study provides a conceptual background for GPP estimation using real satellite data and a better understanding of the spatio-temporal variations of productivity. The choice of the index depends on the spectral characteristics of the satellite sensor being used. In particular, MTCI can be derived from satellite systems with spectral bands in the red edge region (MERIS in this study), EVI and NDVI from satellites having blue, red and near-infrared bands (MODIS in this study) and PRI from satellites with a narrow green band centered at 531 nm (MODIS in this study). Our results show that red edge indexes like MTCI can be used both as single variables or in combination with PRI and meteorological variables to obtain accurate estimations of GPP in a grassland ecosystem. Unfortunately, the computation of MTCI and PRI from a single satellite is currently only feasible from the NASA Earth Exploring One (EO-1) Hyperion sensor, which is near the end of its lifetime with 12 years in orbit (launched November 2000). The launching of new image spectrometers, such as the NASA HyspIRI or the DLR EnMAP, will allow the calculation of a greater number of indexes, including MTCI and PRI, thus offering significant potential to enhance the accuracy of the assessment of CO_2 uptake in terrestrial ecosystems from space. Finally, we remark that NDVI and EVI showed poorer performances when used as single variables to predict GPP and it is preferable to use these indexes in combination with PRI and meteorological variables to improve accuracy in GPP modelling."

Some references are missing (Cheng et al., 2010, 2011; Middleton et al. 2011 review chapter).

The references were added to the manuscript in the introduction and discussion sections

We carefully formatted the tables according to your suggestions.

Table 1. Why are MTCI wavelengths reported to more than 2 decimal places?

*The MTCI wavelengths were reported as specified in the MERIS product handbook (http://envisat.esa.int/pub/ESA_DOC/ENVISAT/MERIS/meris.ProductHandbook.2_*

1.pdf)

Please add a column (or 2) to this table for band descriptions (band center and width, mean $\pm$ FWHM; SNR if known) and whether index is computed from MODIS or MERIS band information in this paper.

Table 1 was modified as suggested.

Table 2. this information could be moved to text in the Methods sections

Table 2 was removed as suggested.

I suggest the authors replace this table with a more important one that provides the annual means for environmental conditions a tower values. Provide annual mean and a measure of variance (e.g., SD), with units used for reporting. Columns should include these headings: Year, PAR (umol m-2 s-1), T (oC), Precip (mm), SWC (mm3 mm-3), LAImax (m2 m-2), LAImean (m2 m-2), Chlmax (ug g-1), Chlmean (ug g-1), GPPdaily EC (gC m-2 y-1), LUEmid-day (umol CO2 umol-1 photon), LUEg (g C MJ-1)

Regarding this point, we think that these information are already reported in the text and shown in Figures 1 to 4 and we believe that adding these information also in table form would make the manuscript heavier. If you think that this table is essential for the manuscript, we can add it in a second revised version of the manuscript.

Table 3 was formatted as suggested, table caption was modified as follows: "Table 3 (now Table 2). Coefficients of correlation (r) between the HSI VIs and ancillary and eddy data (LUE_g) measured at the study site. n is the number of samples for each correlation analysis. The asterisk indicates significance of correlation: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; n.s.: not significant (Pearson's correlation test). The VI best-correlated with each variable is in bold print, the second most correlated is in italic."

Tables 4 to 7 were formatted as suggested, grey highlighting the most successful of all models for each analysis. Table captions were modified as follows:

"Table 4 (now Table 3). Summary of statistics in fitting (r^2 and RMSE) and cross-validation (r^2_{cv}, $RMSE_{cv}$ and AIC) of different models tested in this study using average GPP_m and PAR_m data. The best-performing models in each class are in bold print. The most successful of all models is grey highlighted."

"Table 5 (now Table 4). Summary of statistics in fitting (r^2 and RMSE) and cross-validation (r^2_{cv}, $RMSE_{cv}$ and AIC) of different models tested in this study using GPP_d and PAR_d data. The best-performing models in each class are in bold print. The most successful of all models is grey highlighted."

"Table 6 (now Table 5). Summary of statistics in fitting (r^2 and RMSE) and cross-validation (r^2_{cv}, $RMSE_{cv}$ and AIC) of different models tested in this study using average GPP_m and PAR_m data and resampled VI time series. The best-performing models in each class are in bold print. The most successful of all models is grey highlighted. "

"Table 7 (now Table 6). Summary of statistics in fitting (r^2 and RMSE) and cross-validation (r^2_{cv}, $RMSE_{cv}$ and AIC) of different models tested in this study using GPP_d and PAR_d data and resampled VI time series. The best-performing models in each class are in bold print. The most successful of all models is grey highlighted."

Figures: Figure 1. OK. But, could you add the months below DOY on X axis, since you describe months in text, but reader will have to guess. (Prefer different order, see comment for next figure.)

As suggested, we added months on X axis.

*Figure caption was modified as follows: Figure 1 (now Figure 2). Seasonal variation of 2009 (solid line, black bars) and 2010 (dotted line, white bars) for: **(a)** midday average air temperature (Air T,C); **(b)** PAR (µmol $m^{-2}\,s^{-1}$); and **(c)** precipitation (mm) and soil water content (SWC, %) at 10 cm.*

Figure 2. OK, but could you add months on X axis (see fig. 1 comment above)? Prefere rewrite of figure caption. Seasonal variation of 2009 (filled circles, solid

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line) and 2010 (open circles, dotted line) for: (a) leaf area index, LAI (m^2 m^{-2}, mean $\pm$ SD, n=12); (b) leaf chlorophyll content, Chl µg g^{-1}, mean $\pm$ SD, n=12); (c) mid-day IPAR, IPARm µmol m^{-2} s^{-1}); and (d) mid-day green IPAR, (IPARg)m (µmol m^{-2} s^{-1}). SD = standard deviation.

As suggested, we added months on X axis.

*Figure caption was modified as follows: Figure 2 (now Figure 3). Seasonal variation of 2009 (filled circles, solid line) and 2010 (open circles, dotted line) for: **(a)** Leaf Area Index (LAI, $m^2\,m^{-2}$, mean $\pm$ SD, $n = 12$); **(b)** leaf chlorophyll concentration (Chl, µg g^{-1}, mean $\pm$ SD, $n = 12$); **(c)** midday IPAR (IPAR$_m$, µmol $m^{-2}\,s^{-1}$); and **(d)** midday green IPAR ((IPAR$_g$)$_m$), µmol $m^{-2}\,s^{-1}$). SD is standard deviation.*

Figure 3. Use "filled circles" and "open circles", and add months to X axis. Suggest that you add vertical lines in each plot at the maximum value, which will clearly guide the reader to see the difference in the phenology related to two PRIgreen (551, 555) indexes vs. the 4 other indexes. I would also put ovals around the points that show clear annual differences (DOY 220-240 in panels b,d,g). It is worth noting that NDVI does not discriminate any annual differences, whereas the others do.

As suggested, we added months on X axis. We agree that adding vertical lines in each plot at the maximum or minimum value would be helpful for the reader, but two years of data are shown in each plot and they didn't always reach their maximum (minimum) on the same DOY. Adding two vertical lines on each graph resulted very confusing. For this reason, we preferred adding only ovals around the points that show clear annual differences (DOY 220-240 in panels b,d,g).

*Figure caption was modified as follows: Figure 3 (now Figure 4). Seasonal temporal profiles of measured vegetation indexes in 2009 (filled circles) and 2010 (open circles) for: **(a)** NDVI; **(b)** MTCI; **(c)** EVI; **(d)** PRI$_{645}$; **(e)** PRI$_{555}$; **(f)** PRI$_{551}$; and **(g)** PRI$_{667}$. Each point indicates the average value between 11:00 and 13:00 (local solar time).*

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Figure 4. Add months to X axis. Add vertical lines at Max or Min values (GPP, DOY 190; LUE, DOY 225.). Seasonal variation of mid-day carbon variables in 2009 (filled circles) and 2010 (open circles: (a) gross primary productivity, GPP (ïĄ■mol CO2 m-2 s-1); and (b) green LUE, (LUEg)m (ïĄ■mol CO2 ïĄ■mol-1 photon).

As suggested, we added months on X axis but, as above, we prefer not adding vertical lines

Figure caption was modified as follows: Figure 4 (now Figure 5). Seasonal variation of midday carbon variables in 2009 (filled circles) and 2010 (open circles) for: **(a)** *gross primary productivity (GPP$_m$, $\mu mol\,CO_2\,m^{-2}\,s^{-1}$); and* **(b)** *green LUE ((LUE$_g$)$_m$, $\mu mol\,CO_2\,\mu mol^{-1}$ photon).*

Figure 5. OK. ButâĂťadd the two other bands used in other indexes (858 and 460 nm), and link to Table 1. Add more ticks on both axes.

Figure 5 was modified as suggested and moved in the materials and methods section. Figure caption was modified as follows: Figure 5 (now Figure 1). Temporal changes of monthly grassland reflectance spectra collected at midday during 2009. Grey shaded areas represent the position and bandwidth of the MODIS spectral bands: B1 centered at 645 nm, B2 at 858.5 nm, B3 at 469 nm, B4 at 555 nm, B11 at 531 nm, B12 at 551 nm and B13 at 667 nm. White areas represent those of the MERIS sensor: b8 centered at 681.25 nm, b9 at 708.75 nm and b10 at 753.75 nm.

Figure 6. Label the two columns 2009 and 2010. Label rows by model. What is the black curve in (a) and (b)?

We modified figure 6 according to your suggestions There is not a black curve in (a) and (b), but it is the effect of the filled triangles very close to each other.

Add this to caption. Add months to X axis. Redo the caption, as per the suggestions given for previous figure captions.

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As suggested, we added months on X axis

Figure caption was modified as follows: Figure 6. Time courses of GPP$_d$ ($g\,C\,m^{-2}\,d^{-1}$) estimated from EC measurements (EC-GPP$_d$) (filled circles), GPP$_d$ modelled (open circles) with models fed with measured daily inputs (RS-GPP$_d$) and GPP$_d$ modelled (filled triangles) with models fed with resampled daily inputs (RS-GPP$_{res}$) in 2009 (left panels) and 2010 (right panels) for the best performing formulation of each class of models: **(a** *and* **b)** *model 1 parameterized with MTCI;* **(c** *and* **d)** *model 2 parameterized with MTCI and ln(PAR);* **(e** *and* **f)** *model 3 parameterized with MTCI and ln(PAR);* **(g** *and* **h)** *model 4 parameterized with MTCI, PRI$_{555}$ and ln(PAR); and* **(i** *and* **j)** *MOD17 parameterized with MTCI and ln(PAR).*

Figure 7. Are these annual values? If so, add "Annual " GPP to Y axis.

We have modified the title of Y axis in "Annual GPP"

Other Comments:

1] Use consistent variable names throughout (e.g., fg =fIPARg?)

We have checked variable names throughout the manuscript.

2] P. 1716 (l2) should reference Joiner et al. (2010).

The reference Joiner et al. (2010) has been added.

3] Use "nadir", not "nadiral".

This expression was corrected as indicated.

4] Give units for LUEg on p. 1719.

The units for LUEg were added as indicated.

5] Don't keep defining variables over and over (e.g., PAR).

As suggested, unnecessary variable definitions have been removed.

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6] What is IFOV of spectrometer at 3.5 m above surface (p. 1720)?

The spectrometer has a hemispherical field of view: employs a rotating arm equipped with a cosine-response optic to observe alternately the sky and the target surface. With this configuration and an installation height of 3.5 m, 97 % of the total signal comes from a circular ground area with a radius of about 20 m.

7] Give general form of equation IV. (p. 1722) (i.e., GPP = ε * fAPAR * PAR).

The general form of equation IV was added.

8] Give units for $\varepsilon_{\max}$ on p. 1723 (g C MJ-1?).

The units for $\varepsilon_{\max}$ were corrected.

9] p. 1725 (l 28) "...started to decrease earlier and showed year to year variability."

This expression was corrected as indicated.

10] Redo Section 3.3.

As suggested, Section 3.3 was reworded as: "The higher sensitivity of MTCI to chlorophyll content was confirmed by the correlation analysis. Chl was best correlated to MTCI ($r = 0.91$, $p < 0.001$) and two PRI indexes using red reference bands (PRI$_{645}$, PRI$_{667}$) ($r = 0.86$ and 0.84, respectively, $p < 0.001$). NDVI provided a lower correlation ($r = 0.80$, $p < 0.01$) whereas the relationship for EVI was not significant (Table 3). NDVI was the VI that related best to LAI ($r = 0.90$, $p < 0.001$) and f IPAR$_{\mathrm{g}}$ ($r = 0.95$, $p < 0.001$). LUE$_{\mathrm{g}}$ was best explained by PRI$_{551}$ obtained with MODIS band 4 ($r = 0.64$, $p < 0.001$); similar results were obtained for PRI$_{555}$ with MODIS band 12. Therefore, LUE$_{\mathrm{g}}$ was best correlated to PRI indexes based on green reference bands (551, 555 nm), providing results about 20% better than those obtained using the PRI indexes based on red reference bands (645, 667 nm)."

11] p. 1726 (l 25) "...tracked GPPm quite well (delete next phrase)(Fig. 4a)."

This expression was corrected as indicated.

12] p. 1727 (l 5) "...were instead correlated..."

This expression was corrected as indicated.

13] p. 1728 (l 7) "..different VI contributions...(no plural for VI).

This expression was corrected as indicated.

Section 3.5.1. Measured time series. This is a mess! Please rewrite!!!

Section 3.5.1 was rewritten as follows: "The summary statistics in fitting and cross-validation of the different models tested for GPP estimation are shown in Tables 4 and 5. Results of model 1 (simple regression analysis) showed that midday vegetation indexes explained most of the variability in both GPP$_{\mathrm{m}}$ and GPP$_{\mathrm{d}}$: MTCI was the best predictor with a RMSE$_{\mathrm{cv}}$ of 1.50 μmol CO$_2$ m^{-2} s^{-1} and 0.74 g C m^{-2} d^{-1}, respectively, followed by NDVI and EVI. The inclusion of incident PAR as a multiplicative term of VI$_{\mathrm{g}}$ in model formulation (model 2) decreased model performances in GPP$_{\mathrm{m}}$ estimation up to a RMSE$_{\mathrm{cv}}$ of almost double relative to the corresponding model 1. As an example, RMSE$_{\mathrm{cv}}$ of the model using MTCI increased from 1.50 up to 3.30 μmol CO$_2$ m^{-2} s^{-1} and AIC increased from 157 to 417. Similar results were obtained on including the PAR in the form of model 3 for both GPP$_{\mathrm{m}}$ and GPP$_{\mathrm{d}}$ estimation. Thus, in the majority of cases the direct use of PAR did not appear to be a useful model component in estimating GPP. On the contrary, results obtained with model 2 and 3 including the logarithm of the incident PAR in the model showed an improvement of the performances in both GPP$_{\mathrm{m}}$ and GPP$_{\mathrm{d}}$ estimation. The extent of the improvement changed with the different indexes considered. The inclusion of PRI to estimate ε generally increased model performances, in particular when it was used in combination with MTCI and ln(PAR). Model 4 using MTCI, PRI$_{555}$ and ln(PAR$_{\mathrm{m}}$) showed the best performances in estimating GPP$_{\mathrm{m}}$ with a RMSE$_{\mathrm{cv}}$ of 1.42 μmol CO$_2$ m^{-2} s^{-1}. It is interesting to note that this model also showed the lowest AIC, despite the increase in the number of model variables

with respect to model 1. The best-performing model in estimating GPP$_d$ was instead model 2 with ln(PAR$_d$) and MTCI. MOD17, in which ε was expressed as constant ε at its potential maximum adjusted for unfavorable $T_{\min}$ and VPD, showed a RMSE$_{cv}$ between 0.78 g C m^{-2} d^{-1} for the model driven by MTCI and ln(PAR$_d$) and 1.57 g C m^{-2} d^{-1} for the model driven by EVI and ln(PAR$_d$). These results were slightly poorer than those obtained on estimating ε as a function of PRI and, due to the higher complexity of this model, it had a higher AIC."

14] p. 1729 (l 19) "…both GPPm (Tab. 6) and GPPdaily (Tab. 7)…"

The references to Tables 6 and 7 were added.

(l 20) As before, ln(PAR) … than linear PAR…improvement (delete section here) was higher for GPPm estimation.

This sentence was corrected as suggested.

[l 23) "…in estimating resampled GPPm…"

This sentence was corrected as suggested.

(l 24-26) Parenthses needed. "model 1 (estimating… MTCI) and model 4 (estimating…PRI555). However, Model 2 , driven…ln(PAR), (delete section here) performed better for GPPd estimation."

This sentence was corrected as suggested.

15] p. 1730 (l 6) "…described the seasonal dynamics…"

This sentence was corrected as suggested.

(l 13) "…seasons (Tabs. 5 vs. 7)."

This sentence was corrected as suggested.

(l 14) "…each model class. On days for…"

This sentence was corrected as suggested.

(l 27) EC, GPPd, [delete] especially at…"

This sentence was corrected as suggested.

16] p. 1731 (l 9-12). Rewrite sentence.

(l 19-20) ????

The whole paragraph was corrected as

"In particular, MTCI was the index most related to Chl content and NDVI to fIPAR$_g$ and LAI, confirming previous studies on different ecosystems (Dash and Curran, 2004; Huemmrich et al., 2010; Panigada et al., 2010). PRI indexes based on green reference bands (555 and 551 nm) were instead the indexes most related to LUE$_g$ (Table 3). To our knowledge this is the first study showing the potential of PRI to estimate ε expressed in terms of LUE$_g$, representing a more physiologically realistic way of quantifying the PAR effectively used for photosynthesis compared to ε more widely computed as GPP/APAR or GPP/incident PAR (see the recent review by Garbulsky et al. (2011)). It is worth noting that, as opposed to PRI$_{555/551}$, PRI computed using a reference band positioned in proximity of the Chl absorption well (645 and 667 nm) were more related to leaf Chl concentration than LUE$_g$ (Table 3)."

(l 21-22) "…well, MODIS bands 1 and 13, ..."

This sentence was corrected as suggested.

17] p.1732 (l 17-20) (delete section). "MTCI was the best predictor for both GPPm and GPPd, confirming the better performances of MTCI, with respect to EVI, in estimating GPP in grassland …"

This sentence was corrected as suggested.

18] p. 1733 (l 6-7) Edit this. "This higher efficiency at lower PAR can…light

scattered within the canopy. . ..**Furthermore,**. . .**lower PAR**. . ."

This sentence was corrected as suggested.

(l 19) Add comma. ". . .ecosystem, APARg. . ."

This expression was corrected as suggested.

19] p. 1734 (l 9) ". . .inevitably provide. . ."

This expression was corrected as suggested.

(l 15) ". . .better understanding of the. . ."

This expression was corrected as suggested.

(l 23-24) "Unfortunately, the computation. . .**satellite is currently ONLY feasible from the NASA Earth Exploring One (EO-1) Hyperion sensor, which is near the end of its lifetime with 12 years in orbit (launched Nov. 2000)."**

This sentence was corrected as suggested.

20] p. 1735 (l 12-13) ". . .as an indicator for LAI. . .**, the MTCI for leaf**. . .**PRI552 for LUEG. . ."**

This expression was corrected as suggested.

(l 14) insert MTCI

This expression was corrected as suggested.

(l 19-21) Add parentheses. ". . .fAPARg (estimated. . .**MRCI) and ε (as a function of PRI551);"**

This expression was corrected as suggested.

(l 23) ". . .than those obtained from. . ."

This expression was corrected as suggested.

References

Aubinet, M., Grelle, A., Ibrom, A., Rannik, U., Moncrieff, J., Foken, T., Kowalski, A. S., Martin, P. H., Berbigier, P., Bernhofer, C., Clement, R., Elbers, J., Granier, A., Grunwald, T., Morgenstern, K., Pilegaard, K., Rebmann, C., Snijders, W., Valentini, R., and Vesala, T.: Estimates of the annual net carbon and water exchange of forests: the EUROFLUX methodology, Adv. Ecol. Res., 30, 113–175, 2000.

Baldocchi, D., Valentini, R., Running, S., Oechel, W., and Dahlman, R.: Strategies for measuring and modelling carbon dioxide and water vapour fluxes over terrestrial ecosystems, Glob. Change Biol., 2, 159–168, 1996.

Barton, C. V. M., and North, P. R. J.: Remote sensing of canopy light use efficiency using the photochemical reflectance index - Model and sensitivity analysis, Remote Sens. Environ., 78, 264–273, 2001.

Billings, W. D. and Mooney, H. A.: The ecology of arctic and alpine plants, Biol. Rev., 43, 481–529, doi:10.1111/j.1469-185X.1968.tb00968.x, 1968.

Chen, J., Shen, M., and Kato, T.: Diurnal and seasonal variations in light-use efficiency in an alpine meadow ecosystem: causes and implications for remote sensing, J. Plant Ecol.-UK, 2, 173–185, 2009.

Cheng, Y. B., Middleton, E. M., Huemmrich, K. F., Zhang, T., Campbell, P., Corp, L., Russ, A., and Kustas, T.: Utilizing in situ directional hyperspectral measurements to validate bio-indicator simulations for a corn crop canopy, Ecol. Inform., 5, 330–338, 2010.

Cheng, Y. B., Middleton, E. M., Huemmrich, K. F., Zhang, T., Corp, L., Campbell, P., and Kustas, T.:Spectral Bio-indicator simulations for tracking photosynthetic activities in a corn field , SPIE Remote Sensing and Modeling of Ecosystems for Sustainability VIII Conference, 2011.

Dash, J. and Curran, P. J.: The MERIS terrestrial chlorophyll index, Int. J. Remote Sens., 25, 5403–5413, 2004.

Coops, N. C., Hilker, T., Hall, F. G., Nichol, C. J., and Drolet, G. G.: Estimation of light-use efficiency of terrestrial ecosystem from space: a status report, Bioscience, 60, 788–797, 2010.

Garbulsky, M. F., Penuelas, J., Gamon, J., Inoue, Y., and Filella, I.: The photochemical reflectance index (PRI) and the remote sensing of leaf, canopy and ecosystem radiation use efficiencies – a review and meta-analysis, Remote Sens. Environ., 115, 281–297, 2011.

Gitelson, A. A., Vina, A., Verma, S. B., Rundquist, D. C., Arkebauer, T. J., Keydan, G., Leavitt, B., Ciganda, V., Burba, G. G., and Suyker, A. E.: Relationship between gross primary production and chlorophyll content in crops: implications for the synoptic monitoring of vegetation productivity, J. Geophys. Res.-Atmos., 111, D08S11, doi:10.1029/2005JD006017, 2006.

Gitelson, A. A., Vina, A., Masek, J. G., Verma, S. B., and Suyker, A. E.: Synoptic monitoring of gross primary productivity of maize using Landsat data, IEEE Geosci. Remote S., 5, 133–137, 2008.

Goerner, A., Reichstein, M., Tomelleri, E., Hanan, N., Rambal, S., Papale, D., Dragoni, D., and Schmullius, C.: Remote sensing of ecosystem light use efficiency with MODIS-based PRI, Biogeosciences, 8, 189–202, doi:10.5194/bg-8-189-2011, 2011.

Harris, A. and Dash, J.: The potential of the MERIS Terrestrial Chlorophyll Index for carbon flux estimation, Remote Sens. Environ., 114, 1856–1862, 2010.

Hilker, T., Coops, N. C., Hall, F. G., Black, T. A., Wulder, M. A., Nesic, Z., and Krishnan, P.: Separating physiologically and directionally induced changes in PRI using BRDF models, Remote Sens. Environ., 112, 2777–2788, 2008a.

Hilker, T., Coops, N. C., Wulder, M. A., Black, T. A., and Guy, R. D.: The use of remote sensing in light use efficiency based models of gross primary production: A review of current status and future requirements, Sci. Total Environ., 404, 411–423, 2008b.

Huemmrich, K. F., Gamon, J. A., Tweedie, C. E., Oberbauer, S. F., Kinoshita, G., Houston, S., Kuchy, A., Hollister, R. D., Kwon, H., Mano, M., Harazono, Y., Webber, P. J., and Oechel, W. C.: Remote sensing of tundra gross ecosystem productivity and light use efficiency under varying temperature and moisture conditions, Remote Sens. Environ., 114, 481–489, 2010.

Korner, C. and Diemer, M.: In situ photosynthetic responses to light, temperature and carbon dioxide in herbaceous plants from low and high altitude, Funct. Ecol., 1, 179–194, 1987.

Migliavacca, M., Galvagno, M., Cremonese, E., Rossini, M., Meroni, M., Sonnentag, O., Cogliati, S., Manca, G., Diotri, F., Busetto, L., Cescatti, A., Colombo, R., Fava, F., di Celia, U. M., Pari, E., Siniscalco, C., and Richardson, A. D.: Using digital repeat photography and eddy covariance data to model grassland phenology and photosynthetic CO_2 uptake, Agr. Forest Meteorol., 151, 1325–1337, doi:10.1016/j.agrformet.2011.05.012, 2011.

Middleton, E. M., Cheng, Y. B., Hilker, T., Black, T. A., Krishnan, P., Coops, N. C., and Huemmrich, K. F.: Linking foliage spectral responses to canopy-level ecosystem photosynthetic light-use efficiency at a Douglas-fir forest in Canada, Can. J. Remote Sens., 35, 166–188, 2009.

C1487

Middleton, E. M., Huemmrich, K. F., Cheng, Y. B., and Margolis, H. A. : Spectral Bioindicators of Photosynthetic Efficiency and Vegetation Stress, in: Hyperspectral Remote Sensing of Vegetation, edited by: Thenkabail, P. S., Lyon, J. G., and Huete, A. R., CRC Press, 265–288, 2011.

Panigada, C., Rossini, M., Busetto, L., Meroni, M., Fava, F., and Colombo, R.: Chlorophyll concentration mapping with MIVIS data to assess crown discoloration in the Ticino Park oak forest, Int. J. Remote Sens., 31, 12, 3307-3332, 2010.

Peng, Y., Gitelson, A. A., Keydan, G., Rundquist, D. C., and Moses, W.: Remote estimation of gross primary production in maize and support for a new paradigm based on total crop chlorophyll content, Remote Sens. Environ., 115, 978–989, 2011.

Penuelas, J., Garbulsky, M. F., and Filella, I.: Photochemical reflectance index (PRI) and remote sensing of plant CO(2) uptake, New Phytol., 191, 596–599, 2011.

Polley, H. W., Phillips, R. L., Frank, A. B., Bradford, J. A., Sims, P. L., Morgan, J. A., and Kiniry, J. R.: Variability in light-use efficiency for gross primary productivity on great plains grasslands, Ecosystems, 14, 15–27, 2011.

Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P., Bernhofer, C., Buchmann, N., Gilmanov, T., Granier, A., Grunwald, T., Havrankova, K., Ilvesniemi, H., Janous, D., Knohl, A., Laurila, T., Lohila, A., Loustau, D., Matteucci, G., Meyers, T., Miglietta, F., Ourcival, J. M., Pumpanen, J., Rambal, S., Rotenberg, E., Sanz, M., Tenhunen, J., Seufert, G., Vaccari, F., Vesala, T., Yakir, D., and Valentini, R.: On the separation of net ecosystem exchange into assimilation and ecosystem respiration: review and improved algorithm, Glob. Change Biol., 11, 1424–1439, 2005.

Rossini, M., Meroni, M., Migliavacca, M., Manca, G., Cogliati, S., Busetto, L., Picchi, V., Cescatti, A., Seufert, G., and Colombo, R.: High resolution field spectroscopy measurements for estimating gross ecosystem production in a rice field, Agr. Forest Meteorol., 150, 1283–1296, 2010.

Sims, D. A., Luo, H. Y., Hastings, S., Oechel, W. C., Rahman, A. F., and Gamon, J. A.: Parallel adjustments in vegetation greenness and ecosystem CO_2 exchange in response to drought in a Southern California chaparral ecosystem, Remote Sens. Environ., 103, 289–303, 2006a.

Terashima, I., Fujita, T., Inoue, T., Chow, W. S., and Oguchi, R.: Green light drives leaf photosynthesis more efficiently than red light in strong white light: revisiting the enigmatic question of why leaves are green, Plant Cell Physiol., 50, 684–697, doi:10.1093/pcp/pcp034, 2009.

Wu, C. Y., Niu, Z., Tang, Q., Huang, W. J., Rivard, B., and Feng, J. L.: Remote estimation of

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gross primary production in wheat using chlorophyll-related vegetation indices, Agr. Forest Meteorol., 149, 1015–1021, 2009.

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