Interactive comment on "On the relationship between ecosystem-scale hyperspectral reflectance and CO_2 exchange in European mountain grasslands" by M. Balzarolo et al.

Anonymous Referee #2
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General comments:
This paper reports an experimental study for spectral assessment of grassland CO2 exchange. This study utilizes several datasets in grassland sites that may be unpublished, but the study motivation, research concept and analytical methods do not include any original/innovative ones. In other words, this study seems to be a simple exercise using some new datasets based on similar research motivation, concept and methods as in preceding papers. Although a plenty of results are shown in Tables and Figures, the obtained results do not seem to include any essential findings or robust/useful relationships for remote sensing of ecosystem CO2 exchange. Despite the plenty of dataset, fitting results are not validated using independent dataset. More importantly, the majority of conclusions, insights and messages are confirmation or repetition of well-reported ones in preceding papers. Since this type of datasets have been collected through so-called FLUXnet as well as many other individual experiments, similar analysis can easily be done using a new dataset by using similar analytical approach as in this paper. However, preliminary exercises are not very worthwhile in the context of science and technology as well as operational applicability. Truly comprehensive or comparative studies are strongly expected.

Therefore, unfortunately, it is difficult to recommend this paper for publication as an independent scientific paper

Since this type of datasets have been collected through so-called FLUXnet as well as many other individual experiments, similar analysis can easily be done using a new dataset by using similar analytical approach as in this paper

Reviewer #2 reports that the paper is not an "original/innovative study" and the obtained results do not include "any essential findings or robust/useful relationships for remote sensing of ecosystem CO_2 exchange". We disagree with the reviewer on this position and instead think that the paper contains novel information and results that are of interest for the scientific community, but obviously that we need to better demonstrate the value and strengths of our study. Here below and in the revised version of the manuscript we will try to better explain which was the objective of the work and which are the findings.

A unique feature of our work, which contrasts with previous work relying on multi-spectral data in few wavebands only, is that we explore the entire visible to NIR space for correlations with the CO_2 exchange of European mountain grasslands. In this regard we would appreciate if the reviewer could substantiate his/her claim that this is a repetition of previous papers.

While it is true that our study does not yield robust and significant relationships, we still think that this is an essential finding and that the reviewer is misled in thinking that only significant results should be published. In our understanding this is a gross misconception as such an approach would bias science towards results that yield significant results. Note that we do not overstate our results, but openly acknowledge that despite major efforts to standardize measurements and rather similar ecosystems largely fail to detect robust general patterns. This in our view is a result worth publishing as it may help to design future studies and experiments to track down the underlying causes in addition to serve as reference in the definition of continuous reflectance measurements at eddy covariance sites in large organized networks such ICOS, AmeriFlux or NEON.

The dataset used in this paper was built based on a coordinated field experiment by three groups in order to standardize in-situ hyperspectral measurements and make these measurements comparable. We used the same experimental design at all sites by mounting the same model of spectroradiometer (i.e. ASD Hand Held) on aluminum boom of 1.5 m height in the footprint area of the flux tower. Generally, hyperspectral measurements in flux networks (e.g. FLUXNET, CarboEurope) are made individually by different groups, following their own methodologies and on few selected spectral wavelengths. As shown in Balzarolo et al. (2011), there exists no common protocol for hyperspectral measurements in the eddy covariance networks. Therefore, available hyperspectral measurements are not standardized and comparable between different sites: how to standardize measurements and make results comparable are still open questions. Thus, the dataset used in this paper is unique as it combines hyperspectral and flux measurements from three different studies based on common protocol. Obviously, the reviewer would like to see a different paper, namely one that takes a broader approach by including more sites from a more diverse set of ecosystems. While we acknowledge that such a global synthesis would be a highly interesting scientific endeavor, this is not the scope of our study and we will better clarify this in the introduction of the revised version of the manuscript. In addition we also anticipate major uncertainties to result from the lack of standardization of optical measurements that would be a potentially added problem for such global synthesis with the actual measurements available.

Although in the paper we considered similar ecosystems (belonging to the same vegetation type) the investigated canopies are very different and include Mediterranean, extensive alpine and intensive alpine grasslands with very different canopy structures in terms of leaf orientation, amount and spatial distribution of green and non-photosynthetic components, leaf nitrogen and water content (see Vescovo et.al, 2012). The different grassland structures (spatial distribution of photosynthetic, and also non photosynthetic material, leaf angles, etc.) is affecting our ability to use traditional indices to estimate fAPARgreen (and fluxes) when we consider different grasslands together because the structural effects on scattering are very complex in the NIR response (Jacquemoud et al., 2009; Knyazikhin et al., 2012).

In addition, it is not the main motivation of our study to devise the best possible model for estimating GPP or other carbon flux metrics (which the reviewer apparently would like to see), rather, as formulated in the title, the main objective is to explore the links between the vast information contained in hyperspectral reflectance in the VIS to NIR range and the relationships to CO_2 exchange.

The suggestion of the reviewer to add further sites and data to validate the found relationships is appreciated and carefully take into account by the authors by answering to his/her comments. In the revised version of the manuscript the metrics obtained by the leave-one-out procedure will be applied to BGD dataset and the results will be reported and discussed. In particular, the robustness of the models will be evaluated by: cross validated R-Squared (R^2cv) and cross validated Root Mean Squared Error (RMSEcv). The new figure C1 (here below) will be added to the revised version of the manuscript. Cross-validation showed that the selected models are robust. In addition, in order to evaluate the performance of the found relationships and the new selected bands the authors included three new sites in their database (validation sites – see Tab. S1 below). These three additional sites were already part of the preceding study by Vescovo et al. (2012) and used exactly the same methodology as applied at the main three study sites and thus fully comply with our own standards of intercomparability.

Unfortunately join spectral and eddy covariance measurements are available only for few days and this is why were not included in the BGD paper and in the correlation matrix analysis. Validation will be performed applying to the three new sites all the three site specific models (Amplero, Neustift and Monte Bondone) and a model parameterized grouping Neustift and Monte Bondone since the two sites are characterized by similar environmental conditions. The figure C2 here below shows the results of the validation of the models against validation sites for the midday time scale. In the revised version of the manuscript these results and the results of the validation of the models against validation sites for daily time scale will be added and commented. As shown in this figure, correspondence between simulated and measured VIs was reasonable when using the models developed for Monte Bondone and Neustift or both sites pooled, but less so with the models of Amplero. This is understandable as Monte Bondone and in particular Neustift are structurally and functionally much more similar to the validation sites compared to Amplero. Overall, the validation shows that the models developed are transferable.

The authors think that following unexpected and novel results are presented in the paper.

Considering all sites pooled together, NSD-type "Visible vs. NIR" band combinations (i.e. traditional "greenness" indices) show a very poor correlation with GPP. It is well-reported in the literature (Rossini et al., 2010, 2012; Peng et al., 2010; Sakowska et al., 2014) that “greenness” indices, for grasslands and crops, are good proxies of fAPARgreen (and thus carbon fluxes). Interestingly, in our paper their performance is considerably poorer than expected. This result is of importance for the community which still relies a lot on these relationships, also favored by the availability of cheap narrow-band sensors that allow continuous monitoring of e.g. NDVI. This finding has also a relevant impact concerning the ability to upscale grassland fAPARgreen and carbon fluxes using upcoming sensors (e.g. Sentinel 2).

NSD-type "Visible vs. Visible" band combinations show a better performance than "Visible vs. NIR" ones. "Visible vs. visible" NSD (e.g. green vs. blue or red, green vs. green wavelengths; see e.g. Inoue et al, 2008) are also known to work as “greenness” indices, although their performance is generally much poorer than “Visible vs. NIR" indices. These results are likely due to the confounding effect of the different structures (and consequently of the different NIR response; Vescovo et al, 2012) of the investigated grasslands.

Chlorophyll indices (e.g. NDVI red-edge = (R750−R720)/(R750+R720) – which are considered the best indices for estimating carbon fluxes on grasslands and crops) – show in our dataset a very low performance. It was demonstrated many years ago that the red edge domain, where reflectance changes from very low in the absorption region to high in the NIR, is one of the best descriptors of chlorophyll concentration. On the other hand, it is well known that the canopy structure can be a very strong confounding factor. Our results confirm that this topic needs to be further investigated, as this finding has a relevant impact concerning the use of Sentinel 2 to upscale fAPAR and carbon flux observations.

It is quite interesting to see that the NSD "NIR vs. NIR" (structural indices) appear to be the best proxy for GPP fluxes when all the grasslands are analyzed together. These results can be linked to the controversial paper focused on the strong impact of structure on the ability to estimate canopy nitrogen content (Knyazikhin et al., 2012) and confirm the need for more studies in this direction.

In summary, we will modify the manuscript to better emphasize the novelty and value of our study by including the reasoning above.

<u>The following new Table S1 will be added to the revised version of the manuscript:</u>

Table S1. Description of the validation study sites and period.

Site characteristics	Längenfeld (AT-Lan)	Leutasch (AT-Leu)	Scharnitz (AT-Sch)
Latitude	47.0612	47.3780	47.3873
Longitude	10.9634	11.1627	11.2479
Elevation (m)	1180	1115	964
Mean annual temperature (˚C)	5.8	4.8	6.4
Mean annual precipitation (mm)	733	1309	1418
Vegetation type	*Phyteumo-Trisetion*	*Astrantio-Trisetetum*	*Arrenatherum montanum*
Study period[1]	163, 2006 (1)	227, 2006 (1)	184-284, 2006 (5)
Sonic anemometer model	R3, Gill Instruments Ltd., Lymington, UK	R3, Gill Instruments Ltd., Lymington, UK	R3, Gill Instruments Ltd., Lymington, UK
Infrared gas analyser model	Li-7500, Li-Cor Inc., Lincoln, Nebraska, USA	Li-7500, Li-Cor Inc., Lincoln, Nebraska, USA	Li-7500, Li-Cor Inc., Lincoln, Nebraska, USA
Data acquisition frequency (Hz)	20	20	20
Post-processing software	EdiRE (Version 1.4.3.1021, R. Clement, University of Edinburgh)	EdiRE (Version 1.4.3.1021, R. Clement, University of Edinburgh)	EdiRE (Version 1.4.3.1021, R. Clement, University of Edinburgh)
Outlier removal (method)	-	-	-
CO_2/H_2O signal lag removal	Covariance maximization	Covariance maximization	Covariance maximization
Coordinate rotation (method)[2]	3D	3D	3D
Detrending of time series (method)	-	-	-
Density corrections applied[3]	X	x	x
Sonic buoyancy to sensible heat flux conversion and cross-wind correction[4]	X	x	x
Low- and high-pass filtering corrected for (method)	Moore (1986)	Moore (1986)	Moore (1986)

[1] from-to DOY, year (number of hyperspectral measurement dates); [2] according to Wilczak et al. (2001); [3] according to Webb et al. (1980); [4] according to Schotanus et al. (1983); [5] according to Mauder et al. (2008).

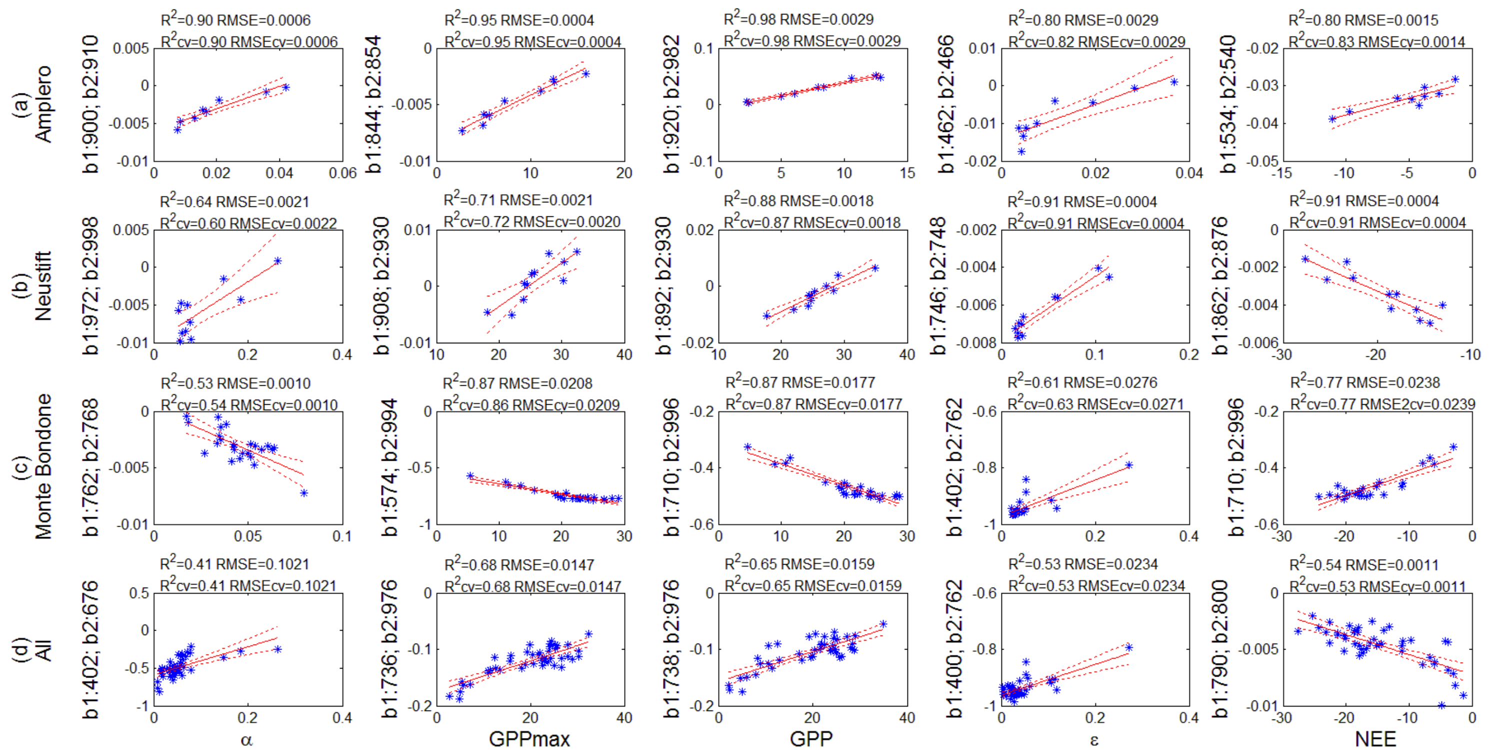

Fig. C1: Results of linear correlation analysis for α, GPPmax and midday averaged GPP, ε and NEE and selected NSD-type indices for (a) Amplero, (b) Neustift,(c) Monte Bondone (both study years pooled) and (d) all sites pooled. R^2—Coefficient of determination; RMSE—Root Mean Square Error; R^2cv—Cross-validated coefficient of determination; $RMSE_{cv}$— Cross-validated root Mean Square Error. The red lines indicate the fitted models and the red dotted lines represent the 95% upper and lower confidence bounds.

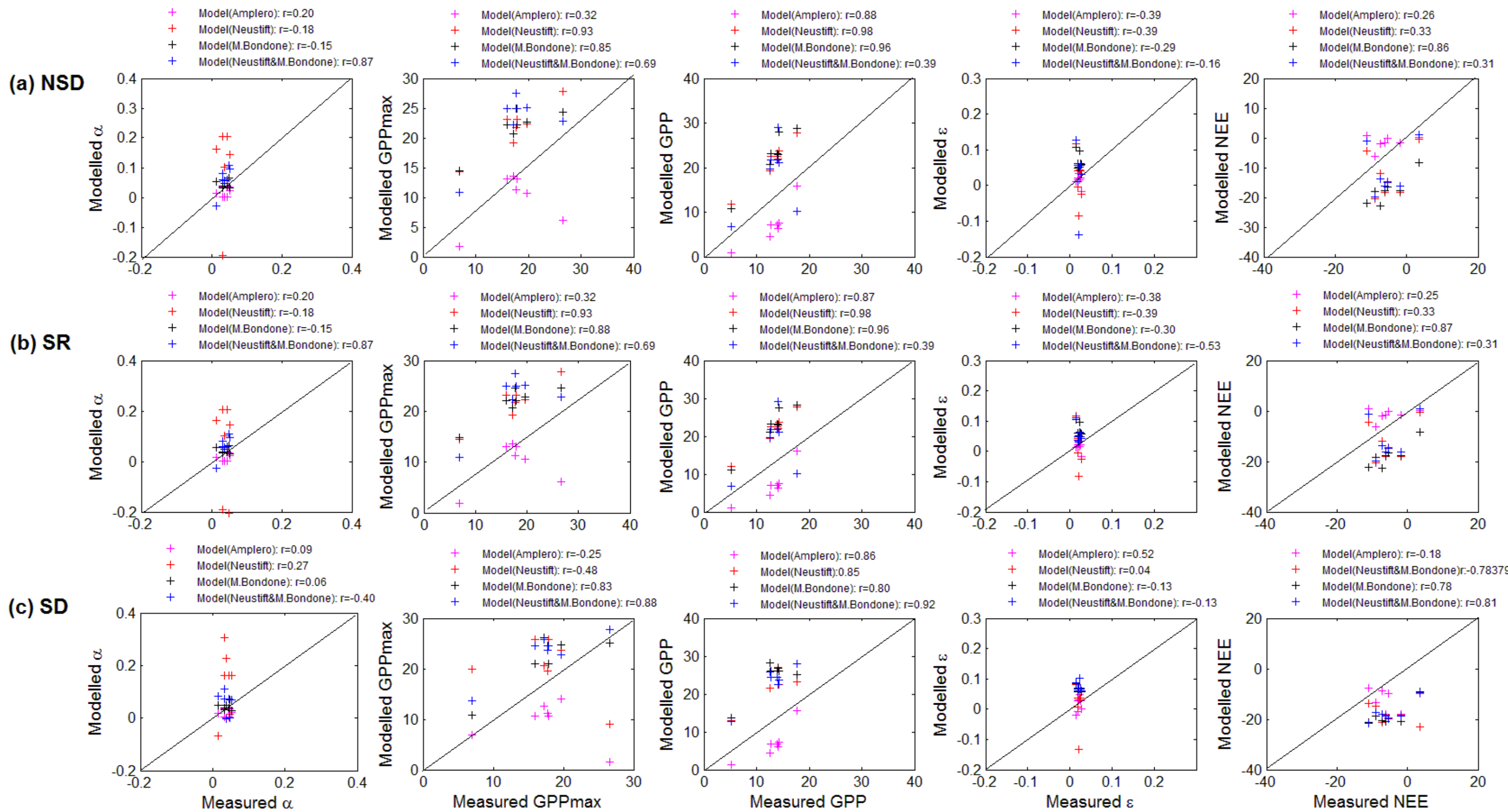

Fig. C2 – Results of validation of linear regression models between VIs ((a) NSD type; (b) SR-type; (c) SD-type) and ecophysiological parameters: α, ε (midday average), GPP_{max} and midday average CO_2 fluxes (NEE and GPP). r—coefficient of correlation. Different colours represent results of the validation performed applying to the three new sites the model for Amplero (in magenta), Neustift (in red) and Monte Bondone (in blue) and a model parameterized grouping Neustift and Monte Bondone (in black).

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Specific comments:

1. P26L6-8: This statement may be misleading because "plant functioning" can be represented by the combination of canopy structure (LAI, 3D distribution), components (chlorophyll, nitrogen, water, etc.), and biophysical/physiochemical reactions. In addition, the observational time resolution would greatly affect the definition and analysis of the "photosynthetic functioning". More precise discussion is needed.

RESPONSE

We agree and we will change this sentence into "…indicators of the amount of green biomass, fAPAR green, rather than plant light use efficiency"

2. P26L24-P27L10: Methodological review in this section is very insufficient. Note that a number of approaches have been investigated for remote sensing of ecophysiological variables such as chlorophyll, nitrogen, LUE, water, LAI, fAPAR, etc. not only in grassland but in the other vegetation types. From methodological point of view, it is not appropriate to limit things to grassland.

RESPONSE

We agree and we will rewrite this part including more approaches used in remote sensing and we will not focus only on grassland. We will include a new part in the revised version of the manuscript where related to the investigation of biophysical variables by remote sensing. Please see the revised version of the introduction in the second part of the answer to the comment 3.

3. P26L24-P27L10: Analytical approaches of hyperspectral reflectance are 1) hyperspectral index methods, 2) multi-variable statistical methods (PLSR etc.), and 3) use of radiative transfer models (PROSAIL etc.). Hence, more comprehensive reviewing on methodologies is needed. In addition, this paper seems to focus only on a part of the approach 1) without showing any rationale. Some reasons and theoretical necessity should be provided.

RESPONSE

The general aim of our paper was to understand if there were some spectral regions where VIs and fluxes and biophysical variables showed the same performance for each site or for all sites pooled together. A set of traditional VIs was selected to analysis the behavior of the three different grasslands. Once to note the specific response of the three grasslands to each biophysical parameter, we processed with correlation matrix analysis to see if there were spectral region where VI vs. biophysical parameters performed in the same ways. We agree that we partially explore the approach (1). By validating the selected models (see general comment) we will improve the BGD paper and we will fully apply this analytical approach.

It is true that there are many studies that showed this type of analysis but there are not studies were different grasslands with different structural and functional characteristics are compared. This is the first reason for which we did this study. Another reason is related to the selection of the spectral bands to use for investigating grassland dynamics.

The introduction of the BGD paper will be restructured and the reasons and theoretical necessity of the study will clearly state in the revised version of the manuscript.

In addition we will include comments on the most used analytical approaches of hyperspectral reflectance. We will add also a new part related to the investigation of biophysical variables by remote sensing (see answer to the comment 2).

In detail, to answer to the comments 2 and 3 the introduction of the BGD paper will be restructured and the reasons and theoretical necessity of the study will clearly state in the revised version of the manuscript. Here below the introduction that will be included in the revised version of the manuscript with the new added references.

Understanding the mechanisms that drive the carbon dioxide (CO_2) uptake of the terrestrial ecosystems is one of the main challenges for the ecologists working on climate changes (Beer et al., 2010). Plant photosynthesis, also referred to as gross primary productivity (GPP), is one of the major components of the global carbon cycle. It interacts in complex ways with environmental factors such as radiation, nutrients, soil water, vapor pressure deficit, air temperature and soil temperature (Drolet et al. 2005). Plant biochemistry and structure determine many fundamental ecosystem patterns, processes and dynamics (Lambers et al. 1998; Waring and Running 1998). The canopy nitrogen content regulates the canopy photosinthtic capacity and the canopy light use efficency (LUE) (Ollinger et al., 2008). In addition, the canopy chlorophyll content plays an important role in controlling ecosystem photosynthesis and the carbon gain (Peng et al., 2011, Gitelson et al., 2006).

Optical remote sensing can help ecologists in qualitatively and quantitatively assessing the plant and canopy properties (e.g. biomass (Vescovo et al. 2012), water content (Clevers et al., 2010), nitrogen content (Chen et al., 2010; Ollinger et al., 2008; Knyazikhin et al., 2012) and chlorophyll content (Gitelson et al., 2006) and photosynthetic rate (Inoue et al., 2008)) that drive ecosystems processes related to the carbon cycle.

Empirical and physical-based methods have been proposed to interpret optical plant and canopy properties. The empirical method consists of (linear) regression analysis between plant or canopy properties and optical data. The most used empirical methods are: hyperspectral index methods (Peñuelas et al., 1993; Sims and Gamon, 2002; Inoue et al., 2008) and multi-variable statistical methods (e.g. stepwise linear regression, genetic algorithm, neural network (Grossman et al., 1996; Riaño et al., 2005a; Li et al., 2007). The physical methods are based on the use of radiative transfer models (RTMs) to simulate light absorption and scattering trough the canopy as a function of canopy structure and leaf biochemical composition (Jacquemoud et al., 2000; Zarco-Tejada et al., 2003). Therefore, RTMs models help in quantifying the contribution of canopy biophysical and biochemical variables to canopy reflectance. The most popular RTM is PROSAIL model based on the coupling of the SAIL bidirectional canopy reflectance model (Verhoef et al., 1984) and the PROSPECT leaf optical properties model (Jacquemoud and Baret, 1990). The model simulations by PROSAIL demonstrated that the red-edge region (between 680 nm to 730 nm) of the spectrum is sensitive to the chlorophyll and leaf area index (LAI) (Baret et al., 1992). It is also well accepted that an increase of LAI includes a decrease of reflectance in the red and da increase in near-infrared (NIR) region (Jacquemoud, 1993). In the NIR region LAI and the leaf angle contribute in the same portions to the reflectance (Bacour et al., 2002a). NIR reflectance between 800 nm and 850 nm is also related to canopy N content (Ollinger et al., 2008; Knyazikhin et al., 2012). In addition, the combination of the reflectance in NIR and in the short wave infrared region (SWIR) is correlated to canopy water content (Colombo et al., 2008) but the reflectance between 1000 nm and 1400 nm is also highly sensitive to LAI. So, some attention is needed when these spectral regions are used to retrieve water content considering that the canopy properties in a given ecosystem often co-vary (Bacour et al., 2002c). Those remarkable optical properties of the canopy need to be taken into account to quantify vegetation properties by hyperspectral index method. The hyperspectral index method consists of the use of spectral vegetation indices (VIs) defined as spectral band ratios, or normalized band ratios between the reflectance in the visible and near-infrared (NIR) region.

The typical optical sampling approach to estimate GPP, which is linking spectral observations with carbon fluxes, is based on the Monteith equation (1972, 1977):

$$GPP = \varepsilon * PAR * fAPAR \quad (1)$$

where ε is the light use efficiency (LUE) and fAPAR is the fraction of absorbed photosynthetically active radiation); both ε and fAPAR can be retrieved by remote optical observations. A wide number of VIs that can potentially be used to model the productivity of terrestrial ecosystems (as a proxy of LUE and fAPAR) has been suggested (Inoue et al., 2008; Coops et al., 2010; Peñuelas et al., 2011; Rossini et al. 2012). The various VIs differ in their sensitivity to changes in photosynthetic status. "Greeness indices" – such the widely used Normalized Difference Vegetation Index (NDVI) – demonstrated to be a good proxy for fAPAR, but are not sensitive to rapid changes in plant photosynthesis which are induced by common environmental and anthropogenic stressors (Gitelson et al., 2008; Hmimina et al., 2014; Soudani et al., 2014). However, in ecosystems characterized by strong dynamics (e.g. grasslands and crops with a strong green-up and senescence), other VIs are able to effectively monitor seasonal changes in biophysical parameters controlling canopy photosynthesis such as fAPAR and chlorophyll content and~~,~~ consequently, can be adopted to monitor seasonal and spatial variability of carbon fluxes (Gitelson et al., 2012; Sakowska et al., 2014). Short-term changes in LUE can be remotely detected through a spectral proxy of the xanthophyll cycle (Photochemical Reflectance Index, PRI; Gamon et al., 1992). The PRI is one of the most promising VIs for a direct estimation of photosynthetic light use efficiency (LUE) and of its seasonal and diurnal variations (Nichol et al., 2002). Latest developments of the sun-induced fluorescence method may allow even more direct remote sensing of plant photosynthesis in the near future (Meroni et al., 2009; Rossini et al., 2010; Frankenberg et al., 2011). At canopy scale, the relationship between PRI and LUE was shown to be site dependent (Garbulsky et al., 2011; Goerner et al., 2011) and strongly affected by environmental conditions (Soudani et al. 2014).

Whereas previous studies have demonstrated the ability of remote sensing data to model ecosystem GPP (e.g. Gianelle et al., 2009; Wohlfahrt et al., 2010; Rossini et al. 2012; Sakowska et al., 2014), a universal model for GPP estimation applicable across different ecosystems and a wide range of environmental conditions is still missing. In addition, those previous studies focussed on single sites with specific characteristics (e.g. climate, vegetation composition, soil type; see Wohlfahrt et al., 2010) and were often based on the use of different sensors, platforms and protocols (Balzarolo et al., 2011), making generalisation difficult. Moreover, most of the studies have either relied on reflectance measurements in a few spectral wavebands (e.g. Wohlfahrt et al., 2010 and Sakowska et al, 2014) or a minimum number of bands needed to calculate the most common VIs, missing potentially important information in under-sampled spectral regions that could explain carbon fluxes and variability. In recent years, SpecNet (http://specnet.info; Gamon et al., 2006), the European COST Action ES0903 (EUROSPEC) (http://cost-es0903.fem-environment.eu/) and the COST Action ES1309 (OPTIMISE;

http://www.cost.eu/domains_actions/essem/Actions/ES1309) focused on the definition of a standardized protocol for making optical measurements at the eddy covariance CO_2 flux towers (Gamon et al., 2010).

The overarching objective of the present paper is thus to develop a common framework for predicting grassland carbon fluxes and ecophysiological parameters based on optical remote sensing data. To this end we combine eddy covariance CO_2 flux measurements with ground-based hyperspectral reflectance measurements at six different grasslands in Europe using a standardised common protocol. This database is unique and we are not aware of any other study collating a similar multi-site dataset. We focused on European grasslands since covering roughly 22% (80 million ha) of the EU-25 land area, grasslands are among the dominating ecosystem types in Europe (EEA, 2005) and their role in the European carbon balance has received a lot of scientific interest (Soussana et al., 2007; Gilmanov et al., 2007; Wohlfahrt et al., 2008; Ciais et al. 2010). While direct measurements of the carbon exchange have been carried out and are still ongoing at a number of different grassland sites in Europe –notably in the two EU projects GreenGrass (Soussana et al., 2007) and CarboMont (Cernusca et al., 2008) – scaling up these plot-level measurements to the continental scale requires a modelling approach, typically based on or supported by remotely sensed data. Therefore, we believe that this study will improve the current knowledge on modelling the carbon dynamics of European grasslands.

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4. P26L24-P27L10: The biophysical and ecophysiological processes for spectral reflection, transmission and absorption by ecosystems have already been understood very well in physical principle, and the major parts of such processes have been modeled. Therefore, it is already obvious that simple linear/non-linear regression models using VIs can never be applicable universally to a wide range of vegetation and/or environmental conditions. Therefore, the simple confirmation of such well-known facts using different datasets is neither new nor useful. Hence, new research should focus on 1) innovative methods to overcome such limitations, or 2) optimization for higher accuracy and applicability using simple approach. Nevertheless, this study is quite insufficient in both aspects.

RESPONSE

We agree with the reviewer and in the revised version of the manuscript we will add some explanations of the existence of the correlation in some spectral regions. To investigate more the basis of the correlation between the selected band combinations and ecophysiological variables (e.g. alpha, GPPmax, GPP, epsilon) in the revised version of the paper we will analyse the relationship between the selected bands and biophysical parameters such as dry phytomass, nitrogen and water content collected during the field campaign in the same footprint of hyperspectral measurements. We selected these biophysical variable because they are related to the vegetation structure and can be helpful for interpreting the spectral response of the grassland in the NIR region. The new tables S2 and S3 (here below) will be added to the revised version of the manuscript. This analysis confirmed that the that the spectral response in the selected band combinations for NDS, SR and SD-type indices is strongly related to structural characteristics of the vegetation of the three grasslands (e.g. nitrogen and phytomass) that impact on their spectral response in NIR and VIS regions. For the Mediterranean site (Amplero site) and for all eco-physiological parameters (i.e. a, GPPmax, GPP, epsilon) the dry phytomass is the main driving factor of the spectral response in the selected bands while nitrogen content drives the spectral response in the NIR region for Neustift. For Monte Bondone both dry phytomass and nitrogen content affect the spectral response of the grassland. Similar results were obtained for SR and SD-type indices.

Therefore, according to the obtained results, more studies are needed to understand the physical basis of this correlation. In addition, these new analysis will substantially contribute to the analysis of the structural effect on the ability to estimate canopy nitrogen content that is still a controversial issue (Knyazikhin et al., 2012).

In addition, to investigate more the basis of the correlation between the NIR band combinations and GPP, we analyzed a similar dataset collected in summer 2013 on Monte Bondone. Measurements were acquired using the same ASD FieldSpec spectrometer used for Monte Bondone in 2006 (serial number: 6354). The measurements were taken on the tower at a height of 6 m, with a field of view of 25°. To obtain reflectance values, white panel radiance spectra and canopy radiance spectra were acquired at approximately weekly intervals. At the same time of the hyperspectral measurements, measurements of the canopy chlorophyll and canopy water content were performed within the spectrometer footprint (5 m2). In the Figure C3, it is possible to see that, NSD- and SR-type indices for the selected bands for estimating GPP (i.e. 710 nm and 996 nm) are strongly correlated with canopy total chlorophyll content ($R^2 > 0.90$). For the band combinations < 750 nm, the correlation is related to chlorophyll content while for band combinations > 750nm (which is the most common situation; e.g. 761 and 770, 761 and 850, 800 and 850, etc.) there is a structural effect which needs to be further investigated (confirmed by Gitelson by a personal communication). In fact, the literature indicates that the wavelenghts in the NIR (>750nm) are not sensitive to chlorophyll content. They are sensitive to leaf and canopy structure (and around the 970nm area to water). These new analysis will substantially help to the analysis of the structural effect on the ability to estimate canopy nitrogen content that is still a controversial issue (Knyazikhin et al., 2012).

Table S2. Results of the correlation (r – correlation coefficient) between the best NDS, SR and SD-type indices and dry phytomass and nitrogen content for Amplero, Neustift, Monte Bondone for the alpha, GPPmax, midday GPP, midday epsilon and midday NEE.

Index	Site	Parameter	α Band center [i,j] (nm)	R^2 (-)	GPPmax Band center [i,j] (nm)	R^2 (-)	GPP Band center [i,j] (nm)	R^2 (-)	ε Band center [i,j] (nm)	R^2 (-)	NEE Band center [i,j] (nm)	R^2 (-)
NSD-type	Amplero	Dry phytomass (g m-2)	[900, 910]	-0.81**	[844, 854]	-0.85**	[920, 982]	-0.76*	[462, 466]	-0.87**	[534, 540]	0.60
	Amplero	Nitrogen content (%)		0.54		0.57		0.44		0.70*		-0.39
	Amplero	Water content (%)		0.53		0.73*		0.75*		0.66		-0.74*
	Neustift	Dry phytomass (g m-2)	[972, 998]	-0.04	[908, 930]	0.51	[892, 930]	0.59	[746, 748]	-0.66*	[862, 876]	0.15
	Neustift	Nitrogen content (%)		0.40		-0.39		-0.46		0.88**		0.18
	Neustift	Water content (%)		-0.07		0.03		-0.18		0.77*		0.31
	Monte Bondone	Dry phytomass (g m-2)	[762, 768]	-0.13	[574, 994]	-0.77***	[710, 996]	-0.70***	[402, 762]	-0.74***	[710, 996]	-0.70***
	Monte Bondone	Nitrogen content (%)		0.29		0.72***		0.62**		0.69***		0.62**
	Monte Bondone	Water content (%)		0.31		0.69***		0.59**		0.65***		0.59**
	All	Dry phytomass (g m-2)	[402, 676]	0.23	[736, 976]	0.12	[738, 976]	0.14	[400, 762]	-0.22	[790, 800]	0.06
	All	Nitrogen content (%)		0.51***		0.19		0.13		0.64***		0.30
	All	Water content (%)		0.03		-0.09		-0.09		0.32*		0.05
SR-type	Amplero	Dry phytomass (g m-2)	[900, 910]	-0.81***	[844, 854]	-0.85**	[920, 982]	-0.76*	[462, 466]	-0.87*	[534, 540]	0.60
	Amplero	Nitrogen content (%)		0.54		0.57		0.43		0.70*		-0.39
	Amplero	Water content (%)		0.53		0.73**		0.74*		0.66		-0.74*
	Neustift	Dry phytomass (g m-2)	[972, 998]	-0.04	[908, 930]	0.51	[892, 930]	0.59	[746, 478]	-0.66*	[862, 876]	0.15
	Neustift	Nitrogen content (%)		0.40		-0.39		-0.46		0.88**		0.18
	Neustift	Water content (%)		-0.07		0.03		-0.18		0.77*		0.31
	Monte Bondone	Dry phytomass (g m-2)	[762, 768]	-0.13	[570, 994]	-0.77***	[714, 996]	-0.73***	[402, 762]	-0.74***	[570, 574]	0.61**
	Monte Bondone	Nitrogen content (%)		0.29		0.73***		0.64***		0.69***		-0.53**
	Monte Bondone	Water content (%)		0.31		0.69***		0.61**		0.64***		-0.50*
	All	Dry phytomass (g m-2)	[402, 676]	0.28	[736, 976]	0.14	[738, 976]	0.15	[400, 762]	-0.22	[790, 800]	0.06
	All	Nitrogen content (%)		0.51***		0.19		0.13		0.63***		0.30
	All	Water content (%)		-0.01		-0.10		-0.10		0.33*		0.05
SD-type	Amplero	Dry phytomass (g m-2)	[900, 910]	-0.80***	[844, 866]	-0.90**	[920, 982]	-0.77*	[492, 496]	-0.76*	[422, 432]	-0.50
	Amplero	Nitrogen content (%)		0.47		0.55		0.46		0.55		0.19
	Amplero	Water content (%)		0.41		0.67*		0.77*		0.43		0.70*
	Neustift	Dry phytomass (g m-2)	[474, 494]	-0.45	[736, 968]	0.20	[878, 922]	0.61	[732, 942]	-0.45	[402, 456]	-0.04
	Neustift	Nitrogen content (%)		0.33		0.09		-0.34		0.90**		-0.28
	Neustift	Water content (%)		0.15		0.51		-0.04		0.80*		-0.72*
	Monte Bondone	Dry phytomass (g m-2)	[762, 768]	-0.38	[444, 482]	0.65***	[436, 488]	0.60**	[658, 682]	0.67***	[450, 486]	0.60**
	Monte Bondone	Nitrogen content (%)		0.53***		-0.58**		-0.58**		-0.62**		-0.59**
	Monte Bondone	Water content (%)		0.52***		-0.58**		-0.58		-0.56**		-0.55**
	All	Dry phytomass (g m-2)	[822, 824]	0.45***	[550, 560]	0.12	[414, 470]	0.00	[732, 928]	0.55***	[468, 660]	-0.11
	All	Nitrogen content (%)		-0.09		-0.09		-0.15		0.16		-0.33*
	All	Water content (%)		-0.08		0.18		0.19		-0.53***		0.24

Statistical significance is indicated as * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$).

Table S3. Results of the correlation (r – correlation coefficient) between the best NDS, SR and SD-type indices and dry phytomass and nitrogen content for Amplero, Neustift, Monte Bondone for daily GPP, ε and NEE.

Index	Site	Parameter	GPP Band center [i,j] (nm)	r (-)	ε Band center [i,j] (nm)	r (-)	NEE Band center [i,j] (nm)	r (-)
NSD-type	Amplero	Dry phytomass (g m-2)	[868, 878]	-0.82**	[896, 904]	-0.89**	[902, 922]	-0.83**
	Amplero	Nitrogen content (%)		0.61		0.54		0.56
	Amplero	Water content (%)		0.81**		0.53		0.85**
	Neustift	Dry phytomass (g m-2)	[972, 988]	-0.14	[722, 942]	-0.54	[422, 516]	-0.25
	Neustift	Nitrogen content (%)		0.27		0.91**		0.15
	Neustift	Water content (%)		0.19		0.80*		0.06
	Monte Bondone	Dry phytomass (g m-2)	[580, 986]	-0.75***	[658, 682]	0.69***	[712, 714]	-0.52*
	Monte Bondone	Nitrogen content (%)		0.71***		-0.66***		0.50*
	Monte Bondone	Water content (%)		0.67***		-0.61**		0.43*
	All	Dry phytomass (g m-2)	[736, 976]	0.12	[404, 944]	-0.21	[790, 798]	0.02
	All	Nitrogen content (%)		0.19		0.68***		0.32*
	All	Water content (%)		-0.09		0.36*		0.08
SR-type	Amplero	Dry phytomass (g m-2)	[868, 878]	-0.82**	[896, 904]	-0.89**	[902, 922]	-0.83**
	Amplero	Nitrogen content (%)		0.61		0.54		0.561
	Amplero	Water content (%)		0.81*		0.53		0.85**
	Neustift	Dry phytomass (g m-2)	[868, 878]	-0.14	[722, 942]	-0.54	[422, 516]	-0.254
	Neustift	Nitrogen content (%)		0.27		0.92**		0.142
	Neustift	Water content (%)		0.19		0.80*		0.056
	Monte Bondone	Dry phytomass (g m-2)	[600, 608]	0.56**	[658, 682]	0.69***	[712, 714]	-0.52*
	Monte Bondone	Nitrogen content (%)		-0.52**		-0.66***		0.50*
	Monte Bondone	Water content (%)		-0.54**		-0.61**		0.43*
	All	Dry phytomass (g m-2)	[736, 976]	0.14	[404, 944]	-0.21	[790, 798]	0.021
	All	Nitrogen content (%)		0.19		0.67***		0.32*
	All	Water content (%)		-0.10		0.37*		0.083
SD-type	Amplero	Dry phytomass (g m-2)	[894, 998]	-0.81**	[844, 856]	-0.89**	[816, 834]	-0.84**
	Amplero	Nitrogen content (%)		0.49		0.51		0.56*
	Amplero	Water content (%)		0.76*		0.59		0.84**
	Neustift	Dry phytomass (g m-2)	[972, 988]	-0.16	[732, 942]	-0.45	[400, 410]	0.092
	Neustift	Nitrogen content (%)		0.33		0.90**		-0.672
	Neustift	Water content (%)		0.25		0.80*		-0.293
	Monte Bondone	Dry phytomass (g m-2)	[444, 502]	0.57**	[658, 680]	0.72***	[468, 496]	0.47*
	Monte Bondone	Nitrogen content (%)		-0.56**		-0.67***		-0.55**
	Monte Bondone	Water content (%)		-0.57**		-0.63***		-0.48*
	All	Dry phytomass (g m-2)	[424, 446]	0.28	[734, 928]	-0.44**	[444, 464]	0.167
	All	Nitrogen content (%)		0.14		0.56***		0.070
	All	Water content (%)		-0.16		0.16		-0.032

Statistical significance is indicated as * ($p < 0.05$), ** ($p < 0.01$), and *** ($p < 0.001$).

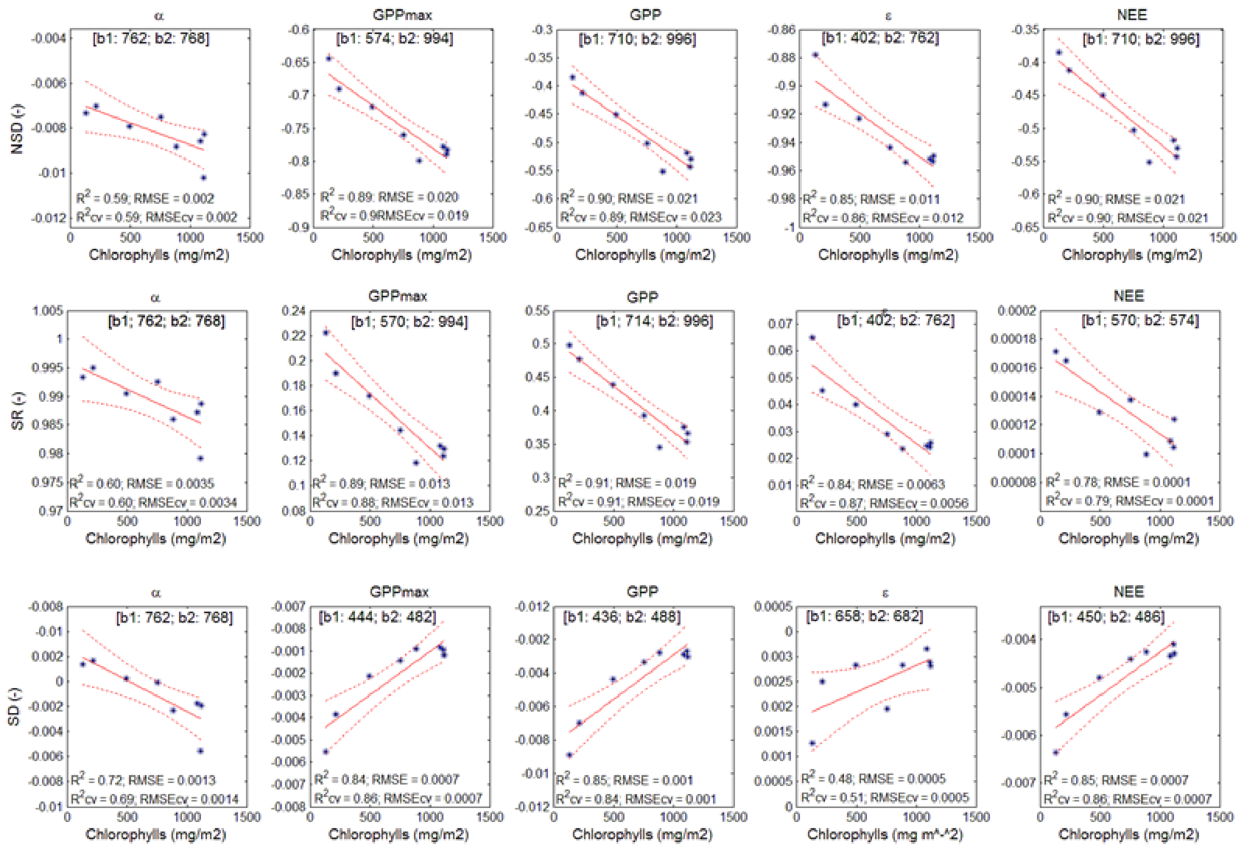

Fig. C3 – Correlation between selected NSD-, SR- and SD-type indices and the total chlorophyll content content for Monte Bondone in 2013. R^2—coefficient of correlation; RMSE—root mean square error; R^2cv— cross-validated coefficient of correlation; RMSEcv— cross-validated root mean square error. The red lines indicate the fitted models and the red dotted lines represent the 95% upper and lower confidence bounds. In the brackets are reported the selected bands to compute NSD-, SR- and SD-type indices.

In the revised version of the manuscript CI index reported in the Table 2 will be re-defined using the following formula: CI = (R750/R720) – 1 as reported in Gitelson et al. (2005). In addition, Red-edge (Red-edge NDVI = (R750–R720)/ (R750+R720); Gitelson and Merzlyak (1994)) will be added to the elaboration. Consequently, Figure 1 of BGD paper will be modified by showing the positions of these new indices and removing the old CI. In addition, in the revised version of the manuscript the Table 3 and Table 4 of the BGD paper and the Table S1 in the BGD supplemental will be modified showing the results of the correlation analysis between biophysical parameters and the new indices.

5. P27L11-15: Note that some comprehensive analytical studies have already been reported for the other type of ecosystems. Therefore, the differences in spectral response between grassland and the other herbaceous or tree plants have to be investigated quantitatively. If such advanced or in-depth investigations are not included, this study may be a kind of routine exercise using preceding approaches and grassland datasets.

It is difficult to address this very general comment not knowing which "comprehensive analytical studies" the reviewer refers to. As detailed above, the focus of the present paper is on a comparison of three mountain grasslands which have been studied with a standardized methodology. Clearly, comparing with other ecosystem types is the desired next step, but the essential prerequisite for doing so is to be able to reconcile how different experimental protocols followed at different sites affect results. We believe that this step still has to be taken, before tackling a global cross-site synthesis.

6. P29L14-16: This averaging around midday (10:00-14:00) is questionable because high time-resolution measurements (both remote sensing and flux data) would be needed to detect the rapid change of photosynthetic functioning (related to CO2 exchange). More essentially, the analytical time-scale is not clear throughout the paper.

This comment refers to analytical time-scale but if not clear if the Reviewer #2 refers only to flux measurements or to both flux and spectral measurements. Trying to answer to this comment, we would specify that the hyperspectral measurements were made during the time frame between 10:00-14:00, but they actually took much less time and therefore they were not average over this time frame. On the other hand, the flux measurements were averaged over this time frame. We selected this time frame since we don't expect fast changes in the photosynthesis for these periods when light is not limiting the process and other the environmental conditions were stable. Moreover, the use of this time frame ensured a reduction of the random noise in the flux data.

7. P29L21-P30L7: The error caused by these simple and conventional assumptions might not be negligible. The possible error should be assessed or discussed. Otherwise, the comparison of predictive accuracy throughout the paper would make little sense. LAI by optical method is basically Plant Area Index rather than Leaf Area Index, so there would be some problem in assessment of green-leaf area index especially during the senescent stage.

We agree that Eq. (3) and the measurements and assumptions used to calculate fAPAR are simplistic and will discuss the implications in more detail in the revised paper.

8. S2.5: Quite similar analytical approach using hyperspectra has been reported in preceding papers (LUE, canopy nitrogen, etc.), so most readers would think that this study is a simple application of such methods to some grassland datasets. See the comments 4 and 5. Hence, first, such preceding studies should be referenced sufficiently. Second, the motivation of the application to grassland should be explained clearly with relevant logic.

Thanks for the suggestion. We agree and we will rewrite this part by clearly explaining the motivation of the research and showing the novelty of the research approach.

9. P33L26: It is strange that graphs for SRs have triangular shape (e.g., Fig. 5). SR maps would have to have a square shape because Ri/Rj and Rj/Ri have different predictive power.

Thanks, we agree – we will show "the other side" of the triangle as well.

10. P37L18-20: This has been a well-known fact in remote sensing of ecosystems. Therefore, investigations should focus on reduction of such confounding factors. Unfortunately in this paper, no alternative methods, findings or insights in such aspects are obtained. Since this type of datasets have been collected through so-called FLUXnet as well as many other individual experiments, similar analysis can easily be done using a new dataset by using similar analytical approach as in this paper.

However, preliminary exercises are not worthwhile in the context of science and technology as well as operational applicability. Please see the comment 4.

As proposed by responding to the comment 4, in the revised version of the manuscript we will put more emphasis on the confounding factors that impact on the spectral response of the vegetation in the NIR. In particular, we will focus on the use of canopy water, nitrogen and chlorophyll content in order to understand if these biophysical variables can help current understanding on this field that is still controversial issue (Knyazikhin et al., 2012).

See our reply above to the general comment regarding the feasibility of a global synthesis study and the value of our study which used a standardized common protocol.

11. S4&5: It is difficult to find significantly original or innovative findings, insights, or message. Major parts in these sections seem to be simple confirmation or repetition of well reported facts, insights or messages by preceding papers. Please see the comments 4 and 5.

RESPONSE
As commented by answering to the general comment part, the authors agree with the reviewer that the discussion of the paper need improvements for clarifying the main important findings obtained by this study (see answer to the general comment) and we hope that we have been able to better clarify and explain why the study should be considered for publication.