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Interactive comment on "Combining hyperspectral remote sensing and eddy covariance data streams for estimation of vegetation functional traits" *by* Javier Pacheco-Labrador et al.

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Dear Referee #1, we would like to thank the valuable comments received. Different modifications have been planned accordingly in order to improve the readability and to better present the manuscript contents. We think part of the suggestions and criticisms received are motivated by an unclear description of the implications of the work for the community, as well as an unclear description of the aims and the methodology for the evaluation of the results. Therefore, we will improve the description of the aims, the motivations behind this analysis and improve the readability.

We try also to clarify the aim and contribution of this manuscript here: Literature shows

that understanding and modeling of carbon and water fluxes suffers from the static parameterization of plant functional traits (see Rogers et al., 2017 or Walker et al., 2017); in this context, the use of novel remote sensing data, such as hyperspectral imagery, can contribute to better monitor and characterize vegetation function (see Schimel et al., 2019). However, traits describing vegetation function are only weakly encoded in the optical reflectance vegetation; and previous works involving coauthors of this manuscript showed that to retrieve such traits, hyperspectral data must be combined with thermal radiation and fluxes (Pacheco-Labrador et al., 2019). This idea is also summarized by Schimel et al., (2019). Our manuscript hypothesize that it is possible characterizing the temporal variability of functional traits at ecosystem scale combining eddy covariance and remote sensing imagery (which in this case is emulated from airborne data since no time series of satellite hyperspectral imagery are available at the study site yet). We demonstrate that this is possible with certain limitations that we thoroughly discussed. This manuscript provides the Biogeosciences community with an innovative methodology for the estimation of key functional traits in eddy covariance stations. This work can be a first step towards the characterization of functional traits that could happen when we have hyperspectral data available at several ecosystem stations. Later on, once functional traits have been characterized in a sufficiently large number of sites and ecosystems it would be possible globally upscaling this information (see Moreno et al., 2018 or Walker et al., 2017); filling this way a knowledge gap that limits the understanding and modeling of carbon and water fluxes. Therefore, we consider that our manuscript makes a relevant contribution for the Biogeosciences community and is suitable for this journal.

We will modify the manuscript to better explain and justify this idea and the logic behind our analyses; and to better explain the potential of the method in a broader context. This is also discussed in the point-by-point reply to the Referee #1 comments and questions below.

Also, notice that in the new version we have introduced two changes:

1) A bug in the code that preserved carotenoids in the senescent leaves was been corrected. This has produced minimal differences in the results compared with the previous manuscript version.

2) A third step in the inversion has been implemented and tested to improve the characterization of the relationship between soil moisture and soil resistance to evaporation from the pore space. This had been only commented as a possibility in the discussion, but has been tested in the new version to confirm whether this could increase the certainty of this characterization without strongly modifying the estimates of other functional parameters.

References:

Rogers, A., Medlyn, B.E., Dukes, J.S., Bonan, G., von Caemmerer, S., Dietze, M.C., Kattge, J., Leakey, A.D.B., Mercado, L.M., Niinemets, Ü., Prentice, I.C., Serbin, S.P., Sitch, S., Way, D.A., & Zaehle, S. (2017). A roadmap for improving the representation of photosynthesis in Earth system models. New Phytologist, 213, 22-42Walker, A.P., Beckerman, A.P., Gu, L., Kattge, J., Cernusak Lucas, A., Domingues, T.F., Scales Joanna, C., Wohlfahrt, G., Wullschleger, S.D., & Woodward, F.I. (2014). The relationship of leaf photosynthetic traits – Vcmax and Jmax – to leaf nitrogen, leaf phosphorus, and specific leaf area: a metaâĂŘanalysis and modeling study. Ecology and Evolution, 4, 3218-3235 Schimel, D., Schneider, F.D., Carbon, J., & Participants, E. (2019). Flux towers in the sky: global ecology from space. New Phytologist, 224, 570-584 Pacheco-Labrador, J., Perez-Priego, O., El-Madany, T.S., Julitta, T., Rossini, M., Guan, J., Moreno, G., Carvalhais, N., Martín, M.P., Gonzalez-Cascon, R., Kolle, O., Reischtein, M., van der Tol, C., Carrara, A., Martini, D., Hammer, T.W., Moossen, H., & Migliavacca, M. (2019). Multiple-constraint inversion of SCOPE. Evaluating the potential of GPP and SIF for the retrieval of plant functional traits. Remote Sensing of Environment, 234, 111362 Moreno-Martínez, Á., Camps-Valls, G., Kattge, J., Robinson, N., Reichstein, M., van Bodegom, P., Kramer, K., Cornelissen, J.H.C., Reich, P., Bahn, M., Niinemets, Ü., Peñuelas, J., Craine, J.M., Cerabolini, B.E.L., Minden, V.,

Laughlin, D.C., Sack, L., Allred, B., Baraloto, C., Byun, C., Soudzilovskaia, N.A., & Running, S.W. (2018). A methodology to derive global maps of leaf traits using remote sensing and climate data. Remote Sensing of Environment, 218, 69-88

Referee #1 comment: The paper by Pacheco-Labrador et al. jointly uses airborne hyperspectral reflectance data and eddy covariance data to retrieve ecosystem traits in a Mediterranean tree-grass ecosystem. They use 17 hyperspectral images over three different flux towers (control, N addition, N+P addition) in an inversion framework which couples radiative transfer and soil-vegetation atmosphere transfer using a modified version of the SCOPE model to incorporate leaf senescence. The results suggest that such a framework can estimate vegetation traits and energy fluxes in this ecosystem. The authors also 'scale' their results using synthetic emulated hyperspectral satellite imagery to place in the context of future hyperspectral missions. The work described here is a significant effort, integrating many different datasets collected across a range of temporal and spatial scales over the course of 6 years. While this effort is very much appreciated, the many different data sources and complexity of the approach make it challenging to review. It requires a significant amount of background knowledge on the many papers previously published by the authors to completely understand the approach. Despite my best attempt at this, I still found this manuscript very difficult to evaluate. There are too many assumptions made for a complete evaluation of the paper's rigor, leaving the reader to have to place a lot of trust in the authors. If the assumptions are indeed valid (but again, too many to look into to fully address each one) then the paper comes across as a sound methodological approach. Despite these limitations, I think there is value in this work, but I would recommend the authors consider re-evaluating how to best distill this complex story into something more tangible and coherent.

Authors' response: We agree with the Referee #1 that this manuscript makes use of a wide range of measurements and observations, and there are some assumptions that are discussed in previous works of the co-authors. We agree that probably we did not explain the details in an easy way to follow by the reader without knowing previous our work. In order to improve the readability of the manuscript we will modify the methodological section including a diagram showing how these datasets are generated and combined. Moreover, we will include, in the supplementary material, a more extended description of the generation and scaling of field observations and estimates of biophysical parameters in order to facilitate a better understanding of the different datasets, so there is no need to consult additional literature.

Referee #1 comment: To me (and I could be missing the point), the paper reads very much like a methodological paper, perhaps better fit for a journal like EGU's Geoscientific Model Development. The paper does not go far enough into describing the "interactions between the biological, chemical, and physical processes in terrestrial or extraterrestrial life with the geosphere, hydrosphere, and atmosphere" – as stated as a goal of Biogeosciences. There is very little information regarding what the authors have learned about this ecosystem; the main result is that a seemingly complex approach can produce key functional parameters of vegetation that are robust to several sources of uncertainty. The discussion of sources of uncertainty, in particular, is extremely robust and very much appreciated.

Authors' response: We agree with the Referee #1 that our manuscript presents a methodology; however we still think it fits Biogeosciences' goals as the method proposed allows estimating key biophysical parameters but also -and this is the most innovative part-, functional parameters of vegetation, and their relationship with other variables. This is done by combining hyperspectral remote sensing and eddy covariance datastreams. These estimates are relevant to improve our understanding of the vegetation-atmosphere interactions and to parameterize terrestrial biosphere models. For instance Rogers et al., (2017) suggests the use for novel remote sensing datastreams (e.g. hyperspectral satellite missions) as a way forward to characterize the evolution in time of functional traits useful for earth system modeling. Our work was inspired by Rogers et al (2017) and we think that the methodology developed can be of

interest for a community that is beyond the model developers. Also, our work is not a strict modeling work. Indeed we do not develop any new model (notice that senSCOPE is described and evaluated in a manuscript currently under review that has been openly archived in Pacheco-Labrador et al., (2020)); rather we develop a model data integration schemes combining a variety of measurements. Similar approaches are behind recent papers published in Biogeosciences. For example, Dutta et al. (2019) presented a different method to estimate Vcmax and the Ball-Berry slope (m) combining remote sensing and eddy covariance data. Also Biogeosciences publishes articles that, even if methodological can be of interest for the community, for example Papale et al., (2006), and more recently Wutzler et al., (2018), or Kang et al., (2018) presented packages or methods to gap-fill and partition water and/or carbon fluxes measured with eddy covariance.

We leave the final decision to the Editor but we think that, like in these and other similar articles, our manuscript focuses on understanding the advantages and caveats of the method and its potential to provide robust estimates of parameters that are meaningful for the understanding and modeling of interactions between vegetation and atmosphere.

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Rogers, A., Medlyn, B.E., Dukes, J.S., Bonan, G., von Caemmerer, S., Dietze, M.C., Kattge, J., Leakey, A.D.B., Mercado, L.M., Niinemets, Ü., Prentice, I.C., Serbin, S.P., Sitch, S., Way, D.A., & Zaehle, S. (2017). A roadmap for improving the representation of photosynthesis in Earth system models. New Phytologist, 213, 22-42 Pacheco-Labrador, J., El-Madany, T.S., van der Tol, C., Martín, M.P., Gonzalez-Cascon, R., Perez-Priego, O., Guan, J., Moreno, G., Carrara, A., Reichstein, M., & Migliavacca, M. (2020). senSCOPE: Modeling radiative transfer and biochemical processes in mixed canopies combining green and senescent leaves with SCOPE. bioRxiv, 2020.2002.2005.935064 Dutta, D., Schimel, D.S., Sun, Y., van der Tol, C., & Frankenberg, C. (2019). Optimal inverse estimation of ecosystem parameters from

observations of carbon and energy fluxes. Biogeosciences, 16, 77-103 Papale, D., Reichstein, M., Aubinet, M., Canfora, E., Bernhofer, C., Kutsch, W., Longdoz, B., Rambal, S., Valentini, R., Vesala, T., & Yakir, D. (2006). Towards a standardized processing of Net Ecosystem Exchange measured with eddy covariance technique: algorithms and uncertainty estimation. Biogeosciences, 3, 571-583 Wutzler, T., Lucas-Moffat, A., Migliavacca, M., Knauer, J., Sickel, K., Šigut, L., Menzer, O., & Reichstein, M. (2018). Basic and extensible post-processing of eddy covariance flux data with REddyProc. Biogeosciences, 15, 5015-5030 Kang, M., Kim, J., Malla Thakuri, B., Chun, J., & Cho, C. (2018). New gap-filling and partitioning technique for H2O eddy fluxes measured over forests. Biogeosciences, 15, 631-647

Referee #1 comment: Based on the strengths of this paper, I would suggest a path forward might be to remove the analysis in Figs. 5 and 7. To me, these figures raise more questions than answers. The attempt by the authors to say something more ecological about how vegetation traits co-vary takes away from the paper. Focusing on the key results, Fig. 3, 4, and 6 (Figs. 1 and 2 are also nice) seems like it would help to distill the information content. A reduction in the amount of parameters the authors are trying to predict might also help (moving the rest to the supplementary material). Focusing on a few key vegetation parameters – as opposed to trying to model everything, all at once – followed by a concrete discussion on where and why model-data mismatch or over/underprediction happens might also be a path forward.

Authors' response: We appreciate the thoughts of the Referee #1 how to better present and align the results. Still, we feel that these are key results to the manuscript and want explain in more details why they should stay within the main text. Figures 5 and 7 do not aim to attach any ecological meaning to the retrievals, but to indirectly evaluate their feasibility, since direct evaluation is not possible. Notice that overarching goal of this manuscript is allowing the remote estimation of functional parameters such as the evaluated in these figures; these parameters are not traditionally estimated from satellite imagery since they have little effect on vegetation reflectance. This will be

better explained in the manuscript.

Here we detail part of this rationale: Remote sensing has traditionally provided estimates of biophysical parameters such as LAI or pigment's content which have a relatively strong influence on the signals perceived from remote sensors (e.g., reflected radiances). The interest on the estimation of parameters describing plant functions which have little effect on remote sensing signals, such as Vcmax or the Ball-Berry slope m, is lately increasing. This is the main contribution and innovation of our manuscript; which proposes a method combining radiative transfer, energy balance and photosynthesis models with remote sensing data and eddy covariance fluxes to constrain these functional parameters describing vegetation function. Nonetheless, these biophysical parameters have to be also retrieved since they strongly control the absorption of light and therefore photosynthesis and energy balance.

Figures 4, 5 and 7 evaluate the estimates of biophysical and functional parameters using different approaches, which are selected according to the field data available. In order to understand the quality of the estimates of functional parameters, we need first to understand the capability of the approach to estimate the biophysical parameters, since these have a strong control on the absorption of radiation in the canopy. However, the direct evaluation of all these parameters is not always possible. One of the challenges that this and other research works face in Mediterranean tree-grass ecosystems (and others) is the evaluation of remote sensing based estimates. This ecosystem features high species richness and spatial variability in the grassland, and a structural heterogeneity imposed by the coexistence of scattered tress and the grassland itself. This spatial variability must be accounted for during the estimation of ecosystem-scale vegetation parameters; thus measurements must be taken at different locations and vegetation types, and then integrated according to the representativeness of the different samples in the ecosystem. Therefore, ecosystem-scaled parameters always carry uncertainties arising during their integration. Despite these uncertainties, sufficient sampling effort (e.g., number, distribution and size of samples) allows obtaining robust scaled values, representative of the study area averages. Years of sampling experience have shown the researchers working in this site the needs, in terms of sampling strategies, to characterize some vegetation biophysical parameters such as leaf biochemical contents or leaf area index (e.g., see Mendiguren et al., 2015 or Melendo-Vega et al., 2017). Therefore, we have relied on these ground-based estimates, scaled at ecosystem level, to evaluate biophysical vegetation parameters estimated with the approach proposed in this manuscript.

Specifically, the assessment of the biophysical parameters analysis is presented in Figure 4 and Figure 5a-b. When available, ecosystem-scaled measurements of the biophysical parameters are directly compared with the estimates. However, in the case of chlorophyll no field measurements in the grassland are available for several of the field campaigns; for this reason, this parameter is also evaluated indirectly. We used the relationship between chlorophyll content (Cab) and nitrogen (N) of the data available in these and other unrelated campaigns (see Melendo-Vega et al., 2017) to estimate grass Cab when missing, and then we scaled using trees Cab estimated in the field with a SPAD meter. On the contrary, the measurement of Cab in trees leaves using a SPAD meter took place in all the campaigns. It relies on solid and extensive datasets as well as on laboratory analyses that coauthors of this manuscript specifically refined to improve the photometric determination of pigments in the Holm oak leaves (Gonzalez-Cascon et al., 2017). Since most of the field estimates rely on the grass Cab-N relationship, we do not compare estimated and field Cab directly, but rather look at their relationship with N at ecosystem scale. This will be also clarified in the text.

After assessing biophysical parameters, we assess the retrieval of functional parameters of vegetation in Figure 5c-h and of a functional ecosystem relationship in Figure 7. However, the aim of Figure 5 and 7 is evaluating the plausibility of the functional parameter estimates; not establishing ecological conclusions about how vegetation traits co-vary. Functional parameters such as Vcmax or the Ball-Berry model slope m cannot be determined from bulk samples of vegetation; but must be measured leaf by leaf

using gas exchange chambers for long periods of time (e.g. 40 min). Considering that the objective of such measurements would be providing values of the functional parameters representative of the eddy covariance footprint, the high spatial variability and species richness (quite evenly distributed in the grassland) would make necessary a huge number of measurements which could not be acquired due to time and technical limitations. Also, since these measurements would be species-based, the up-scaling process would be prone to high uncertainty. This problem is not only related to the study site, but to extensive areas comprehending numerous species or to diverse and rich ecosystems. For these reasons, we propose alternative methods (pattern-oriented evaluation approach) to assess estimates of functional parameters of vegetation. This approach relies on the capability of the model to reproduce expected patterns, either from the literature or from observations, with no prior knowledge about them. In order to evaluate Vcmax we rely on its relationship with nitrogen (N) assuming that the larger the presence of N in the leaf, the larger is the chance that this is placed in the Rubisco enzyme, therefore enhancing Vcmax. The specific relationship between both variables is species-dependent and changes according to different plant strategies. However, the existence of a positive relationship between N and Vcmax is known and has been shown for different vegetation types in the literature (e.g., Quebbeman and Ramirez, 2016; Walker et al., 2014; Feng and Dietze, 2013 or Kattge et al., 2011). Therefore, we exploit this knowledge to assess whether our estimates are plausible and reproduce expected relationships with other parameters or they are just loose equifinality or ill-posed solutions of the inversion. We are aware that there might be sources of uncertainty, but the fact that Vcmax scales with N according to what expect from a large body of literature shows that the retrieval of Vcmax is realistic. In the case of the Ball-Berry model slope m, we use the 13C discrimination as discussed and suggested by Seibt et al., 2008. Under certain conditions 13C discrimination and water use efficiency are inversely related. We are also aware of the limitations of this approach (e.g. Seibt et al., 2008; Medlyn et al., 2017); which we discussed in the manuscript. We took measures to minimize the effect of these additional factors, for example, we evaluated also underlying water use efficiency to minimize the effect of VPD, and considered only estimates close to the peak of the season, since 13C discrimination represents an integrative process whereas the m and uWUE vary in time or are rather instantaneous. Also in this case, the fact that the relationship found between the estimated m parameter and the independent measure of 13C is coherent with literature give us confidence on the robustness of the methodology.

In the case of Figure 7, we assess the retrievals of the soil resistance to evaporation from the pore space (rss); this resistance is known to increase as soil dries Mohamed et al., (1997), and is affected by other factors such as physical properties of soil, which make this relationship site-specific (e.g., Lawrence et al., 2011;Swenson and Lawrence 2014). Therefore, we use this knowledge to assess if the retrievals of rss are plausible. We acknowledge that this parameter is also potentially loose in the inversion, since its effect on the model outputs can saturate above some threshold (for Pacheco-Labrador et al., 2019); and in fact, the relationships between rss and soil moisture content presented in Figure 7 are poorly fit due to the presence of extreme values. Aware of this fact, we have implemented and tested a third step in the inversion where the relationship presented in Figure 7 is used as a prior to repeat the inversion carried out in Step #2. This leads to a much closer fit of the relationship between rss and soil moisture and more importantly, has little effect on the retrieval of Vcmax and m. This process was suggested in the discussion of the manuscript, but not carried out. We will include these results in the new version of the manuscript to show that a more robust relationship can be obtained.

The evaluation of our estimates is as thorough as possible given the constraints imposed by the ecosystem under study. We have carried out an evaluation effort not typically present in this sort of analyses, in order to assess the feasibility of our method to provide plausible estimates; however, this process requires relying on some assumptions; which we acknowledge in the manuscript. Notice that many of the works dealing with the inversion of SCOPE evaluate Vcmax against NDVI, or simply compare

predicted and observed fluxes. Our work proposes the use of new evaluation methods that could contribute to other studies in the future. This is also relevant since functional parameters such as Vcmax and m cannot be measured from destructive sampling of vegetation which can allow integrating the variability of the vegetation without specifically accounting for it; therefore technical and resource limitations to obtain validation data of these parameters is prone to appear in many other ecosystems featuring high species richness and variability; or when remote sensors feature low or mid spatial resolutions and therefore the estimates represent large areas.

We will more strongly justify this rationale in the manuscript. We will also better detail which are the assumptions behind the evaluations we carried out, especially in the case of the functional parameters, and clarify in the discussion what could be the consequences of their violation. We will strength the discussion of the relevance of indirect evaluations when direct one are not feasible; this is necessary since functional parameters are more and more often estimated from remote sensing, but not direct assessment is typically available at this scales.

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Referee #1 comment: Currently - while there is a lot of good content in the discussion - it should relate explicitly back to the key results and answer bigger questions about how such analytical techniques could be used to map vegetation traits going forward. I realize this a fairly vague suggestion, but a substantial reframing of the story will also help this paper reach a broader audience.

Authors' response: At the beginning of the discussion section we stated that this approach could be used in eddy covariance networks to characterize functional properties at large scale; which could lately contribute to improve our estimates and predictions of global carbon and water fluxes. We will strengthen this part of the discussion better showing the potential of the method at global scale over networks of eddy covariance stations, partly following the rationale shown in the first comment presented to Referee #1. We will discuss about the possibility of applying this method to a sufficiently large number of ecosystems and the later possibility of up-scaling these estimates globally sensu Moreno et al., (2018) or Walker et al., (2017).

References:

Moreno-Martínez, Á., Camps-Valls, G., Kattge, J., Robinson, N., Reichstein, M., van Bodegom, P., Kramer, K., Cornelissen, J.H.C., Reich, P., Bahn, M., Niinemets, Ü., Peñuelas, J., Craine, J.M., Cerabolini, B.E.L., Minden, V., Laughlin, D.C., Sack, L., Allred, B., Baraloto, C., Byun, C., Soudzilovskaia, N.A., & Running, S.W. (2018). A methodology to derive global maps of leaf traits using remote sensing and climate data. Remote Sensing of Environment, 218, 69-88 Walker, A.P., Beckerman, A.P., Gu, L., Kattge, J., Cernusak Lucas, A., Domingues, T.F., Scales Joanna, C., Wohlfahrt, G., Wullschleger, S.D., & Woodward, F.I. (2014). The relationship of leaf photosynthetic traits – Vcmax and Jmax – to leaf nitrogen, leaf phosphorus, and specific leaf area: a metaâĂŘanalysis and modeling study. Ecology and Evolution, 4, 3218-3235.

Minor comments are as follows:

Referee #1 comment: Abstract (and elsewhere): The authors use the word "prove" to describe their findings. This language is too strong, consider "suggest." The first sentence of the introduction, I would perhaps not mention just climate change as an application for this work, as climate change is never again discussed and by using it as the only potential application, it implies that this might feature into the work more prominently.

Authors' response: We will replace prove by suggest. "Climate change" will be replaced by "environmental changes"

Referee #1 comment: The introduction is well written, the authors touch on pretty much every aspect of the paper. If one had time to read all of these papers from a wide range of disciplines, it would certainly make the methods and results easier to interpret. In order to reach a broader audience, I'd suggest a little more 'hand-holding' though, particularly with regard to what exactly some of the plant functional traits are and why they are important.

Authors' response: We will stress the need of obtaining estimates of plant functional traits from remote sensing in the introduction and why they are important for a broader audience. We will further develop the explanation of how the use of fixed values of these parameters in terrestrial biosphere models induce uncertainties in the prediction of global carbon and water fluxes; and we will detail what exactly these functional parameters represent in the photosynthetic process and why they are important.

Referee #1 comment: One main point made clear in the introduction is that an attempt to jointly retrieve functional traits using hyperspectral imagery combined with EC data is lacking. But it's not clear why we need this? How are the other methods failing that require this new approach?

Authors' response: We will extend this point in the introduction and in the discussion. Alternative methods exist, relying for example on the inversion of terrestrial biosphere models as presented in the introduction. These often make use of remote sensing products describing the spatial and temporal distributions of biophysical parameters

such as LAI. Other works have exploited optical signals such as sun induced fluorescence or optical and thermal imagery. However, photosynthetic plant traits such as Vcmax or Ball-Berry m have little influence on optical signals; and might be spuriously related with these (e.g., for Vcmax, via chlorophyll). However, the combination of remote sensing and eddy covariance data: 1) brings the best of both worlds: high temporal frequency of fluxes and spatially resolved information of remote sensors and 2) multiple-constraint approaches combining remote sensing and eddy covariance information allowing for a simultaneous estimation of biophysical and functional traits, regularizing the inverse problem.

Line 111: The authors note that only one of the examples from the previous paragraph validates retrievals against actual measurements from gas-exchange measurements but this paper doesn't do that. They make assumptions about other traits or use data from existing literature in combinations that is difficult to follow. Authors' response: The aim of this statement was showing that field data for the evaluation of these estimates are not usually available, and that in some ecosystem or at certain scales their acquisition could just be not possible. Thus new methods to evaluate such retrievals, like the ones used in this manuscript are needed. We will rephrase this statement to make this idea neater.

Lines 124-130: The attempt to relate this work to future satellite missions is appreciated, but the amount of detail necessary to introduce readers to how the emulation works is lacking.

Authors' response: We think that a detailed description of the functioning of a remote sensing mission emulator is out of the scope of this manuscript, and it is addressed to a publication fully describing this tool. However, we will briefly describe what an emulator is and what it does to generate synthetic imagery

Line 143: Describe CT. . .I'm guessing Control Treatment

Authors' response: Thanks for noticing this, the description of this acronym will be added.

Line 157: ‘mayor’ to ‘major’. . .there are quite a few grammatical mistakes throughout, I won’t comment on them, but please address these. Given the large quantity of coauthors, one would think these could be addressed.

Authors’ response: This correction will be applied. The updated version of the manuscript will be carefully reviewed by a native speaker.

Table 1: This table is appreciated, but for the many other variables used during this entire study it would help to add them as additional columns.

Authors’ response: We will add an additional table with the description of all the variables.

Line 213: Why aren’t data from these additional campaigns included?

Authors’ response: Field campaigns including vegetation destructive sampling are carried out regularly in the study site. However, not all these campaigns are carried out simultaneously to the acquisition of hyperspectral airborne imagery. Due to logistic constrains some variables were not measured in all the airborne campaigns. We have gap-filled variables missing in some of the airborne campaigns exploiting annual time series in the case of the trees, which are much less dynamic than the grassland, or the relationships between variables measured at the site in some of the airborne campaigns used in the manuscript as well as others. We will improve the description of these processes in the methods section and in the supplementary material produced to better describe this gap filling and the scaling of field measurements.

Line 210-250: There are many assumptions made regarding the biophysical variables used. For example, deriving Vcmax from Nmass,green and a relationship from an existing paper. While there isn’t much of an alternative, it should be noted that many of the biophysical parameters are very much inferred.

Authors’ response: As previously discussed, the generation of values representative

of the ecosystem requires an integration process to scale spatial samples from trees and grasses. This exercise is compulsory in an ecosystem with the structure and species richness as the one under study; this limitation was already acknowledged in the discussion section. However, we will state more clearly the existence of this scaling process and better described it in the new version of the manuscript.

Concerning the connection Vcmax – N, as we will also clarify in connection with a previous comment, that we use this relationship as an indirect evaluation of our estimates and that the use of literature data is just a reference to compare patterns. We will better justify and describe the aim and limitations of the pattern-oriented evaluation of our estimates in the manuscript.

Line 269: To assume that carotenoid concentration will covary with Chl concentration (derived from a SPAD meter) is one example of gross oversimplification.

Authors’ response: We are aware that the relationship between chlorophyll and carotenoids (Car) content is more complex. This choice is a compromise between equifinality of the inversion and accuracy of the prediction. We also included random noise in this relationship to increase variability of the Cab / Car ratio. We tried to use a “generalizable” relationship according to the ratio found by Sims and Gamon 2002 in several species where pigments were determined by leaf extractions and a spectrophotometer. The ratio reported by Sims and Gamon 2002 is similar to values determined from vegetation samples and laboratory analyses in our study site; however, these values were not used to prove that a more general relationship could be used instead of a local one; and that the method did not necessarily depend on this site-specific information. Nonetheless, specificities of different ecosystems can require adapting this assumption. Notice that Sims and Gamon 2002 determined pigments concentrations using a spectrophotometer and pigment e, not from a SPAD meter. The ratio reported by Sims and Gamon 2002 was only used to train the neural network predicting the green fraction of LAI from averaged leaf parameters, so that this variable was not totally unconstrained during inversion. Estimated Cab and Car do not stick to the relationship during the training of the Neural Network, which proves that the relationship was not forced into the solution. This is described in the manuscript presenting senSCOPE model; however, in order to clarify this and support our choice, this fact and the comparison with the Cab / Car relationship found in our site will be included in the discussion.

References:

Sims, D.A., & Gamon, J.A. (2002). Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. Remote Sensing of Environment, 81, 337-354 Pacheco-Labrador, J., El-Madany, T.S., van der Tol, C., Martín, M.P., Gonzalez-Cascon, R., Perez-Priego, O., Guan, J., Moreno, G., Carrara, A., Reichstein, M., & Migliavacca, M. (2020). senSCOPE: Modeling radiative transfer and biochemical processes in mixed canopies combining green and senescent leaves with SCOPE. bioRxiv, 2020.2002.2005.935064

Line 299: 'close to solar noon'. Are the actual flight times used to compare to the EC data? Solar noon is much less relevant here as are the incident irradiance conditions. Diffuse/direct fraction, time of year, solar zenith angle. It's unclear how these are considered.

Authors' response: For the Step#1 of the inversion, data are matched to the time of the overpass. Illumination conditions are considered for each individual overpass since solar angles are inputs of the radiative transfer model. Diffuse and direct irradiances are internally estimated by senSCOPE from standard atmospheric transfer functions and scaled according to observed long and short wave down-welling irradiances measured by the eddy covariance sensors. In order to clarify this, we will improve this description in the manuscript.

Figure 2: This is a useful figure, the axes need labels.

Authors' response: Axes labels will be added

Figure 3: The x axes are displayed as a time series, at equally spaced intervals that make this difficult to interpret. Consider removing the vertical lines and the x ticks, and simply note the date of acquisition horizontally in each shaded or non-shaded bin.

Authors' response: X-ticks will be removed and dates will be centered to the period of each campaign. However, shaded areas will be left to separate the different campaigns. Notice that not all the campaigns were carried out when three eddy covariance towers operated at the site. Before April 2014 only the control tower was present.

Figure 4: Many of these fits violate the assumptions of linear regression, in which case I don't think it's useful to include a line of best fit, or the statistics. Also the figure legend has subplots labeled wrong.

Authors' response: The references to the subplots in the caption will be corrected. Regarding the assumptions of the linear regression, we carried out Shapiro-Wilk and Levene's tests on the residuals of all the linear models adjusted in Figure 4 as well as in Figure 5e-f. We will only plot the regression lines when the hypothesis of normality and homoscedasticity of the residuals could not be rejected for a significance level of 0.05. This will be clarified in the manuscript as "Shapiro-Wilk (Shapiro and Wilk, 1965) and Levene's (Levene and Olkin, 1960) tests assessed the normality and homoscedasticity of the model residuals in all the cases with a 95 % of confidence, respectively. Linear regression models are shown only when these assumptions could not be rejected." Consequently the models and statistics will be preserved in the figures when meet statistical assumptions are met.

References:

Shapiro, S.S., & Wilk, M.B. (1965). An Analysis of Variance Test for Normality (Complete Samples). Biometrika, 52, 591-611 Levene, H., & Olkin, I. (1960). Robust tests for equality of variances.

Figure 5 and Fig 7: I feel that these take away from the main message the authors are trying to communicate. How are these figures adding to the main results? Am I missing something? Another confusing part of the analysis is that it appears as if the authors are predicting ecosystem traits, which are a combination of both grass and tree

Authors' response: As we explained in a previous comment, these figures are relevant for the analysis of our results, and for the assessment of parameters with a more functional nature with little effect on spectroradiometric signals captured by remote sensors. We will better stress these ideas in the new version of the manuscript.

Referee #1 comment: Generally, there is a lot of good information in the discussion. However, much of it reads as 'intro' material and it does not relate directly back to the results. While a lot of the points regarding uncertainty are important, I do not feel as though the discussion drives home the main results, or how such an analysis could be used in the future. The authors have a deep understanding about many of the uncertainties associated with their approach, and that is much appreciated. It is of my (potentially naïve) opinion, that their discussion is not useful for informing future research that is conducted outside of their own particular research group. I would advise the authors to pay close attention to how this work is perceived by individuals outside of their niche team. After all, this will not only help the authors consider the broader importance of their work, but it will help the rest of the research community.

Authors' response: Thanks for the comments and suggestions. We discussed many of them in the responses above and we hope we have clarified the aim and objectives of the manuscript. We will extend the discussion, especially the first part to stress the potential of this method and the need to test it in more and different ecosystems. It should be noted that we demonstrated that the method is applicable in 3 different eddy covariance systems and with multiple imagery. We therefore think the method can be generally used, and the fact that it has been tested in a challenging ecosystem suggests that it could better perform in ecosystems where model assumptions are better met. The next steps will be an application on multiple sites with multiple hyperspectral imageries as soon as they will be available from recent or forthcoming space mission

such as EnMAP, PRISMA, SBG, and/or DESIS, among others.

Regarding the part of the discussion on the uncertainties, we will try to streamline this section to meet the comment of Referee #1, but we also think that an open discussion on the uncertainties is very useful for the community. Some of the uncertainties discussed are specific of the ecosystem under study but not exclusive and a can affect also grasslands, or other ecosystems structurally heterogeneous. For example, it is well known that unidimensional homogeneous radiative transfer models do not accurately represent canopies with strong geometrical scattering components due to the presence of occluding volumes. It is also known that the absorption coefficients and the refractive index used by leaf radiative transfer models are effective averages determined from different species. Thus, the properties of some types of vegetation might not be always accurately represented. Our manuscript does not cover a large and diverse range of ecosystems, but we deal with problems that, with some differences, can be found in other remote sensing studies and sites. We have tried to reinforce this idea in the discussion, and reinforce the need of thorough evaluation of these estimates. Notice, that the aim of this manuscript and the main value is not a set of estimated parameters, but the method its robustness, and the potential of the alternative methods for evaluation of estimates, which is what we aim to discuss. In the discussion will emphasize the general applicability of this method to other ecosystems, and that results for those are likely to be better as many of the complexities from the analyzed ecosystem might not occur.

Interactive comment on Biogeosciences Discuss., https://doi.org/10.5194/bg-2019-501, 2020.