Interactive comment on “A Deep-Learning Hybrid-Predictive-Modeling Approach for Estimating Evapotranspiration and Ecosystem Respiration” by Jiancong Chen et al.

Jiancong Chen et al.

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We appreciate the reviewer’s efforts in reading our manuscript and providing useful comments and recommendations. In this document, we provide answers to reviewer’s questions and explain how we have modified and improved our manuscript.

Reviewer general comment: the topic is very interesting, but the manuscript needs strong improvements and clarifications. Main concerns are on i) Reco, which is included as second variable in the study, while the net ecosystem exchange (NEE) can be more appropriate because it is the actual key term of ecosystem carbon exchanges and it is also directly estimated by eddy covariance based towers (see comment 1), ii) HPM seems interesting but key elements of the model calibration are not provided (e.g., time and spatial scales, parameters), iii) innovative and relevant findings need to be clarified, showed and highlighted.

Response: We made a concerted effort to incorporate the reviewer’s suggestions into the revised version of the manuscript. With regard to replacing R_{ECO} by NEE in our study (reviewer’s concern #1), we agree that net ecosystem exchange (NEE) is a key variable considered worldwide, and eddy covariance towers directly measure NEE. However, R_{ECO} is also a very important parameter recognized by researchers (Le Quéré et al., 2009). In this study, we decided to concentrate on estimating R_{ECO}, and more thorough response on the reasons can be found in Q1. With regard to describing the key elements of the model calibration (reviewer’s concern (ii)), we clarified the configuration of the deep learning module we used in addition to the information that was provided in table 1 in the supplementary material. We have also demonstrated how we selected parameters used for HPM. Related responses can be found at Q6, Q7, Q8, Q9 and Q15. Finally, with regard to innovative and relevant findings needing clarification (reviewer’s concern (iii)), we expanded the discussion on providing more process-based interpretation of watershed dynamics and highlighted the relevant innovative results. With the guidance of the reviewer, we think the quality of the manuscript has been improved.

Specific Comments:

Q1: Row 34: why Reco? I can’t understand why the second variable considered in the study was the ecosystem respiration. It is not observed directly by FLUXNET network, but can be estimated indirectly from net ecosystem exchange (NEE) measurements made by eddy covariance towers during the night. The main term is NEE, why are you not considering it directly? NEE is the key variable considered world wide. Please, include NEE.

Response: We agree that NEE is one of the key variables considered worldwide, and is directly measured by eddy covariance flux towers. However, R_{ECO} is also very important as it represents the total ecosystem carbon emissions from land to the atmosphere, and is very sensitive to climate change (Le Quéré et al., 2009), and thus quantifying and estimating R_{ECO} is needed. This study is not the only one that concentrates on R_{ECO}. For example, Ai et al. (2018) developed a semi-empirical, physiologically based, remote sensing model to estimate R_{ECO} using MODIS data; Solomon et al. (2013) estimated daily respiration rates using maximum likelihood fits of a free-water metabolism to quantify respiration dynamics in six lakes.

An additional reason to consider R_{ECO} and not NEE in this study is that one of the major objectives of this study is to provide an estimate of ET and R_{ECO} at watersheds where flux towers are not available. The daytime and nighttime partitioning methods (van Gorsel et al., 2009; Reichstein et al., 2005) requires sub-daily scale NEE data to compute daily scale R_{ECO}. However at these sparsely monitored watersheds, sub-daily scale NEE data is not available and could not be predicted with weather reanalysis and remote sensing data that are at coarser temporal scales. Thus developing methods that estimate daily scale R_{ECO} is still needed and will help advance our understanding of ecosystem dynamics and carbon cycling at the inadequately monitored watersheds.

While we decided to not include NEE in our manuscript, we have tested the HPM approach to estimate NEE at CA-OAS and US-NR1. We observed a R^2 larger than 0.8 between the measurements and predictions (Figure 1). With this result, we believe HPM can be an appropriate approach for estimating daily NEE with right choices of variables. However, we believe replacing R_{ECO} with NEE will change the scope of this study, and thus we do not plan to include NEE at the current stage.

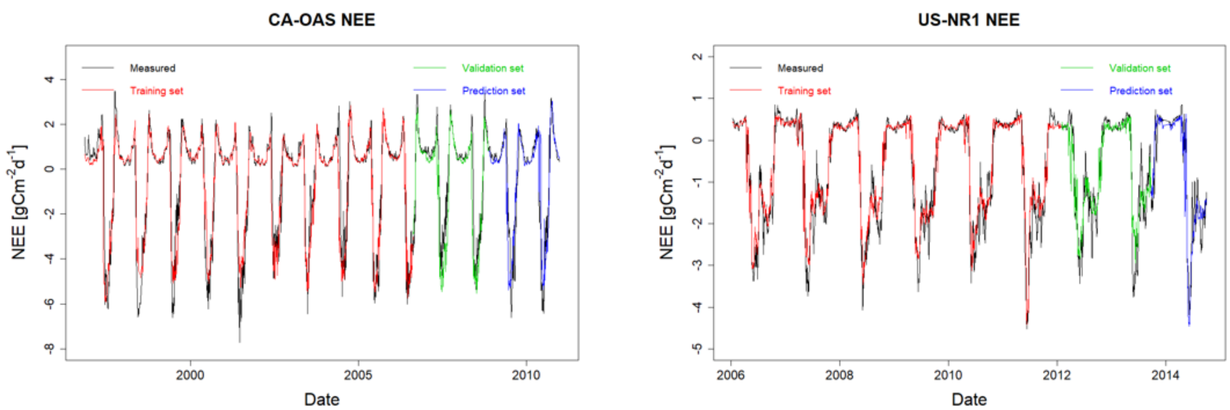

Figure 1. HPM estimate of NEE at CA-OAS and US-NR1. R^2 between estimation and measurements are 0.87, 0.83 and 0.81 at CA-OAS; 0.94, 0.88 and 0.90 at US-NR1 for the training set, validation set and prediction set, respectively. Model inputs include air temperature, soil temperature, sn, precipitation and radiation.

Q2: Rows 101-105: please, include also SENTINEL 2, the new satellite for NDVI observations with better time and spatial resolutions, available from 2015.

Response: We considered using SENTINEL 2 data but our evaluation has shown that LANDSAT was more adapted for the period of time we are concentrating on in this study. From our knowledge, the Sentinel 2 surface reflectance data has a 10m resolution for the red and near infrared band with an averaged revisit time of 5 days since March 2017 (Main-Knorn et al., 2017). In Use Case I, II and III scenarios, our HPM estimates covered the period up to 2016 as we were using FLUXNET2015 datasets. For Use Case IV, we have checked the data availability of Sentinel 2 surface reflectance data over the East River Watershed. A total of 106 Sentinel 2 dataset is available till 2018, however only 13 of them have a cloud cover less than 10% during the sampling period. We tested with the additional Sentinel-2 NDVI data, but we did not observe notable changes in ET and R_{ECO} estimations compared to previous ones with only Landsat data. Meanwhile, we also checked out other satellite products, including the Planet-Lab (McCabe et al., 2017); the harmonized Landsat-Sentinel product (Claverie et al., 2018) as well as other satellite data fusion products (Shao et al., 2019). However, they still do not increase the temporal resolution prior to 2017. Based on the above assessment we decided to use Landsat data only. We agree that future work could expand HPM based ET and R_{ECO} estimations using various combination of satellite products.

Q3: Rows 162-165: mean annual precipitation of the watershed is 1200 mm/y. Hence, how can be representative these stations?

Response: We agree the manuscript did not clearly describe the reason of using FLUXNET site with very different meteorological forcing from the East River watershed. We have improved the manuscript to make it clearer. The FLUXNET sites considered in this study is mainly used in Use Case I and Use Case II. We wanted to explore the capability of HPM under different climate conditions. For example, we selected US-Ton to test whether HPM is able to provide reasonable estimate of ET and R_{ECO} under Mediterrean climate (Csa) whereas at US-NR1 for subarctic environment (Dfc). We did not intend to use HPM developed at US-Ton and other FLUXNET sites to be representative stations for the East River Watershed. We have further clarified the major objective of and the various Use Cases in the revised manuscript (L157-L167).

Q4: Rows 194-196: basin areas? slope?

Response: We were describing the general characteristic of the East River Watershed, which include both basin areas and montane areas.

Q5: Rows 207: why 16 locations? And not 10 or 20? Please, any sensitivity analysis? Any uncertainty estimate?

Response: We focused on four main vegetation types within the East River Watershed, including deciduous forests, evergreen forests, riparian shrublands and meadow grasslands. We defined 16 locations to have some replicates to evaluate the spatial variability. Given the 30-m spatial resolution of Landsat, we tried to select locations at the center of vegetation patched and covered or at least strongly dominated by one vegetation type. We evaluated it manually and decided that 16 locations (4 for each vegetation type) was a pragmatic choice.

Equation (1): this equation is the NDVI definition, you don't need to include in the text, it is well known.

Response: We have made the necessary change in the revised manuscript.

Q6: Row 264: please, include the time resolution of the model, its space resolution, and the size of the domain.

Response: The time resolution of HPM is daily. The spatial resolution depends on different Use Cases and spatial resolution of data inputs. We have made these changes in the revised manuscript, and also further clarified in each of the Use Cases in section 4 (L337-L338).

Q7: Row 291: how is estimated g?

Response: g is the hyperbolic tangent activation function. It is used to determine candidate cell states and update the hidden states (Hochreiter and Schmidhuber, 1997; Kratzert et al., 2019). g is not estimated.

Q8: Row 300: how are estimated Wf, Uf, and bf?

Response: We clarified this. W_f, U_f and b_f are representing learnable parameters for the forget gates. There are other W, U and b for the internal states and hidden states. We used the Adam algorithm (Kingma and Ba, 2014) with a mean absolute error loss function built in Keras (Chollet, 2015).

Q9: Row 318: how many parameters in total?

Response: We thank the reviewer's comment. There are 11600 and 7600 parameters for the first and second LSTM layers; 208 and 9 for the first and second dense layers and no parameters for the dropout layers. These information is available in Table 1 in the supplementary material.

Q10: Equations (10) and (11): you don't need to include these equations. These are statistical index very well known.

Response: We have made the necessary change in the revised manuscript.

Q11: Row 362-363: I looked at section 4.1 and it doesn't estimate any temporal dependency. It just tested the model at a not very clear time scale.

Response: We used the word "long term temporal dependency" in a deep learning (or statistical) context where there are significant temporal correlation and long time lags in time series. LSTM and recurrent neural networks are one of the very efficient and effective deep learning models that are capable to capture such long term dependencies. In the revised manuscript, we have been more careful in terms of the wording that overlap among different fields.

Q12: Row 374: again, what is the time scale?

Response: We thank the reviewer's comment. Our ET and R_{ECO} estimations are at daily scale. We have better clarified the time scale in the manuscript.

Q13: Row 390: Is it always at monthly time scale? please, again, define the time scale.

Response: We thank the reviewer's comment. Our estimate is at daily scale, which are used to calculate monthly means. In figure 5 and following figures, we presented the results of both daily and monthly mean between HPM and measurements in order to check model performance. We also aggregated our daily estimates to 8-day mean at the East River sites, which enabled us to compare our results to Mu et al. (2013) as shown in Figure S1

Q14: Row 396-307, '…which also indicates that soil moisture data is necessary to increase Reco prediction accuracy in this ecoregion…". how can you support this statement?

Response: We thank the reviewer's comment. The decreasing prediction accuracy occurred at sites limited by water and moisture conditions (e.g., US-Ton and US-Var) where other studies investigated how ecosystem respond to subsurface water availability (Von Buttlar et al., 2018; Song et al., 2014). At sites with seasonally dry periods (e.g., US-NR1), other studies have also identified the occurrences of fore-summer drought and water limiting condition (Sloat et al., 2015; Wainwright et al., 2020). Due to practical reasons, current HPM models did not include soil moisture as an input to capture these seasonally dry periods. Thus we believe modified HPM models with soil moisture as inputs can increase prediction accuracy in these ecoregions when soil moisture data becomes more available in space and time.

Q15: Row 415: Are the model parameters changing for each site? What are the parameter values?

Response: We thank the reviewer's comment. Deep learning parameters for US-Ton, CA-Oas and US-Wkg are different as they are three different developed HPM models used to represent different ecoregions. As mentioned in the response to Q9, there are many deep learning parameters and it is not feasible to directly present the values of these learnable parameters here. But all of these parameter values are available in the data package we submitted to ESS-DIVE and can be downloaded at https://data.ess-dive.lbl.gov/view/doi:10.15485/1633810 named 'LSTM_model.zip'.

Q16: Row 419-420: I don't agree, Reco predictions are not good in US Whs and US Var

Response: We thank the reviewer's comment. HPM achieved a daily scale adjusted R^2 of 0.70 and 0.78 and MAE at 0.67 and 0.22 at US-Whs and US-Var respectively, in Use Case II scenario. We agree that the statistical measure is not as satisfactory as R^2 over 0.9. In the revised manuscript, we have made the necessary changes correspondingly (L433-L435).

Q17: Row 518-519, "This result indicates small-scale meteorological forcing and vegetation heterogeneity are the major controls of differences in ET and Reco at the East River Watershed": please, highlight and clarify what is the new finding. We know already that meteorological forcing (which is the model input), and vegetation heterogeneity (model parameter) are the controlling factors of the model.

Response: We thank the reviewer for the comment. We have expanded our discussion on how ET and R_{ECO} dynamics vary at different years (e.g., years with earlier snowmelt versus later snowmelt). We have emphasized how vegetation types contribute to ET and R_{ECO} spatiotemporal heterogeneities. We also discussed the limitations and practical perspectives of current HPM models in feature selection and how to improve estimation accuracy at seasonally dry periods. In addition, we clarified the role of meteorological forcing attributes and vegetation types in ET and R_{ECO} dynamics at the East River Watershed and tested how these input variables contribute to ET and R_{ECO} differences at different years among different sites. These findings have been revised in the result and discussion sections.

Q18: Row 673: please add the journal name of this reference, I can't find it.

Response: We thank the reviewer's comment. The journal name of this reference is '*Journal of Geophysical Research: Biogeosciences*' (L734-L736). We have double checked and made sure the bibliography is correctly and clearly presented.

Reference:

Ai, J., Jia, G., Epstein, H. E., Wang, H., Zhang, A. and Hu, Y.: MODIS-Based Estimates of Global Terrestrial Ecosystem Respiration, J. Geophys. Res. Biogeosciences, 123(2), 326–352, doi:10.1002/2017JG004107, 2018.

Von Buttlar, J., Zscheischler, J., Rammig, A., Sippel, S., Reichstein, M., Knohl, A., Jung, M., Menzer, O., Altaf Arain, M., Buchmann, N., Cescatti, A., Gianelle, D., Kiely, G., Law, B. E., Magliulo, V., Margolis, H., McCaughey, H., Merbold, L., Migliavacca, M., Montagnani, L., Oechel, W., Pavelka, M., Peichl, M., Rambal, S., Raschi, A., Scott, R. L., Vaccari, F. P., Van Gorsel, E., Varlagin, A., Wohlfahrt, G. and Mahecha, M. D.: Impacts of droughts and extreme-temperature events on gross primary production and ecosystem respiration: A systematic assessment across ecosystems and climate zones, Biogeosciences, doi:10.5194/bg-15-1293-2018, 2018.

Chollet, F.: Keras: The Python Deep Learning library, Keras.Io, 2015.

Claverie, M., Ju, J., Masek, J. G., Dungan, J. L., Vermote, E. F., Roger, J. C., Skakun, S. V. and Justice, C.: The Harmonized Landsat and Sentinel-2 surface reflectance data set, Remote Sens. Environ., doi:10.1016/j.rse.2018.09.002, 2018.

van Gorsel, E., Delpierre, N., Leuning, R., Black, A., Munger, J. W., Wofsy, S., Aubinet, M., Feigenwinter, C., Beringer, J., Bonal, D., Chen, B., Chen, J., Clement, R., Davis, K. J., Desai, A. R., Dragoni, D., Etzold, S., Grünwald, T., Gu, L., Heinesch, B., Hutyra, L. R., Jans, W. W. P., Kutsch, W., Law, B. E., Leclerc, M. Y., Mammarella, I., Montagnani, L., Noormets, A., Rebmann, C. and Wharton, S.: Estimating nocturnal ecosystem respiration from the vertical turbulent flux and change in storage of CO 2, Agric. For. Meteorol., 149(11), 1919–1930, doi:10.1016/j.agrformet.2009.06.020, 2009.

Hochreiter, S. and Schmidhuber, J.: Long Short-Term Memory, Neural Comput., doi:10.1162/neco.1997.9.8.1735, 1997.

Kingma, D. P. and Ba, J.: Adam: A Method for Stochastic Optimization, , 1–15 [online] Available from: http://arxiv.org/abs/1412.6980, 2014.

Kratzert, F., Klotz, D., Herrnegger, M., Sampson, A. K., Hochreiter, S. and Nearing, G. S.: Toward Improved Predictions in Ungauged Basins: Exploiting the Power of Machine Learning, Water Resour. Res., doi:10.1029/2019WR026065, 2019.

Main-Knorn, M., Pflug, B., Louis, J., Debaecker, V., Müller-Wilm, U. and Gascon, F.: Sen2Cor for Sentinel-2., 2017.

McCabe, M. F., Aragon, B., Houborg, R. and Mascaro, J.: CubeSats in Hydrology: Ultrahigh-Resolution Insights Into Vegetation Dynamics and Terrestrial Evaporation, Water Resour. Res., 53(12), 10017–10024, doi:10.1002/2017WR022240, 2017.

Mu, Q., Zhao, M. and Running, S. W.: MODIS Global Terrestrial Evapotranspiration (ET) Product (MOD16A2/A3), Algorithm Theor. Basis Doc., 2013.

Le Quéré, C., Raupach, M. R., Canadell, J. G., Marland, G., Bopp, L., Ciais, P., Conway, T. J., Doney, S. C., Feely, R. A., Foster, P., Friedlingstein, P., Gurney, K., Houghton, R. A., House, J. I., Huntingford, C., Levy, P. E., Lomas, M. R., Majkut, J., Metzl, N., Ometto, J. P., Peters, G. P., Prentice, I. C., Randerson, J. T., Running, S. W., Sarmiento, J. L., Schuster, U., Sitch, S., Takahashi, T., Viovy, N., Van Der Werf, G. R. and Woodward, F. I.: Trends in the sources and sinks of carbon dioxide, Nat. Geosci., doi:10.1038/ngeo689, 2009.

Reichstein, M., Falge, E., Baldocchi, D., Papale, D., Aubinet, M., Berbigier, P., Bernhofer, C., Buchmann, N., Gilmanov, T., Granier, A., Grünwald, T., Havránková, 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. Chang. Biol., doi:10.1111/j.1365-2486.2005.001002.x, 2005.

Shao, Z., Cai, J., Fu, P., Hu, L. and Liu, T.: Deep learning-based fusion of Landsat-8 and Sentinel-2 images for a harmonized surface reflectance product, Remote Sens. Environ., doi:10.1016/j.rse.2019.111425, 2019.

Sloat, L. L., Henderson, A. N., Lamanna, C. and Enquist, B. J.: The Effect of the Foresummer Drought on Carbon Exchange in Subalpine Meadows, Ecosystems, 18(3), 533–545, doi:10.1007/s10021-015-9845-1, 2015.

Solomon, C. T., Bruesewitz, D. A., Richardson, D. C., Rose, K. C., Van de Bogert, M. C., Hanson, P. C., Kratz, T. K., Larget, B., Adrian, R., Leroux Babin, B., Chiu, C. Y., Hamilton, D. P., Gaiser, E. E., Hendricks, S., Istvá, V., Laas, A., O'Donnell, D. M., Pace, M. L., Ryder, E., Staehr, P. A., Torgersen, T., Vanni, M. J., Weathers, K. C. and Zhu, G.: Ecosystem respiration: Drivers of daily variability and background respiration in lakes around the globe, Limnol. Oceanogr., doi:10.4319/lo.2013.58.3.0849, 2013.

Song, B., Niu, S., Luo, R., Luo, Y., Chen, J., Yu, G., Olejnik, J., Wohlfahrt, G., Kiely, G., Noormets, A., Montagnani, L., Cescatti, A., Magliulo, V., Law, B. E., Lund, M., Varlagin, A., Raschi, A., Peichl, M., Nilsson, M. B. and Merbold, L.: Divergent apparent temperature sensitivity of terrestrial ecosystem respiration, J. Plant Ecol., doi:10.1093/jpe/rtu014, 2014.

Wainwright, H. M., Steefel, C., Trutner, S. D., Henderson, A. N., Nikolopoulos, E. I., Wilmer, C. F., Chadwick, K. D., Falco, N., Schaettle, K. B., Brown, J. B., Steltzer, H., Williams, K. H., Hubbard, S. and Enquist, B. J.: Satellite-derived foresummer drought sensitivity of plant productivity in Rocky Mountain headwater catchments: spatial heterogeneity and geological-geomorphological control, Environ. Res. Lett., doi:10.1088/1748-9326/ab8fd0, 2020.