Response to Referee #2 (hess-2022-90)

In the revised version of this manuscript, the authors have addressed most of my concerns raised in my first review. Overall, I still believe that the authors need to make a clear distinction between this paper and the BG paper. I have a few suggestions, before this manuscript could be further considered for publication, please accept them as constructive criticism.

Response: Thank you very much for your insightful comments, and we have revised this manuscript based on your concerns.

1, as a reader, I may ask: why can these two papers be just one paper? These two meta-analyses are based on nearly identical sampling of studies. As a way to address this, the authors could try to add a few papers that only models ET;

Response & Actions: We performed these two meta-analyses separately because the mechanisms of the NEE and ET anomalies, and the predictor variables used, can be considerably different. Only one paper (Jung et al., 2011) modeled both ET and Net ecosystem exchange (NEE) was included in both these two meta-analyses, and the overlap between the papers included in the two meta-analyses was very low. The vast majority of papers in this meta-analysis modeled only ET.

Meta-analysis	Papers included
BG (40 NEE papers)	(Berryman et al., 2018; Braybrook et al., 2021; Cho et al., 2021; Cleverly et al., 2020; Cui et al., 2021; Evrendilek, 2013; Fu et al., 2014, 2009; Huemmrich et al., 2019; Ichii et al., 2017; **Jung et al., 2011**; Kato and Tang, 2008; Kondo et al., 2015; Krasnova et al., 2019; Liu et al., 2016, 2018; Lucas-Moffat et al., 2018; Madani et al., 2017; Melesse and Hanley, 2005; Moffat et al., 2010; Mueller et al., 2010; Papale and Valentini, 2003; Park et al., 2018; Reed et al., 2021; Reitz et al., 2021; Ryu et al., 2018; Schubert et al., 2010; Stiegler et al., 2019; Sun et al., 2020, 2019; Teklemariam et al., 2010; Tian et al., 2017; Tramontana et al., 2016; Ueyama et al., 2013; Virkkala et al., 2021; Xiao et al., 2008; Zeng et al., 2020; Zhang et al., 2014; Zhou et al., 2020)
HESS (32 ET papers)	(Bai et al., 2021; Dou and Yang, 2018, 2017; Fang et al., 2020; Feng et al., 2020; Gerken et al., 2019; Granata, 2019; Granata and Di Nunno, 2021; Guo et al., 2019; **Jung et al., 2011**; Kafer et al., 2020; Li et al., 2018, 2021; Lu and Zhuang, 2010; Pang et al., 2021; Papale et al., 2015; Qin et al., 2005b, a; Safa et al., 2018; Shang et al., 2021; Van Wijk and Bouten, 1999; Vrugt et al., 2002; Vulova et al., 2021; Wang et al., 2021a, b; Xie et al., 2021; Xu et al., 2018; Yin et al., 2021; Zhang et al., 2021, 2020; Zhao et al., 2019)

2, at the same time, I believe the users can open up by addressing the differences between the predictions of these two fluxes in the discussion. What are the major differences between the predictions, is it generally easier to predict ET?

Response & Actions: This is a good suggestion. Here we simply discussed the major differences between the predictions in the beginning discussion:

'In the above meta-analysis of the models, we found that water flux simulations based on EC observations can achieve high accuracy but also have high uncertainty through the modeling workflow. The R-squared of many water flux simulation models exceeds 0.8, possibly higher than some remote sensing-based and process-based models, and possibly higher than carbon flux simulations such as the net ecosystem exchange (NEE) in a similar modeling framework (Shi et al., 2022). This may be because many data on important variables affecting carbon flux such as soil and biomass pools, disturbances, ecosystem age, management activities, and land use history are not yet effectively and continuously measured (Jung et al., 2011) with the global spatially and temporally explicit information. While ET simulations rely on observations of moisture and energy conditions and vegetation conditions, much of the current available meteorological and remote sensing data have been effective to represent and capture the spatial and temporal dynamics of these predictors well.' (line 325-334)

Also, the discussion of major differences between the predictions is added as the additional section 4.1.2:

4.1.2 Differences from NEE predictions in the similar model framework

'In general, predictors related to meteorological, vegetation, and soil conditions were common to both ET and NEE simulations in a similar framework (Shi et al., 2022). However, in NEE predictions, explanatory variables such as soil organic content, photosynthetic photon flux density, and growing degree days (Shi et al., 2022) are not necessary for ET predictions. The selection of these variables requires our prior knowledge of the dominant drivers of ET and NEE anomalies of particular ecosystems and their differences.

The accuracy of NEE predictions (Shi et al., 2022) can be more limited by global variability across biomes and locations (Nemani et al., 2003) given the lack of locally measured data on soil and biomass pools, disturbances, ecosystem age, management activities and land use history (Jung et al., 2011). It can result in a higher heterogeneity of the training data in large-scale modeling with multiple flux sites (Shi et al., 2022) and the weak ability to capture the NEE anomalies. In contrast, in ET predictions, meteorological variables and vegetation conditions appear to be already sufficient to capture a considerably large fraction of the ET variations in most conditions.

In future ET prediction studies, given that few current ET products have time scales smaller than daily scale (Jung et al., 2019; Pan et al., 2020), improvements in the accuracy of daily and hourly models may be necessary to fill this gap. Besides, the partitioning of ET components (i.e., transpiration, interception evaporation, and soil evaporation) can be more focused to better decouple the contributions of vegetation and soil to ET with machine learning (Eichelmann et al., 2022). It can be further matched with the partitioning of NEE (i.e., to GPP and ecosystem respiration) to increase our knowledge of the global water cycle and ecosystem functioning and obtain further refined global carbon-water fluxes coupling relations (Eichelmann et al., 2022). Also, the above two promising improvements can be beneficial for research on topics related to the global terrestrial water cycle (Fisher et al., 2017).' (line 383-406)

3, In the current version, the authors added a section of "Linear correlation of quantitative features and R-squared". Some of the arguments in this section are somewhat controversial to me. For instance, the authors seem to be arguing that a higher ratio towards the training set would lead to a higher R^2. However, when there's a really small validation set, it would be very challenging to determine which model is better (very random). I.e. the authors of these studies may actually look only at the testing set and it might not be a good practice.

Response & Actions: It is elaborated in the discussion section:

'Among the validation methods, random cross-validation has higher accuracy than spatial cross-validation and temporal cross-validation. However, spatial cross-validation and temporal cross-validation may be able to better help us recognize the robustness of the model when extrapolated (i.e., applied to new stations and new years). The lower accuracy in the temporal cross-validation approach implies that we need to focus on interannual hydrological and meteorological variability in the water flux simulations. In cropland sites, we may also need to pay more attention to the effects of interannual variability in anthropogenic cropping patterns. If some extreme weather years are not included, the robustness of the model when extrapolated to other years may be challenged, especially in the context of the various extreme weather events of recent years. This can also inform the siting of future flux stations. Regions where climate extremes may occur and biogeographic types not covered by existing flux observation networks should be given more attention to achieve global-scale, accurate and robust machine learning-based spatio-temporal prediction of water fluxes. Furthermore, although the R-squared and the training/validation ratio show a positive correlation (Fig. 7) (i.e., a higher training/validation ratio may correspond to a higher R-squared), we should still be cautious in reducing this ratio in our modeling. For a really small validation set, it would be very challenging to determine which model is better given the potential uncertainty caused by the considerable randomness.' (line 368-382)

Monir comments:

Figure 3: R^2

Response & Actions: modified (and also modified in other figures)

L340-341: it should be paid more attention to?

Response & Actions: elaborated as:

'A possible explanation is that vegetation-related variables such as NDVI and LAI at the daily scale, 8-day scale, and 16-day scale have limited explanatory ability for hourly or daily-scale variability in ET, especially under cloudy conditions (e.g., tropical rainforest regions), the temporal continuity of the vegetation index data may be greatly limited (Zeng et al., 2022). This should be given more attention and some vegetation indices derived from hourly temporal resolution satellite remote sensing data such as GOES (Zeng et al., 2022) can be used for ET simulations to investigate the possible adding-values of vegetation indices at smaller time scales.' (line 340-346)

L395: remove the ();

Response & Actions: removed

L425: I do not know whether all the site PIs care about machine learning at global scale. I think a better suggestion may be for the networks;

Response & Actions:

revised as you suggested: 'We performed a meta-analysis of the water flux simulations combining in situ flux observations from flux stations/networks, meteorological, biophysical, and ancillary predictors, and machine learning.' (line 458)

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