Reviewer 1:

Accurate quantification of the climatic contributions for global land evapotranspiration change is necessary for understanding variability in the global water cycle. This study assembled four ET datasets based on various methodological sources, further adopted the Budyko framework and sensitivity experiment analysis to quantifying the contribution of climatic variables (P, Rn, T, VPD and u) to ET trend. The analysis identified the main climatic factor controls ET trend on a global scale. This research is systemic and detailed, helps reveal the controlling factors of global ET change. The main comments can be found as follows:

**Response:** We thank this reviewer for constructive comments, which significantly improves the quality of the manuscript. The following is our detailed responses to the reviewer's comments.

1.The expression should be improved.

**Response:** We have improved unclear expressions in the manuscript**.**

2.Budyko method was used to conduct a control experiment to compare with ET product results, and the ω parameters were obtained by least squares fitting, did the authors use annual data for the entire period for the fitting? If this were the case, it would not be possible to consider the effect of land use changes on the ω parameters and thus bias the estimated ET simulations, especially considering that such a long study period (1980-2010) with significant land use changes must have an important impact on ω.

**Response:** We appreciate this comment.

In this study, ω parameters are fitted with annual precipitation, potential evapotranspiration, and actual evapotranspiration. The parameters ω in Budyko framework are determined by landscape characteristics (e.g. vegetation cover, soil properties, and topography) (Yang et al., 2008), in particular ω, which parameters can be related to vegetation changes (Greve et al., 2014). As the reviewer pointed out, land-use changes during such a long study period (1980-2010) significantly affect evapotranspiration as a function of ω. For example, vegetation greening is indicated to control interannual evapotranspiration variation (Lu et al., 2021). However, all the four ET data used in this paper assume no interannual vegetation changes (satellite phenology driven), when simulating ET(detailed landcover types in each product have been shown in Table S1). It is worth noting that the assumption mentioned above does not discredit the reliability of the ET products. Furthermore, the contributions of climatic variables to ET trends already include information of the vegetation indirectly. The accuracy of the ET products has been validated in different studies such as Li et al (2018) in China, Wang et al (2018) over the Yellow River basin, and Nooni et al (2019) in the Nile River basin, among others, suggesting good performances of these products. Therefore, our study only focuses on climatic factors affecting interannual ET changes.

We have added discussions about vegetation changes in the manuscript. The text there reads as: "*Vegetation can alter water cycle, and energy cycle by biophysical and biochemical feedback to climate change (Forzieri et al., 2020). For example, global surface greening increases ET/transpiration (Lian et al., 2018; Lu et al., 2021), and reduce soil water content (Li et al., 2018a). However, the complex interaction between vegetation and surface makes it difficult to simulate the influence of dynamic vegetation change on ET (Gentine et al., 2019). Meanwhile, strictly disengaging the contributions of climatic variables and vegetation to ET is very difficult due to the interaction between vegetation and climatic variables (Li et al., 2018b). For water-limited regions, precipitation as main water supply to vegetation controls interannual ET changes (Wang et al., 2021). Thus, the dominating factor of interannual ET changes is not vegetation, but rather, atmospheric climate variables (Zhang et al., 2020). Those studies indicate that contribution of climatic variables have already included information of vegetation, indirectly.*

*Given the above reasons, the ET products used in this study do not consider the effect of land use /vegetation changes on ET. When simulating ET, the model frameworks assume no interannual land use changes, so they are regarded as static conditions. Detailed landcover types in each product have been shown in Table S1*".

Table S1. Comparisons of landcover types data used by the four ET products

| ET product | | Landcover types data | Period |
|---|---|---|---|
| GLEAM3.0a | | MOD44B | Static |
| GLDAS2.0-Noah | | MCD12Q1 | Static |
| MERRA-Land | | Global Land Cover Characterization | Static |
| EartH2Observe-En | W3RA | MOD44B | Static |
| | HTESSEL-CaMa | Global Land Cover Characterization | Static |
| | JULES | | Static |
| | PCR-GLOBWB | | Static |
| | LISFLOOD | GlobCover2009 | Static |
| | HBV-SIMREG | | Static |
| | WaterGAP3 | MOD12Q1 | Static |

Note: However, regarding EartH2Observe-En, the LUC datasets used by seven (in this table) and two models (i.e., ORCHIDEE and SURFEX-TRIP) are available and unavailable, respectively; the LUC is not the necessary input for SWBM.

**References:**


Forzieri, Giovanni; Miralles, Diego G.; Ciais, Philippe; Alkama, Ramdane; Ryu, Youngryel; Duveiller, Gregory; Zhang, Ke; Robertson, Eddy; Kautz, Markus; Martens, Brecht; Jiang, Chongya; Arneth, Almut; Georgievski, Goran; Li, Wei; Ceccherini, Guido; Anthoni, Peter; Lawrence, Peter; Wiltshire, Andy; Pongratz, Julia; Piao, Shilong; Sitch, Stephen; Goll, Daniel S.; Arora, Vivek K.; Lienert, Sebastian; Lombardozzi, Danica; Kato, Etsushi; Nabel, Julia E. M. S.; Tian, Hanqin; Friedlingstein, Pierre; Cescatti, Alessandro. Increased control of vegetation on global terrestrial energy fluxes. Nat. Clim. Chang. 2020, 10, 356–362.

Gentine P, Green J K, Guerin M, et al. Coupling between the terrestrial carbon and water cycles - a review. Environmental Research Letters, 2019, 14(8).

Greve P, Orlowsky B, Mueller B, et al. Global assessment of trends in wetting and drying over land. Nature Geoscience, 2014, 7(10):716-721.

Li, S.J., Wang, G.J., Sun, S.L., Chen, H.S., et al., 2018. Assessment of Multi-Source Evapotranspiration Products over China Using Eddy Covariance Observations. Remote Sensing, 210(11), 1692.

Lian, X., Piao, S., Huntingford, C., Li, Y., Zeng, Z., Wang, X., Wang, T., 2018. Partitioning global land evapotranspiration using CMIP5 models constrained by observations. Nature Climate Change 8 (7), 640–646.

Lu, J., Wang, G., Li, S., Feng, A., Zhan, M., Jiang, T., et al. (2021). Projected land evaporation and its response to vegetation greening over China under multiple scenarios in the CMIP6 models. Journal of Geophysical Research: Biogeosciences, 126, e2021JG006327.



Lu, J., Wang, G., Li, S., Feng, A., Zhan, M., Jiang, T., et al. (2021). Projected land evaporation and its response to vegetation greening over China under multiple scenarios in the CMIP6 models. Journal of Geophysical Research: Biogeosciences, 126, e2021JG006327.



Nooni, I.K.; Wang, G.; Hagan, D.F.T.; Lu, J.; Ullah, W.; Li, S. Evapotranspiration and its Components in the Nile River Basin Based on Long-Term Satellite Assimilation Product. Water 2019, 11, 1400.

Wang, G.J., Pan, J., Shen, C.C., Li, S.J., Lu, J., Lou, D., Hagan, D. F. T., et al., 2018. Evaluation of Evapotranspiration Estimates in the Yellow River Basin against the Water Balance Method. Water, 10(12):1884.

Wang, H.N., Lv, X.Z., Zhang, M.Y., 2021. Sensitivity and attribution analysis of vegetation changes on evapotranspiration with the Budyko framework in the Baiyangdian catchment, China. Ecol. Indic. 120, 106963.

Y. Li, S. Piao, L. Z. X. Li, A. Chen, X. Wang, P. Ciais, L. Huang, X. Lian, S. Peng, Z. Zeng, K. Wang, L. Zhou, Divergent hydrological response to large-scale afforestation and vegetation greening in China. Sci. Adv., 2018a, 4, eaar4182.

Yang, H., Yang, D., Lei, Z., & Sun, F. (2008). New analytical derivation of the mean annual water-energy balance equation. Water Resources Research, 44(3), W03410.

Yue Li, Zhenzhong Zeng, Ling Huang, Xu Lian and Shilong Piao. Science. Comment on "Satellites reveal contrasting responses of regional climate to the widespread greening of Earth". Science, 2018b, 360 (6394), eaap7950.

Zhang, D., Liu, X., Zhang, L., Zhang, Q., Gan, R., Li, X., 2020. Attribution of evapotranspiration changes in humid regions of China from 1982 to 2016. J. Geophys. Res.: Atmos., 125 (13), e2020JD032404.

3. Figure 7: As the percentage of grids in each dominant factor controlling annual ET linear trends has been distinguished in Table 2, I suggest to focus on the regions where VPD plays a dominant factor in Figure 7.

**Response:** Thank you for your comment.

We have highlighted the regions where VPD plays a dominant factor with the dotted areas in Figure 7.

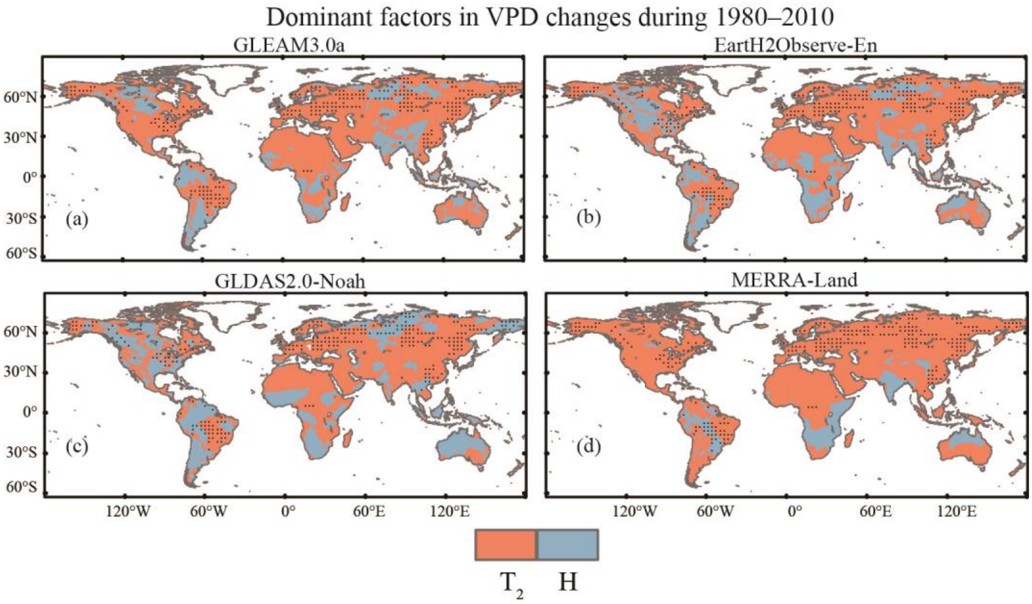


**Figure 7.** Distribution of dominant factor in VPD changes in global land during 1980-2010 for GLEAM3.0a (a), EartH2Observe-En (b), GLDAS2.0-Noah (c), and MERRA-Land (d). $T_2$ and H mean air temperature and specific humidity respectively. Dotted areas are where VPD is a dominant factor.

4. 3.3 Validations of attribution method belongs to the 4.2 Uncertainties, as this section discusses the reliability of Budyko method in ET estimation and attribution analysis.

**Response:** Thank you for your comment.

We have added section 3.3 Validations of attribution method into section 4.2.1 Validations of attribution method.

5. Abstract Line 22: "land-atmosphere interactions" & Page 10 Line 24: "The positive feedbacks": The main conclusion of this article is demonstrating the main factor affecting ET trend. However, it appears that this study did not address the interaction or feedback between ET and VPD.

**Response:** Thank you for your comment.

Abstract Line 22: "land-atmosphere interactions" has been changed to "carbon-water-energy cycle".

Page 10 Line 24: "The positive feedbacks" has been changed to "The positive influences".

6. As the authors mentioned choice of ET data may add significant uncertainties into the ET attribution. The authors need to show how the impact of the results due to ET datasets uncertainty is reduced and summarize the combined results from multiple data sets, rather than one data set with one result without giving a combined conclusion. And this should also be summarized in Conclusion.

**Response:** Thank you for your comment.

It is challenging to study ET change mechanisms only depending on one product. Because the model structures, algorithms, and forcing data sets can affect ET accuracy (Martens et al., 2017), when simulating ET. Therefore, we decided to use multi-source ET products and their forcing data sets. As described in Figure 2, there are evident differences in ET trends among those products. Different trends of climatic variables can directly affect ET trends. Figure S2 shows the spatial distribution of the annual linear trend in each driving factor (i.e., P, $R_n$, T, VPD, and u) during 1980-2010. We can find that precipitation and net radiation have differences between the products, especially for precipitation trends in MERRA-Land and net radiation trends in GLDAS2.0-Noah. By the attribution method with Budyko framework, the global long-term annual ET linear trend responses to climatic variables' changes can be quantified in Figure S3. Compared to air temperature and wind speed, precipitation, net radiation, VPD provide the biggest contribution to ET trends. As the reviewer said, we need to summarize ET conclusions from different products' results. To do this, we obtain the consistency of the dominant factor in ET trends among those products by summarizing the results in Figure 4.

Similar descriptions in this manuscript can be added. The text there reads as: "Spatially, *P, $R_n$, VPD also provide the biggest contributions to ET trend (Figure S3), which are positively correlated with their respective trends (Figure S2)*". Meanwhile, we summarize this in Conclusion, and the text there reads as "Global ET trends among the products are determined by their climate variables. Different sources of forcing data sets result in different magnitudes of ET trends, even the reversing signs. But consistent above attribution results in those products confirm that ET mechanisms are robust".

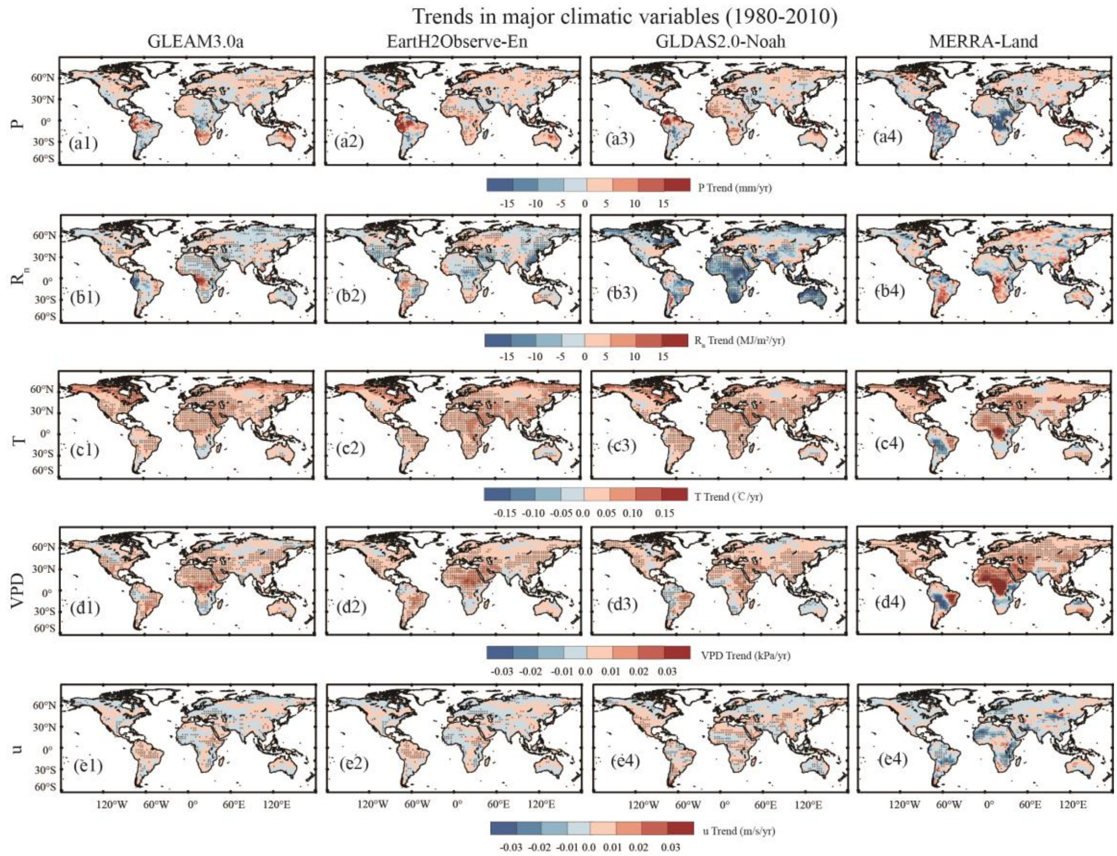


Figure S2. Spatial distribution of annual linear trend in each driving factor during 1980-2010. Small letters (a-e) respectively indicate P, Rn, T, VPD, and u and numbers (1-4) represent GLEAM3.0a, EartH2Observe-En, GLDAS2.0-Noah, and MERRA-Land. Dotted area indicates the trend passes significance level ($p<0.05$).

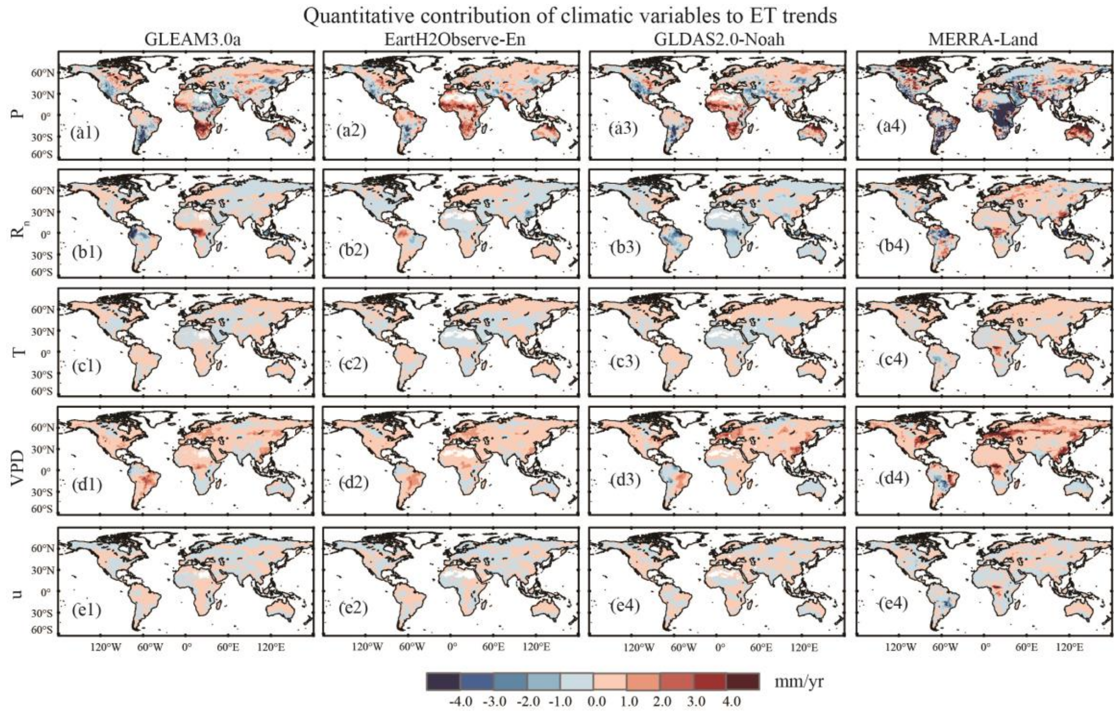

Figure S3. Attributions of the global long-term annual ET linear trend during 1980-2010. Small letters (a-e) indicate P, Rn, T, VPD and u respectively; and numbers (1-4) indicate the ET products of GLEAM3.0a, EartH2Observe-En, GLDAS2.0-Noah and MERRA-Land respectively.

**References:**

Martens, B., Miralles, D.G., Lievens, H., van der Schalie, R., de Jeu, R.A.M., Fernández-Prieto, D., Beck, H.E.,Dorigo,W.A., Verhoest, N.E.C.: GLEAM v3: Satellite-based land evaporation and root-zone soil moisture. Geosci. Model Dev. 10, 1903–1925, 10.5194/gmd-10-1903-2017, 2017.

7. Table 2 gives the percentage of grids in each dominant factor controlling annual ET linear trends with positive and negative. Meanwhile, Figure 2 shows the spatial distribution of annual ET linear trends for 4 datasets, opposite trends between different products in the same pixel can be found. My concern is whether the areas with positive ET trend in one dataset are changing negatively in the other dataset.

**Response:** Thank you for your comment.

As shown in Figure 2, there are divergences in the ET trends of the products over some regions. Different ET trends among the products result from different forcing data (Table 1). Each climatic factor's contribution to ET trends in Figure S3 is determined by the respective factor's trend in Figure S2. For example, MERRA-Land has abnormal negative ET trends over South America and the central part of Africa. By comparing Figure S1 with Figure S2, we find that negative ET trends over the central part of Africa are due to abnormally decreased precipitation providing a negative contribution to ET trends. Similar description has been added, and The text there reads as: "*As shown in Figure 2, there are divergences in the ET trends of the products over some regions. For example, MERRA-Land has abnormal negative ET trends over South America and the central part of Africa. This is due to abnormally decreased precipitation providing a negative contribution to ET trends*".

Some specific comments:

1 Page 1, Line 25: As you mentioned "terrestrial water flux component", "accounting for more than 60% of global precipitation" should be "land precipitation".

**Response:** Thank you for your comment.

We have changed "global precipitation" to "global land precipitation".

2 Page 3, 2.1 Data: Forcing data in Budyko framework and Köppen climate classification should also be summarized.

**Response:** Thank you for your comment.

We have added the description, liking "*In the attribution method with Budyko framework, we use respective forcing data of each product (please see detail* *description in section 2.2 Forcing data)*"; and "*The Köppen climate classification is produced according to the empirical relationship between climatic variables and vegetation*".

3 Page 5, Line 35: What's the meaning of Ci?

**Response:** Thank you for your comment.

Ci means the contribution of each factor to ET change in each product.

4 Figure 4: The image color scheme can be more distinguishable.

**Response:** Thank you for your comment.

Figure 4's color scheme has been changed:

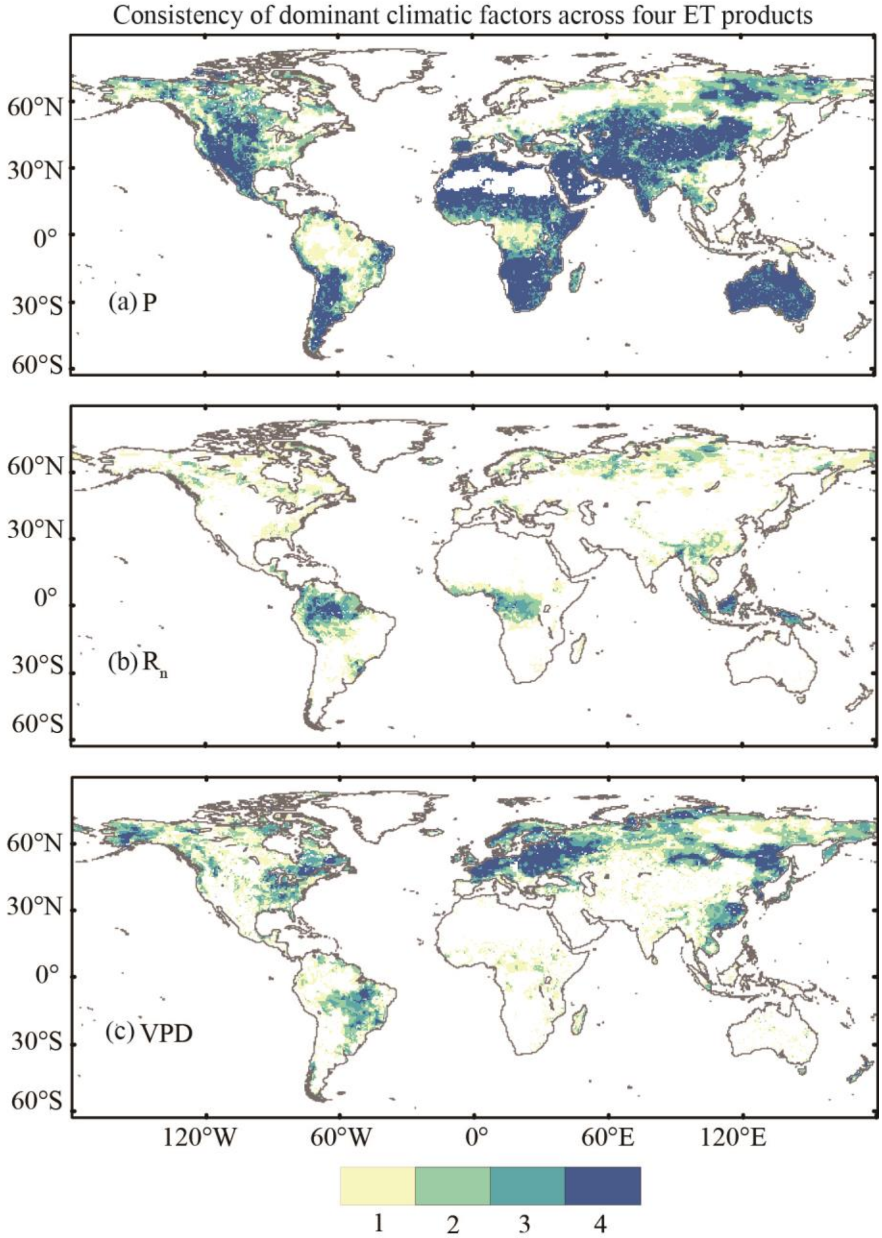


Figure 4. The consistency of spatial distribution of dominant climatic factors to global long-term ET trends between GLEAM3.0a, EartH2Observe-En, GLDAS2.0-Noah and MERRA-Land for Precipitation (a), net radiation (b), and VPD (c). The land fraction of air temperature (T1) and

wind speed is limited so their results are not shown here. Numbers 1-4 represent the count of these models with the same dominant factor in one pixel, and indicate different confidence level from low to high.

5 Page 5, Line 10: How do you define the "dominant factor of ET trends"? Please give an explanation or algorithm.

**Response:** Thank you for your comment.

We have added the explanation. The text there reads as: "The dominant climatic factor is identified with the absolute value of maximum contribution to ET trends among those factors".

6 Figure 5 & 8: Please use density scatter plot to improve image quality.

**Response:** Thank you for your comment.

Figure 5 & 8's color scheme have been changed:

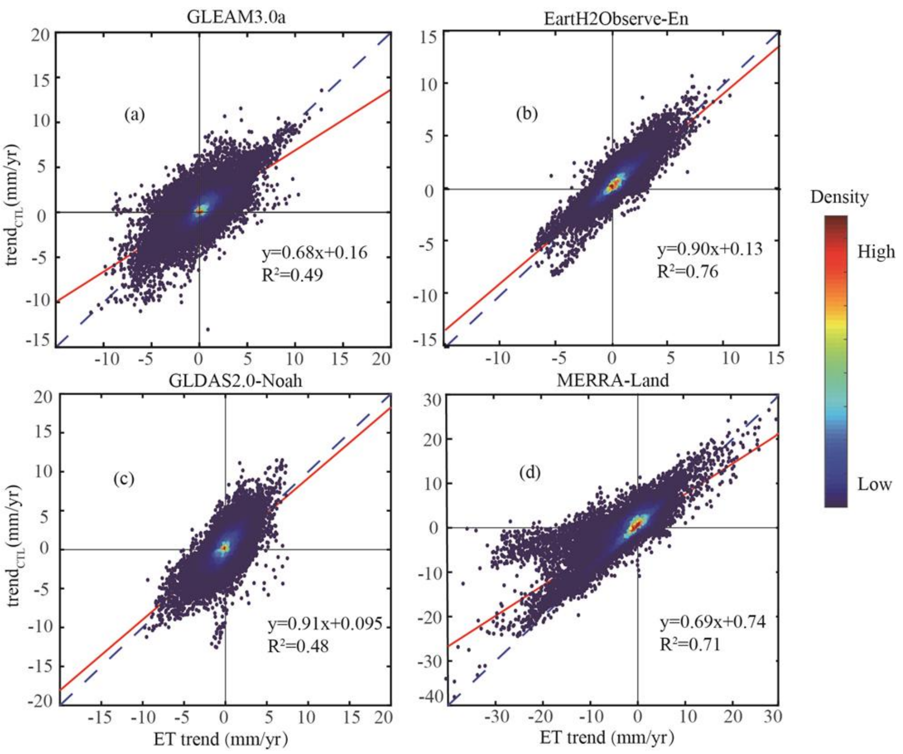


Figure 5. The pixel-wise scatterplots of global long-term annual ET linear trend against the control trend (trendCTL) in ET for GLEAM3.0a (a), EarthH2Observe-En (b), GLDAS2.0-Noah (c), and MERRA-Land (d). The red line indicates a fitted line of the scatter points along with the 1:1 blue dotted line.

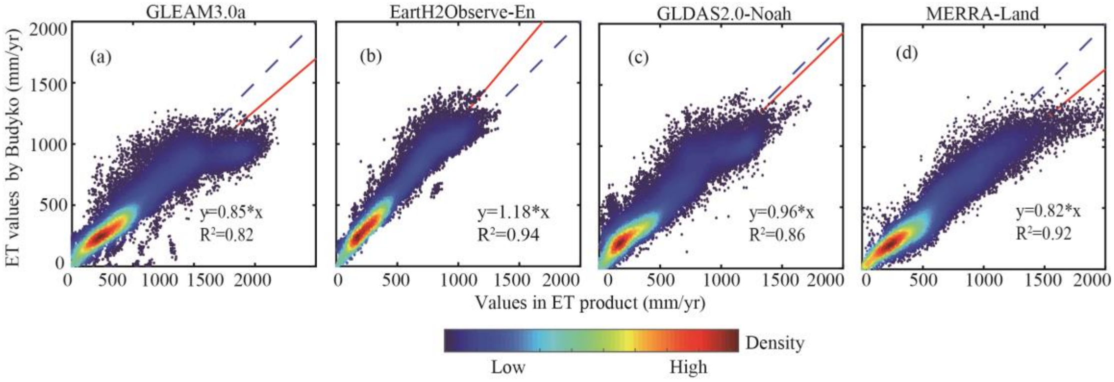


Figure 8. Pixel-wise scatterplots of (x-axis) annual ET in each product against (y-axis) annual ET estimated by Budyko Framework. Small letters (a-d) represent GLEAM3.0a, EartH2Observe-En, GLDAS2.0-Noah, and MERRA-Land, respectively.

7 Please avoid citing a large number of references in one place.

**Response:** Thank you for your comment.

We have deleted some unnecessary references in one place.