Reviewer 2:

The manuscript "Attributing of global evapotranspiration trends based on the Budyko framework" by Li et al. investigated the trend of evapotranspiration (ET) at global scale and its contributing factors, including precipitation (P), net radiation (Rn), air temperature (T1), VPD, and wind speed (u), by using multiple datasets (GLEAM3.0a, EartH2Observe ensemble, GLDAS2.0-Noah and MERRA-Land). The methods and datasets used in this study is similar to a previous study (Li. et al., Journal of Hydrology, 2021) by the same author except this manuscript extends previous study in China to global. This study is more like a numerical sensitivity exercise, suffers from methodological methodological flaws and does not provide insights to understand ET trend and its contributing factors.

Response: We thank this reviewer for constructive comments about the accuracy of the attribution method in our work, which significantly improves the quality of the manuscript. The following is our detailed responses to the reviewer's comments. Compared to JH et al., 2021, we discuss evident differences in results and uncertainties of the attribution method in this manuscript.

For result differences, "*Li et al (2021) attempted to quantify the contribution of those forcing variables to ET trends over China with the Budyko theory. Their study indicates that precipitation dominates ET trends over water-limited regions, while VPD controls ET of energy-limited regions. However, there are still unclear questions about the global land ET mechanism. For example, how differently would the conclusions of dominating ET factors over water-limited regions be for global dry lands? Which variable controls ET over the global tropical zone is unclear, despite the results of VPD controlling ET over the energy-limited region of China. Wang et al (2022) indicate that global significantly increased ET mostly results from increasing air temperature, especially in the humid region. Pan et al (2020) point out that precipitation, air temperature, and radiation control Amazon's ET changes. On the other hand, the boreal ET mechanisms are also not entirely clear. Increasing air temperature is significantly correlated with ET (Wang et al., 2022), while increasing VPD contributes to ET process over the boreal region (Helbig et al., 2020). Therefore, it is necessary to assess global ET mechanisms using the same attribution method for solving these problems*".

For uncertainties of the attribution method, we quantify the contribution of air temperature T2 and specific humidity to global VPD changes following our proposed sensitivity method in Figure 5. Our study concludes that the specific humidity controls VPD only in some regions of North and South Asia, northern Australia, southern Africa, and South America. We also discuss the relationship between fitted parameter ω and ET trend analysis, vegetation. The text there reads as: "Here, we compare ET trends in each product to climate zones, *which are represented by aridity index. The aridity index (PET/precipitation) in each product is calculated with respective precipitation and PET data. Figure S5(a1-d1) show that the biggest ET trends of all products exit the wettest regions (low aridity index). To study the influence of fitted parameter ω on ET trend analysis, we compare the control on ET trend (trend$_{CTL}$) to the aridity index. The results in Figure S5(a2-d2) show similar results to the actual ET trend, meaning the ET trend analysis in the attributed method can capture actual ET change characteristics. Meanwhile, we also quantify the relationship of parameter ω fitted by precipitation, potential evapotranspiration, and actual evapotranspiration in each product to multi-year average GIMMS NDVI during 1982-2010. Figure 8 shows the linear relationship between fitted parameter ω and NDVI for all products with R2 values of 0.13-0.38. In general, parameter ω can be calculated according to the linear relationship between ω and NDVI (Bai et al, 2019; Greve et al, 2014). The results show that our trend analysis keeps the relationship, spatially. However, we admit that time-varying ω (e.g. vegetation, soil property) will directly affect ET (Lu et al., 2021). The impact of ω would vary as a function of the chosen timescale which requires a more indepth study beyond the scope of the current study*".

References:

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Major comments

1. The Budyko equation assumes that precipitation is the only water supply for ET. At global scale during the study period (1980-2010), many regions have experienced long-term trends in groundwater storage. For example, in many regions (e.g., the

North Plain in China, the High Plain in US, the northern India) where groundwater is used for agricultural irrigation, the depleted groundwater provides an additional source for ET. In this study, both the analytical framework (Budyko equation) and some of the datasets (e.g., GLDAS2-Noah) do not capture groundwater dynamics. Therefore, this study only investigated the climatic factors on ET trend and cannot provide a full picture of ET trend. Even if the ET trend caused by groundwater is captured (e.g., by the remote sensing based GLEAM ET product), this manuscript may mistakenly attribute ET trend caused by groundwater to climatic factors.

Response: Thank you for your comments.

We agree that human activities (irrigation and reservoir construction) have been playing an important role in water cycle. To discuss that, we add a new section. The text there reads as: such as "*Human activities (e.g. irrigation and reservoir construction) have been affecting the components (i.e. ET, runoff, and groundwater storage) of water cycles (Ashraf et al., 2017; Long et al., 2017). For example, the groundwater over North Plain in China, the High Plain in US, and northern India is pumped for agricultural irrigation and contribute to accelerate ET process. Lv et al (2017) indicate that the estimated ET will be more accurate if irrigation water affects hydrological cycles. Unfortunately, most ET products do not consider human activities due to the limited factors of estimated algorithm and model parameters. The GLDAS2.0-Noah and MERRA-Land in this study also do not consider the effect of human activities. GLEAM3.0a partly contains the information of groundwater by considering the effect of ESA-CCI soil moisture on ET. As for EartH2Observe-En, the six models either consider one of groundwater, reservoir, or water use (see Table S1 from Li et al., 2021). However, the attribution results to ET trends in this study show GLEAM3.0a and EartH2Observe-En's validation results are good, indicating that the effect of human activities on ET may be contained in climatic variables. These ET products are produced with appropriate algorithms, parameterizations of models and forcing data sets. The accuracy of ET has been validated by the respective developers; Li et al (2018) in China, Wang et al (2018) in Yellow River basin, and Nooni et al (2019) in Nile River basin, suggesting good performances of these products. Therefore, our study only focuses on climatic factors affecting interannual ET changes. For future studies, the contribution of land surface such as human activities to ET should be investigated to understand the mechanism of global ET trend better. Additionally, we only consider local contributions of ET here. In fact, large-scale* *modes of climate variability (e.g. El Niño Southern Oscillation, the North Atlantic Oscillation,) can also affect terrestrial evaporation. For example, Martens et al (2018) indicate that El Niño Southern Oscillation controls the overall dynamic of global land ET, while some models dominate regional ET change, such as East Pacific–North Pacific teleconnection patterns*".

Therefore, the direct contributions of ground water and soil moisture are not considered, although we are aware that they do play a role since we mainly focus on atmospheric factors. Additionally, water transport from the ocean and other sources (remote sources) such as shown in Wei et al. (2012, 2016) are also not considered. The goal was to simplify this whole framework and then in following studies, we also look into the impact of land and other remote sources.

Table S1. Members of Eearth2Observe-En ET product of considering human activities (ground water, reservoir lakes, and water use) (Li et al., 2021).

Name	Ground water	Reservoir/ Lakes	Water use
HTESSEL-CaMa	NO	NO	NO
JULES	NO	NO	NO
LISFLOOD	YES	YES	YES
ORCHIDEE	YES	NO	Irrigation only
PCR-GLOBWB	YES	Only lakes	NO
SURFEX-TRIP	YES	NO	NO
HBV-SIMREG	NO	NO	NO
SWBM	NO	NO	NO
W3RA	YES	NO	NO
WaterGAP3	YES	YES	YES

Note: HTESSEL-CaMa is Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land-Catchment-based Macro-scale Floodplain model; JULES is the Joint UK Land Environment Simulator; PCR-GLOBWB is PCRaster GLOBal Water Balance model; HBV-SIMREG is Hydrologiska Byråns Vattenbalansavdelning model; SWBM is Simple Water Balance Model; W3RA is Water Resources Assessment; WaterGAP3 is Water-Global Assessment and Prognosis. Detail information refers to Schellekens et al. (2017).

References:

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Lv, M., Ma, Z., Yuan, X., et al., 2017. Water budget closure based on GRACE measurements and reconstructed evapotranspiration using GLDAS and wateruse data for two large densely-populated mid-latitude basins. J. Hydrol. 547, 585–599.

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Schellekens, J., Dutra, E., Martínez-de la Torre, A., Balsamo, G., van Dijk, A., et al., 2017. A global water resources ensemble of hydrological models: The eartH2Observe Tier-1 dataset. Earth Syst. Sci. Data. 9, 389–413.

2. The parameter w in Budyko equation in Equation 1 is obtained by regression using each set of data product (Line 7-8). I assume that the authors repeat the regression four times using the four sets of P, PET and ET data. The parameter w is usually associated with land surface characteristics (e.g., land use, vegetation). However, this study assumes the parameter w is static. Therefore, the trends of ET caused by land surface characteristics are neglected.

Response: Thank you for your comments.

We apologize for the confusion. It is true that ω are fitted with annual precipitation, potential evapotranspiration, and actual evapotranspiration with the least-squares regression in this study. Actually, ω in Budyko framework are determined by landscape characteristics (e.g. vegetation cover, soil properties, and topography) (Yang et al., 2008). Generally, ω parameters can be calculated by vegetation changes (Greve et al., 2014). During a long study period (1980-2010), Land surface characteristics significantly affect evapotranspiration by ω parameters. For example, vegetation greening controls 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.

To explain this, we have discussed the influences of vegetation and climate change on ET changes. The text there reads as: such 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
	W3RA	MOD44B	Static
	HTESSEL-CaMa		Static
	JULES	Global Land Cover Characterization	Static
EartH2Observe-En	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.

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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.

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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.

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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.

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3. The parameter w is more sensitive to regression in arid climate than in humid climate based on Budyko Equation 1. Therefore, without a detailed study of w, the ET trend analysis in this study may be biased for different climate zones. In addition, as this study uses four sets of data, it is unclear how w's obtained from each data set are different from each other.

   Response: Thank you for your comments.

   We appreciate this suggestion. The fitted parameter ω includes landscape characteristics (e.g. vegetation cover, soil properties, and topography), leading to the parameter with climatic characteristics (Xu et al., 2013). Meanwhile, ET trends of used products in this study are directly related to climate zones. Here, we compare ET trends in each product to climate zones, in which are represented by aridity index. Aridity index (PET/precipitation) in each product is calculated with respective precipitation and PET data. Figure S5(a1-d1) show that the biggest ET trends of all products exit the wettest regions (low aridity index). To study the influence of fitted parameter ω on ET trend analysis, we compare control ET trend ($trend_{CTL}$) to aridity index. The results in Figure S5(a2-d2) show similar results with actual ET trend, meaning the ET trend analysis in the attributed method can capture actual ET change characteristics.

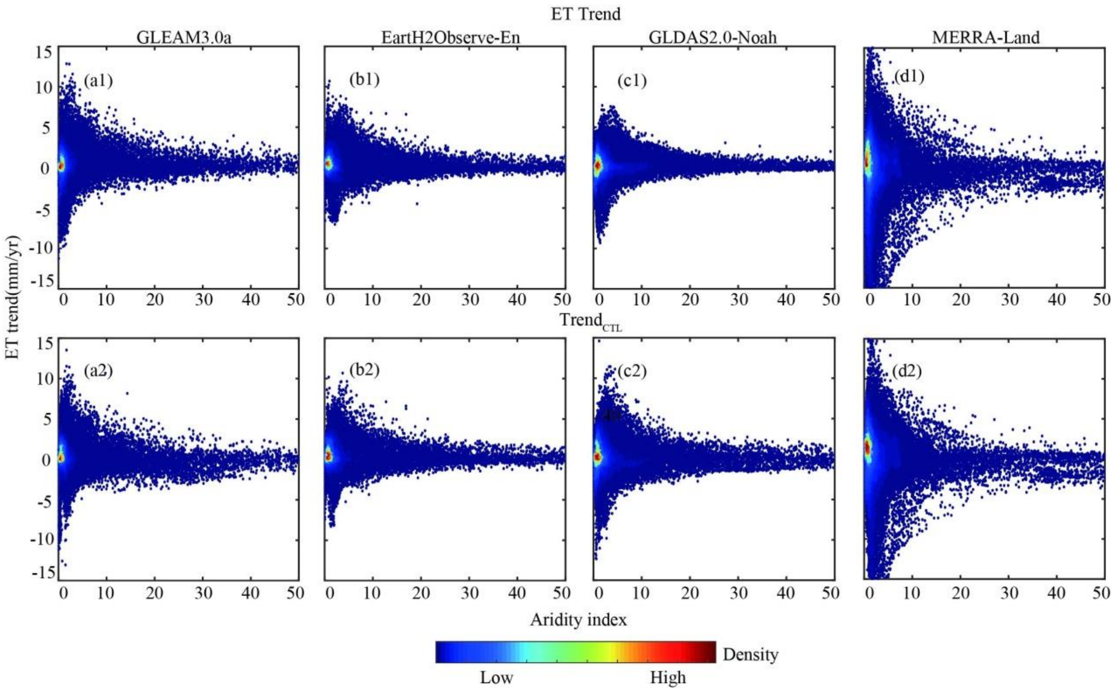

Figure S5. The pixel-wise scatterplots of multi-year average aridity index against actual ET annual values for GLEAM3.0a (a1), EartH2Observe-En (b1), GLDAS2.0-Noah (c1), and MERRA-Land (d1), the control ET trend ($trend_{CTL}$) for GLEAM3.0a (a2), EartH2Observe-En (b2), GLDAS2.0-Noah (c2), and MERRA-Land (d2). Aridity index (PET/precipitation) in each product is calculated with respective precipitation and PET data.

Meanwhile, we also quantify the relationship of parameter ω fitted by precipitation, potential evapotranspiration, and actual evapotranspiration in each product to multi-year average GIMMS NDVI during 1982-2010. Figure 8 shows linear relationship between fitted parameter ω and NDVI for all products with R^2 value with 0.13-0.38. In general, parameter ω can be calculated according to the linear relationship between ω and NDVI (Bai et al, 2019; Greve et al, 2014). The results show that our trend analysis keeps the relationship, spatially.

Similar description is also added into the manuscript. The text there reads as: "*Here, we compare ET trends in each product to climate zones, in which are represented by aridity index. Aridity index (PET/precipitation) in each product is calculated with respective precipitation and PET data. Figure S5(a1-d1) show that the biggest ET trends of all products exit the wettest regions (low aridity index). To study the influence of fitted parameter ω on ET trend analysis, we compare control ET trend (trendCTL) to aridity index. The results in Figure S5(a2-d2) show similar results with actual ET trend, meaning the ET trend analysis in the attributed method can capture actual ET change characteristics. Meanwhile, we also quantify the relationship of parameter ω fitted by precipitation, potential evapotranspiration, and actual evapotranspiration in each product to multi-year average GIMMS NDVI during 1982-2010. Figure 8 shows the linear relationship between fitted parameter ω and NDVI for all products with R2 values of 0.13-0.38. In general, parameter ω can be calculated according to the linear relationship between ω and NDVI (Bai et al, 2019; Greve et al, 2014). The results show that our trend analysis keeps the relationship, spatially. We admit that time-varying ω (e.g. vegetation, soil property) will directly affect ET (Lu et al., 2021). The impact of ω would vary as a function of the chosen timescale which requires a more indepth study beyond the scope of the current study*".

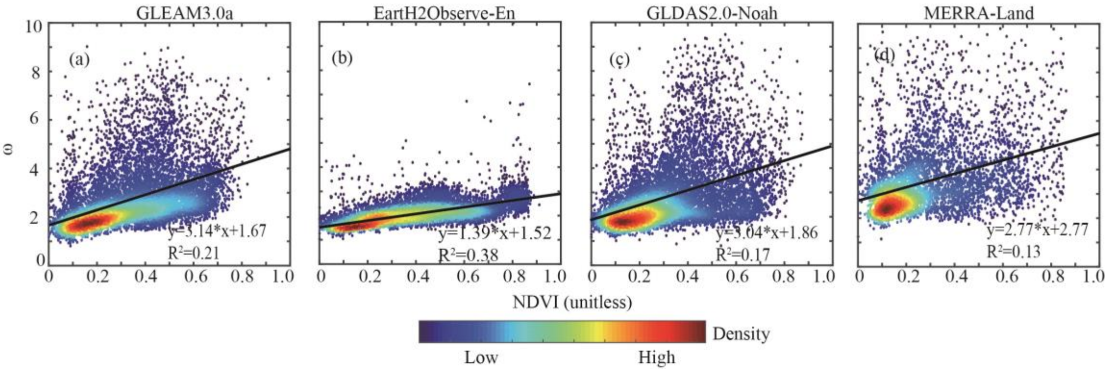

Figure 8. Pixel-wise scatterplots of (x-axis) multi-year average NDVI against (y-axis) their fitted ω values in each product. Small letters (a-d) represent GLEAM3.0a, EartH2Observe-En, GLDAS2.0-Noah, and MERRA-Land. GIMMS NDVI data during 1982-2010 is used here.

References:

Bai P, Liu X, Zhang D, Liu C. Estimation of the Budyko model parameter for small basins in China. Hydrological Processes. 2019;1–14.

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.

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4. It is a bit confusing on the control experiment setup for sensitivity analysis. The impact of a contributing factor trend on ET trend is analyzed by the difference using 1980 data and the 1980-2010 average (Line 30-34). As there is inter-annual variability in the climate foricngs, why comparing the 1980-year data to 1980-2010 average would reflect the true trend. For example, if a pixel has a decreasing trend in P during 1980-2010 and a dry year in 1980 (i.e., P in 1980 is below average), the experiment setup then would predict an opposite increasing P trend. Therefore, I am not sure if choosing a different year (e.g., 1981) would lead to different results on the trend analysis.

Response: Thank you for your comments.

In this study, the sim_CTL experiment can obtain the control ET changes for each product by using all the factors of 1980-2010, and the ET change controlled by one certain factor is simulated by the sensitivity experiment with the factor only in the 1980 and the others factors of 1980-2010. The difference in ET trends between control experiment and each sensitivity experiment is considered as the contribution of that particular climatic variable to ET trends. Actually, choosing a different year in the sensitivity experiment of one factor may lead to different results. In general, there are two choices (i.e. one year or multi-year average) for this. The two choices are both applied to the attribution analysis of reference evapotranspiration and meteorological drought (Sun et al., 2017; Sun et al., 2019). We compare the PET/precipitation values between 1980s and multi-year average among those products (Figure S1). Overall results show a slight difference between 1980s and multi-year average for PET/precipitation. Similar description is added. The text there reads as: "*The multiyear average can also replace a factor in 1980 during 1980-2010. Figure S1 shows that precipitation and PET values between 1980 and the multiyear average are very close*".

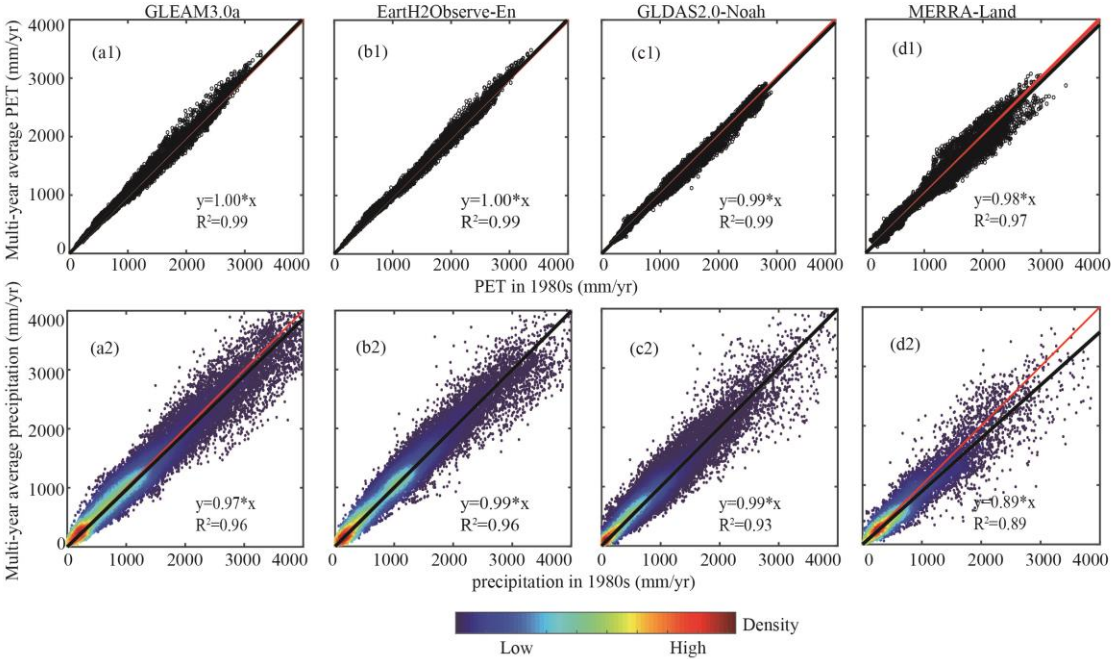

Figure S1. The pixel-wise scatterplots of PET in 1980s against multi-year average PET for GLEAM3.0a (a1), EarthH2Observe-En (b1), GLDAS2.0-Noah (c1), and MERRA-Land (d1) and precipitation in 1980s against multi-year average precipitation for GLEAM3.0a (a2), EarthH2Observe-En (b2), GLDAS2.0-Noah (c2), and MERRA-Land (d2).

References:

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