Response to Reviewer #2:

General Comments:
This manuscript presents an analysis of critical soil moisture (CSM) across China using multiple satellite-based datasets of evapotranspiration (ET), gross primary production (GPP), and soil moisture (SM). The authors apply two methods to detect CSM - a correlation-difference approach and a VPD-GPP-SM covariance approach. They evaluate the spatial patterns of CSM across different land cover types, soil textures, and regions of China, and analyze the factors driving shifts between water and energy-limited regimes.
Overall, this study represents a substantial contribution within the scope of HESS. The use of multiple satellite datasets to examine CSM at large scales is novel and provides new insights into water and energy limitations across diverse landscapes in China. The methods are generally sound and though the results are discussed not comprehensively in the context of related work. The manuscript is in general structured, though some sections could be more concise and many textual improvements might be needed. I will give a major revision for this work.

Response: We thank the reviewer for the positive evaluation and constructive comments. We have carefully revised the manuscript based on your suggestions and addressed your concerns as detailed below.

Specific Comments:

1. The methods section is quite detailed, which is good for reproducibility. However, some of the **dataset descriptions are too redundant** right now and could potentially be shortened or moved to data availability statement to improve readability of the main text. For example, subsections such as 2.1.2, 2.1.4, 2.1.5.

Response: Thanks for your suggestion. We moved the websites of the data to the Section of Data Availability.

Below is the revised main text:

"2.1 Data

The eddy covariance flux datasets were compared with eight satellite-based ET and GPP in Section 3.1. Then, CSM derived from the relationship between SM and evaporative fraction (EF) was used to evaluate the performance of CSM derived from the covariance and correlation-difference methods in Section 3.2. The layer-wise SM and satellite-based ET and GPP were used for the large-scale detection of CSM. Land cover type, soil texture, and water resource regionalization were all used to examine CSM variations in Section 3.3. The SM, ET, GPP, and meteorological data were all used to investigate the dominant factors influencing water-energy limit shifts in Section 3.4. All energy, vegetation, and water variables were resampled or combined to 0.1°-8 days resolution. The period, limited by the temporal availability of several data sources, covered 2001–2018.

2.1.1 Evapotranspiration and gross primary production

Eddy covariance-derived measurements were used to evaluate the performance of satellite-based ET and GPP. Figure 1 illustrates the locations of 21 flux sites and Table 1 shows the detailed information on flux sites. Given the fact that Huazhaizi, Dashalong, Luodi, Arou, Guantao, Huailai, Miyun, and Daxing did not have GPP data, the REddyProc website (https://www.bgc-jena.mpg.de/5622399/REddyProc/) was used to calculate GPP.

Table 2 contains a list of all spatial data sets used in this study. Advances in remote sensing have substantially fostered the development of global ET and GPP products for CSM simulation. Four ET products and four GPP products were employed. Penman-Monteith-Leuning (PML) and Global LAnd Surface Satellite (GLASS) provide both ET and GPP. PML, with a spatiotemporal resolution of 500 m and 1 day during February 2000–December 2020, integrates the stomatal conductance theory to relate the GPP process using the Penman-Monteith-Leuning model (Zhang et al., 2019; He et al., 2022) and applies daily meteorological data, land surface temperature from ERA5, enhanced Whittaker-filtered MODIS LAI, albedo, and emissivity. The interdependency and mutual restrictions between GPP and ET considerably increase the accuracy of ET simulation. For GLASS with 0.05° resolution and every 8 days, ET integrates the MOD16, a revised remote sensing-based Penman-Monteith, the Priestley-Taylor Jet Propulsion Laboratory, a modified satellite-based Priestley-Taylor, and the Semi-Empirical Algorithm of the University of Maryland using the Bayesian model averaging approach (Yao et al., 2013, Yao et al., 2014); GPP algorithm incorporates the effects of atmospheric carbon dioxide content, radiation components, and VPD based on the eddy covariance-light use efficiency model introduced by Yuan et al., (2007). It is founded on two underlying assumptions: the fraction of absorbed photosynthetically active radiation has a linear relationship with the normalized difference vegetation index; constant light use efficiency is governed by either air temperature or soil moisture, depending on which component imposes the greatest limitation.

In addition, Collocation-Analyzed Multi-source Ensembled Land Evapotranspiration (CAMELE) provides a long-term (1981–2020) collocation-analyzed multi-source ensembled land ET, employing ERA5, FLUXCOM, PML, GLDAS, and GLEAM (Li, C. et al., 2022), at 0.1°-8 days and 0.25°-daily resolutions. Surface Energy Balance Algorithm for Land evapotranspiration in China (SEBAL) ET focuses on 1 km-daily resolution during 2001–2018. This product integrates GMAO's meteorological data and NASA's MOD43A1 daily surface albedo, MOD11A1 daily surface temperature, and MOD13 vegetation index (Cheng et al., 2021). Two-Leaf light use efficiency model based (TL) GPP offers comprehensive worldwide assessments of GPP, shaded GPP, and sunlit GPP at a spatiotemporal resolution of 0.05°-8 days, covering the period from 1992 to 2020. This model applies recent data inputs such as the GLOBMAP LAI, CRUJRA meteorological data, and ESA-CCI land cover information (Bi et al., 2022). Global, Orbiting Carbon Observatory-2 SIF-based (GOSIF) GPP spans from 2000 to 2020 with 0.05°-8 days resolution. A total of eight SIF-GPP relationships including both universal and biome-specific formulations were used to estimate GPP from SIF on a per-pixel basis. These relationships were examined with and without intercept terms to account for the uncertainty in converting SIF into the GPP estimates (Li and Xiao, 2019).

2.1.2 Layer-wise soil moisture and meteorological data

Given the recent availability of state-of-the-art gridded SM in China released by Li, Q. et al. (2022), CSM can now be investigated in the context of the SM state. The data comprises gridded datasets reaching 100 cm soil depth with 10 cm intervals at 1 km-daily resolution during 2000–2020. The robust random forest machine learning technique was used to train the predictors of ERA5-Land time series, leaf area index (LAI), land cover type, topography, and soil attributes using in situ observations from 1789 stations throughout China. Based on the findings of Li, Q. et al. (2022), the product demonstrates notable benefits over both the ERA5-Land and SMAP-L4 datasets, especially in terms of a superior quality level compared to the SoMo.ml dataset at soil depths of 10, 20, 80, and 100 cm. Thus, this study utilized SM at these layers.

Yang et al. (2010) and He et al. (2020) put forth a comprehensive dataset for Chinese regional surface meteorological forcing. This dataset encompasses air temperature, air pressure, specific humidity, wind speed, downward shortwave radiation, downward longwave radiation, and precipitation. It is presented in the NetCDF format with a spatiotemporal resolution of 0.1°-3 hours during 1979–2018. The primary data sources include international Princeton reanalysis data, GLDAS data, GEWEX-SRB radiation data, TRMM precipitation data, and meteorological from the China Meteorological Administration. Data quality control techniques include the elimination of physically implausible values and statistical interpolation using ANU-Spline. In addition, this dataset demonstrates precision levels that lie between those of site-based observation and satellite-based estimation, therefore exceeding the accuracy of current international reanalysis datasets. In this study, specific humidity and air temperature were used to compute VPD, while precipitation and downward shortwave radiation were employed in the examination of water and energy limitations.

2.1.3 Land cover types, soil textures, and Water resource regionalization

Land cover types (2020) were created by human visual interpretation relying on Landsat satellite remote sensing images. It utilized a categorization scheme including cropland, forests, grassland, water bodies, urban, and barren. Soil textures were compiled from the 1:1,000,000 soil type map and the second national soil survey. It is expressed as sand, silt, and clay content within each grid cell to accurately depict distinct textures.

To conduct a thorough examination of regional CSM, 15 sub-regions divided by the China Geological Survey were applied, including Zhungaer Basin, Pearl River Basin, Yangtze River Basin, Southwestern River Basin, Tarim Basin, Songhua River Basin, Changthang Region, Inner Mongolian Plateau Region, Liaohe River Basin, Yellow River Basin, Huaihe River Basin, Hexi Corridor Region, Haihe River Basin, Southeastern River Basin, and Qaidam Basin. The regionalization of water resources is based on the principles of groundwater systems and water cycles. The suggested concepts for subregions are focused on the inherent features of groundwater resources within distinct natural units.”

Below is the revised data availability:

“Data availability

National Tibetan Plateau Data Center (TPDC) offers eight flux sites, consisting of four locations inside the Hexi Corridor Region (Huazhaizi, Dashalong, Luodi, and Arou) and four cropland sites within the Haihe River Basin (Guantao, Huailai, Miyun, and Daxing) with half-hour records (http://data.tpdc.ac.cn/). ChinaFlux offers data from Damshung, Xilingela, Xishuangbanna, Dinghushan, Qianyanzhou, Changbaishan, Yucheng, Haibei1, and Haibei2 flux sites (http://www.chinaflux.org/). Fluxnet includes four grassland sites, CN-Sw2, CN-Du2, CN-Du3, and CN-Cng with daily records, which are available at https://fluxnet.org/data/download-data/. PML provides ET and GPP on TPDC website. GLASS ET and GPP are provided by http://glass.umd.edu/. CAMELE ET is available at Zenodo: https://zenodo.org/record/6283239. SEBAL ET is publicly accessible from the Zenodo repository at https://doi.org/10.5281/zenodo.4243988 and https://doi.org/10.5281/zenodo.4896147. TL GPP is available at https://doi.org/10.5061/dryad.dfn2z352k. GOSIF GPP is obtained from https://globalecology.unh.edu/.Gridded soil moisture and meteorological data is available in TPDC. Land cover types and soil textures were contributed by Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (http://www.resdc.cn).”

2. The manuscript uses **too many abbreviations** from various categories (region name, physical variable, mathematical methods, etc), making it difficult to read. Consider retaining full names for less frequently used terms to improve clarity.

Response: Thanks for your suggestion. In the revision, we have substantially reduced the usage of abbreviations. We chose to retain the abbreviations of the eight satellite-based products, six main variables (ET, GPP, VPD, SM, EF, and CorrVPD), and site names. Acronyms for temperature and radiation in the relevant Correlation-difference method were deleted. Thus, we only kept CorrVPD = Corr(ET,VPD) - Corr(ET,SM). In addition, the full names of land cover types and sub-basins were used and the occurrence of land cover types and sub-basins was also reduced.

3. The evaluation of satellite-based ET and GPP products against flux tower data (Section 3.1) is valuable. However, **more discussion (section 4) of the implications of biases** in these products for the CSM analysis would strengthen the paper.

Response: Thanks for your suggestion. We have added the discussion of the implications of biases in the products in Section 4 as follows:

Lines 378–382: “ET and GPP exhibited great uncertainties (Liu et al., 2021) in areas with barren land as indicated in Section 3.1. Thus, eight satellite-based SM regimes were in good agreement in the eastern and southern regions (Figure 4) where satellite-based methods were more reliable. Secondly, since the CAMELE ET combined PML ET, they showed consistency in cropland and forests with a lower CSM than GLASS and SEBAL (Section 3.3).”

4. The comparison of CSM detection methods at flux tower sites (Section 3.2) is an important component. The authors could consider adding **a quantitative metric of agreement** between methods and also a statistical test to assess the **significance of the agreement** to supplement the qualitative comparisons.

Response: Thanks for the suggestion. We introduced the agreement and chi-square test to test the difference and significance between the models, and modified the text as follows:

Lines 279–281: “The number of wet binary bit was used to quantify the agreement among eight ET and GPP-based models at 10 cm soil depth. If CSM was identified, the SM wetter-than-CSM was assigned as 1, and others as 0. If CSM was not identified within a year, the digits of the mode were treated as 0. If CSM was not detected for all 18 years, it was displayed as empty.”

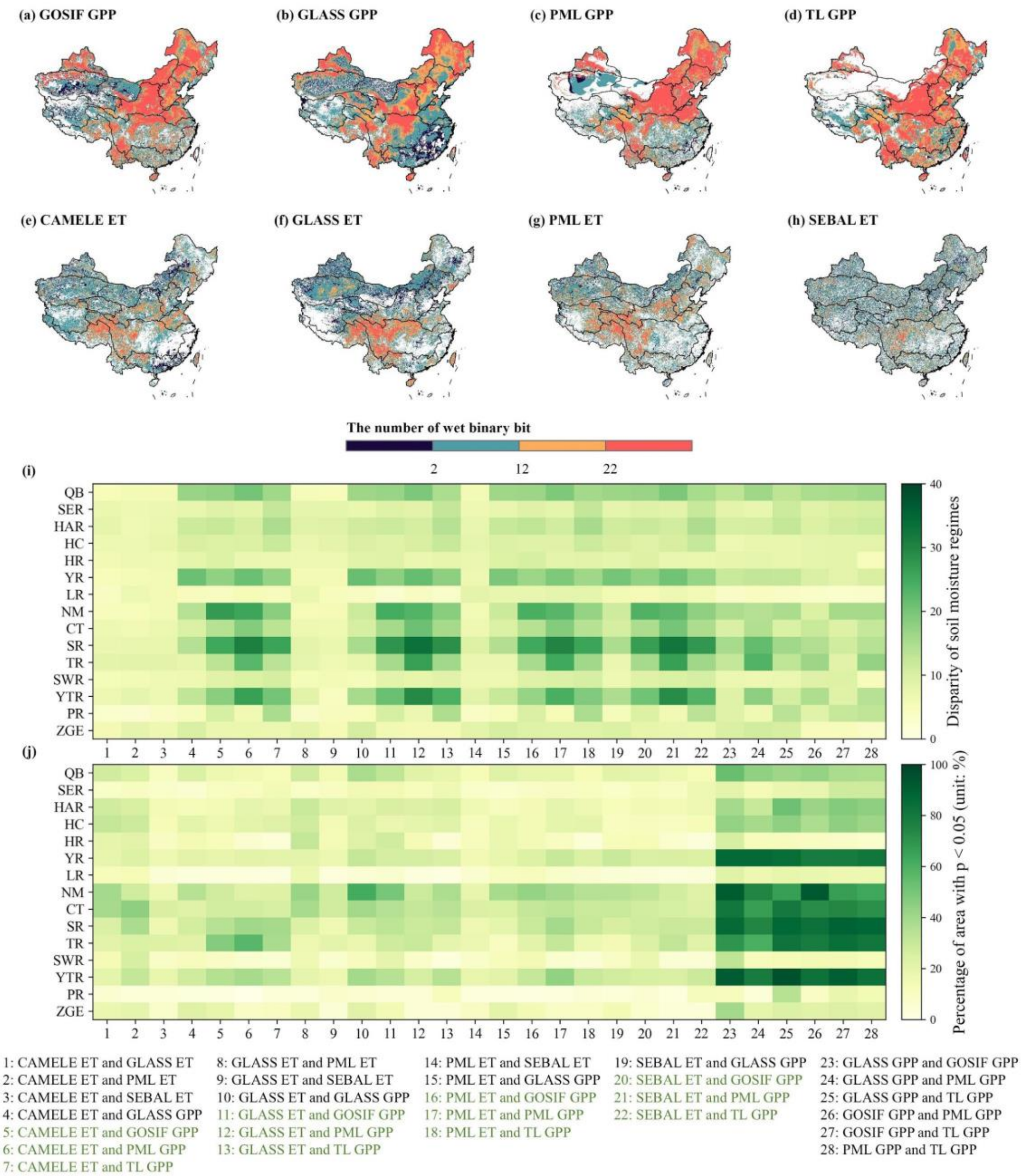

Figure 4: Spatial pattern of number of wet binary bit at 10 cm depth using covariance between vapor pressure deficit (VPD) and gross primary production (GPP) from (a) GOSIF, (b) GLASS, (c) PML, (d) TL. CSM using correlation-difference metric with Kendall's rank correlation (Corr) between detrended anomaly soil moisture (SM) and evapotranspiration (ET) from (e) CAMELE, (f) GLASS, (g) PML, and (h) SEBAL and Corr between detrended anomaly VPD and those ET products. (i) Disparity of soil moisture regimes among all the methods and (i) their percentage of area with p < 0.05. ZGE: Zhungaer Basin, PR: Pearl River Basin, YTR: Yangtze River Basin, SWR: Southwestern River Basin, TR: Tarim Basin, SR: Songhua River Basin, CT: Changthang Region, NM: Inner Mongolian Plateau Region, LR: Liaohe River Basin, YR: Yellow River Basin, HR: Huaihe River Basin, HC: Hexi Corridor Region, HAR: Haihe River Basin, SER: Southeastern River Basin, QB: Qaidam Basin.

5. The high level of alignment in CSM estimates among different ET products and soil moisture layers is surprising given the potential variability in these datasets.

Additional analysis or explanation is needed to **justify this consistency** and **discuss potential uncertainties**.

Response: Thanks for the question. This alignment comes from two reasons:

(1) the first is that we have done an average for each tipping point in each year and treated it as a critical value, which will reduce the difference between different products. In the revised version, we consider that only one tipping point in each year is the critical value. We added the constraints in Method "2.2

Determination of CSM”:

Lines 163–165: “For each grid cell and the entire period, negative metrics were displayed when SM was less than CSM, and positive metrics were shown when SM was greater than CSM. If there was more than one value where SM shifts between positive and negative metrics, CSM was treated as unidentified.”

In the response to question 3, we can see that in the process of SM from low to high, if there are multiple times that metrics (Cov and CorrVPD) change from negative to positive, it means that this CSM does not conform to the change process of water stress to energy stress caused by SM from low to high.

We can see that the critical values obtained for the eight products in Figure 5 also show varying undetected areas.

(2) then, the spatial variation in the study area is too great, and the CSM and SM in spatial and depth are represented by a gradual color, resulting in the depth difference is not obvious compared to the spatial difference. The color of the previous drawing can only reflect the difference in space, not the difference in depth. Therefore, we averaged the CSM and SM by land cover and soil texture, highlighting differences in SM and CSM at different depths for each type.

After the constraint was added in question 3, we modified the code, redrawn Figure 5 and added the error bars, and redrawn Figure 6.

We improved the representation of Figure 6 to make the differences between the different depths more noticeable and changed the corresponding description as follows.

Lines 300–310: “Furthermore, large-scale CSM varied across vegetation types and soil textures at four soil layers (Figure 6). With shorter root systems and less vegetation (i.e., barren), areas with low CSM were water-limited. Forested regions displayed a relatively high CSM (e.g., 0.18 m3/m3 using PML ET and 10 cm depth SM). As for the soil types, sand covering the large area was further part into content of less than 60%, 60–70%, 70–80%, 80–90%, and higher than 90%. Soils with a majority of clay had a wetter CSM than others (e.g., 0.38 m3/m3 using PML ET and 10 cm depth SM) and was to be expected given that clay had a larger negative matric potential compared to coarse soil textures dominated by sand and silt. In summary, fine soils and luxuriant vegetation had wetter CSM. Additionally, a layer-wise CSM analysis was conducted to highlight variations in SM properties for different soil layers. It was evident that there were variations in the CSM behavior across layers with higher SM and CSM at 20 cm soil depth than at other depths. We also found that there was higher CSM than SM at all four layers for grassland and clay, which identified a large range of SM within the water-limited regimes. However, for cropland and forests, differences existed in the CSM among four ET-based methods, with higher CSM from GLASS and SEBAL than others.”

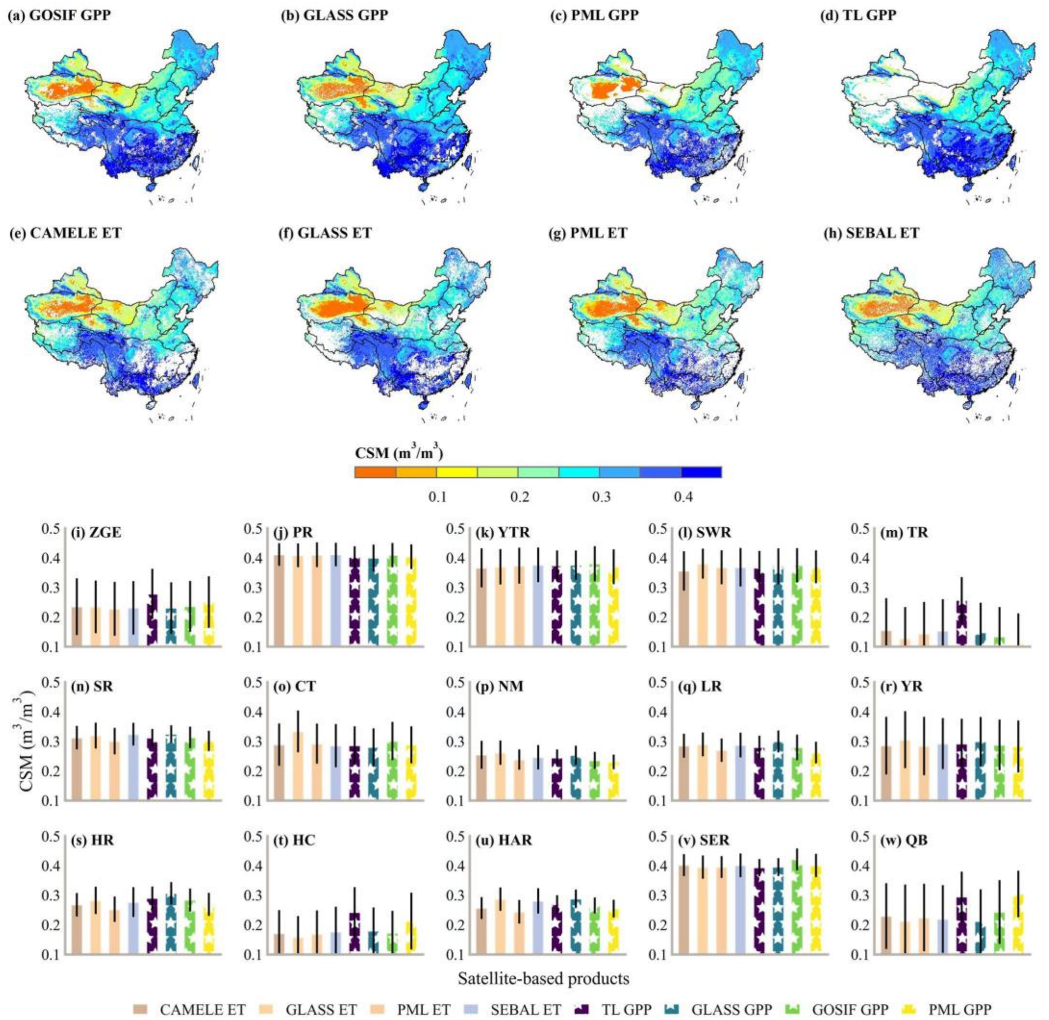

Figure 5: The spatial pattern of critical soil moisture (CSM) at 10 cm depth using covariance between vapor pressure deficit (VPD) and gross primary production (GPP) from (a) GOSIF, (b) GLASS, (c) PML, (d) TL and CSM using correlation-difference metric with Kendall's rank correlation (Corr) between detrended anomaly soil moisture (SM) and evapotranspiration (ET) from (e) CAMELE, (f) GLASS, (g) PML, and (h) SEBAL and Corr between detrended anomaly VPD and ET. (i–w) the basin-average values of ZGE: Zhungaer Basin, PR: Pearl River Basin, YTR: Yangtze River Basin, SWR: Southwestern River Basin, TR: Tarim Basin, SR: Songhua River Basin, CT: Changthang Region, NM: Inner Mongolian Plateau Region, LR: Liaohe River Basin, YR: Yellow River Basin, HR: Huaihe River Basin, HC: Hexi Corridor Region, HAR: Haihe River Basin, SER: Southeastern River Basin, QB: Qaidam Basin.

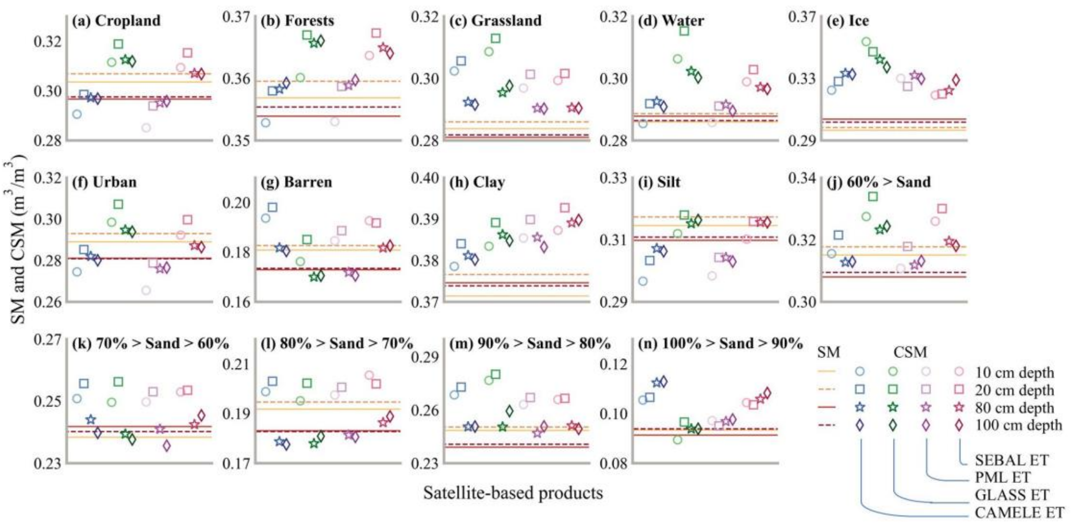

Figure 6: Soil moisture (SM) at (a) 10 cm, (b) 20 cm, (c) 80 cm, and (d) 100 cm soil depths across China, and critical soil moisture (CSM) derived from CAMELE, GLASS, PML, and SEBAL ET and SM at corresponding soil depths for (a) cropland, (b) forests, (c) grassland, (d) water, (e) ice, (f) urban, (g) barren, soils with a majority of (h) clay, (i) silt, and sand with content (j) less than 60, (k) between 60% and 70%, (l) between 70% and 80%, (m) between 80% and 90%, and (n) higher than 90%.

6. Moreover, the consistency in CSM values across different soil depths raises questions about the reliability of deeper soil moisture data. Consider providing additional analysis of deep soil moisture to showcase **the possible difference** between the soil layers and discussing **the uncertainties** associated with these measurements.

Response: According to the previous version, the results were too consistent, and additional analysis was required to demonstrate the differences between the different depths. However, according to our latest version, the differences in different depths have been shown by land cover types and soil textures as shown in Figure 6 in question 5. Therefore, instead of providing additional analysis, we have modified the original representation as shown in Figure 6.

Because this SM dataset is based on site observation data, the uncertainty of SM comes from the spatial interpolation, and the interpolation factors affecting different depths are different. Here we add a description to the Section Discussion:

We discussed the uncertainty of four soil layers in Discussion:

Lines 383–385: For gridded SM, surface climate shows a significant effect on the upper soil layer SM modeling, while the background aridity could lead to low variability of the deeper layer SM (Li, Q. et al., 2022)."

7. The attribution analysis of water/energy limit shifts (Section 3.4) provides valuable insights. The authors could consider **expanding on the implications of these findings** for water resource management or ecosystem responses to climate change, perhaps in discussions part.

Response: Thanks for your suggestion. We have added the implications of these findings for water resource management or ecosystem in Section 4 as follows:

Lines 416–420: "It should be noted that the South-to-North Water Diversion Project and the Pinglu Canal Project in China would result in significant modifications to SM characteristics, which are fundamental components of the concept known as CSM. These water management measures may reduce water stress in grasslands affected by climate change and make southern coastal clay areas more resistant to possible disturbances. Thus, our research could inform the large-scale water conservancy projects for better conservation and allocation of water supply resources."

8. The discussion section effectively contextualizes the results within existing literature. However, it could be **strengthened by more explicitly addressing the limitations of the approach** used in this manuscript and potential future research directions.

Response: Thanks for your suggestion. We have added the limitations and potential opportunities in Section 4 as follows:

We added the limitations:

Lines 409–413: "This study focusing on a specific time of year may not be enough to explain the critical value that may be shown in the rest of the year. Since CSM values in some grids were not detected by eight products, further research is needed for the CSM that may appear in the rest of the year in different regions. In addition, to compare the performance of multi-source remotely sensed water and carbon fluxes, we unified all data into the 8-day resolution. Therefore, a more refined time scale, such as a one-day scale study, is also needed."

We added the potential opportunities:

Lines 420–422: "Future research directions could include the impact of hydraulic projects such as inter-basin water diversion on CSM, the impact of extreme disturbances such as tropical cyclones and wildfires on CSM, and possible changes in CSM."

Some textual suggestions:

1. Line 10: "suffer from water limitation", this kind of metaphor is not suitable I assume, please change it to some words that are not for humans.

Response: We have changed this sentence from to "Critical soil moisture (CSM), a tipping point of soil moisture (SM) at which surface fluxes shift from energy- to water-limited regimes, is essential for the vegetation state and corresponding land-atmosphere coupling".

2. Line 14: Put "were assessed over China" before "derived" in the sentence to let the colon directly connecting the following methods.

Response: We have changed this sentence as suggested.

3. Line 24: Maybe change the sentence to "Through intercomparison, CSM from multi-source ET and GPP datasets across China is found to be consistent and robust."

Response: We have changed this sentence as suggested.

4. Line 34: Please don't repeat sentences in your manuscript, this one is the same with that in your abstract, please revise either of them.

Response: We have changed this sentence to "Critical soil moisture (CSM) serves as an indicator of shifts in the relationship between water and energy availability (Schwingshackl et al., 2017; Denissen et al., 2020) and is essential in shaping regional climates".

5. Line 44: "customary" and "matric", change them to some others relatively commonly used.

Response: We have changed this sentence to "Diagnosing CSM across various biomes and climatic zones helps to understand water-energy limit regimes determined by distinct flora, soil types, and meteorological elements (Homaee et al., 2002; Hsu and Dirmeyer, 2023a)".

6. Line 98: "comparability" is not common in papers. Some noun forms of words are not common to be used even in academic world. Please consider adjective forms and revise the relevant sentence or use other nouns. These are just what I roughly found, please read the text thoroughly after revision and also consider a text revision service.

Response: We have deleted this sentence and made corrections to the whole text.

7. Figure 1: Consider changing the colors of forest and grassland to make them easier to differentiate as the landcovers you have are not so many

Response: We have changed the colors to make it easier to differentiate forest from grassland. Below is the revised figure:

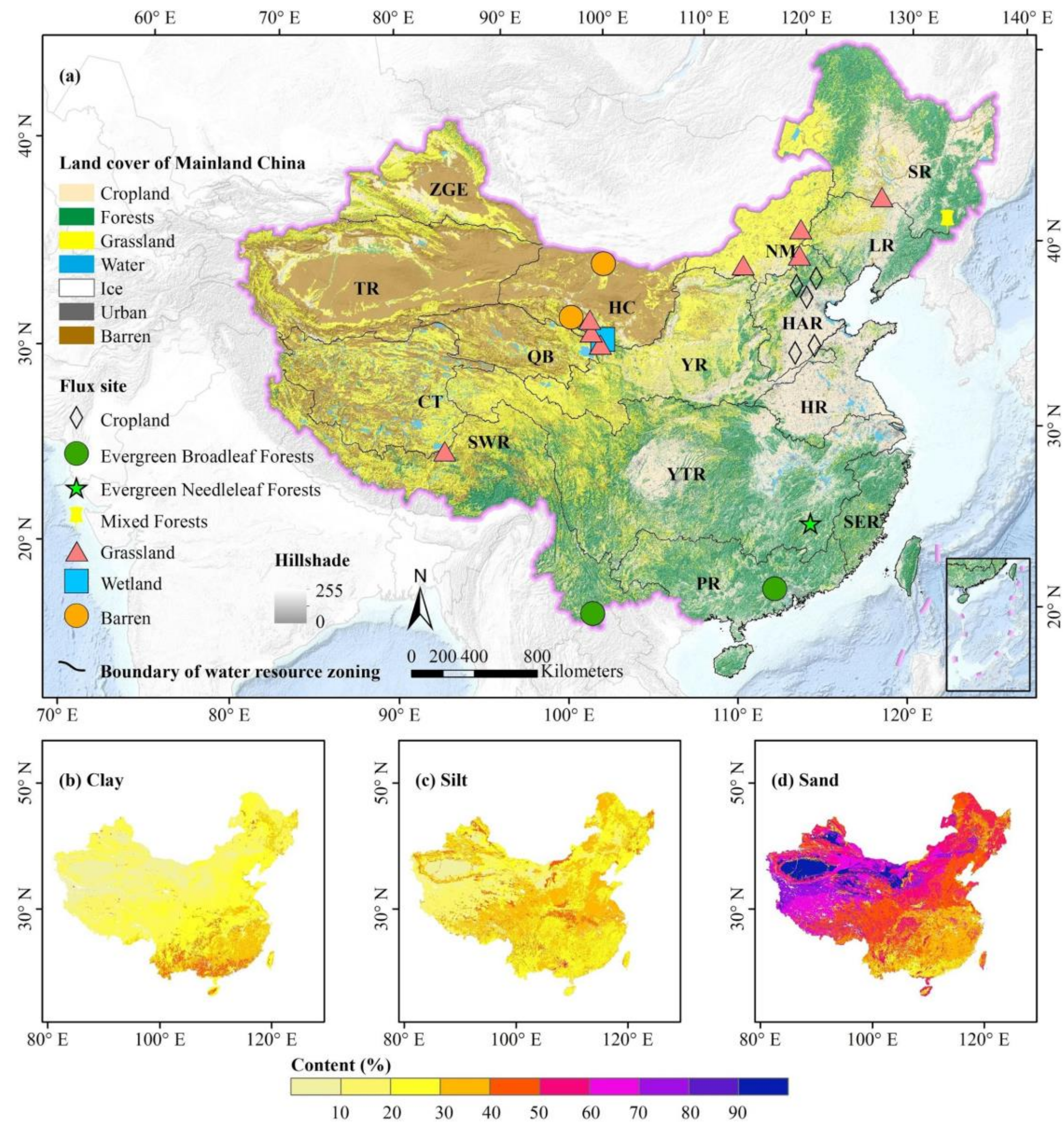

Figure 1: (a) Locations of the flux sites, land cover types (2020), and fifteen water resource subregions of China. Distributions of (b) clay, (c) silt, and (d) sand content (1995). ZGE: Zhungaer Basin, PR: Pearl River Basin, YTR: Yangtze River Basin, SWR: Southwestern River Basin, TR: Tarim Basin, SR: Songhua River Basin, CT: Changthang Region, NM: Inner Mongolian Plateau Region, LR: Liaohe River Basin, YR: Yellow River Basin, HR: Huaihe River Basin, HC: Hexi Corridor Region, HAR: Haihe River Basin, SER: Southeastern River Basin, QB: Qaidam Basin.

8. Figure 5: Consider making it into two columns

Response: Thanks for your suggestion. We have changed the Figure 5 to:

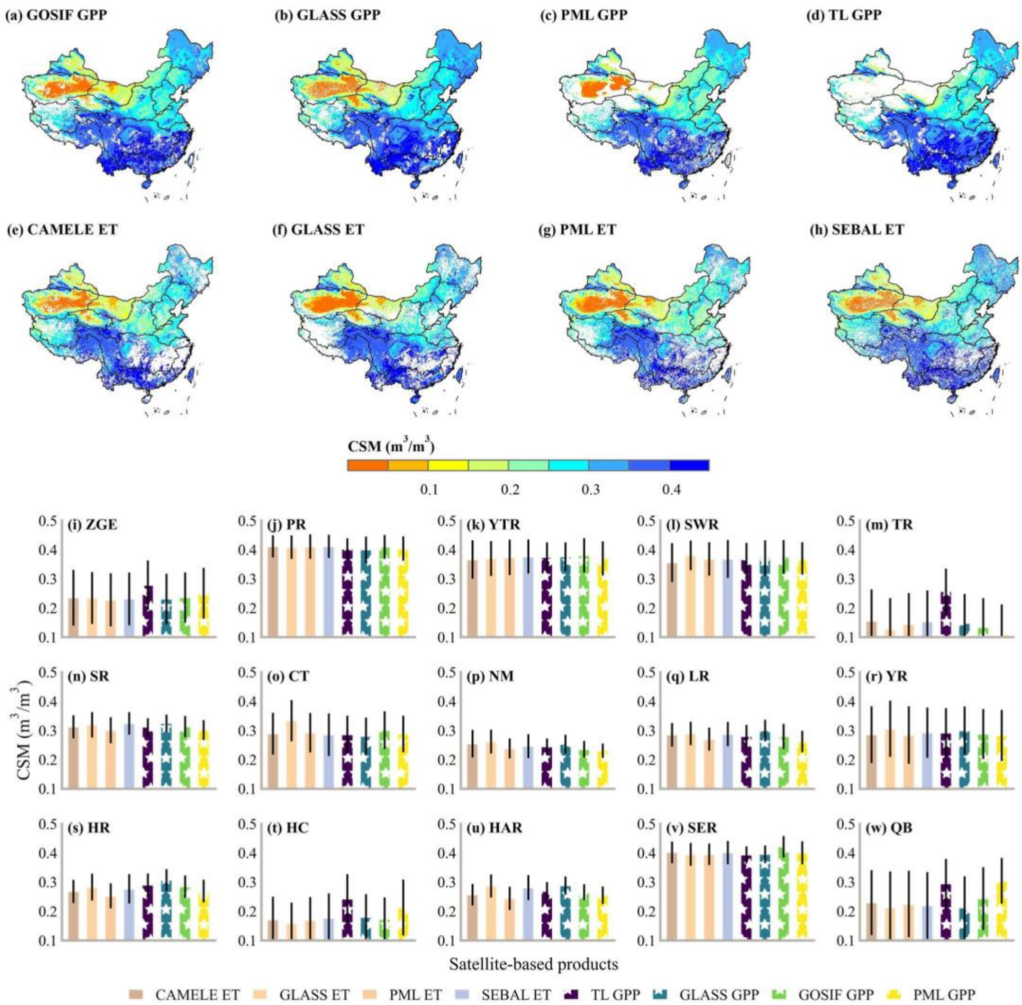

Figure 5: The spatial pattern of critical soil moisture (CSM) at 10 cm depth using covariance between vapor pressure deficit (VPD) and gross primary production (GPP) from (a) GOSIF, (b) GLASS, (c) PML, (d) TL and CSM using correlation-difference metric with Kendall's rank correlation (Corr) between detrended anomaly soil moisture (SM) and evapotranspiration (ET) from (e) CAMELE, (f) GLASS, (g) PML, and (h) SEBAL and Corr between detrended anomaly VPD and those ET products. And (i–w) the basin-average values of ZGE: Zhungaer Basin, PR: Pearl River Basin, YTR: Yangtze River Basin, SWR: Southwestern River Basin, TR: Tarim Basin, SR: Songhua River Basin, CT: Changthang Region, NM: Inner Mongolian Plateau Region, LR: Liaohe River Basin, YR: Yellow River Basin, HR: Huaihe River Basin, HC: Hexi Corridor Region, HAR: Haihe River Basin, SER: Southeastern River Basin, QB: Qaidam Basin.

9. Figures 3 and 4: consider use noun as the subject in the titles rather than using verbs

Response: Thanks for your suggestion. We have changed the titles to

"Figure 3: Variations of soil moisture and evaporative fraction at (a) Xilingela in 2004, (c) Damshung in 2004, (e) CN-Sw2 in 2011, (g) CN-Du2 in 2007, (i) CN-Cng in 2010, (k) Miyun in 2009, (m) Huailai in 2015, (o) Qianyanzhou in 2010. Variations of covariance (referred to as Cov) between vapor pressure deficit and gross primary production, and correlation-difference metric (referred to as CorrVPD) at (b) Xilingela in 2004, (d) Damshung in 2004, (f) CN-Sw2 in 2011, (h) CN-Du2 in 2007, (j) CN-Cng in 2010, (l) Miyun in 2009, (n) Huailai in 2015, (p) Qianyanzhou in 2010."

and "Figure 4: Spatial pattern of number of wet binary bit at 10 cm depth using covariance between vapor pressure deficit (VPD) and gross primary production (GPP) from (a) GOSIF, (b) GLASS, (c) PML, (d) TL. CSM using correlation-difference metric with Kendall's rank correlation (Corr) between detrended anomaly soil moisture (SM) and evapotranspiration (ET) from (e) CAMELE, (f) GLASS, (g) PML, and (h) SEBAL and Corr between detrended anomaly VPD and ET. (i) Disparity of soil moisture regimes among all the methods and (i) their percentage of area with $p < 0.05$. ZGE: Zhungaer Basin, PR: Pearl River Basin, YTR: Yangtze River Basin, SWR: Southwestern River Basin, TR: Tarim Basin, SR: Songhua River Basin, CT: Changthang Region, NM: Inner Mongolian Plateau Region, LR: Liaohe River

Basin, YR: Yellow River Basin, HR: Huaihe River Basin, HC: Hexi Corridor Region, HAR: Haihe River Basin, SER: Southeastern River Basin, QB: Qaidam Basin."

10. Line 199: "9-day moving windows"?

Response: We have changed the sentence to "we concentrated on the warm season, June–September over the period 2001–2018, including 16 data each year with eight covariance values within 9 values moving windows".