Responses to RC #2:

In this paper, the authors developed satellite-based high spatial resolution soil moisture data and applied it to drought analysis in China. They show better accuracy of their newly developed monthly soil moisture estimation than previous global products. In addition, they reveal the long-term trend of soil moisture in China.The topic of this paper is suitable for HESS. However, I believe that this paper does not show enough novelty to be published. I do not recommend this paper for publication. First, it is unclear to me if there is anything methodologically new in this paper. Although their method was carefully designed and their evaluation results look sound, the authors basically rely on the widely adopted triangle relationship between vegetation dynamics and temperature. I think their method is not intrinsically new, and their advantage is that they focus only on data in China to train their model and outperform the existing global estimates in China, which may not be recognized as a novel contribution from potential HESS readers.

Reply: We sincerely thank the reviewer for this insightful and constructive comment. Your guidance has been extremely valuable in improving the quality of our manuscript. We realize that our original presentation may have failed to clearly articulate the novelty of our methodology.

Soil moisture (SM) data are fundamental for agricultural drought identification. However, existing global or continental SM products exhibit limited accuracy over China, making them insufficient for fine-scale drought monitoring. Consequently, very few studies have used SM data to investigate agricultural drought at the national scale across China; most studies are limited to basin or provincial scales. To support the analysis of agricultural drought dynamics across China, we aimed to develop a higher-accuracy, spatiotemporally seamless SM dataset.

Passive microwave SM products, although containing missing values, can provide high-accuracy SM information across China. Therefore, downscaling these products holds promise for obtaining high-spatial-resolution SM data over China. The Temperature Vegetation Dryness Index (TVDI) can effectively characterize the spatiotemporal pattern of SM, and TVDI-based spatial weight decomposition (SWD) models have been widely used for SM downscaling. For example, Meng et al. (2021) published in Earth System Science Data utilized the SWD model to decompose coarse-resolution SM products into 0.05° SM data using TVDI. However, the relationship between TVDI and SM is non-linearly modulated by multiple environmental factors. Using TVDI as the sole predictor for spatial downscaling introduces systematic biases due to the neglect of environmental heterogeneity.

Therefore, in our work, we aimed to learn the relationship between TVDI and SM under varying environmental conditions using machine learning, thereby improving downscaling accuracy while also performing gap-filling to achieve seamless coverage. Considering the heavy workload of producing a long-term dataset, we deliberately chose the random forest algorithm because it is widely known, easy to implement, and offers a low barrier for method transfer. After comparing several algorithms, we selected random forest based on a trade-off between accuracy and runtime. This effort successfully generated a high-accuracy 0.05° seamless SM dataset for China. Using this dataset, we applied the SSI to characterize the spatiotemporal dynamics of agricultural drought.

Following the reviewer's suggestions, we have since performed two algorithm optimization attempts to further improve downscaling accuracy and drought identification precision:

First, to avoid introducing spurious fine-scale artifacts in the downscaling process, we optimized the downscaling algorithm. After the first-stage random forest (RF1) produced an initial 0.05° SM estimate, we aggregated it back to the original coarse resolution, calculated the residual (observed minus aggregated), and trained a second random forest (RF2) using the same environmental predictors to learn the residual. We then designed a fully connected neural network to adaptively fuse the initial RF1 prediction and the residual information to generate the final 0.05° SM product. However, this improvement did not yield a significant accuracy gain, while it substantially increased code runtime and data preprocessing time. This conflicted with our goal of keeping the model easily transferable with a low entry barrier. Since the original model already achieved our objectives, we decided not to adopt this optimization.

Second, to improve drought identification accuracy, we first revised the SSI calculation scheme according to your suggestion by recalculating all SSI values using monthly mean and monthly standard deviation instead of annual statistics. Based on the revised SSI dataset, the coefficient of determination (R^2) between the extracted drought area and observed drought area reached 0.746 (Fig.1 (b)). The observed drought areas used for validation were derived by integrating multiple authoritative data sources, including: (i) government-published crop drought-affected area statistics (from the China Statistical Yearbook and China Flood and Drought Disaster Bulletin), (ii) the China Agricultural Meteorological Disaster Dataset compiled by the China Meteorological Administration (CMA), which contains key fields such as disaster name, occurrence date, intensity, affected area, and damage percentage, derived from agrometeorological dekad/monthly bulletin data submitted by CMA stations since 1991 (with partial data from the National Climate Center's Agrometeorology Office and the National Meteorological Center's 9210 Element Database), and (iii) the daily agricultural drought comprehensive monitoring spatial distribution data from the Open Laboratory of the National Meteorological Center Forecast System. These observed drought areas were constructed as follows. First, we used the daily agricultural drought comprehensive monitoring spatial distribution data as the baseline spatial dataset and validated its accuracy against the CMA Agricultural Meteorological Disaster Dataset. Second, from the validated daily drought distribution data, we extracted annual drought-affected areas at different severity levels. Finally, we cross-compared these extracted areas with the two official statistical sources and integrated them to obtain the final observed drought-affected area used for validation.

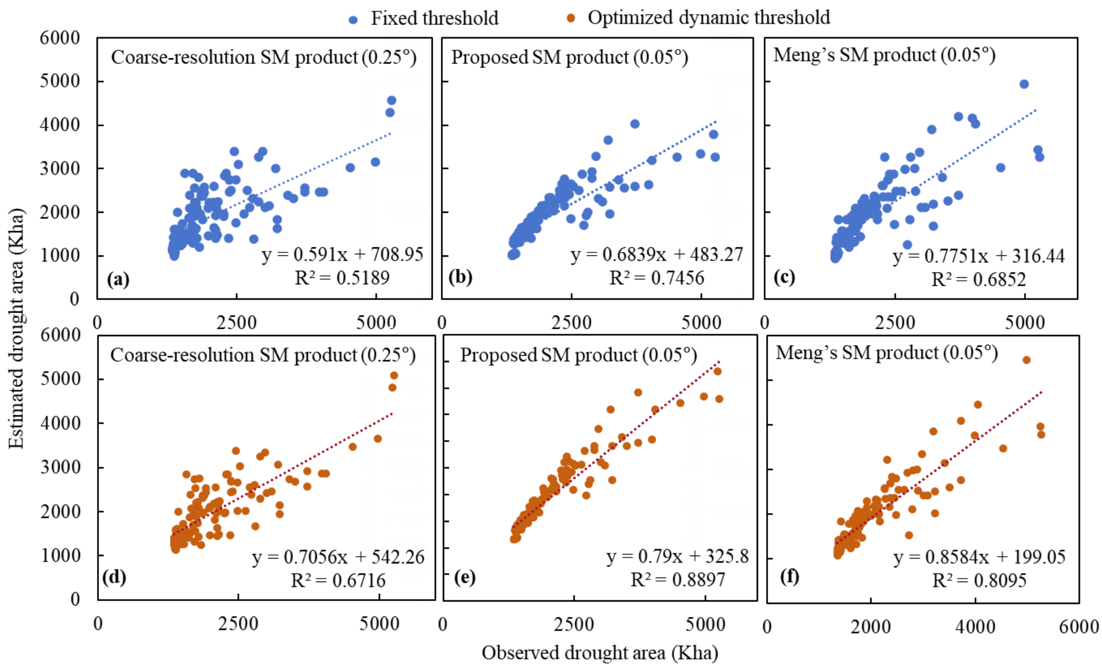

Fig.1 Validation of drought area identification using different SSI thresholds across three soil moisture products with varying resolutions. The top row (a-c) shows results from the fixed threshold SSI method (blue points), and the bottom row (d-f) shows results from the KDE-based optimized dynamic threshold SSI method (orange points). Linear fitting equations and coefficients of determination (R^2) are provided in each subplot.

Furthermore, we optimized the drought thresholding method. In the original manuscript, we used a fixed threshold (SSI < 0) to identify drought. To make the threshold adaptive to region, month, and interannual variability, we developed a dynamic threshold method based on kernel density estimation (KDE) and multi-source historical drought records. Specifically, we first divided China into four climatic zones (arid, semi-arid, sub-humid, humid). For each climatic zone and each calendar month, we extracted all valid SSI values from 2003–2023, removed outliers (values beyond ±3 standard deviations), and applied KDE to obtain a smoothed probability density curve. Using the same three complementary datasets mentioned above, we identified the SSI intervals corresponding to agricultural drought, yielding a set of dynamic thresholds that vary spatially (by climate zone) and temporally (by month). Subsequently, we extracted drought areas using both the original fixed threshold and our newly constructed dynamic threshold across three soil moisture products: the coarse-resolution SM product, the SM dataset proposed in this study, and the SM product developed by Meng et al. (2021). Validation results demonstrate that the proposed dynamic threshold method effectively improved drought identification accuracy across all three datasets (Fig. 1). Quantitatively, compared with the fixed threshold, the dynamic threshold achieved relative improvements in R^2 between estimated and observed drought areas of 23% for the coarse-resolution product, 19% for our proposed product, and 22% for Meng's product.

We have re-identified all drought areas in the revised manuscript using the revised SSI calculation method and optimized dynamic threshold approach, and all corresponding updates have been fully integrated into the revised manuscript. In addition, we have added a dedicated Discussion subsection that elaborates on the gains in drought area identification achieved by improved spatial resolution and accuracy of SM data, as well as the accuracy improvements brought by the optimized dynamic threshold method. Together, these methodological enhancements and the newly developed high-resolution SM dataset provide a more reliable scientific basis for national-scale agricultural drought monitoring in China, clearly demonstrating the necessity and value of our research.

Once again, we deeply appreciate the reviewer's critical and constructive guidance, which has significantly improved our work.

Second, the connection between high resolution soil moisture data and drought analysis is largely unclear. The authors did not take any advantage of their accurate and high-resolution soil moisture data. I believe that their analysis can be performed by conventional soil moisture data. The authors may elaborate more on the advantages of their new data toward the assessment of long-term drought hazards.

Reply: We thank the reviewer for this constructive comment. We agree that conventional soil moisture data (e.g., at 0.25° or coarser resolution) can capture large-scale drought trends and seasonal patterns. However, we would like to clarify that our 0.05° seamless high-resolution dataset offers advantages over coarser-resolution data for agricultural drought assessment.

First, following the reviewer's guidance, we recalculated the monthly SSI using both our 0.05° data and coarser (0.25°) soil moisture data. We then estimated drought-affected areas across different regions of China based on these two datasets and compared the results with observed crop drought-affected areas (Fig.1 (a), (b), (d) and (e)). The comparison shows that the drought-affected areas derived from our high-resolution data are considerably more consistent with the observed statistics than those derived from the coarser data. This demonstrates that higher spatial resolution enables more accurate extraction of drought-affected areas.

Second, we also calculated the SSI and drought-affected areas using a benchmark dataset (e.g., the 0.05° product from Meng et al., 2021) for comparison. Our data achieved higher accuracy in identifying drought-affected areas (Fig.1 (b), (c), (e) and (f)). In addition, the case of May 2009 clearly illustrates this. In Heilongjiang Province, the drought-affected cropland area reached 6.17×10^6 hm^2, accounting for 53% of the province's total farmland, of which 2.49×10^6 hm^2 suffered severe drought. Our data detected that 49.48% of the pixels in Heilongjiang experienced drought in that month, including severe drought. In contrast, Meng's data showed only 32.79% of pixels with mild drought.

Therefore, the soil moisture dataset developed in this study is highly effective for agricultural drought analysis in China. Following the reviewer's suggestion, we have added a dedicated paragraph in the Discussion section to elaborate on these advantages. These revisions will be visible in the revised manuscript. We believe this elaboration clearly justifies the value of our high-resolution dataset for long-term agricultural drought hazard assessment—a capability that cannot be achieved with conventional coarse-resolution data. Again, we appreciate the reviewer's insightful comment, which has helped us better articulate the contribution of our work.

Third, I believe that their computation of SSI has an error. I agree that monthly soil moisture follows Gaussian distribution, so that any transformation is unnecessary. However, their mean and standard deviation should be calculated each month during study period, not using all months in study period. Figure 9 clearly indicates that their SSI has a seasonal cycle, which is not consistent with drought indices conventionally implemented. Seasonally dry periods are not normally called drought. In most cases, drought is evaluated as the deviation (or anomaly) from the average conditions in each month. I do not think their approach is aligned with the previous efforts on drought quantification.

Reply: We sincerely thank the reviewer for this highly insightful comment, which prompted us to thoroughly re-evaluate our SSI calculation methodology and has significantly strengthened the scientific rigor of our drought analysis.

We would like to clarify the rationale behind our initial approach. Our original design was motivated by the unique characteristics of agricultural drought in China, where cross-seasonal persistent droughts—such as winter-spring continuous drought in North China and autumn-winter drought in Southwest China—have become increasingly frequent and destructive in recent decades. We initially used annual-scale means and standard deviations to retain inter-seasonal comparability, aiming to capture the cumulative effects of soil moisture deficits spanning multiple growing seasons. This choice was also partly inspired by some early regional soil moisture drought studies that adopted simplified annual statistics when long-term monthly data were limited.

However, guided by the reviewer's expert feedback, we fully recognize that this approach is methodologically flawed. Therefore, following the reviewer's suggestion, we have recalculated the SSI using month-by-month means and standard deviations (i.e., climatological monthly standardization). Specifically, we now compute the long-term mean and standard deviation independently for each calendar month over the 2003–2023 study period. This approach properly removes the inherent seasonal cycle of soil moisture and ensures that the SSI reflects only anomalous deviations from the expected conditions for that specific month. We have fully recalculated the entire SSI dataset and updated all related results and figures. Based on the revised SSI, R^2 between the extracted drought-affected areas and the observed drought areas reached 0.746 (Fig. 1(b)). Compared with our original SSI calculation method, the agreement with observed areas improved significantly, with the correlation coefficient increasing by 18.7%.

All relevant sections of the manuscript have been thoroughly revised. The core conclusions of our study—regarding the overall drying trend, spatial heterogeneity, migration of drought centers, pyramidal severity distribution, and high drought frequency in ecologically vulnerable regions—remain robust and are now supported by a methodologically sound drought index. We greatly appreciate the reviewer's guidance, which corrected a critical methodological flaw and substantially improved the quality and reliability of our work. All the above revisions have been fully incorporated into the revised manuscript. Since this response is intended solely to address the reviewer's comments, the revised manuscript will be submitted separately in due course.

Specific comments:

Major points:

L149-156: There are several AMSR-based SM products. Which did the authors use? Is it the JAXA standard product? Please refer to the appropriate reference.

Reply: We thank the reviewer for this constructive and detailed guidance. The AMSR-E and AMSR2 soil moisture data used in this study are the standard Level 3 products released by the Japan Aerospace Exploration Agency (JAXA). Specifically, we employed the JAXA AMSR-E L3 soil moisture product for the period 2003–2011, and its successor, the JAXA AMSR2 L3 0.25° soil moisture product, for the period

2012–2023. The 0.25° resolution version of AMSR2 was chosen to maintain spatial consistency with the AMSR-E product. Additionally, the SMOS-IC V105 soil moisture product, used to fill the data gap between AMSR-E and AMSR2, was obtained from the Centre Aval de Traitement des Données SMOS (CATDS). In the revised manuscript, we have explicitly clarified the specific versions and sources of all three satellite soil moisture products and have added the corresponding official references for each product. These revisions have been fully incorporated into the submitted revised manuscript.

L356-362: As I pointed out above, mean and standard deviation are computed using time series of each month in most of the previous works. I do not intend to say that the authors' computation is wrong. But I can say that it largely deviates from previous exercises. The authors need to explain what they intended or fix this error.

Reply: Thanks a lot for pointing this out. As detailed in our response to the third general comment, we fully agree with the reviewer's suggestion and have completely recalculated the SSI dataset following the standard climatological monthly standardization method. Specifically, we now compute the long-term mean and standard deviation independently for each calendar month over the 2003–2023 study period, which properly removes the inherent seasonal cycle of soil moisture and ensures SSI only reflects true drought anomalies. The revised SSI shows a significant improvement in correlation with national agricultural disaster statistics compared to the original version.

Furthermore, we have further optimized the drought threshold determination method to enhance the accuracy of drought area extraction. We replaced the original fixed threshold (SSI < 0) with a spatiotemporal dynamic threshold method based on KDE, calibrated against three complementary authoritative datasets: government-published annual crop drought-affected areas, the daily agricultural drought comprehensive monitoring spatial distribution data and the China Agricultural Meteorological Disaster Dataset from the China Meteorological Administration. This dynamic threshold, which varies by climatic zone and calendar month, has improved the consistency with official drought statistics by an additional 23%.

All sections related to drought analysis in the manuscript, including the SSI calculation method, drought characterization results, and all relevant figures, have been thoroughly revised. The core conclusions of our study remain robust and are now supported by a methodologically sound drought index. We greatly appreciate the reviewer's guidance, which has significantly improved the scientific rigor and reliability of our work.

L422-436: I think the authors would like to refer Figure 6 in this paragraph. Also, I do not think Figure 6 is easy to understand. Why not just show table to report evaluation metrics?

Reply: We thank the reviewer for this constructive suggestion. We agree that a table could also present the evaluation metrics. However, in the initial version of our manuscript, we actually prepared two tables (5 rows × 8 columns) to report the R and ubRMSE values of our downscaled product, the original coarse product, and two benchmark products against in-situ measurements. Because many of these values were very close to each other, we found that readers would struggle to quickly identify the relative performance differences across products and sites using tables alone.

Therefore, we converted the numerical comparison into Figure 6. Its key advantages include visual clustering of similar values: by using a color gradient, values that are numerically close can be grouped visually, allowing readers to immediately see which products perform better or worse without scanning dozens of numbers.

We have improved the readability of Figure 6 in the revised manuscript by enlarging the font, enhancing color contrast, and adding a clear legend.

L443-453: I think the authors elaborate more on evaluating their drought index. The current result is not so convincing that their SSI may not be able to reproduce real drought events. First, as I discussed above, they may design the evaluation activity to feature high spatial resolution of their data, for example, show spatial distribution of drought maps and SSI. Please show that higher resolution data is more useful than previous works. Second, please consider the other indicator of droughts such as (detrended) crop yield to be compared with SSI. Also, clarify what "officially reported crop drought-affected areas" indicate. Are there any solid criteria to identify drought affected areas? I did not understand what the authors exactly compare. Third, I could not agree that yearly SSI was useful to quantify real drought events. The authors may focus more on monthly SSI in growing and/or harvesting seasons.

Reply: We thank the reviewer for these insightful and constructive suggestions. Following the reviewer's guidance, we have recalculated the SSI using month-by-month climatological standardization. The revised SSI during crop growing seasons shows a much higher consistency with the annual drought-affected areas. Moreover, we optimized the drought thresholding method (KDE-based dynamic thresholds), which improved the accuracy of extracted drought-affected areas by 23% compared to the fixed threshold. Regarding the three specific issues you raised, we respond as follows.

For the advantages of high-resolution data in drought monitoring, we have supplemented a comparative analysis of drought identification accuracy between different resolution soil moisture products. As shown in Fig 1 above, R^2 between the drought area extracted by our 0.05° high-resolution product and official statistical data reaches 0.7456, which is significantly higher than 0.5189 for the 0.25° coarse-resolution product. This indicates that high-precision and high-spatial-resolution soil moisture data can effectively reduce errors caused by mixed pixels and more accurately capture small-scale drought hotspots and drought characteristics in fragmented agricultural areas. We have added a dedicated paragraph in the Discussion section of the revised manuscript to elaborate on this advantage in detail.

Regarding the validation indicators of the drought index, we have fully considered your suggestion of crop yield validation. However, it is difficult to obtain accurate detrended yield data at the national scale by region and crop, and the data are significantly interfered by non-drought factors such as pests and diseases and extreme temperatures, making it challenging to isolate the impact of drought on yield alone. Therefore, we optimized the validation scheme and adopted a more accurate drought area, derived by integrating multiple sources of agricultural drought-affected areas including official publications and the Open Laboratory of the National Meteorological Center Forecast System (i.e. the observed drought area described above), as the core validation indicator.

Regarding the selection of time scales, we fully agree with your view that annual average SSI smooths out key drought signals during the growing season and cannot accurately reflect seasonal drought events that have the greatest impact on agricultural production. Therefore, in the revised manuscript, we focus on the monthly scale SSI during the main crop growing season for drought analysis and validation. The results show that the growing-season SSI exhibits a significantly stronger correlation with real drought events than the annual SSI. All the above analyses and revisions have been fully incorporated into the revised manuscript, and we believe these supplementary contents have significantly enhanced the scientific and persuasiveness of our drought index evaluation. We thank the reviewer again for your valuable guidance.

Additional remark:

Lines 758-759 in the revised manuscript: "The authors are grateful to the editor, five reviewers, and one reader for their constructive comments and suggestions on this paper." has been added to Acknowledgments.

Special thanks are extended to you for your valuable comments.

We are doing our best to improve the manuscript and are making substantial changes to address the concerns raised.

We greatly appreciate your help and hope that the revisions will meet with approval once we submit the updated manuscript.

Once again, we would like to extend our sincere gratitude and appreciation for your valuable comments and suggestions.