General Comments:

The authors did a thorough analysis of the future droughts in Monsoon-dominant Asian under the worst-case emission scenario of SSP5-8.5. The analysis of propagation from meteorological to hydrological droughts is new, and the use of bivariate copula function for analyzing drought propagation and spatial concurrence is interesting. I only have a few comments as listed below.

Authors' Response: We thank the reviewer for taking time to review our work and for providing valuable comments to improve the manuscript. We have tried to respond to each of the comments and will incorporate the suggested changes in the revised version. Addressing these comments in the revised version will surely enhance the quality of the manuscript immensely.

Specific comments:

Reviewer Comment #1: Abstract: since the propagation from meteorological drought to agricultural drought is a highlight of this work. It's helpful to indicate in the abstract that meteorological and agriculture droughts are measured using SPI and SSI, respectively.

Authors' Response #1: We agree that indicating the indices of SPI and SSI explicitly in the abstract is necessary and will do so in the revision version.

Reviewer Comment #2: Line 61: I believe there are quite a few studies on drought analysis under climate change. I am not sure whether "only" is the most accurate or appropriate term in this case. Citing these works can help readers better understand the current state of research on this topic.

Authors' Response #2: We regret this oversight. There are indeed some seminal works on the propagation of meteorological to agricultural droughts. We will revise the sentence to clarify that existing drought propagation studies generally do not examine the repercussions of propagation, specifically the persistence and concurrence of agricultural droughts.

Additionally, we will cite the recent seminal works on meteorological to agricultural drought propagation (Dai et al., 2022; Ding et al., 2021; Fawen et al., 2023; Xu et al., 2023). Accordingly, we propose to include the following revised sentence:

"*While several studies have examined the propagation from meteorological to agricultural droughts (Dai et al., 2022; Ding et al., 2021; Fawen et al., 2023; Xu et al., 2023), their repercussions, such as the persistence and cross-regional concurrence of agricultural droughts, are often overlooked.*"

Reviewer Comment #3: Lines 155-160, a common practice in climate impact studies is to use bias correction techniques and correct the biases in GCM output before any further analysis. Do you think this can help reduce the errors in Figure 2c and Fig. S1? How about the difference between observation and GCM output in Fig. S2?

Authors' Response #3: We thank the reviewer for bringing this up. We agree that bias correction can improve the data quality by minimizing errors. However, since this work focuses on drought propagation, it is essential to preserve the interrelationship between precipitation and soil moisture. We refrained from using traditional univariate bias correction techniques, as correcting individual variables (precipitation and soil moisture) could distort the time lags involved in propagation and weaken their correlation.

That said, multivariate bias correction techniques, as explored in recent studies, could be helpful for analyzing future drought propagation (Dieng et al., 2022). These methods preserve the inherent relationships between corrected variables, which is crucial for studying extreme events driven by multiple factors (Zscheischler et al., 2019). For example, Meng et al. (2022) applied multivariate bias correction between precipitation and temperature to analyze compound dry and hot events. Similarly, applying such techniques to precipitation and soil moisture could enhance the study of drought propagation dynamics.

In the revised manuscript, we will explicitly acknowledge the limitation of not employing a multivariate bias correction approach in the current study. Nonetheless, the Multi-Model Ensemble (MME) used here still performs well. In response to the reviewer's suggestion, we will include monthly plots showing the mean difference between GCM data (Multi Model

Mean using Bayesian Model Averaging) and GLDAS (Observed data). We will also incorporate maps comparing drought properties from historical GCM data and GLDAS.

Reviewer Comment #4: Line 245: why is R^2 the only performance metrics for soil moisture prediction? With some R^2 values lower than 0.5 in the results, how to justify the accuracy of the RF model or the reliability of its feature importance results?

Authors' Response #4: We will add a map showing RMSE values to complement the existing R^2-themed maps in validating the random forest (RF) models. These RF models predict time series of soil moisture using temporally varying climatic predictors to understand their influence. A total of 5,364 (1,788 grids x 3 timeframes) RF models were developed, one for each grid across three timeframes. Apart from the climatic variables, other grid-specific predictors such as elevation (Zhang et al., 2024) and climate characteristics (Zhang et al., 2021), which play a crucial role, are not included in these RF models. Since these variables are temporally constant for a given grid, they do not affect the time series prediction. Consequently, at certain grid points with low R^2 values, factors beyond the selected climate variables may influence soil moisture.

Despite low R^2 values in some cases, the variable with the highest feature importance still demonstrates a relatively stronger influence to the other climate predictors. To complement these temporal RF models, which help identify key climatic drivers of soil moisture, spatial RF models will be developed. These will incorporate grid-specific predictors, such as elevation and climate classification, along with aggregated climate variables to predict propagation probability. Please refer to **Author's Response #5** for more details on these spatial RF models.

Reviewer Comment #5: Line 250: The predictors that are important in the RF model, are the ones that are important for the estimation of soil moisture. Are they necessarily the same as the ones that may lead to soil moisture deficit? How could the feature importance results be best interpreted?

Authors' Response #5: We thank the reviewer for the insightful comment. We understand the concern that the important variables identified in the temporal RF models predicting soil moisture do not explicitly relate to soil moisture deficit. To address this, and to complement the grid-specific temporal RF models, we plan to include spatial RF models that directly predict drought propagation probabilities (P(SSI<-0.5|SPI<-0.5)) for each timeframe (three RF models in total). These spatial models aims to address the reviewer's concern by using soil moisture deficit, expressed as a conditional probability, as the predictand. Hu et al. (2024) developed similar spatial RF models to assess the relative importance of variables in drought propagation. In our case, these are considered spatial models because each grid has a single propagation probability value, which forms one row in the training dataset.

The predictors for these models will include elevation, climate zones, and the monthly means of climate variables (i.e. temperature, precipitation, humidity, vegetation cover, solar radiation at 100 m, and wind speed). Since the propagation probability is computed over an entire timeframe, the climate variables are aggregated as monthly means for each timeframe. We intend to retain the results from the temporal RF models, as they complement the spatial models. The spatial RF models capture the influence of stationary predictors (e.g. elevation and climate zone), which the temporal models cannot. Conversely, the temporal RF models (5,364 in total: 1,788 grids x 3 timeframes) capture temporal climatic variations, where each month's data forms a row of training data for a given grid-specific model. These variations must be aggregated in the spatial RF models.

Technical corrections:

Reviewer Comment #6: Line 100: the "+" sign suggests a summation of these variables inside the function, which is not a rigorous expression. Since SM depends on these variables separately, the notation f(T, Pr, H, VC, SR100, W, TS) would be more appropriate.

Authors' Response #6: We thank the reviewer for this comment and agree that it is more appropriate for the RF model to be denoted as SM = f(T, Pr, H, VC, SR, W, TS), instead of using "+" sign. We will incorporate this in the revised version.

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