General Comments:

The authors investigate the impacts of climate change on drought propagation from meteorological to agricultural droughts in monsoon-dominant Asian regions. Understanding drought propagation mechanisms under climate change is crucial, particularly in assessing temporal transitions in drought propagation, persistence, and spatial concurrence.

Authors' Response: First of all, we thank the reviewer for taking time to review our article. The reviewer has raised several valid and pertinent questions, which we have attempted to address. Incorporating these modifications and clarifications in the revised version will greatly improve the manuscript.

While the study addresses an important research gap, several critical issues undermine the validity of the findings:

Reviewer Comment #1: The manuscript does not adequately justify the need to study drought propagation, persistence, and spatial concurrence together. Additionally, the claim that studies on meteorological-to-agricultural drought propagation are lacking is inaccurate, as several previous studies already exist (Ding et al., 2021; Dai et al., 2022; Fawen et al., 2023; Xu et al., 2023). Lastly, since this study also focuses on a regional scale, the authors should explicitly clarify its novel contributions and regional significance.

Authors' Response #1: We appreciate the reviewer for bringing this up and would like to clarify the overall structure and contribution of the work. The first part of the study focuses on understanding the propagation from meteorological to agricultural droughts using temporal lags and propagation strengths. This analysis helps in forecasting impending agricultural droughts, thereby aiding preparedness efforts. After establishing the relationship between precursor meteorological and antecedent agricultural droughts, the subsequent sections on drought persistence and cross-regional concurrence shift the focus to agricultural droughts. This is because soil moisture deficits (i.e., agricultural droughts) directly impact crop and vegetation growth (Modanesi et al., 2020).

Regarding the novel contributions of this study, while most existing works focus on the propagation process, they often do not examine the subsequent persistence and spatial concurrence of agricultural droughts. In contrast, the present study aims to analyse the persistence and spatial concurrence of agricultural droughts (using SSI directly) and explore their potential interrelationship with the initial propagation process. Our work attempts to access these crucial aspects holistically, rather than examining them in isolation.

We apologize for the earlier oversight in stating that studies on meteorological-to-agricultural drought propagation are lacking. We acknowledge that several seminal works do exist on this topic. We will rephrase the relevant sentence to indicate that existing studies primarily focus on the propagation process and tend to overlook its repercussions, namely the persistence and spatial concurrence of agricultural droughts. We will also cite the relevant seminal works on meteorological-to-agricultural drought propagation as mentioned by the reviewer (Dai et al., 2022; Ding et al., 2021; Fawen et al., 2023; Xu et al., 2023).

Reviewer Comment #2: Unclear Monsoon-Based Classification for Drought Persistence: The rationale for categorizing drought persistence into pre-monsoon, monsoon, and post-monsoon periods is not well-explained. It remains unclear whether this classification is tied to SPI-SSI propagation dynamics or solely based on SSI thresholds (e.g., SSI < -0.5). A stronger theoretical or empirical basis for this approach is needed. Justify the focus on monsoonal seasons for drought propagation implications.

Authors' Response #2:

We deeply appreciate the reviewer's concern on the monsoon-based classification, and offer the following justification:

Rationale for categorizing seasons to analyse drought persistence:

Crops are cultivated across multiple seasons throughout the study area, with different stages of crop growth aligning with the pre-monsoon, monsoon, and post-monsoon seasons. Adequate soil moisture during all these periods is critical for crop development. For example, in China, spring crops are typically sown in May and harvested around October, while winter crops like wheat are planted in September and harvested by following June (Li and Lei, 2021). Similarly, in South Asia, different crops are grown in three different phases including Zaid, Kharif, and Rabi, that correspond to the pre-monsoon, monsoon, and post-monsoon seasons, respectively (Joseph and Ghosh, 2023). The pre-monsoon season is particularly important for rain-fed agriculture, especially during early crop planting in May. Soil moisture at the end of the monsoon season (September) aligns with the heading stage of Kharif crops such as rice. Both the pre-monsoon (May) and post-monsoon (December) months also coincide with the initial stages of planting for summer (monsoonal) and winter (Rabi) crops like wheat. While monsoonal droughts are a key focus, given that these months account for the majority of annual rainfall, droughts during the pre- and post-monsoon periods can also severely impact crop growth.

Yang et al. (2021) highlight that soil moisture deficits prior to planting can impair seedling root development, significantly affecting crop yields. Thus, droughts in May (pre-monsoon) that coincide with land preparation and early sowing stages must also be analysed. Moreover, residual soil moisture from the monsoon is crucial for winter crop growth during the post-monsoon season (represented by December soil moisture). Ford and Labosier (2014) define drought persistence as the tendency of drought to continue across seasons. When drought conditions persist across the end of pre-monsoon, monsoon, and post-monsoon periods, the risk of widespread crop failures increases. Prior studies (Fang et al., 2019; Swain et al., 2024) have used bivariate copulas to examine the intra-seasonal drought between dry and wet seasons. In this study, we extend this approach using a trivariate copula (with SSI values from the end months of the pre-monsoon, monsoon, and post-monsoon seasons) to better understand drought persistence across the key agricultural seasons in the region.

Drought persistence in this study is calculated directly using a soil moisture-based index (SSI at a monthly timescale), which reflects agricultural droughts. It is not derived from SPI values (meteorological droughts) or drought propagation probability (defined by Conditional Probability, CP). However, as shown in Fig. 10, there is a strong linear relationship between drought persistence (defined by Joint Probability, JP) and drought propagation (CP). In Fig. 10, changes in CP values between future and historical timeframes were compared with the corresponding JP values across all grids using scatterplots and thematic maps. This highlights regions with high drought persistence. The strong correlation (approximately 0.85, $p < 0.001$) suggests that grids experiencing accelerated drought propagation are also likely to face persistent droughts across seasons in the future, and vice versa. Further details explaining the rationale for explicitly studying drought persistence and spatial concurrence using SSI values are provided in our next response (**Authors' Response #3**). We kindly refer the reviewer to that section.

Reviewer Comment #3: Ambiguity in Drought Concurrence Analysis: The assessment of spatial drought concurrence relies on SSI thresholds but does not explicitly link to SPI-driven propagation. The authors should clarify whether the observed concurrence reflects independent agricultural droughts or is influenced by meteorological drought propagation.

Authors' Response #3: We thank the reviewer for the observation and will clarify the ambiguity regarding the drought concurrence analysis. As mentioned in earlier responses, the persistence and spatial concurrence of agricultural droughts are not explicitly based on SPI-driven propagation measures in their methodological computation. However, the resulting patterns from both persistence and spatial concurrence analyses are compared with propagation probabilities to understand their influence.

Although SPI-driven propagation values were not directly used in calculating the spatial concurrence of agricultural droughts (only SSI value were considered), several key findings align with those from the propagation analysis. For instance, our results indicate an increase in concurrent cross-regional droughts between South Asia (SAS) and East Asia (EAS) in the far-future timeframe (Fig. 9). In contrast, Southeast Asia (SEA) is projected to experience more non-synchronous (i.e., decreased concurrence) droughts with SAS and EAS in the future compared to the historical period. These findings are consistent with the trends in propagation probabilities: both SAS and EAS show an increase in propagation from meteorological to agricultural droughts in the future (Fig. 4(a)), while SEA shows a decrease in propagation probability in the far-future compared to the historical timeframe. Thus, the results from the propagation and concurrence analyses are in agreement. These consistencies suggest that propagation characteristics (from meteorological to agricultural droughts) play a significant role in shaping the persistence (Fig. 10) and spatial concurrence of subsequent agricultural droughts.

Rationale for using agricultural droughts (SSI) directly to analyse drought persistence and spatial concurrence:

The reviewer's 2nd and 3rd comments raise a common concern about whether the agricultural drought indices used in analysing drought persistence and concurrence are directly influenced by meteorological drought propagation. To address this, we computed the probability of meteorological droughts occurring under the condition of existing agricultural droughts ($P(SPI<0|SSI<-0.5)$) across three timeframes, and compared it with the forward propagation probability (P(SSI<0|SPI<-0.5)) shown in **Fig. R1**. This reverse propagation probability, (P(SPI<0|SSI<-0.5)), reflects the extent to which an agricultural drought is linked to a prior meteorological drought. The density plots show a decline in reverse propagation probability values in both the near- and far-future scenarios relative to the historical period across all regions, with the most significant decrease observed in EAS in the far-future timeframe. This suggests that the number of agricultural drought events not directly attributable to meteorological droughts is expected to rise.

Simultaneously, the forward propagation probability (P(SSI<0|SPI<-0.5)) indicates that meteorological droughts are increasingly driving agricultural droughts in SAS and EAS in the future (Fig. 4). Thus, while meteorological-driven agricultural droughts are projected to increase, so too are those unrelated to rainfall deficits. Random forest models used to predict soil moisture further reveal that temperature becomes the dominant driver of agricultural droughts across more than 50% of the study area in future scenarios, compared to about 25% in the historical period (Fig. 5(c)). This supports the observed increase in non-rainfall-related agricultural droughts. Under the SSP5-8.5 scenario, significant temperature increases are expected towards the end of the century (Qiao et al. 2023). This warming could intensity soil moisture deficits, leading to a shift from meteorological-driven to temperature-driven agricultural droughts. Additionally, above-average rainfall (SPI>0) may occur in the form of short-term, intense storms, which may not adequately replenish soil moisture under higher temperatures, which is a situation exacerbated by climate change. These findings support the methodological decision to use SSI directly to assess drought persistence and concurrence, rather than relying solely on SPI. In EAS, and SAS, although meteorological-driven agricultural droughts are projected to rise in the far-future, they are likely to be more severe due to the increasing influence of temperature, potentially resulting in more frequent compound drought-heatwave events.

We hope these new insights address the methodological concerns raised and justify the direct use of SSI in our analysis. We intend to incorporate these findings in the revised manuscript.

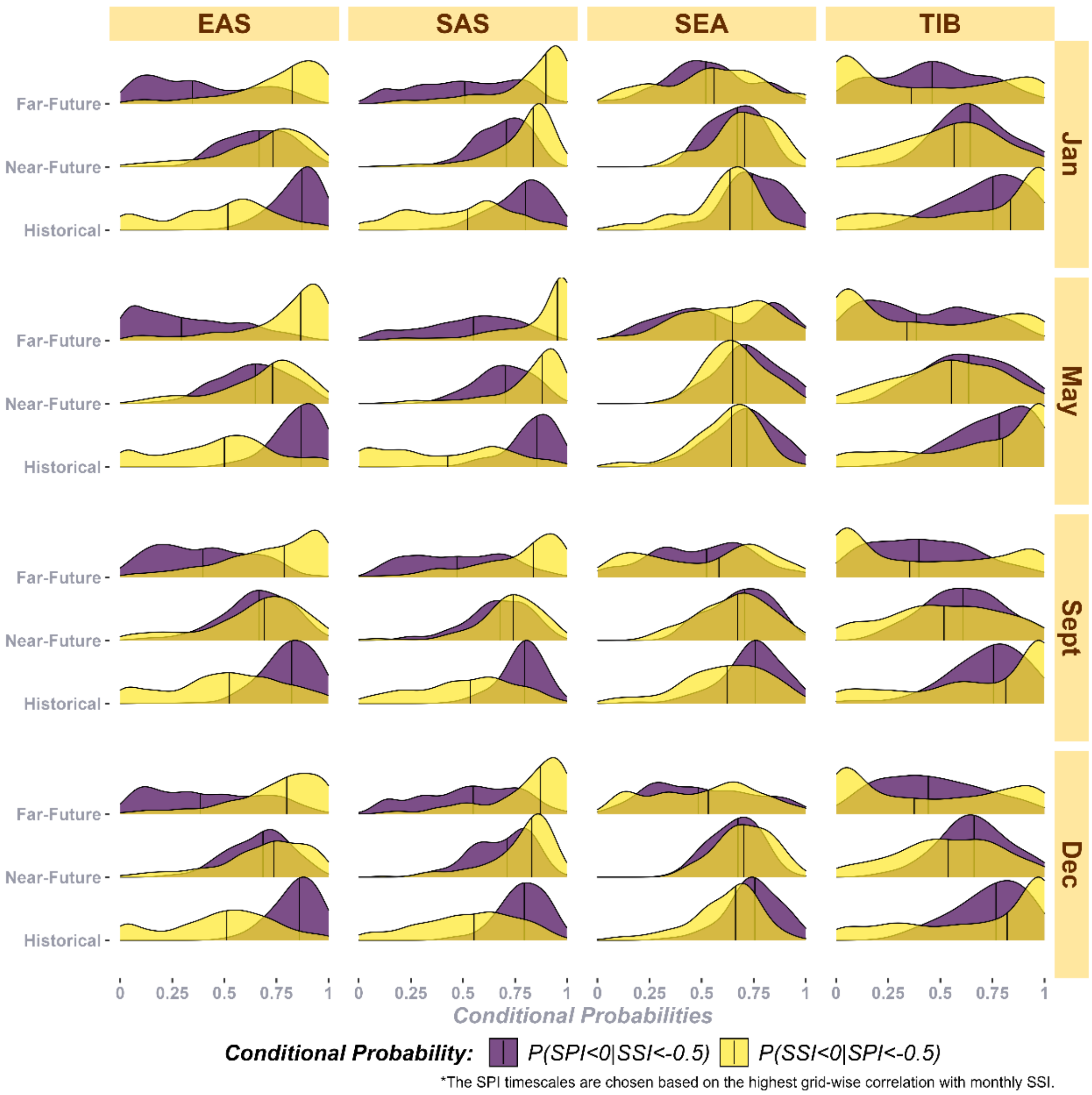

Figure R1. Reverse propagation probability (P(SPI<0|SSI<-.5)) indicates if an agricultural drought is linked to a prior meteorological drought.

Reviewer Comment #4: L93: Random Forest Model Design: The use of soil moisture as the predictand (rather than drought propagation metrics) limits the model's ability to identify key drivers of propagation. Restructuring the model to treat propagation as the predictand (with climatic variables as predictors) would better address the study's primary objective.

Authors' Response #4: 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 drought propagation. To address this, we plan to complement the grid-specific temporal RF models with spatial RF models aimed at directly predicting drought propagation probabilities (P(SSI<-0.5|SPI<-0.5)) for each timeframe (i.e., three separate RF models). These spatial RF models are designed to predict propagation probabilities at each grid, with each grid contributing one training data row per model. The predictors will include elevation, climate zones, and the monthly means of climate variables (i.e., temperature, precipitation, humidity, vegetation cover, solar radiation at 100 m, wind speed, and surface temperature). Since the propagation probabilities are computed over the entire timeframe, the climate variables are aggregated as monthly mean for the respective timeframe in the spatial models.

We intend to retain the temporal RF models as they offer complementary insights. While the spatial RF models account for the influcence of stationary predictors (such as elevation and climate zone), which temporal models cannot, the grid-specific RF models (1,788 grids x 3 timeframes = 5,364 models) can capable of capturing temporal variability, with each month's data contributing a separate row of training data. Moreover, results from the far-future temporal RF models further support the observed shift towards temperature-driven soil moisture droughts, as discussed in **Authors' Response #3**.

Minor comments:

Reviewer Comment #5: L13-L16: " In terms of the return period, all-season droughts that historically occurred once in more than 50 years could happen as frequently as every five years by the far-future (2061-2100) at the hydrologically significant Tibetan Plateau." The statement is confusing. Rephrase for clarity.

Authors' Response #5: We thank the reviewer for the comment and would like to rephrase the statement as follows:

"At the hydrologically significant Tibetan Plateau, all-season droughts that were historically rare (with return periods exceeding 50 years) could occur as frequently as once every 5 years in the far-future period (2061-2100)."

Reviewer Comment #6: L17-L19: "The spatial concurrence of monsoonal agricultural droughts between region pairs such as South Asia (SAS), East Asia (EAS), Southeast Asia

(SEA), and Tibetan region (TIB) was also assessed." Replace methodological descriptions (e.g., region pairs assessed) with concrete findings.

Authors' Response #6: We thank the reviewer for this comment and will replace this statement based on methodology with more appropriate findings in the abstract.

Reviewer Comment #7: L27: Cite specific literature comparing disaster impacts.

Authors' Response #7: We will add appropriate literatures for the specified statement in the revised version.

Reviewer Comment #8: L40-41: "While comparing propagation between basins of different climate zones, Zhang et al. (2021) found arid basin to have lower propagation durations compared to humid and sub-humid basins" Rephrase for clarity.

Authors' Response #8: We thank the reviewer for the suggestion and will rephrase the sentence for improved clarity as follows:

"Climate characteristics are known to influence drought propagation. In this context, Zhang et al. (2021) found that arid basins tend to have shorter propagation durations compared to humid and sub-humid basins."

Reviewer Comment #9: L64-65: "To address the aforementioned gaps, this study proposes a comprehensive copula-based multivariate probabilistic approach, utilizing climate model projection data." Separate the copula method and climate model applications to avoid logical gaps.

Authors' Response #9: We thank the reviewer for the suggestion and will rephrase the sentence for improved clarity as follows:

"To address the aforementioned gaps, this study proposes a comprehensive copula-based multivariate probabilistic framework, which will be applied to climate model projection data."

Reviewer Comment #10: 2.1.1: Describe monthly precipitation, SPI/SSI calculations, and soil moisture datasets.

Authors' Response #10: We thank the reviewer for the comment, and we will include a detailed description of monthly precipitation, SPI/SSI calculations, and soil moisture datasets in section 2.1.1.

Reviewer Comment #11: 2.1.3: Please provide a detailed description of the hyperparameters in the random forest model (e.g., the number of trees, maximum depth), explaining the parameter tuning process to validate the robustness of the model. Furthermore, it is recommended to include other evaluation metrics (e.g., RMSE) to more accurately demonstrate model performance. Please provide the cross-validation of RF models and shows the R2 of different regions.

Authors' Response #11: We appreciate the reviewer's suggestion regarding hyperparameter tuning and performance evaluation of the RF models. Due to the computational intensity involved in training 5364 (1788 grids X 3 timescales), we adopted a fixed set of fixed hyperparameters similar to the ones used by Dai et al. (2022). The hyperparameters are listed as follows:

- ntree = 500 (number of trees)
- mtry = 5 (number of variables tried at each split)
- nodesize = 5 (minimum size of terminal nodes)

In addition to the R^2 value (Fig. 5(a)), RMSE values will be plotted spatially for evaluation.

However, for the spatial RF models to predict drought propagation probabilities with timeframes (3 RF models), extensive grid-based hyperparameter tuning with cross-validation will be performed in the revised version. The three RF models will be evaluated using metrics such as R^2 and RMSE.

Reviewer Comment #12: Fig.2b: Provide citations for the basis of regional divisions, which is crucial to spatial concurrence analysis.

Authors' Response #12: The regional divisions are based on thematic maps from works such as Giorgi and Bi (2009) and Sillmann et al. (2013). The citations will be added appropriately in the revised version.

Reviewer Comment #13: Fig. 2c: Compare GLDAS and GCM-derived SPI monthly drought characteries (not average precipitation) to validate GCM reliability for drought propagation.

Authors' Response #13: We thank the reviewer for the insightful comment. We will prepare thematic maps of cumulative drought severities from GLDAS and GCM data.

Reviewer Comment #14: Datasets: Replace GLDAS precipitation/soil moisture with more reliable datasets (e.g., MSWEP for precipitation, GLEAM for soil moisture).

Authors' Response #14: MSWEP and GLEAM (with MSWEP as the major input) have been commonly used in drought propagation studies to minimize uncertainty arising from disparate data sources (Gupta and Karthikeyan, 2024; Odongo et al., 2023). For a similar reason, ensuring consistency between precipitation and soil moisture data, GLDAS was used in this study. GLDAS datasets are widely employed in drought research and have been shown to effectively capture major historical drought events. For instance, we plotted the percentage of areas affected by meteorological and agricultural droughts using GLDAS data (**Fig. R2**), which clearly reflects significant events such as the 2009 drought (Barriopedro et al., 2012).

Additionally, Gupta and Karthikeyan (2024) reported good agreement in meteorological drought characteristics across MSWEP, CHIRPS, and GLDAS, supporting the reliability of GLDAS. While MSWEP and GLEAM are excellent datasets for drought propagation studies, existing literature suggests that the GLDAS performs comparably well. Furthermore, the three timeframes used in the study, historical (1975-2014), near-future (2021-2060, and far-future (2061-2100), were selected to ensure equal-length epochs of 40 years for consistent comparison of drought propagation, persistence, and spatial concurrence. However, MSWEP and GLEAM begin only in 1979 and 1980, respectively, making them unsuitable for this time range. Given these these considerations, we believe GLDAS is an appropriate choice for the present study.

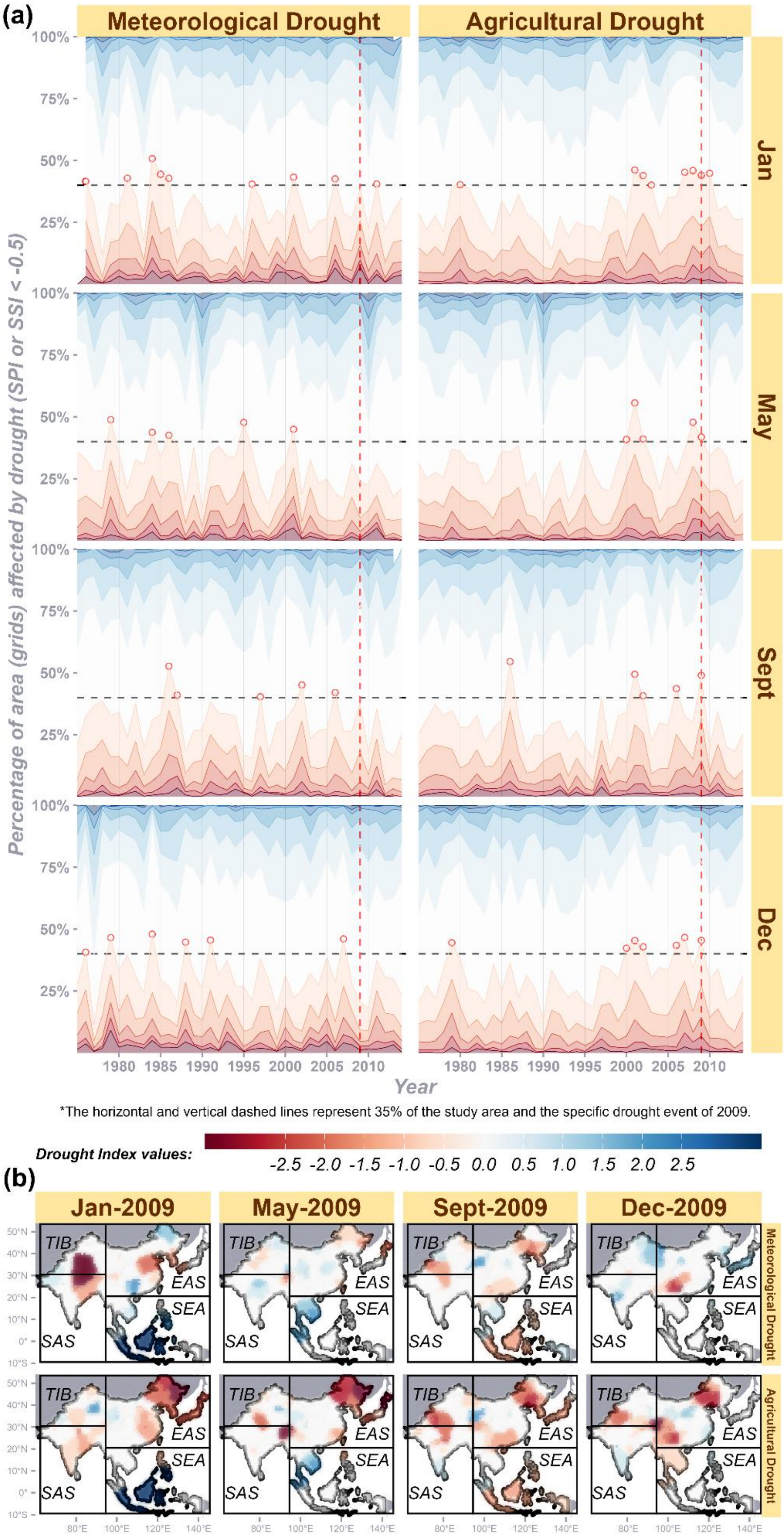

Figure R2. The percentage of drought-affected areas (based on the percentage of grids falling at different ranges of SPI and SSI values) annually. Spatial maps of 2009 drought events.

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