Dear Editors and Reviewers:

We would like to express our sincere appreciation for your letter. We would like to thank two anonymous reviewers for reviewing our manuscript. Their constructive comments are important to improve the present manuscript. In the following, we address comments of the reviewers point-by-point. Please find in Black (*italicized*) the reviewer's comments and in Blue our responses.

Response to comment of Reviewer #1

First of all, I would like to thank for inviting me to review the manuscript entitled "Model Comparisons between Canonical Vine Copulas and Meta-Gaussian for Agricultural Drought Forecasting over China" for possible publication in HESS. I return comments on the above-referenced manuscript. This manuscript has organized pretty well and can be accepted for publication in this journal if the authors carefully revised the following issues. The topic falls into the scope of HESS.

Response: We thank you for your constructive comments on our manuscript. We have revised the manuscript point-by-point based on your suggestions. Please note that the line numbers used in our Response refer to the revised version (tracked changes).

(1) *The authors shall do more work to present the topic well so that it is easy for the readers to follow. For example, it is mentioned in lines 95-97, "The objective of this study therefore was to compare the forecast ability of agricultural drought in August of every year in the period 1961–2018 between canonical vine copulas (i.e., 3C-vine model) and MG model under three-dimensional scenario." Why did you just choose August? Why does the study examine the performance of these models? What are the problems, and how these models addresses the problems?*

Response: Thank you for the constructive comments and suggestions. Please find our answers to your comments below.

(i) Why did you just choose August?

We have now added details about choosing August as a month of interested. Besides, according to Reviewer #2 comments, we have now provided the results regarding the extreme agricultural drought forecast for July under 1–3-month lead times (Figures 7c and 7d). Specific revisions are as below:

Here, the 6-month timescale SPI (SSI) in August, which is calculated by the cumulative precipitation (soil moisture) from March to August, can indirectly reflect the surplus or deficit situations of water in spring (March-April-May) and summer (June-July-August) seasons. Furthermore, August is a key growth period for crops (e.g., anthesis, fruiting, and seed filling) and vegetation and is also a period with frequent droughts (Wu et al., 2021a). Undoubtedly, agricultural drought forecast can be implemented in any month of interest, based on 3C-vine model and MG model. (See Lines 157-163).

To display the robustness of 3C-vine model for forecasting agricultural drought in any month of interest, we further forecasted extreme agricultural drought in July for D1S–

D7S (Figures 7c and 7d). The difference between forecasted and observed extreme SSIs for the MG model is larger than that of 3C-vine model in distinct typical regions, e.g., the forecasted maximum SSI in July on D4S (Figure 7d). The width of PDF curve qualitatively provides an estimation of forecast uncertainty of 3C-vine model and MG model. As shown in Figure 7, in comparison with the 3C-vine model, we found that the width of PDF curves in the MG model are broadened, indicating that the MG model produced more pronounced uncertainty for agricultural drought forecast. Furthermore, the skills of MG model tended to deteriorate over many selected typical regions, especially for 2–3-month lead times of July and August. Generally, compared with the MG model under different lead times, agricultural drought forecasts made by the 3C-vine model are more accurate across different typical regions, in terms of the predictive uncertainty (i.e., the width of PDF curve) as well as the difference between observed and forecasted extreme SSIs (Figures 7). (See Lines 370-382).

(ii) Why does the study examine the performance of these models?

The meta-Gaussian (MG) model, a popular statistical model in the hydrometeorological community, has explicit conditional distributions, which is apt for forecasting and risk assessment purposes. However, the MG model only depicts the linear relationship among explanatory variables (predictors) and forecasted variable via covariate matrix, it cannot characterize the nonlinear or tail dependence existing in the variables (Hao et al., 2016). Fortunately, vine copulas can flexibly combine multiple variables via bivariate copula to characterize numerous or complex dependencies. We found that only a few have applied vine copulas for drought forecasts (Wu et al., 2021a). Therefore, investigations on drought forecasting skills between vine copulas and MG models are an implication to obtain more reliable drought forecasts.

To clarify and avoid confusion, we have further clarified it in the revised manuscript Lines 94-96, 99-103, and 109-110 as follows:

The meta-Gaussian (MG) model, a popular statistical model in the hydrometeorological community, has explicit conditional distributions, which is apt for forecasting and risk assessment purposes. (See Lines 94-96).

However, the MG model only depicts the linear relationship among explanatory variables (predictors) and forecasted variable via covariate matrix, it cannot characterize the nonlinear or tail dependence existing in the variables (Hao et al., 2016). Vine copulas can flexibly combine multiple variables via bivariate copula to characterize numerous or complex dependencies. (See Lines 99-103).

Therefore, investigations on drought forecasting skills between vine copulas and the MG model are needed to obtain more reliable drought forecasts. (See Lines 109-110).

(iii) What are the problems, and how these models addresses the problems?

We apologize for our unclear description. The MG model only depicts the linear relationship among explanatory variables (predictors) and forecasted variable via covariate matrix, it cannot characterize the nonlinear or tail dependence existing in the variables (Hao et al., 2016). Fortunately, vine copulas can flexibly combine multiple variables via bivariate copula to characterize numerous or complex dependencies. Accordingly, using the same explanatory variables (i.e., antecedent meteorological drought and agricultural drought persistence), we investigate the C-vine copula model for improving the forecast performance of agricultural drought in comparion with the MG model. To address this problem, we compared the forecast ability between 3C-vine copulas and MG models for the spatial patterns of selected typical agricultural drought (e.g., August in 2018) under 1–3-month lead times. Moreover, three performance metrics: NSE, R^2, and RMSE, are used to evaluate the forecast skill between 3C-vine copulas and MG models for agricultural drought. More revised details can be found in the revised manuscript Lines 94-110.

(2) *Data are not described, for example what are the data characteristics, what are the data that are used for the estimations and validations.*

Response: We appreciate the comment and suggestion. We have now modified this to describe it better as follows:

Note that the leave-one-out cross validation (LOOCV) (Wilks, 2014) is applied to forecast agricultural drought for each grid cell in August of every year during 1961–2018 based on the 3C-vine or MG models, namely, each time one sample (or observation) was left for validation, and the rest were used to establish 3C-vine model or MG model and obtain the corresponding parameters of these models. In other words, this process was repeated 58 times (the length of years used in this study) for a specific grid cell. (See Lines 250-255).

(3) *To better understand, it is better to provide a flow chart of proposed method at the end of the materials and methods section.*

Response: As the reviewer suggested, we have provided a flow chart (Figure 3) for the proposed method in the '3.2 Canonical vine copulas model under three-dimensional scenarios' section. More revised details can be found in Lines 181-182, 244-250, 918-925 as follows:

More details about forecasting agricultural drought based on the MG model can be found in Figure 3. (See Lines 181-182).

With agricultural drought forecast via 3C-vine model, as the details presented in Figure 3, we first selected the best 3C-vine model (i.e., selected the best model from Equations 7 and 9 according to AIC). Then, a sample size of 1,000 uniformly distributed random values was generated over the interval [0, 1] by Monte Carlo simulation. Last, the best 3C-vine model was utilized to obtain 1,000 simulations (or estimations) for y_3^{yr}. The best forecast of y_3^{yr} was finally calculated by the mean value of these simulations. (See Lines 244-250).

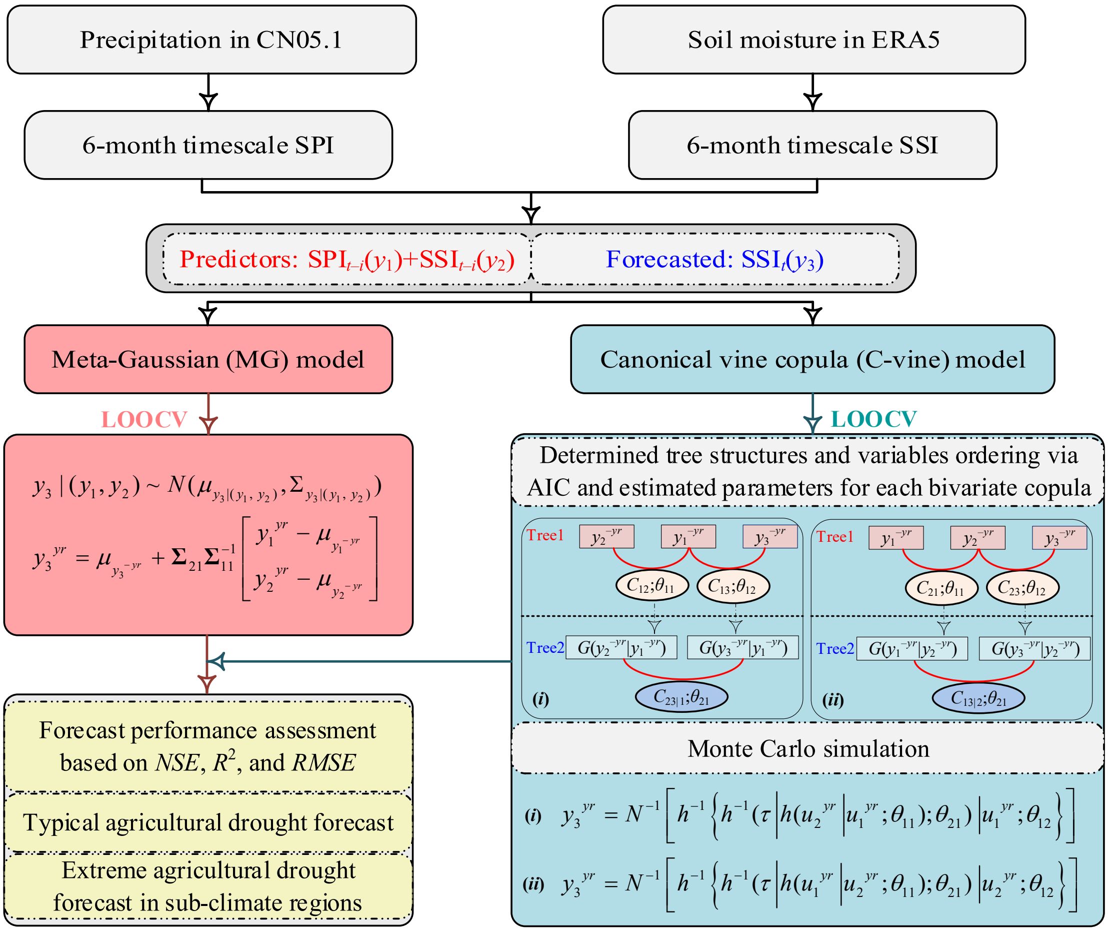

Figure 3. Flowchart of agricultural drought forecasting based on canonical vine copulas (3C-vine) and meta-Gaussian (MG) model under three-dimensional scenarios. Here, t denotes the target month (e.g., August); i signifies the lead times (1–3-months)); LOOCV is the abbreviation of leave-one-out cross validation; $y_1^{-yr}(y_2^{-yr})$ indicates the series after removing a sample $(y_1^{yr}(y_2^{yr}))$ for a specific year; and y_3^{yr} is the agricultural drought forecast value for the target month of a specific year. Note that the optimal tree structure (i or ii on the right-hand side of this figure) is selected based on AIC to forecast agricultural drought. (See Lines 919-926).

(4) *The internal copulas of the C-vine not discussed in the first tree. Also, evaluation statistics on tree structure selection are not clear.*

Response: We sincerely appreciate the reviewer for these valuable comments. In fact, we employed the "*CDVineCopulaConditional*" R package to select the optimal copulas for these pairwise variables that are presented in first and second trees (i.e., jointed by curve lines for rectangular boxes in Figure 2). Moreover, With the help of *CDVineCondFit* R function, we selected the optimal tree structures based on AIC.

More details are in the revised manuscript Lines 205-210 as follows:

The Gaussian (or Normal), Student-t, Clayton, and Frank copulas, as well as their rotated (survival) forms (Dißmann et al., 2013; Liu et al., 2021b) are utilized to obtain the optimal internal bivariate copulas for distinct trees in 3C-vine models based on the

Akaike information criterion (AIC). With the help of *CDVineCondFit* R function in "*CDVineCopulaConditional*" R package (Bevacqua, 2017a), based on the AIC, we selected the optimal tree structures (i.e., detected the suitable variable ordering; seen in Figure 2).

(5) *Last but not least, in Figure 4, the NSE values are between -0.2 to 0.2, is this acceptable?*

Response: We thank the reviewer for this important comment. We apologize for our unclear description with respect to NSE, R^2, and RMSE in the original Figure 4 (now Figure 5). To avoid confusion, the related description was rewritten as "Figures 5a–5i show the difference in *NSE*, R^2, and *RMSE* between 3C-vine and MG models, i.e., $\Delta NSE = NSE_{3C} – NSE_{MG}$, $\Delta R^2 = R^2_{3C} – R^2_{MG}$, and $\Delta RMSE = RMSE_{3C} – RMSE_{MG}$ under 1–3-month lead times for August, respectively." in the revised manuscript Lines 298-301.

In Figure 5a–5c, the difference in *NSE* between 3C-vine and MG models was calculated, i.e., $\Delta NSE = NSE_{3C} – NSE_{MG}$. Here, if the ΔNSE was greater than 0, it indicated the superior agricultural drought forecast ability of 3C-vine model over the MG model, and vice versa. Therefore, the NSE values (i.e., ΔNSE) are accepted over the interval [–0.2, 0.2].

Thank you again for your constructive comments and suggestions, we believe they have helped improve the quality of the manuscript.

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Dißmann, J., Brechmann, E. C., Czado, C., and Kurowicka, D.: Selecting and estimating regular vine copulae and application to financial returns, Comput. Stat. Data Anal., 59, 52–69, https://doi.org/10.1016/j.csda.2012.08.010, 2013.

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Response to comment of Reviewer #2

Review of "Model Comparisons Between Canonical Vine Copulas and Meta-Gaussian for Agricultural Drought Forecasting over China" by Haijiang Wu, Xiaoling Su, Vijay P. Singh, Te Zhang, and Jixia Qi.

This paper developed an agricultural drought forecasting model based on canonical vine copulas under three-dimensions (3C-vine model). With the meta-Gaussian (MG) model as a reference model, they found that the 3C-vine model showed better performances than the meta-Gaussian model for agricultural drought forecasting over China. Any such model aimed at improving the forecasting of drought should be encouraged. The topic falls into the scope of HESS.

Overall, the paper is well written and structured, and I support the publication of this work after major revision based on the comments below. Some works are needed to improve in the methodology, results, and discussion. I have some suggestions/recommendations to improve the manuscript, which are given below:

Response: We would like to thank the anonymous reviewer for reviewing our manuscript. These constructive comments are important to improve the current manuscript. Modifications have been done according to your comments and suggestions. The reviewer's comments (black) are italicized and our responses (blue) immediately follow. Please note that the line numbers used in our Response refer to the revised version (tracked changes).

General concern:

The major concern is about why the authors compare the vine copula model with the Meta Gaussian model. the latter one is generally based on the Gaussian distribution, and the prediction function is expected to be not superior than other competitors. More justifications or involving some other statistical models are expected through the paper.

Response: We agree with the reviewer's suggestion. We answer your constructive comments below:

The Meta-Gaussian (MG) model, a popular statistical model in the hydrometeorological community, has explicit conditional distributions, which is apt for forecasting and risk assessment purposes. The forecast skills of the MG model for drought or compound dry-hot events, for example, outperformed the persistence-based or random forecast models (Hao et al., 2016; Hao et al., 2019; Wu et al., 2021b). Therefore, we selected the MG model as a reference drought model to evaluate the forecast skills of the vine copula model.

Specific revisions listed in the revised manuscript Lines 94-99 as follows:

The meta-Gaussian (MG) model, a popular statistical model in the hydrometeorological community, has explicit conditional distributions, which is apt for forecasting and risk assessment purposes (Hao et al., 2016; Hao et al., 2019; Wu et al., 2021b; Zhang et al., 2021). The forecast skills of the MG model for drought or compound dry-hot events, for example, outperformed the persistence-based or random forecast models (Hao et al., 2016; Hao et al., 2019; Wu et al., 2021b).

Other concerns:

1. *In comparison with the MG model, what are the superiority of the 3C-vine model or C-vine copula? The authors need a further statement about this in the Introduction section or discuss more about this in the Discussion section. Also in Line 57, the authors made a list of exsiting model for the drought prediction; yet those models are all statistical models, some physical-based hydrological models are also widely used in hydrological prediction, the droughts included as well. A elaborate introduction is expected herein.*

Response: According to your valuable suggestions, more information has been added to our revised manuscript Lines 58-63 and 94-110 as follows:

In hydrology, some physically-based hydrological models (e.g., Distributed Time-Variant Gain Hydrological Model (DTVGM; Ma et al, 2021) and Soil and Water Assessment Tool (SWAT; Wu et al., 2019)) are widely used in hydrological simulation and prediction, the droughts included as well. However, the physically-based hydrological models typically apply to a catchment or sub-regional scale, and generally require numerous hydrometeorological variables to achieve more accurate real-time predictions (Liu et al., 2021a; Xu et al, 2021a). (See Lines 58-63).

The meta-Gaussian (MG) model, a popular statistical model in the hydrometeorological community, has explicit conditional distributions, which is apt for forecasting and risk assessment purposes (Hao et al., 2016; Hao et al., 2019; Wu et al., 2021b; Zhang et al., 2021). The forecast skills of the MG model for drought or compound dry-hot events, for example, outperformed the persistence-based or random forecast models (Hao et al., 2016; Hao et al., 2019; Wu et al., 2021b). However, the MG model only depicts the linear relationship among explanatory variables (predictors) and forecasted variable via covariate matrix, it cannot characterize the nonlinear or tail dependence existing in the variables (Hao et al., 2016). C-vine copulas can flexibly combine multiple variables via bivariate copula to characterize numerous or complex dependencies. There has been a rather limited investigation, to our knowledge, that conducting model comparisons between vine copulas and MG for agricultural drought forecasting under the same conditions. Therefore, investigations on drought forecasting skills between vine copulas and MG models are needed to obtain more reliable drought forecasts. (See Lines 94-110).

2. *Page 3 Line 62: I suggest the authors add the 'aforementioned' before the 'conventional statistical methods', to avoid the broad statement.*

Response: It is done accordingly. The original sentence was changed in our revised manuscript Line 70 as follows:

"The copula functions overcome the limitations of aforementioned conventional statistical methods. Since copulas are flexible joining arbitrary marginal distributions of variables, …" (See Line 70).

3. *Page 5 Lines 90-91: "The propagation between meteorological drought and agricultural drought…" should be changes as "The propagation from meteorological drought to agricultural drought…", as the meteorological drought is a source of the agricultural drought. Be careful with the wording.*

Response: The original sentence "The propagation between meteorological drought and agricultural drought was characterized via the MG model (Xu et al., 2021)" was removed in our revised manuscript.

4. *Page 5 Lines 95-97: Authors mentioned that the 3C-vine and MG models are employed to forecast the agricultural drought in August. It is rather confusing. I strongly suggest the authors provide some compelling reasons for choosing this month. Of course, if the authors can display the agricultural drought forecast in any interested months (e.g., the forecasted of extreme agricultural drought in June), it can further strengthen the robust of 3C-vine model.*

Response: We agree with your comments. More information and discussions about this were added to our revised manuscript according to your valuable suggestions.
(i) Authors mentioned that the 3C-vine and MG models are employed to forecast the agricultural drought in August. It is rather confusing. I strongly suggest the authors provide some compelling reasons for choosing this month.

We have now added more details about choosing August as the month of interest in the revised manuscript Lines 157-163 as follows:

Here, the 6-month timescale SPI (SSI) in August, which is calculated by the cumulative precipitation (soil moisture) from March to August, can indirectly reflect the surplus or deficit situations of water in spring (March-April-May) and summer (June-July-August) seasons. Furthermore, August is a key growth period for crops (e.g., anthesis, fruiting, and seed filling) and vegetation and is also a period with frequent droughts (Wu et al., 2021a). Undoubtedly, agricultural drought forecast can be implemented in any month of interest based on 3C-vine model and MG model.

(ii) Of course, if the authors can display the agricultural drought forecast in any interested months (e.g., the forecasted of extreme agricultural drought in June), it can further strengthen the robust of 3C-vine model.

More revised details can be found in Lines 370-382 and 955-963 as follows:

To display the robustness of 3C-vine model for forecasting agricultural drought in any month of interest , we further forecasted extreme agricultural droughts in July for D1S–D7S (Figures 7c and 7d). The difference between forecasted and observed extreme SSIs for the MG model is larger than that of 3C-vine model in distinct typical regions, e.g., the forecasted maximum SSI in July on D4S (Figure 7d). The width of PDF curve qualitatively provides an estimation of forecast uncertainty of 3C-vine model and MG model. As shown in Figure 7, in comparison with the 3C-vine model, we found that the width of PDF curves in the MG model are broadened, indicating that the MG model produced more pronounced uncertainty for agricultural drought forecast. Furthermore, the skills of MG model tended to deteriorate over many selected typical regions, especially for 2–3-month lead times of July and August. Generally, compared with the MG model under different lead times, agricultural drought forecasts made by the 3C-vine model are more accurate across different typical regions, in terms of predictive uncertainty (i.e., width of PDF curve) as well as the difference between observed and forecasted extreme SSIs (Figures 7). (See Lines 370-382).

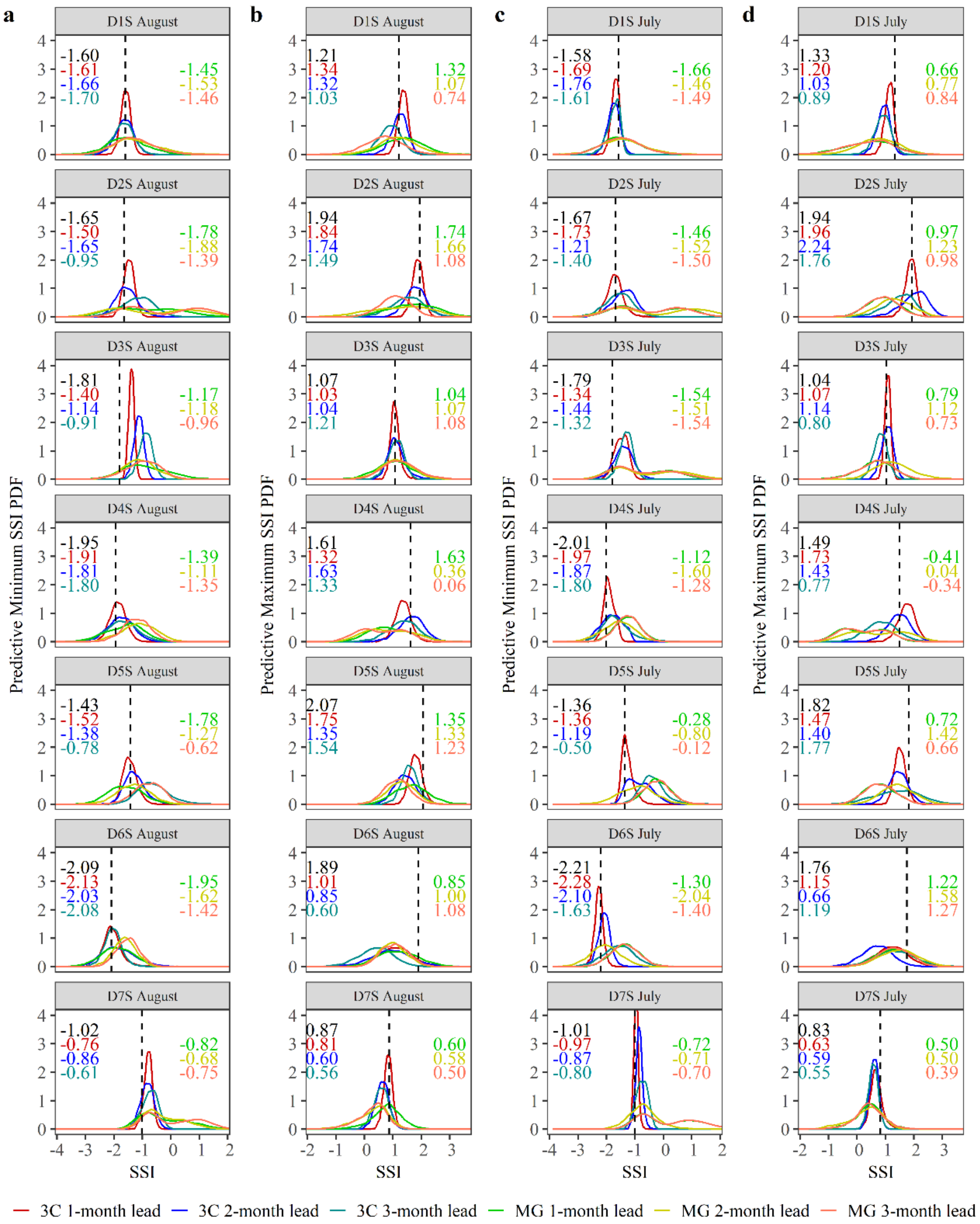

Figure 7. Probability density function (PDF) curve of (a and c) minimum and (b and d) maximum SSI under 1–3-month lead times for August and July during the 1961–2018 period over seven selected typical regions in climate regions D1–D7 (i.e., these black

rectangle boxes in Figure 6b correspond to signify D1S–D7S, respectively). Black dash line and text indicate the minimum and maximum observations of SSI in August and July over D1S–D7S. These texts with red (green), blue (yellow), and cyan (coral) colors of left (right) in each sub-figure are SSI forecasts under 1–3-month lead times of August or July via 3C-vine model (MG model), which correspond to the abscissa projected by the peak point of each PDF. (See Lines 955-963).

5. *Page 6 Line 126: I think the 'three' should be changed to 'top-three'. Please check it.*

Response: We agree and have now revised this. (See Line 143).

6. *Page 8 Line 155: The μy3|(y2,y1) in Equation (3) should be removed. Be careful with the checking.*

Response: We agree and have removed it. (See Line 179).

7. *Page 9 Line 187-188: "Here, regarding the conditional distribution of z given the conditions w…", the terms 'z' is confusing here, maybe it should be revised as 'y' according to the Equation (5). Please check it.*

Response: We apologize for our carelessness. It has been modified in the revised manuscript as follows:

"Here, regarding the conditional distribution of y given the conditions w, …". (See Line 217).

8. *Page 11 Line 213-220: A graphical representation or flowchart of this process would be helpful, maybe in the Methodology section. I am actually quite intrigued by it.*

Response: We appreciate the reviewer's comment. As the reviewer suggested, we have now provided a flow chart (Figure 3) in the '3.2 Canonical vine copulas model under three-dimensional scenarios' section for the proposed method. More revised details can be found in Lines 181-182, 244-250, 919-926 as follows:

More details about forecasting agricultural drought based on the MG model can be found in Figure 3. (See Lines 181-182).

With agricultural drought forecast via 3C-vine model, as the details presented in Figure 3, we first selected the best 3C-vine model (i.e., selected the best model from Equations 7 and 9 according to AIC). Then, a sample size of 1,000 uniformly distributed random values was generated over the interval [0, 1] by Monte Carlo simulation. Last, the best 3C-vine model was utilized to obtain 1,000 simulations (or estimations) for y_3^{yr}. The best forecast of y_3^{yr} was finally calculated by the mean value of these simulations. (See Lines 244-250).

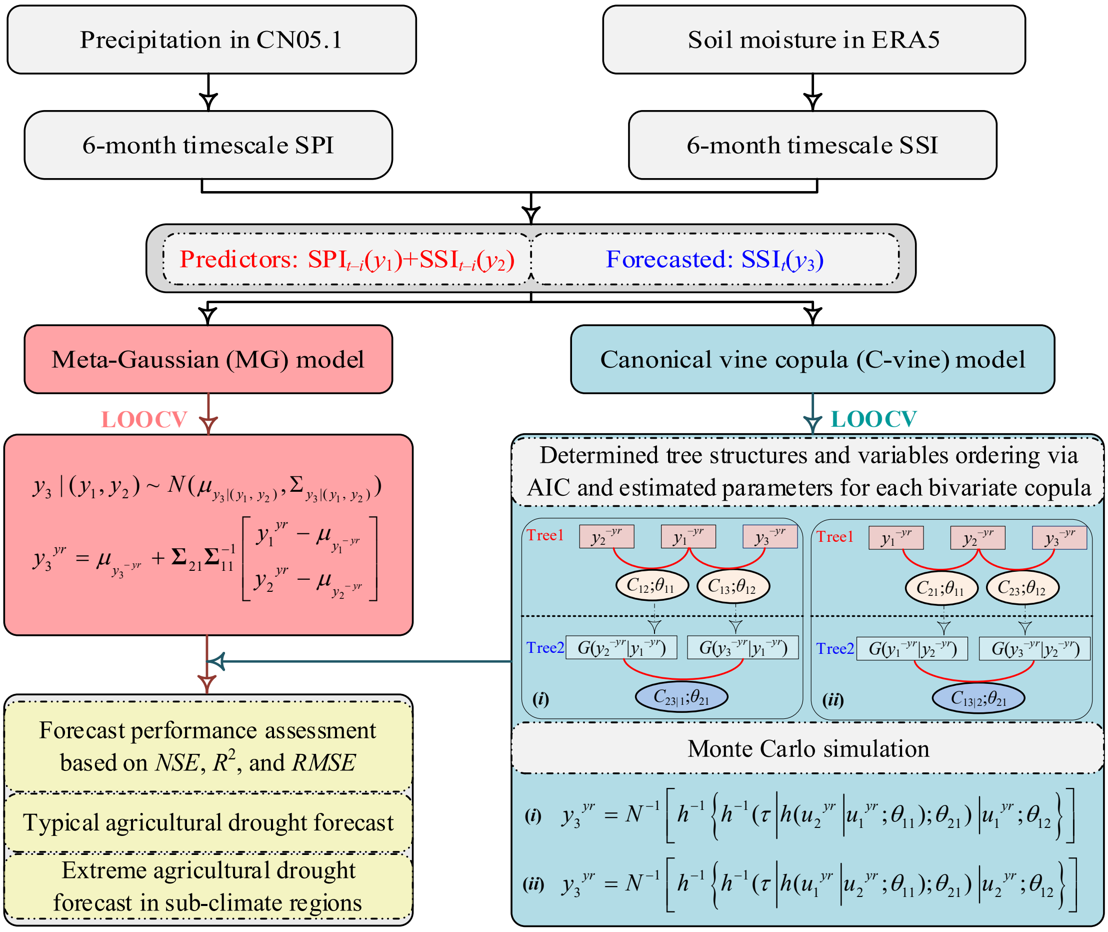

Figure 3. Flowchart of agricultural drought forecasting based on canonical vine copulas (3C-vine) and meta-Gaussian (MG) model under three-dimensional scenarios. Here, t denotes the target month (e.g., August); i signifies the lead times (1–3-months)); LOOCV is the abbreviation of leave-one-out cross validation; y_1^{-yr}(y_2^{-yr}) indicates the series after removing a sample (y_1^{yr}(y_2^{yr})) for a specific year; and y_3^{yr} is the agricultural drought forecast value for the target month of a specific year. Note that the optimal tree structure (*i* or *ii* on the right-hand side of this figure) is selected based on AIC to forecast agricultural drought. (See Lines 919-926).

9. *Page 11 Line 226: The numerator term in the Equation (11) may be have problematic. Be careful with the checking.*

Response: We thank the reviewer for pointing this out. We apologize for our carelessness. It is done accordingly in our revised manuscript Line 266 as follows:

$$R^2 = \frac{\left[\sum_{i=1}^{n}(AO_i - \overline{AO})(AP_i - \overline{AP})\right]^2}{\sum_{i=1}^{n}(AO_i - \overline{AO})^2 \bullet \sum_{i=1}^{n}(AP_i - \overline{AP})^2} \qquad R^2 \in [0,1] \qquad (11)$$

10. *Figure 6: I suggest the authors should add the PDF curve for the MG model. Maybe the authors need to consider completing it via the simulations.*

Response: As you suggested, the PDF curves for MG model have been added in Figure 7. More revised details can be found in Lines 370-382 and 955-963 as follows:

To display the robustness of 3C-vine model for forecasting agricultural drought in any month of interest , we further forecasted extreme agricultural droughts in July for D1S–D7S (Figures 7c and 7d). The difference between forecasted and observed extreme SSIs for MG model is larger than that of 3C-vine model in distinct typical regions, e.g., the forecasted maximum SSI in July on D4S (Figure 7d). The width of PDF curve qualitatively provides an estimation of forecast uncertainty of 3C-vine model and MG model. As shown in Figure 7, in comparison with the 3C-vine model, we found that the width of PDF curves in the MG model are broadened, indicating that the MG model produced more pronounced uncertainty for agricultural drought forecast. Furthermore, the skills of MG model tended to deteriorate over many selected typical regions, especially for 2–3-month lead times of July and August. Generally, compared with the MG model under different lead times, agricultural drought forecasts made by the 3C-vine model are more accurate across different typical regions, in terms of predictive uncertainty (i.e., the width of PDF curve) as well as the difference between observed and forecasted extreme SSIs (Figures 7). (See Lines 370-382).

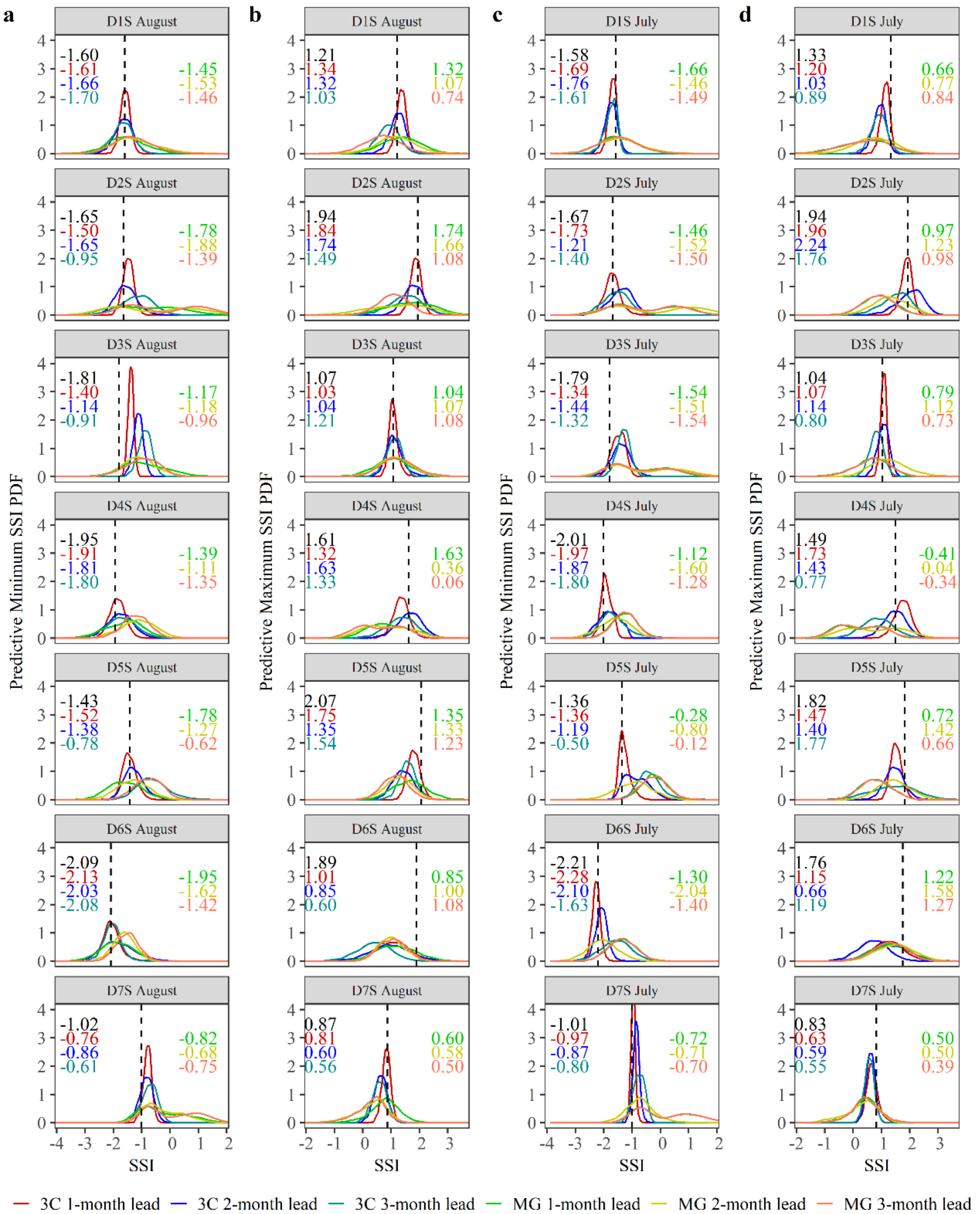

Figure 7. Probability density function (PDF) curve of (a and c) minimum and (b and d) maximum SSI under 1–3-month lead times for August and July during the 1961–2018 period over seven selected typical regions in climate regions D1–D7 (i.e., these black rectangle boxes in Figure 6b correspond to signify D1S–D7S, respectively). Black dash line and text indicate the minimum and maximum observations of SSI in August and July over D1S–D7S. These texts with red (green), blue (yellow), and cyan (coral) colors of left (right) in each sub-figure are SSI forecasts under 1–3-month lead times of August or July via 3C-vine model (MG model), which correspond to the abscissa projected by the peak point of each PDF. (See Lines 955-963).

11 *Page 17 Lines 342-344: I think the 'at time t–1 (t denotes target month)' should be removed. Please check it.*

Response: We have removed it in our revised manuscript.

Many thanks for your insightful comments and suggestions again. We believe your comments have improved the quality of our manuscript.

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