nature portfolio

Peer Review File

Skillful Seasonal Predictions of Continental East-Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution

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This file contains all reviewer reports in order by version, followed by all author rebuttals in order by version.

Attachments originally included by the reviewers as part of their assessment can be found at the end of this file.

Version 0:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
Review of “Skillful Seasonal Predictions of East Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution” by Ma et al.
As well known, it is quite difficult to reasonably predict flooding-season rainfall anomalies as a seasonal mean in the East Asian monsoon region because of the complex features in the monsoonal precipitation and its complicated multi-precursors from worldwide. It would be more difficult for current community to capture seasonal evolution of the summer rainfall anomalies in the continental area of East Asia due to the unique characteristics of stepwise meridional advances and retreats of main rainbelt during boreal summer. However, this study creates a new way toward skillful seasonal predictions of the East-Asian summer rainfall in continent for both summer mean and evolution through garnering the highly predictable signals from space and time. The authors have highlighted the key role of the primary spatiotemporal evolution patterns of rainfall anomalies in extracting their major features and main precursors. Based on their-proposed innovative physical-statistical model, the results show an amazing advancement of the East-Asian summer rainfall prediction, compared with the current most-advanced international multi-model ensemble. I would like to recommend its publication in Nature Communication after some necessary revisions and clarifications.
Comments:
(1) Many previous researches have made big progresses in the summer rainfall prediction over East Asia, but prediction skills distribute mostly in ocean and much less or none in continent. The most extractive thing in this paper, in my opinion, is the impressive positive prediction skills of summer rainfall anomalies over the continental area within East Asia. I strongly suggest that the key word “continental” should appear in the title and abstract as well as the main text. This will make the distinct contribution of this research clearer for both the community and public readers.
(2) The precursors don’t have to be physically connected with the East-Asian rainfall even though they have been effectively employed in the physical-statistical model. Behind the precursors, what climate phenomena mainly contribute to the high predictability of those spatiotemporal patterns in support of the skillful predictions? For example, El Niño-Southern Oscillation (ENSO) has been well recognized as a useful physical precursor and whether it can be indicated in the new prediction model?
(3) In previous studies, the North Atlantic Oscillation (NAO) has been an effective precursor for the East-Asian summer monsoon, which might be also useful for summer rainfall prediction. I wonder whether there is some signal as precursor from the North Atlantic region which is excluded in Figure 3? Aslo, it is wondered whether the precursors defined by sea level pressure are all independent on those defined by surface air temperature?
(4) In most years, the new method has shown much improved results as seen in Figure 4a. However, how can the completely wrong case in the 2007 summer be explained with the new method? Is there the certain weakness of the newly proposed physical-statistical model under some specific situation?
(5) To better represent “skillful”, the quantitative skill score should be mentioned in Abstract.
(6) The introduction of the section “Precursors for year-to-year variations of the spatiotemporal patterns” looks too long and shows too many details which may not be necessary in the journal.
(7) Some related references on seasonal prediction of East Asian climate:
Wu, Z., and P. Zhang, 2015: Interdecadal Variability of the mega-ENSO-NAO Synchronization in Winter. Climate Dyn., 45, 1117-1128.
Wu, Z., and J. Li, 2008: Prediction of the Asian-Australian monsoon interannual variations with the grid-point atmospheric

model of IAP LASG (GAMIL). Adv. Atmos. Sci., 25(3), 387 394.
Zhang, P., Z. Wu and R. Jin 2021: How can the winter North Atlantic Oscillation influence the early summer precipitation in Northeast Asia: effect of the Arctic sea ice. Climate Dyn., DOI: 10.1007/s00382-020-05570-2.
Wu, Z. and H. Lin, 2012: Interdecadal Variability of the ENSO-North Atlantic Oscillation Connection in boreal summer. Quart. J. Roy. Meteor. Soc., 138, 1668 1675.
Jin, R., Z. Wu* and P. Zhang, 2018: Tibetan Plateau Capacitor Effect during the Summer preceding ENSO: from the Yellow River climate perspective. Climate Dyn., 51(1), 57 71.
Wu, Z., and L. Yu, 2016: Seasonal Prediction of the East Asian Summer Monsoon with a Partial-least Square Model. Climate Dyn., 46, 3067 3078.

Reviewer #2

(Remarks to the Author)
Please see attached report

Version 1:

Reviewer comments:

Reviewer #1

(Remarks to the Author)
I am satisfied with the revisions and have no further comments.

Reviewer #2

(Remarks to the Author)
The authors have satisfactorily addressed all points/questions raised, and therefore I recommend the publication of this article.

Responses to reviewers' comments and suggestions about the manuscript, entitled "Skillful Seasonal Predictions of Continental East-Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution"

Response to Reviewer #1's Comments:

Review of "Skillful Seasonal Predictions of East Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution" by Ma et al.

As well known, it is quite difficult to reasonably predict flooding-season rainfall anomalies as a seasonal mean in the East Asian monsoon region because of the complex features in the monsoonal precipitation and its complicated multi-precursors from worldwide. It would be more difficult for current community to capture seasonal evolution of the summer rainfall anomalies in the continental area of East Asia due to the unique characteristics of stepwise meridional advances and retreats of main rainbelt during boreal summer. However, this study creates a new way toward skillful seasonal predictions of the East-Asian summer rainfall in continent for both summer mean and evolution through garnering the highly predictable signals from space and time. The authors have highlighted the key role of the primary spatiotemporal evolution patterns of rainfall anomalies in extracting their major features and main precursors. Based on their-proposed innovative physical-statistical model, the results show an amazing advancement of the East-Asian summer rainfall prediction, compared with the current most-advanced international multi-model ensemble. I would like to recommend its publication in Nature Communication after some necessary revisions and clarifications.

Response: We greatly appreciate your positive and insightful comments. We have carefully addressed all the specific issues raised and fully incorporated your suggestions in the revision. Below are our point-by-point responses - "blue font" for the reviewer's original comments and "black font" for our responses. Please note that the line numbers highlighted in bold correspond to the clean version of the revised manuscript.

Comments:

1) Many previous researches have made big progresses in the summer rainfall prediction over East Asia, but prediction skills distribute mostly in ocean and much less or none in continent. The most extractive thing in this paper, in my opinion, is the impressive positive prediction skills of summer rainfall anomalies over the continental area within East Asia. I strongly suggest that the key word "continental" should appear in the title and abstract as well as the main text. This will make the distinct contribution of this research clearer for both the community and public readers.

Response: Thanks for the suggestion. We have added the key word "continental" to the title and abstract in the revised manuscript as follows:

- Title: "*Skillful Seasonal Predictions of Continental East-Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution.*"
- Abstract: "*Current models, however, face significant difficulties in predicting the summer mean rainfall anomaly over continental East Asia.*"

- Abstract: "*Here we garner power from integrating the rainfall's spatial and temporal evolutions to identify the most crucial spatiotemporal patterns intrinsic to continental East-Asian rainfall anomalies.*"

We have also added "continental" to the main text in the revision.

2) The precursors don't have to be physically connected with the East-Asian rainfall even though they have been effectively employed in the physical-statistical model. Behind the precursors, what climate phenomena mainly contribute to the high predictability of those spatiotemporal patterns in support of the skillful predictions? For example, El Niño-Southern Oscillation (ENSO) has been well recognized as a useful physical precursor and whether it can be indicated in the new prediction model?

Response: Thanks for the comment and question. As shown in Supplementary Table 2, the precursors identified in our study are linked to climate phenomena across the Pacific Ocean, Indian Ocean, Tibetan Plateau, and Mascarene regions, and are associated with well-recognized climate signals in previous studies, such as ENSO and Tibetan Plateau snow depth. As you expected, ENSO is reflected in the precursor related to the year-to-year variability of the third spatiotemporal pattern (Fig. 3d in the revised manuscript), contributing to the skillful predictions. As summarized in Supplementary Table 2, the precursor of EPT shown in Fig. 3d exhibit a strong correlation with ENSO (0.96), while other precursors correlations with other recognized climate signals are relatively lower (less than 0.6). This indicates that the precursors identified in our study not only capture the well-known climate signals like ENSO, but also reveal additional climate factors that influence the year-to-year variation in the seasonal evolution of rainfall anomalies, which cannot be fully explained by the previously recognized climate signals. In the revision, we have added related description as follows: "*As summarized in Supplementary Table 2, these precursors have good correlations with the climate variability modes, such as El Niño-Southern Oscillation (ENSO), which are well recognized as important drivers of East-Asian monsoon rainfall variations through ocean-land-atmospheric feedbacks*." (Please see **lines 161-165**)

The objective of this study is to demonstrate that our proposed physical-statistical prediction model outperforms the MME mean forecast in predicting the seasonal evolution of East-Asian rainfall anomalies for individual years. Toward achieving this, we have identified the main and representative precursors that contribute to the improved predictions of seasonal rainfall evolution. Inspired by your nice comment, we plan to further investigate the dynamic and physical mechanisms underlying the influence of these precursors on seasonal rainfall evolution through a series of climate diagnoses and model simulations in the next step.

3) In previous studies, the North Atlantic Oscillation (NAO) has been an effective precursor for the East-Asian summer monsoon, which might be also useful for summer rainfall prediction. I wonder whether there is some signal as precursor from the North Atlantic region which is excluded in Figure 3? Also, it is wondered whether the precursors defined by sea level pressure are all independent on those defined by surface air temperature?

Response: Thanks for your insightful comment. As shown in the figure below (Fig. R1), the predictable signal from the North Atlantic region is primarily reflected in the representative precursors associated with the year-to-year PC1 (principal component) variation (Figs. R1a and

R1b). This indicates that the **North Atlantic Oscillation (NAO) mainly contributes to the year-to-year variation of the persistent evolving pattern**, with the predictable information contained within the first two precursors identified in this study.

Due to the mutual independence of the three spatiotemporal patterns obtained using the empirical orthogonal function (EOF) method, the criterion for precursor search only requires that the two precursors associated with each PC variation be independent of each other. Therefore, the **two precursors defined by sea level pressure and surface air temperature for each PC variation are reasonably regarded as independent in this study**. We have added the explanation on this in the revision. (Please see **lines 132-133, 138-141, 149-151**)

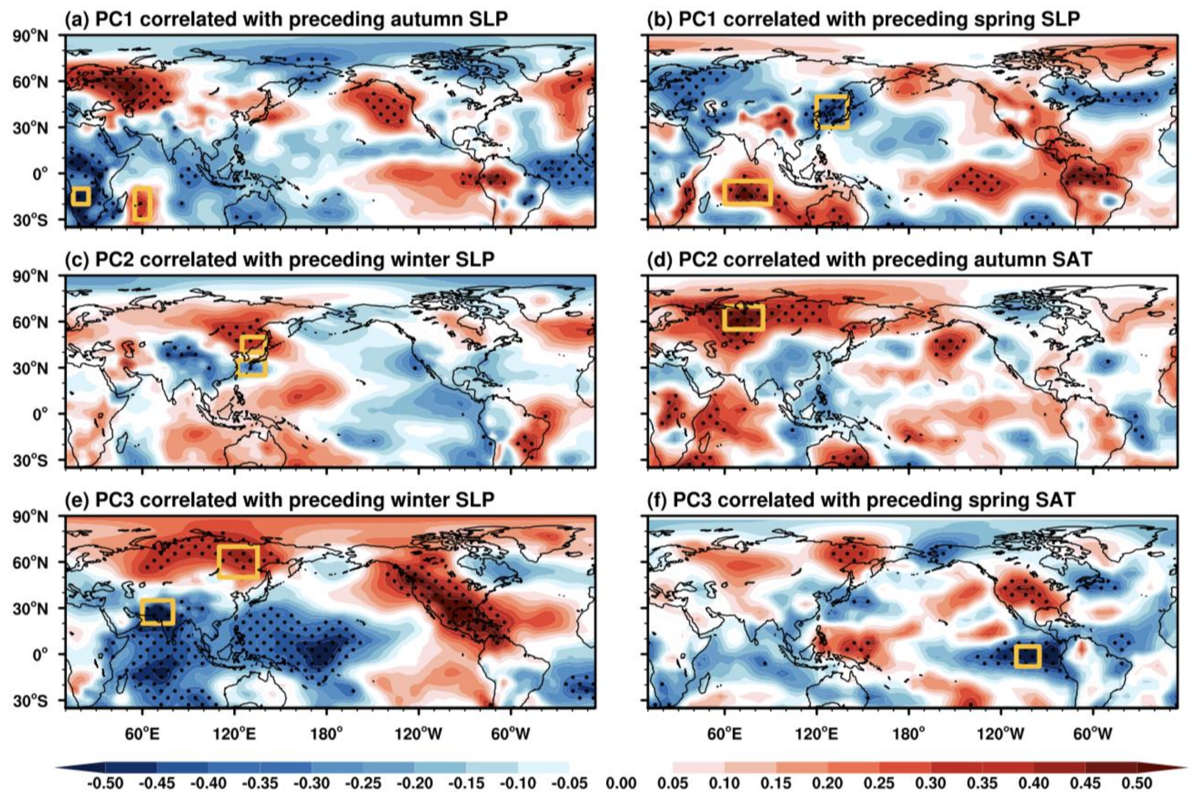

Fig. R1 The correlation maps between year-to-year variations of principle components (PCs) and sea level pressure (SLP) or surface air temperature (SAT) anomalies. The correlation maps of yearly PC1 variation and SLP anomalies in (a) preceding autumn and (b) preceding spring. The correlation coefficients of PC2 variation with (c) SLP anomalies in preceding winter and (d) SAT anomalies in preceding autumn. The correlation maps of PC3 variation with (e) SLP anomalies in preceding winter and (f) SAT anomalies in preceding spring. Significant values marked by black dots exceed the 90% confidence level. The yellow boxes outline the regions used for defining precursors in Table 1.

4) In most years, the new method has shown much improved results as seen in Figure 4a. However, how can the completely wrong case in the 2007 summer be explained with the new method? Is there the certain weakness of the newly proposed physical-statistical model under some specific situation?

Response: Thanks for pointing this out. The newly proposed physical-statistical model has certain limitations in the following situations. When the amplitudes of the precursors are too weak, the model may struggle to accurately capture the predictable signals effectively, resulting in increased forecast uncertainty. Additionally, when applied to more stochastic event occurrences, the model's performance may be limited due to the inherent complexity and rapid variability of these events, which require further considerations of their localized and transient nature. We have added related discussions in the revised manuscript as follows: "*The new model may have certain limitations when the amplitudes of the precursors are too weak or when applied to more stochastic event occurrences. In these cases, it may struggle to capture slowly predictable signals due to the inherent complexity or rapid variability*." (Please see **lines 266-269**)

5) To better represent "skillful", the quantitative skill score should be mentioned in Abstract.

Response: Thanks for your suggestion. We have added the quantitative skill to Abstract in the revised manuscript as follow: "*This innovative model, with the non-conventional predictands implicitly spanning spatiotemporal dimensions, demonstrates a prediction skill of 0.51 at least twice as high as that of the best dynamical models available (0.26), indicating improved predictions for both the spatiotemporal evolution and summer mean of rainfall anomalies*". (Please see **lines 29-30**)

6) The introduction of the section "Precursors for year-to-year variations of the spatiotemporal patterns" looks too long and shows too many details which may not be necessary in the journal.

Response: Thanks for your valuable suggestion regarding this section. In the revised manuscript, we have simplified this section by removing unnecessary details while ensuring that the essential concepts related to the precursors remain clear. (Please see **lines 124-170**)

7) Some related references on seasonal prediction of East Asian climate:

Wu, Z., and P. Zhang, 2015: Interdecadal Variability of the mega-ENSO-NAO Synchronization in Winter. Climate Dyn., 45, 1117-1128.

Wu, Z., and J. Li, 2008: Prediction of the Asian-Australian monsoon interannual variations with the grid-point atmospheric model of IAP LASG (GAMIL). Adv. Atmos. Sci., 25(3), 387-394.

Zhang, P., Z. Wu and R. Jin 2021: How can the winter North Atlantic Oscillation influence the early summer precipitation in Northeast Asia: effect of the Arctic sea ice. Climate Dyn., DOI: 10.1007/s00382-020-05570-2.

Wu, Z. and H. Lin, 2012: Interdecadal Variability of the ENSO-North Atlantic Oscillation Connection in boreal summer. Quart. J. Roy. Meteor. Soc., 138, 1668-1675.

Jin, R., Z. Wu* and P. Zhang, 2018: Tibetan Plateau Capacitor Effect during the Summer preceding ENSO: from the Yellow River climate perspective. Climate Dyn., 51(1), 57-71.

Wu, Z., and L. Yu, 2016: Seasonal Prediction of the East Asian Summer Monsoon with a Partial-least Square Model. Climate Dyn., 46, 3067-3078.

Response: We greatly appreciate your suggestion. To provide a more comprehensive overview and analysis, we have carefully reviewed and incorporated most of these references, along with additional literature, into the Introduction and Discussion sections in the revised manuscript.

Response to Reviewer #2's Comments:

Review of "Skillful Seasonal Predictions of East Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution".

This paper shows results on the prediction of the spatio-temporal evolution of rainfall within the summer monsoon season over East Asia. The authors propose a new statistical dynamical model to predict the spatial-temporal evolution of rainfall during the summer monsoon season over East Asia and argue that their proposed model supersedes the current dynamical prediction systems that are used operationally.

While I agree with the authors that we need models that can predict not only the magnitude of seasonal mean rainfall but also more detailed characteristics like the progression or retreat of monsoon, I have several major concerns requiring further clarification, particularly the distinction between the spatial distribution of monsoon rainfall and spatiotemporal evolution of monsoon rain. In summary, this paper requires significant revisions to clarify its objectives, strengthen the analysis, and address questions raised before it can be considered for publication.

Response: We greatly appreciate your insightful comments. These comments and suggestions are quite valuable for improving our manuscript and have been fully incorporated in the revision. We have substantially revised the manuscript by adding additional observational and dynamical model evidences and by strengthening the analysis and manuscript structure to better clarify this study's objective of improving the seasonal predictions in the spatiotemporal evolution of rainfall anomalies over continental East Asia. Below are our point-by-point responses - "blue font" for the reviewer's original comments and "black font" for our responses. The line numbers highlighted in bold are based on the clean version of the revised manuscript.

Major comments:

1) There is confusion about the terminology and the question that the authors are trying to address in this paper. The paper is targeted toward the prediction of the spatio-temporal evolution of monsoon anomalies (lines 77-81) however most of the analysis and arguments are around models' ability to capture the spatial distribution of monsoon mean rainfall anomalies. To me, these are two different things. The first one refers to the spatial distribution of monsoon rain, e.g. analysis done in Fig. 1 and 2, and most of the statistical analysis focuses on the spatial pattern of monsoon mean rainfall (JJA) or interannual variability. The spatio-temporal evolution implies to me, the progression and retreat of monsoon during/within the monsoon season and involves intra-seasonal analysis. These two are of course interconnected but distinct issues and in many places, spatial distribution and spatiotemporal evolution are used interchangeably. I find it difficult to decipher which issue the authors are trying to address.

Response: Sorry for bringing the confusion and we have done our best to make it clear. We agree with you that the spatial patterns at a given instant and the spatiotemporal evolution are interconnected but distinct features. Our study focuses on the spatiotemporal evolution, which naturally enables us to examine the spatial pattern at any given instant. To better describe and clarify the main theme of this study, which is the seasonal prediction of the spatiotemporal evolution of rainfall anomalies, we have revised original Figs. 1, 4, and 5. As to be elaborated below, these changes would help demonstrate the novelty of this study, namely skillful prediction of spatial distribution at a given instant is merely a by-product of a skillful prediction of the spatiotemporal evolution.

- The revised Fig. 1 shows the seasonal prediction skills of the current dynamical models for the spatiotemporal evolution of rainfall anomalies over time. It shows that dynamical models struggle to predict the spatiotemporal evolution of rainfall anomalies over East Asia, as forecast skills decrease rapidly with increasing forecast lead time.
- Fig. 2 (unchanged) shows that the spatiotemporal evolution of East-Asian summer rainfall anomalies, which vary both seasonally and yearly, can be decomposed into three distinct seasonal spatiotemporal patterns from May to September, each with its own yearly time series (which are referred to principal components or PCs). We believe this is an innovative way to describe the spatiotemporal evolution of East-Asian summer rainfall anomalies as it better captures distinct footprints left by precursory climate signals in the summer rainfall through synthesizing information from both the time and space dimensions. Specifically, the sum of the products of the three distinct seasonal spatiotemporal patterns and their yearly time series can adequately represent the rainfall anomalies both at a given instant and throughout their slow-varying subseasonal to seasonal evolution.
- Now the task of predicting the spatiotemporal evolution of East-Asian summer rainfall anomalies, which vary both seasonally and yearly, ultimately boils down to predicting the three principal components (PCs). The revised Fig. 4 shows the predictions for the (total) seasonal spatiotemporal evolution of East-Asian summer rainfall anomalies in each year and their comparison with the MME mean forecasts. Overall, our prediction skill for the spatiotemporal evolution over the entire 1993–2016 is nearly twice as high as the corresponding skill in MME mean.
- As a by-product of the predictions of the spatiotemporal evolution, we can predict the spatial patterns of East-Asian summer rainfall anomalies in each month of a given year. The revised Fig. 5 summaries our mean prediction skills in individual months (May–September) and in summer mean (JJA). It shows that our predictions outperform those of the MME mean in capturing the spatial patterns of rainfall anomalies in individual months.

We have also added related explanations and discussions in the revised manuscript.

2) Most analyses presented here focus on spatial patterns using correlation coefficients and, in my opinion, these results can be very volatile due to multiple factors (decadal variability, model hindcast period, independent models, and large observational uncertainty). For example, the observations themselves are known to disagree on the spatial pattern, in that case, what is the truth and what do we expect from the models?

Response: Thanks for your suggestion regarding the verification. Our understanding of this comment is that it covers two issues: the robustness of the spatial patterns among observations, and the spatial pattern correlation between observations and forecasts. Because the Reviewer's next comment is more specifically about the spatial patterns using correlation coefficients between observations and forecasts, we here focus on the robustness of the spatial patterns among observations and will come back to the issue of the spatial pattern using correlation coefficients (and the robustness of prediction skills) when replying to the next comment.

In this study, we utilized all available 43 years of daily rain gauge data to capture three relatively stable spatiotemporal patterns of seasonal rainfall anomalies and their yearly time series. In the revision, we also consider three satellite-gauge-based precipitation datasets (GPCP, CMAP, GPCC). As detailed in new Supplementary Table 3, the GPCP and CMAP datasets are satellite-gauge merged precipitation datasets, while the GPCC dataset provides global land-surface precipitation based on the station database from the Global telecommunication System of the World Meteorological Organization (WMO). These datasets are widely utilized for monitoring rainfall variations in East Asia and for model validation. These three additional datasets allow for an examination of the robustness of the results obtained from the 43 years of daily rain gauge data (usually as real values), including the decadal variability and the impacts of different datasets on the skill evaluation in both diagnostic and hindcast periods. These data are monthly mean data and therefore we compare spatiotemporal patterns derived from these three datasets with those derived from 43 years of daily rain gauge data, aggregated to the monthly level.

The newly added Supplementary Figs. 2-4 show that the spatiotemporal seasonal patterns from other three observed datasets closely resemble those from station data based on original daily (Fig. 2 in the main text and Supplementary Fig. 5) and their yearly time series show similar interannual and decadal variations. Specifically, the correlations of the PC1 (yearly time series of the spatiotemporal seasonal pattern 1) derived from the three datasets with the rain gauge data all exceed 0.94; The correlations of the PC2 derived from the three datasets with the rain gauge data are 0.75, 0.82, and 0.91, respectively whereas the correlations of the PC3 are 0.62, 0.66. and 0.86, respectively. Therefore, the observational uncertainties among different datasets primarily impact the interannual and decadal variability of PC3 in the spatiotemporal seasonal pattern, which contributes the least to the variability of seasonal rainfall anomalies. Overall, **the three distinct spatiotemporal patterns and their yearly time series are relatively consistent across the various observation datasets**. These results lend credibility to the original analysis of spatiotemporal patterns based on station data and further support our original conclusions. In the revised manuscript, we have reported this finding. (Please see **lines 115-117**)

3) The authors use gauge data from CMA using land stations and then interpolate the data on a 1x1 grid to correlate the pattern with the models. The spatial pattern using this data could be substantially different from the spatial pattern using satellite data, for instance. I think much more evidence is needed to prove that the proposed statistical-dynamical model is good at capturing the spatial distribution and evolution of monsoon rainfall. I was also hoping to see some dynamic diagnostic that could potentially be used to predict the progression or retreat of East Asian monsoon.

Response: Thanks for the valuable comments. In the revision, we have confirmed that using different observational datasets has minimal impact on the spatial pattern correlation between observations and forecasts (both our forecasts and MME mean forecasts) shown in our original manuscripts. Specifically, we first repeated the same correlation analysis between the MME mean forecasts and each of the three additional observational datasets. The results show that the skill of MME mean forecasts remains largely unchanged regardless of which observational datasets are used for verification (new Supplementary Fig. 10). Secondly, we repeated the same procedures for predicting the three yearly time series (i.e., PC1-PC3) derived from each of the three additional observational datasets using the same predictors for PC1-PC3 derived from the gauge data. The prediction skills of spatial pattern correlation in our forecasts for each of the three additional observational datasets are also very closed to those shown in the original manuscript, although the values of correlation skills are slightly smaller (new Supplementary Fig. 10). Furthermore, the correlation skills of proposed physical-statistical prediction model in predicting spatial distribution and spatiotemporal evolution of rainfall anomalies remain largely unchanged when evaluated using these additional observational datasets (please see new Supplementary Figs. 10-13). Therefore, the conclusion that **our predictions outperform the MME mean forecasts remains valid, regardless of which observational datasets are used for verification**. We have added the explanations on this in the revision. (Please see **lines 234-246**)

In this manuscript, we demonstrate that our proposed physical-statistical prediction model has a better skill than the MME mean forecasts in predicting the seasonal progression or retreat of East-Asian rainfall anomalies in most years. This improvement is achieved by considering the spatiotemporal evolution of rainfall anomalies and associated representative precursors that depict slowly-varying boundary conditions. However, identifying the underlying dynamic and physical mechanisms responsible for year-to-year variation of the progression or retreat of East Asian monsoon is beyond the scope of this study, due to the complexity of the atmosphere-ocean-land interactions. Inspired by your valuable suggestions, we plan to conduct a series of climate diagnoses and model simulations in a follow-up study to gain insights into these underlying dynamic and physical mechanisms.

4) The abstract mentions that the model uses non-conventional predictands, however, the precursors for inter-annual variation of rainfall are already identified by previous studies as mentioned in Supp. Table 2. Hence, I find this statement contradictory to the analysis.

Response: We agree with your that some precursors for inter-annual variation of rainfall, such as ENSO (as shown in original Fig. 3d), have been identified in previous studies. The innovation of our model lies in use of the non-conventional **predictands** (**not predictors**), namely, the three spatiotemporal patterns and their principal components (PCs), rather than the traditionally-used predictands of seasonal mean rainfall anomalies. As stated in our reply to the comment #1 above, the sum of the products of the three distinct seasonal spatiotemporal patterns and their yearly time series can adequately represent these anomalies both at a given instant and throughout their temporal evolution. The better skill is gained through more robust relationships of these (previously known and the newly identified) precursors with the yearly time series of the newly identified spatiotemporal patterns. We have added related explanations in the revised manuscript (please see **lines 263-264**).

5) I think the authors must consider the role of observational uncertainty leading to poor correlation values in this analysis.

Response: Thanks for your suggestion. In the revision, we explicitly document the impact of the observational uncertainty on the prediction skills regarding the correlation values between observations and forecasts (see Supplementary Figs. 10-13). Although the skill is slightly lower when using different satellite-gauge-based datasets, **the results confirm that our predictions still clearly outperform the MME mean forecasts**, as stated in our response to the comment #3.

6) My assumption from Fig. 1d is that the authors have calculated PCC for each year, and then averaged PCC from each year over the full period. Have the authors tried to calculate the PCC for the climatological rainfall anomaly from models and observations? What is the value of PCC in that case? Also, JJA mean doesn't give much information about spatiotemporal evolution, but rather shows information on monsoon rainfall distribution. It would have been better for the authors to look at PCC for each month separately to focus on "evolution".

Response: The pattern correlation coefficient (PCC) in Fig. 1d represents the similarity of the spatial distributions of JJA rainfall anomalies between forecasts and observations in each year and is used to quantify the prediction skills of current dynamical models in capturing the spatial patterns of summer mean rainfall anomalies. Before calculating the PCC in Fig. 1d, we first subtracted the JJA climatology for 1993–2016 from the models and observations to obtain the spatial rainfall anomalies, and then calculated the PCC between the spatial distributions of predicted and observed rainfall anomalies. Therefore, the climatological rainfall anomalies are zero, by definition, in both models and observations.

In addition, we also compared the climatological rainfall evolution between MME mean of models and observations. As shown in the figure below (Fig. R2), the MME of models are not able to capture the spatial and monthly evolution of observed rainfall climatology reasonably well, especially in South China, the Yangtze River Basin, and Northeast China. Therefore, our PCC calculations have excluded the systematic errors in the MME forecasts, a routine approach in the international community. Note that our PSM model is essentially **an anomaly model**. Therefore, it is fair to compare the PCC skill of our predictions with that of MME forecasts by excluding the systematic errors in the MME forecasts, as the PCC skill of MME forecasts would be even lower when including their systematic errors.

As noted in Comment #1, we have substantially revised Figs. 1, 4, and 5 and added related explanations to better illustrate our improved predictions of the spatiotemporal evolution of rainfall anomalies. In particular, the revised Fig. 5a presents the mean prediction skill of PCC for each month separately over the entire period.

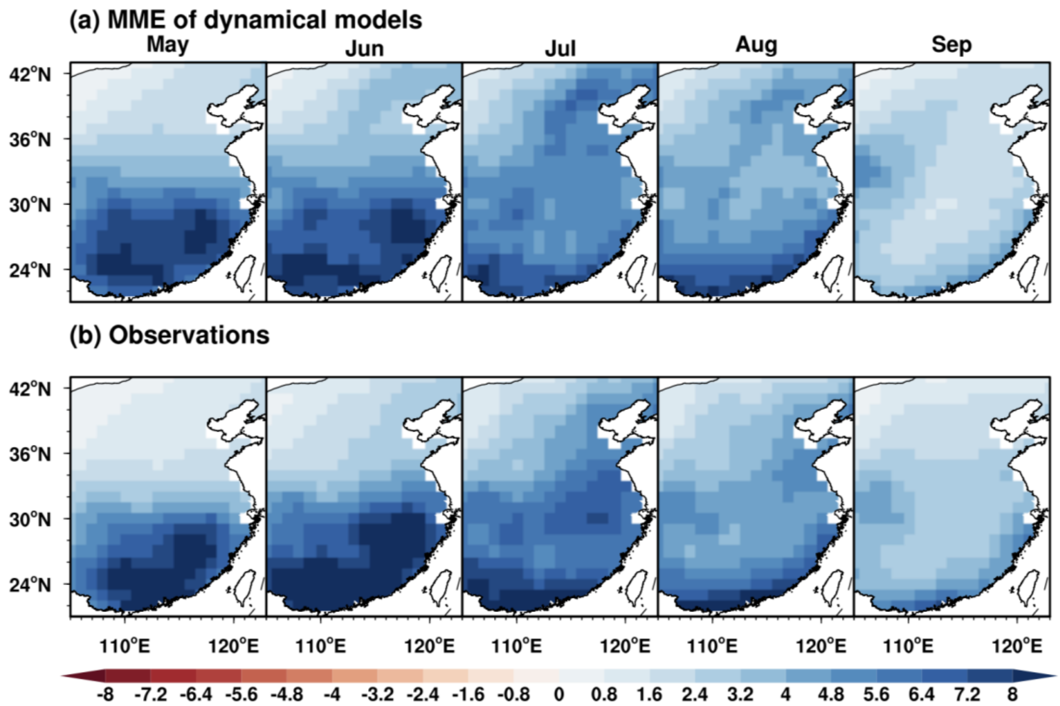

Fig. R2 The spatial distribution of climatological rainfall evolution over East Asia during 1993–2016 based on (a) the multi-model ensemble (MME) mean of the dynamical models, and (b) observations.

7) Fig. 1d shows that the models are not consistently bad in predicting the spatial distribution and there is large year-to-year variability in the ability of models to capture the spatial pattern. Is there a physical explanation for why the models are good for certain years and bad for others? For example, in 2016, 2011, 2014, and 1997 the dynamical models perform reasonably well.

Response: Numerous studies have shown that the ensemble skill of dynamical models in predicting seasonal rainfall anomalies over East Asia remains very low (e.g., Webster et al., 1998; Wang et al., 2004, 2015; Sperber et al., 2013; Huang et al., 2018), which is consistent with the results presented in the original Fig. 1d (now Supplementary Fig. 9). The ensemble forecast skill is very low in most years and high in only a few years, with large uncertainties in different models. The shortcomings of current dynamical models for seasonal predictions of East-Asian rainfall anomalies have been extensively investigated, which is largely attributed to the key factors such as initialization, the ability to reproduce crucial coupled ocean-atmosphere processes, and model resolution and performance (e.g., Wang et al., 2003, 2005; Wu et al., 2009; Zhu et al., 2016; Huang et al., 2018; Wang et al., 2024). We suspect that the good ensemble skills in a few specific years in the dynamical models may be due to their ability to correctly catch the information of some important precursors, also used in our PSM model. We have added related explanations and discussions in the revised manuscript (please see **lines 62-67**).

In this study, we merely use the current MME mean forecast as a reference to evaluate the prediction skill of our PSM model, rather than the variability in the skills of the MME forecasts. Therefore, a detailed physical explanation for such a variability is not the focus of this paper. Nevertheless, this is an excellent question, and in future work, we plan to investigate whether the variability in MME forecast skill is related to the precursors used in our PSM model, with the aim of providing insights into the limitations of current model capabilities.

References:

Huang, B., Cubasch, U., & Kadow, C. Seasonal prediction skill of East Asian summer monsoon in CMIP5 models. *Earth Syst. Dynam*. **9**, 985–997 (2018).

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Wu, Z., Wang, B., Li, J. & Jin, F. An empirical seasonal prediction model of the East Asian summer monsoon using ENSO and NAO. *J. Geophys. Res. Atmos*. **114**, D18120 (2009).
Zhu, Z. & Li, T. A new paradigm for the continental United States summer rainfall variability: Asia–North America teleconnection. *J. Clim*. **29**, 7313–7327 (2016).

8) Again, this is JJA, so figure Fig. 1d essentially captures the spatial distribution of rainfall during JJA and not the spatiotemporal evolution.

Response: Thanks again for your reminder. In the revised manuscript, we have replaced the original Fig. 1 with new Fig. 1 to better illustrate the prediction skills for the spatiotemporal evolution of rainfall anomalies in the MME mean forecasts, comparing it with our PSM forecasts (new Supplementary Fig. 8). Additionally, we have revised Figs. 4 and 5 and included further explanations to clarify our improvements in predicting the spatiotemporal evolution of rainfall anomalies, as detailed in Comment #1.

9) Could we have error bars in Fig. 1d, which shows the PCC from individual models and ensembles?

Response: Thanks for your suggestion. In the revision, we have added error bars to the original Fig. 1d (now Supplementary Fig. 9) and revised Fig. 5a to show the spread of PCC skills across individual models. The results illustrate large differences or uncertainties among individual models, indicating substantial variability in their ability to predict East-Asian rainfall anomalies during JJA. This highlights the clear inconsistencies in the current models for seasonal rainfall predictions over East Asia.

10) Supp. Fig. 1. Columns show different months, but I do not understand what the three rows are showing. Is it the spatial pattern for 10 years? What if a different time block was chosen?

Response: The three rows in Supplementary Fig. 1 represent the spatial patterns in individual months for the three distinct seasonal spatiotemporal patterns identified in Fig. 2. As mentioned in the response to Comment #1, the spatiotemporal patterns in the space-day domain (Fig. 2) allows us to examine the spatial pattern at any given instant. These spatial patterns (Supplementary Fig. 1) were obtained by regressing the total rainfall anomalies at spatial resolutions against the yearly time series of each spatiotemporal pattern during the training period from 1980 to 2009, reflecting the spatial characteristics of the main evolution of seasonal rainfall anomalies. We have added a clearer description to the caption of Supplementary Fig. 1.

11) Fig. 4 shows interesting results. The dynamical model supersedes the skill of both PSMs for May. For all months presented in the figure, the authors have likely used the May start dates and it is not surprising that the skill drops with lead time for MME, which is common in dynamical prediction systems. I suspect that if the authors had used a start date closer to the forecast period, the skill would have increased substantially and would be comparable to the PSMs. Can the authors check this?

Response: Thanks for this good suggestion. In this study, our predictions start in May, which is the same as the MME mean forecasts for comparison. According to your suggestion, we have compared our predictions (which still start from May) with MME forecasts started in June. As shown in the figure below (Fig. R3), the PSM forecasts still outperform MME forecasts, despite that the lead time of MME forecasts is one month shorter.

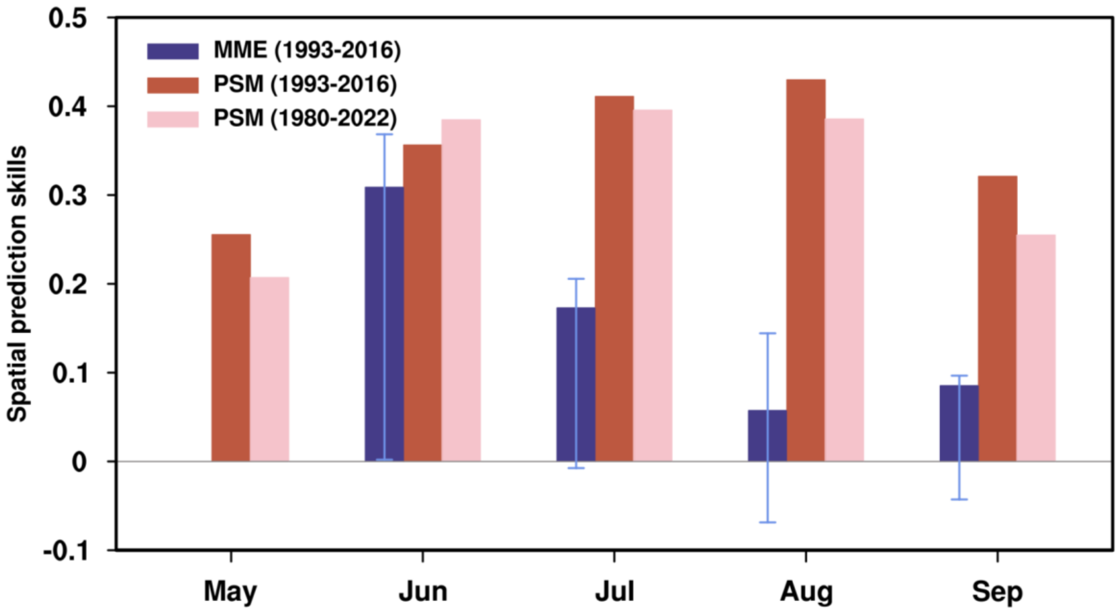

Fig. R3 Multi-year mean forecast skills of the spatial pattern correlation against the total rainfall anomalies in individual months in the multi-model ensemble (MME) mean of the dynamical models initiated from June and the physical-statistical prediction model (PSM) initiated from May. The blue line segments represent the ranges of forecast skills derived from individual dynamical models.

12) Again, for this figure, I would be keen to see the skill of not MME but individual models, and if any models have surpassed the skill of PSMs.

Response: Thanks for this suggestion. We have added new Supplementary Fig. 7 to clearly show the prediction skills of individual dynamical models in capturing the spatial patterns of rainfall anomalies in individual months. The results indicate that the forecasts from all individual dynamical models (blue bars) perform worse than the MME mean forecasts (grey dots) in capturing spatial patterns of rainfall anomalies as the lead time increases. Additionally, we have included the range information of prediction skills among individual models in the original Fig. 4b (now Fig. 5a) and added the following explanation in the revised manuscript: "*Meanwhile, the forecasts from all individual dynamical models perform worse than the MME mean forecasts in capturing spatial patterns of rainfall anomalies as the lead time increases (Supplementary Fig. 7).*" (Please see **lines 219-221**)

13) I do not understand what is spatio-temporal correlation coefficient in Fig 4. Is it the same as pattern/map correlation?

Response: As you mentioned, the spatio-temporal correlation coefficient is similar to map correlation but applied to the latitude-time domain (see new Fig. 4). For example, in new Fig. 4d, the prediction skills, measured by spatiotemporal correlation coefficients, are calculated by the map correlation between observed and forecasted spatiotemporal evolution in the latitude-time domain for each year (Figs. 4a and 4b), as depicted in Method section.

In this study, the spatiotemporal correlation coefficient is a crucial metric for assessing the model performance in predicting spatiotemporal evolution of rainfall anomalies, as it combines both spatial and temporal accuracy. It reflects how well the predicted spatiotemporal evolution match the corresponding observation across both space and time. A higher value indicates the model forecast is better at capturing the observed spatiotemporal evolution. We have added related description in the revision (please see **lines 207-210**).

14) Line 73: It should perhaps be "Only a few studies..."

Response: Thanks for your suggestion. It has been revised to "Only a few studies" in the updated manuscript.

Review of "Skillful Seasonal Predictions of East Asian Summer Rainfall by Integrating its Spatio-Temporal Evolution

This paper shows results on the prediction of the spatio-temporal evolution of rainfall within the summer monsoon season over East Asia. The authors propose a new statistical dynamical model to predict the spatial-temporal evolution of rainfall during the summer monsoon season over East Asia and argue that their proposed model supersedes the current dynamical prediction systems that are used operationally.

While I agree with the authors that we need models that can predict not only the magnitude of seasonal mean rainfall but also more detailed characteristics like the progression or retreat of monsoon, I have several major concerns requiring further clarification, particularly the distinction between the spatial distribution of monsoon rainfall and spatiotemporal evolution of monsoon rain. In summary, this paper requires significant revisions to clarify its objectives, strengthen the analysis, and address questions raised before it can be considered for publication.

Major comments:

There is confusion about the terminology and the question that the authors are trying to address in this paper. The paper is targeted toward the prediction of the spatio-temporal evolution of monsoon anomalies (lines 77-81) however most of the analysis and arguments are around models' ability to capture the spatial distribution of monsoon mean rainfall anomalies. To me, these are two different things. The first one refers to the spatial distribution of monsoon rain, e.g. analysis done in Fig. 1 and 2, and most of the statistical analysis focuses on the spatial pattern of monsoon mean rainfall (JJA) or interannual variability. The spatio-temporal evolution implies to me, the progression and retreat of monsoon during/within the monsoon season and involves intra-seasonal analysis. These two are of course interconnected but distinct issues and in many places, spatial distribution and spatiotemporal evolution are used interchangeably. I find it difficult to decipher which issue the authors are trying to address.

Most analyses presented here focus on spatial patterns using correlation coefficients and, in my opinion, these results can be very volatile due to multiple factors (decadal variability, model hindcast period, independent models, and large observational uncertainty). For example, the observations themselves are known to disagree on the spatial pattern, in that case, what is the truth and what do we expect from the models?

The authors use gauge data from CMA using land stations and then interpolate the data on a 1x1 grid to correlate the pattern with the models. The spatial pattern using this data could be substantially different from the spatial pattern using satellite data, for instance. I think much more evidence is needed to prove that the proposed statistical-dynamical model is good at capturing the spatial distribution and evolution of monsoon rainfall. I was also hoping to see some dynamic diagnostic that could potentially be used to predict the progression or retreat of East Asian monsoon.

The abstract mentions that the model uses non-conventional predictands, however, the precursors for inter-annual variation of rainfall are already identified by previous studies as mentioned in Supp. Table 2. Hence, I find this statement contradictory to the analysis.

I think the authors must consider the role of observational uncertainty leading to poor correlation values in this analysis.

My assumption from Fig 1d is that the authors have calculated PCC for each year, and then averaged PCC from each year over the full period. Have the authors tried to calculate the PCC for the climatological rainfall anomaly from models and observations? What is the value of PCC in that case? Also, JJA mean doesn't give much information about spatiotemporal evolution, but rather shows information on monsoon rainfall distribution. It would have been better for the authors to look at PCC for each month separately to focus on "evolution".

Fig. 1d shows that the models are not consistently bad in predicting the spatial distribution and there is large year-to-year variability in the ability of models to capture the spatial pattern. Is there a physical explanation for why the models are good for certain years and bad for others? For example, in 2016, 2011, 2014, and 1997 the dynamical models perform reasonably well.

Again, this is JJA, so figure Fig. 1d essentially captures the spatial distribution of rainfall during JJA and not the spatiotemporal evolution.

Could we have error bars in Fig. 1d, which shows the PCC from individual models and ensembles?

Supp. Fig. 1. Columns show different months, but I do not understand what the three rows are showing. Is it the spatial pattern for 10 years? What if a different time block was chosen?

Fig. 4 shows interesting results. The dynamical model supersedes the skill of both PSMs for May. For all months presented in the figure, the authors have likely used the May start dates and it is not surprising that the skill drops with lead time for MME, which is common in dynamical prediction systems. I suspect that if the authors had used a start date closer to the forecast period, the skill would have increased substantially and would be comparable to the PSMs. Can the authors check this?

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