

Response

Anonymous Referee #2:

This work develops a statistical approach to attributing correlation skill of dynamical forecast to ENSO teleconnection. It can present regions where the forecast skill is attributed to its teleconnections with ENSO, can serve as an effective tool to investigate the source of predictability. The method and results sound reasonable.

Thank you very much for the positive comments.

It is potentially publication if the following concerns are included, regarding to the lead-lag teleconnections and forecast.

We are grateful to you for the insightful and constructive comments. Please see the point-by-point responses in the following.

- 1. This approach is just applied with concurrent correlation between Niño3.4 index and observations, to represent ENSO teleconnection. But ENSO also has some lead-lag impacts on the precipitation variations, which also involve in the forecast skill and sources of precipitation. How about of the attributions of these processes? More discussions on it are needed.*

Thank you for the comment. New experiments are performed to investigate lagged ENSO teleconnection:

“Lagged ENSO teleconnection and correlation skill by lead time are important issues for seasonal forecasting (Schepen et al., 2012; Peng et al., 2014; Steinschneider & Lall, 2016). A numerical experiment of attribution is performed for Niño3.4 indices at different time lags. Specifically, for precipitation in DJF, the concurrent Niño3.4 in the analysis is replaced by Niño3.4 in November, October and September so as to investigate the overlapping R2 for 1-, 2- and 3-month lag ENSO teleconnection. Figures S7 to S10 in the supplementary material show that the results tend to be similar at the three lags; the similarities are generally owing to the temporal persistency of Niño3.4 (Yang et al., 2018). Furthermore, another experiment is devised for GCM forecasts at the lead time of 1, 2 and 3 months. That is, for precipitation in DJF, forecasts generated in November, October and September are used to replace forecasts generated in

December in the analysis (Figures S11 to S14). It can be observed that the case of significantly positive anomaly correlation attributable to positive ENSO teleconnection remains for southern North America and that the case of significantly positive anomaly correlation attributable to negative ENSO teleconnection remains for northern South America and southern Africa.” (Page 20, Lines 343 to 353)

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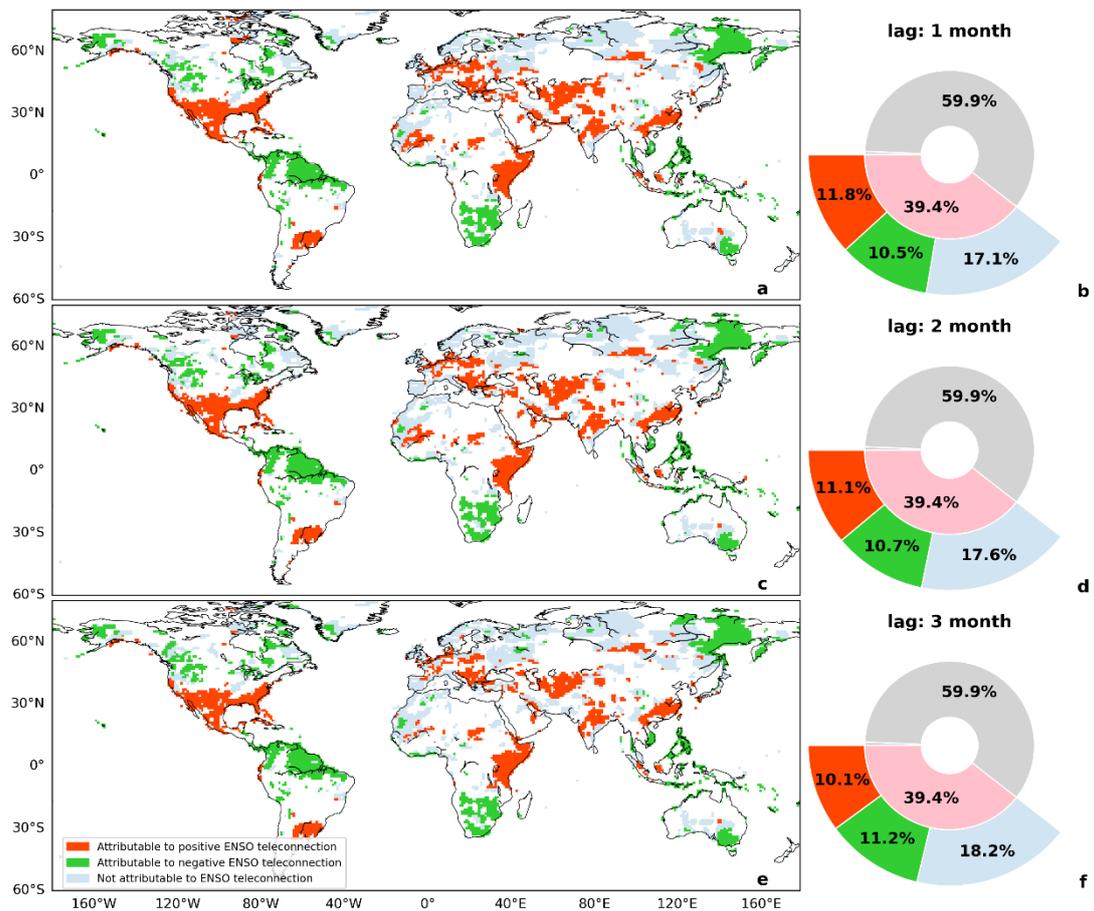


Figure S10: As in Figure 9 but for DJF seasonal precipitation with (a-b) November (1-month lag), (c-d) October (2-month lag) and (e-f) September (3-month lag) Niño3.4 index.”

2. Lines 20-24, and 346-350, for the novelty of this work in Abstract and Conclusion, there is a repetition in writing. Please rewrite them.

Thank you. We have rewritten the Conclusion:

“The spatial patterns of forecast skill attributed to different types of ENSO teleconnections confirm previous studies associating seasonal precipitation variability with ENSO and highlight the capability of CFSv2 in capturing the pathways of ENSO

teleconnections. The attribution method proposed in this paper can lay a basis for future evaluations of other teleconnections and investigations of predictability sources for GCM seasonal precipitation forecasts.” (Page 20, Lines 374 to 378)

3. *Line 94, this work is just “paid to the latest forecasts”. It is also quite interesting to figure out that, are there any differences on the ratio of significantly positive anomaly correlation attributable to different types of ENSO teleconnections, with the increase of lead time?*

Thank you for the constructive comment. New experiments are performed to investigate the effects of lead time:

“Lagged ENSO teleconnection and correlation skill by lead time are important issues for seasonal forecasting (Schepen et al., 2012; Peng et al., 2014; Steinschneider & Lall, 2016). A numerical experiment of attribution is performed for Niño3.4 indices at different time lags. Specifically, for precipitation in DJF, the concurrent Niño3.4 in the analysis is replaced by Niño3.4 in November, October and September so as to investigate the overlapping R2 for 1-, 2- and 3-month lag ENSO teleconnection. Figures S7 to S10 in the supplementary material show that the results tend to be similar at the three lags; the similarities are generally owing to the temporal persistency of Niño3.4 (Yang et al., 2018). Furthermore, another experiment is devised for GCM forecasts at the lead time of 1, 2 and 3 months. That is, for precipitation in DJF, forecasts generated in November, October and September are used to replace forecasts generated in December in the analysis (Figures S11 to S14). It can be observed that the case of significantly positive anomaly correlation attributable to positive ENSO teleconnection remains for southern North America and that the case of significantly positive anomaly correlation attributable to negative ENSO teleconnection remains for northern South America and southern Africa.” (Page 20, Lines 343 to 353)

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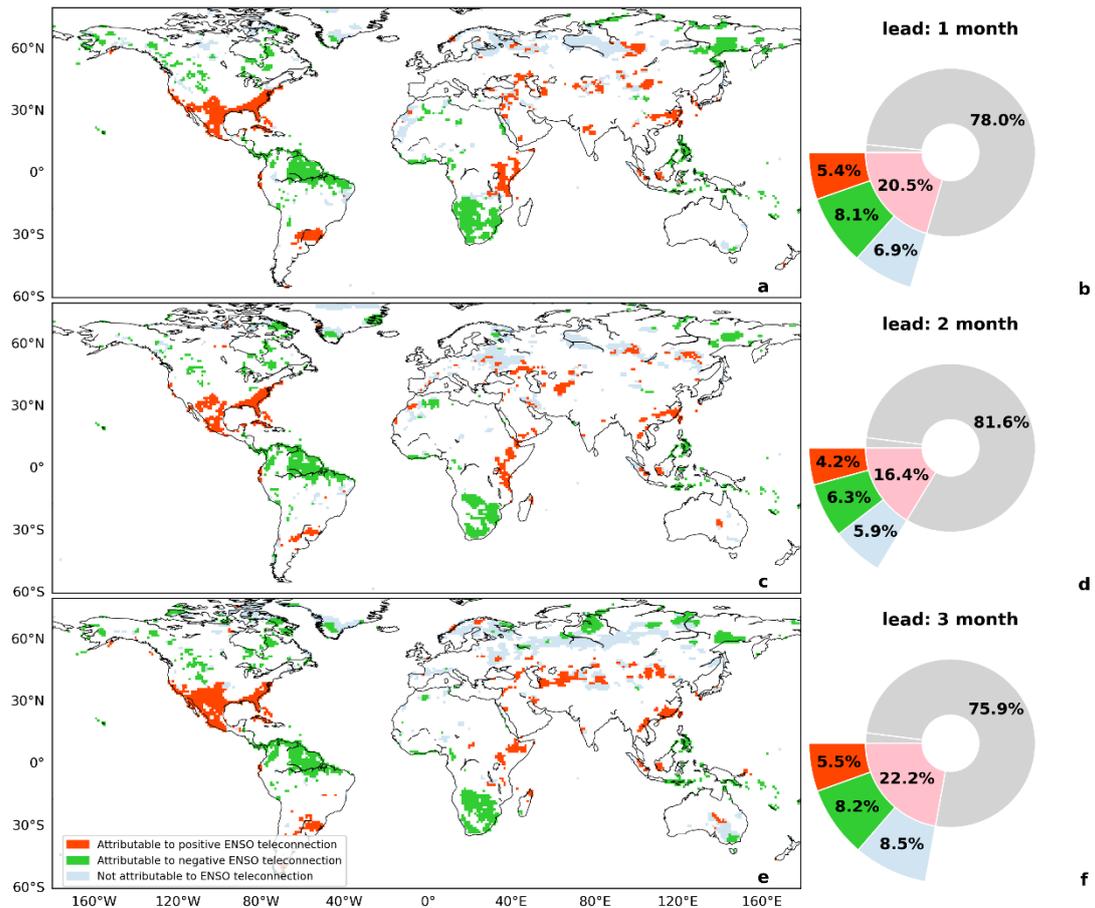


Figure S14: As in Figure 9 but for DJF seasonal forecasts generated in (a-b) November (1-month lead), (c-d) October (2-month lead) and (e-f) September (3-month lead).”

4. For the extended analysis in Section 4.4, the percentage of significantly anomaly correlation in MAM, JJA and SON is largest in SON, but still lower than DJF. It suggests obvious seasonal differences. This may connect with the observed teleconnections with ENSO. It would be better giving more discussions on these differences and more comparisons with previous sections and studies.

Thank you for the insightful comment. More discussions and comparisons are added in Section 4.4:

“The attribution analysis is further extended to the other seasons, i.e., MAM, JJA and SON. Global maps of the three cases of attribution are illustrated by season in Figure 9 and also in Figures S1 to S6 of the supplementary material. Overall, the results of attribution vary considerably across the four seasons. It is generally owing to the facts that ENSO teleconnection varies by season (Kim & Kug, 2018; Steptoe et al., 2018; Wang et al., 2019) and that GCMs formulate not only ENSO but also other

teleconnections (Saha et al., 2014; Jia et al., 2015; Delworth et al., 2020). Overall, the percentage of significantly positive anomaly correlation is 27.0%, 24.0% and 34.6% respectively in MAM, JJA and SON, which tend to be smaller than that in DJF. This result can be due to the seasonal cycle of ENSO, i.e., ENSO forcing tends to be the strongest in DJF and it translates into weaker precipitation variability in the other seasons (Yang et al., 2018).

The percentage of significantly positive anomaly correlation attributable to positive ENSO teleconnection is respectively 7.1%, 6.3% and 7.0% in MAM, JJA and SON. Representative regions for this case are western United States in MAM (Pegion & Kumar, 2013), parts of South America in JJA (Cai et al., 2020) and Middle East in SON (Mariotti, 2007). 7.3%, 7.4% and 14.3% of grid cells are with significantly positive anomaly correlation attributable to negative ENSO teleconnection respectively in MAM, JJA and SON. One representative region is southeast Asia, where precipitation is strongly correlated with ENSO in MAM, JJA and SON (Jiang & Li, 2017); also, in Australia, precipitation in SON is found to be substantially influenced by the extratropical teleconnection pathway of ENSO (Cai & Weller, 2013). Furthermore, 12.6%, 10.3% and 13.3% of grid cells are with significantly positive anomaly correlation not attributable to ENSO teleconnection. This result calls for the investigation of other teleconnection patterns for GCM seasonal precipitation forecasts.” (Pages 17 to 18, Lines 304 to 322)