Dear Editor and Reviewer:

Thank you very much for your insightful comments concerning our manuscript "ENSO-ASC 1.0.0: ENSO Deep Learning Forecast Model with a Multivariate Air–Sea Coupler" (ID: gmd-2021-213). Those comments are all very valuable and helpful for revising and improving our manuscript, we have studied comments carefully and have made revision. The point-by-point responses are as following:

Comment 1: 260: There's an I_n in this formula but was not explained ahead. This is supposed to be an identity matrix, right? Please introduce it clearly.

Response: Thank you for spotting our crucial neglects in calculation description. We have updated the corresponding statements at **line 261** as the **blue** text below:

"*In practical implementation mathematically, we use graph Laplacian matrix* L *to normalize the energy flow of original adjacency matrix* A *as Eq. (11),* **where I_n is an identity matrix with the order $n \times n$.** L can be considered as the directions in which the excess unstable energy will propagate to other variables when the entire system is perturbed (such as external wind forcing)."

Comment 2: Figure17-Figure20: The data seems to be standardized and should be mentioned on the figure.

Response: Thank you so much for your professional attitude and helping us find a mistake. Figure17-Figure20 are used to display the SST and wind anomalies patterns of the model results and observations, which are obtained by subtracting the corresponding climatology (climate mean state). However, we made a mistake. For example, for the SST anomalies patterns in July, we should subtract the climatology of SST in July, but we subtract the average of the climatology of SST in the whole year. By the way, the climatology in July is the average of the data in July of the recent 30 years. So, Figure17-Figure20 in the previous manuscript is wrong shown as Figure1-Figure4.

The corrected Figure17-Figure20 in manuscript are shown as Figure5-Figure 8, which have been updated at **line 665, 690, 695, and 710** in the latest manuscript. We also supplement the related statements at the line 635 as the **blue** text below:

"*Therefore, we make long-term forecasts and majorly trace the evolutions of SST and wind (u-wind and v-wind).* **Note that all of the following patterns describe the evolutions of SST and wind anomalies by subtracting the climatology (climate mean state) of that month (the recent 30-year monthly averaged SST and wind) from the forecasted SST and wind patterns.**"

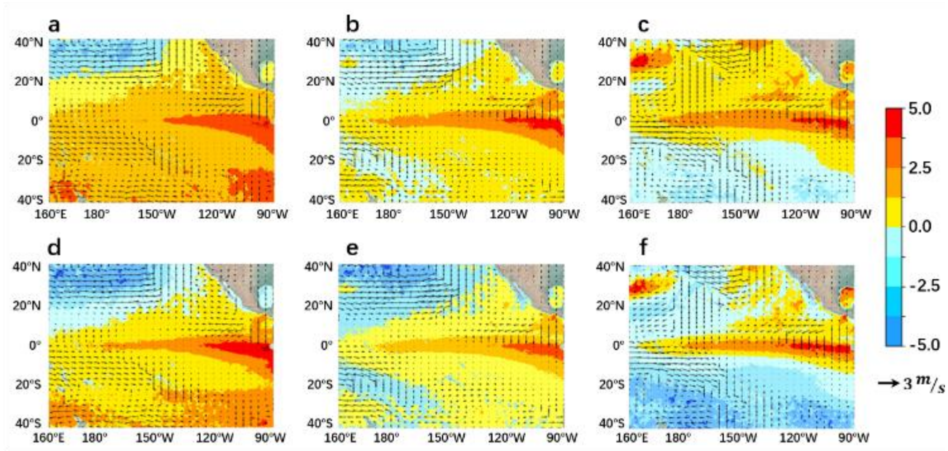

Figure 1: The growth phase of SST anomalies in 2015/2016 super Niño event from 2015.4 to 2015.6. a-c are the forecast results of the ENSO-ASC and d-f are real-world observations.

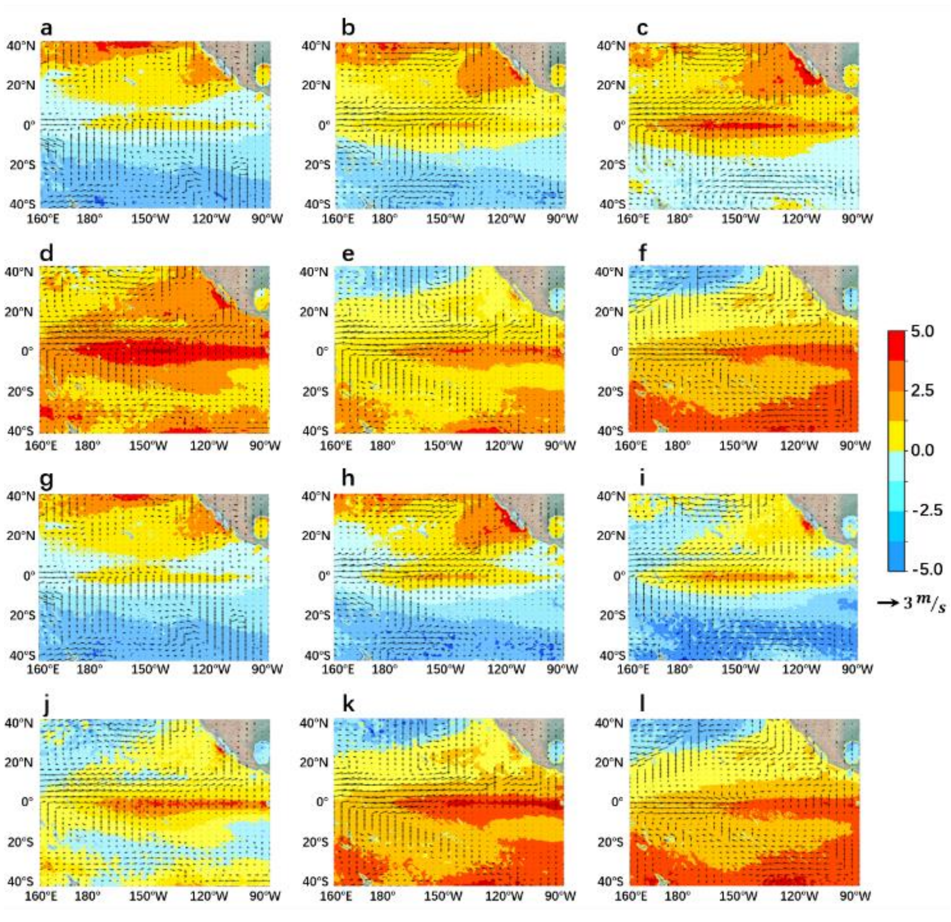

Figure 2: The peak phase of SST anomalies in 2015/2016 super Niño event from 2015.9 to 2016.2. a-f are the forecast results of the ENSO-ASC and g-l are real-world observations.

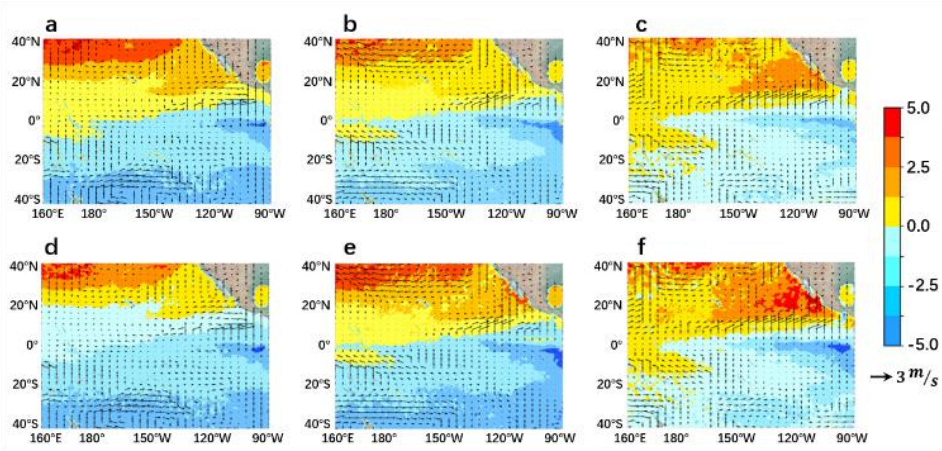

Figure 3: The same with Fig. 17 but for the growth phase of SST anomalies of 2017 weak La Niña event from 2017.9 to 2017.11.

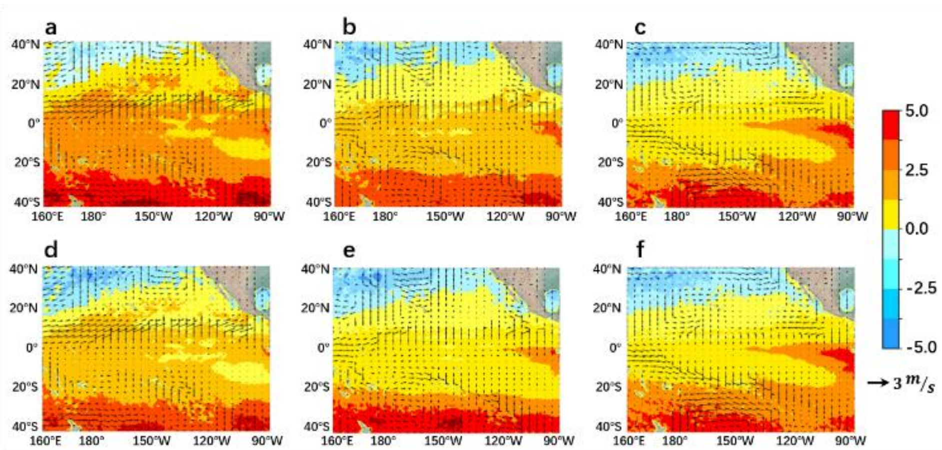

Figure 4: The same with Fig. 17 but for the neural SST evolution in 2020.1 to 2020.3.

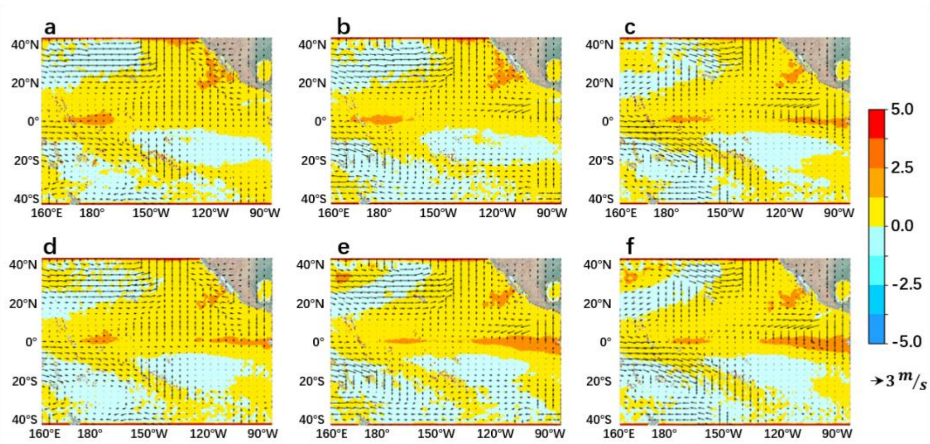

Figure 5: The growth phase of SST anomalies in 2015/2016 super Niño event from 2015.4 to 2015.6. a-c are the forecast results of the ENSO-ASC and d-f are real-world observations.

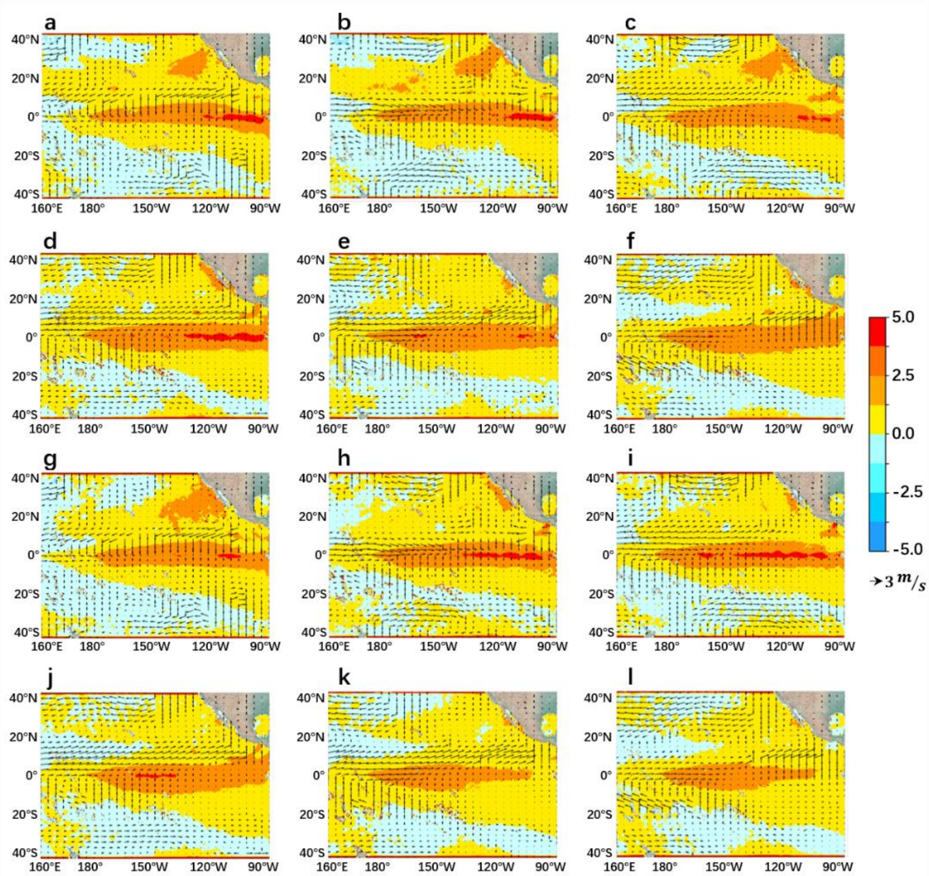

Figure 6: The peak phase of SST anomalies in 2015/2016 super Niño event from 2015.9 to 2016.2. a-f are the forecast results of the ENSO-ASC and g-l are real-world observations.

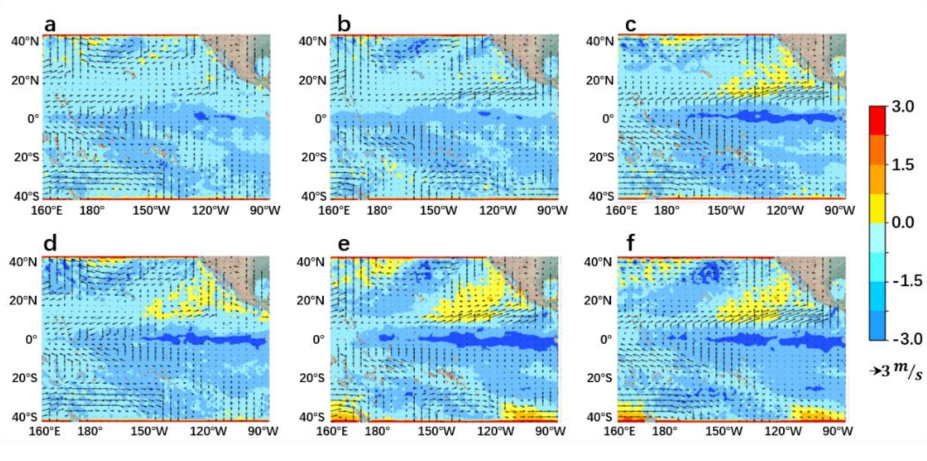

Figure 7: The same with Fig. 1 but for the growth phase of SST anomalies of 2017 weak La Niña event from 2017.9 to 2017.11.

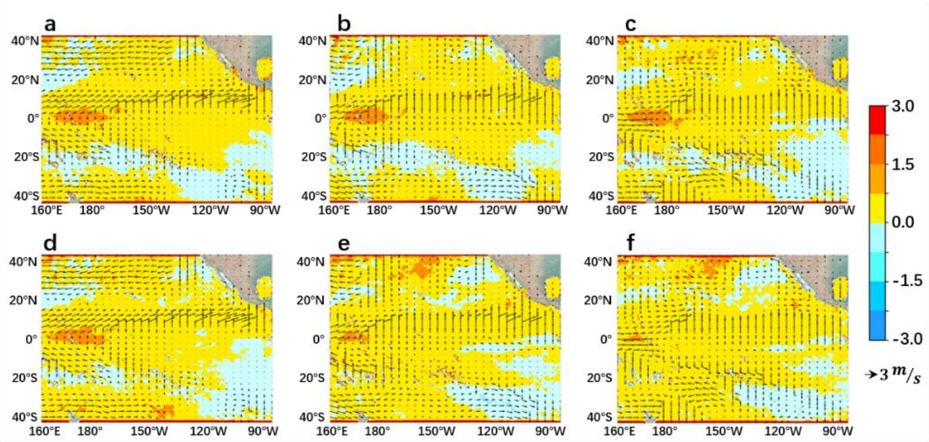

Figure 8: The same with Fig. 1 but for the neural SST evolution in 2020.1 to 2020.3.

Comment 3: A suggestion: In this paper, it is found that the best effect is to set the input sequence length as 3. This may be due to selecting the predictors with short memory (vapor, cloud). If predictors with long memory (such as heat content) are added, it may be more effective to set the length longer. Although Table 3 shows the prediction effect of the model with increased heat content data, the input sequence length is the same. This may be taken into consideration in a future study using global data.

Response: We thank the reviewer for this valuable insight very much. As the reviewer said, from our experiments in Section 4.3.1 *(Influence of the input sequence length)*, we found that the suitable input sequence length for the ENSO-ASC is 3 months according to the trade-off between the time-/resource-consuming and forecast skill when using 6 predictors (SST, u-wind, v-wind, rain, cloud, and vapor), in which 5 variables are related to the atmospheric processes with short memories. In the Section 4.4.1 *(Contributions of different predictors to the forecast skill)*, when we add heat content with long memory into the model, it is indeed necessary to re-investigate the optimal input sequence length by experiments in this manuscript. In fact, in continuous studies following this manuscript, the input length should be at least 6 months with 7 input variables (SST, u-wind, v-wind, rain, cloud, vapor and heat content) using globe data. While with the equatorial Pacific data and the input sequence length varying from 3 to 9 months, the change of forecast skill of ENSO-ASC is not much significant. Because the input region mainly covering the equatorial Pacific and most of the variables are with short memories in this manuscript, the input sequence length is still set as 3 despite adding heat content data into the model shown in Table 3. Let's look forward to our next manuscript following this manuscript.

The related statements are additionally supplemented in the Section 4.4.2 (Contributions of different predictors to the forecast skill) at **line 500** as the **blue** text below:

'The superiority of our proposed model derives from the graph formalization, and the special multivariate coupler can effectively express the processes of synergies between multi-physical variables. From another perspective, the improvement of the forecast skill is not only benefited from graph formalization, but also due to the utilization of multiple variables highly related to ENSO compared to

using limited variable to predict ENSO as previous works. For ENSO forecast, SST is definitely the most critical predictor. Besides SST, other variables have different contributions to the forecast results. Therefore, we design an ablation experiment by removing one of predictors from our proposed model and detect the reduction of forecast skill (Table 3 above). **At the meanwhile, we also add one extra predictor (from surface air temperature, surface pressure and ocean heat content respectively) into our proposed model to investigate the improvement of forecast skill (Table 3 below). Here, the input sequence length is still set to 3.**

Table 1: Model performance when one existing variable removed or one extra variable added

Removed variable	12-month SSIM / PSNR	15-month SSIM / PSNR	18-month SSIM / PSNR
-	92.65 / 22.05	90.31 / 20.97	87.53 / 18.17
RAIN	91.46 / 21.34	88.74 / 18.32	85.86 / 17.35
CLOUD	91.53 / 21.65	88.81 / 18.54	85.93 / 16.16
VAPOR	91.52 / 21.65	88.82 / 18.53	85.92 / 16.16
UWIND	90.08 / 20.93	87.03 / 17.81	83.72 / 13.58
VWIND	91.47 / 21.62	88.65 / 18.42	85.31 / 15.07
Added variable	**12-month SSIM / PSNR**	**15-month SSIM / PSNR**	**18-month SSIM / PSNR**
Surface Pressure	92.74 / 22.13	90.33 / 20.99	87.64 / 17.26
Surface Air Temperature	92.75 / 22.15	90.40 / 21.07	87.71 / 17.25
upper ocean heat content	92.98 / 22.14	90.45 / 21.10	87.79 / 17.34

Table 3 (above) shows that when a variable is removed from the input of the deep learning model, the ENSO forecast skill will be reduced. More specifically, when the zonal weed speed (UWIND) is removed, the reduction is the largest. From the perspective of ENSO physical mechanism, zonal wind anomalies (ZWA) always play a necessary role and are even considered as the co-trigger or driver of ENSO events. As an atmospheric variable, ZWA often gives a direct feedback on oceanic varieties with a shorter response time than oceanic memory. ENSO-ASC uses historical 3-month multivariate data to predict ENSO evolution, which is a quite short sequence length. Under such sequence length, wind speed (including u-wind and v-wind) has a relatively high correlation with SST. In addition, RAIN is another variable that slightly affects the forecast. This is because the precipitation process has a straightforward contact with the sea surface, and the energy transfer is easier.

Table 3 (below) indicates that the model performance improves a little when adding surface air temperature/surface pressure/ocean heat content into the multivariate coupler. This is because that the multivariate graph with existing variables in the ENSO-ASC can almost describe a relatively complete energy loop in Walker circulation, so the effects of the extra added variables to the ENSO forecasts are not obvious. **It is worth noting that the input sequence length should be longer when feeding the ocean heat content into the multivariate coupler, because this predictor is with long memory. However, as the input sequence length varies from 3 to 9 months, the forecast skills of ENSO-ASC have not changed much actually. This is mainly because that the global spatial teleconnections and temporal lagged correlations by Walker Circulation and ocean waves**

(such as Kelvin and Rossby Waves) (Exarchou et al., 2021 and Dommenget et al., 2006) are not caught in the model, the input region of which mainly covers the equatorial Pacific. In addition, the model contains only one long memory predictor besides SST.

In the subsequent experiments, the model will use the chosen 6 variables (SST, u-wind, v-wind, rain, cloud, and vapor) and the input sequence length is set to 3."

The related statements are also additionally supplemented in the Section 5 (Discussions and conclusions) at the **line 845** as the **blue** text below:

"The extensive experiments demonstrate that the ENSO forecast model with a multivariate air-sea coupler (ENSO-ASC) is a powerful tool for analysis of ENSO-related complex mechanisms. Meteorological research does not only pursue skilful models and accurate forecasts, but requires a comprehensive understanding of the potential dynamical mechanisms. **In the future, we will extend our model to more global physical variables with informative vertical layers, such as the thermocline depth, and the ocean temperature heat content, to explore the global spatial remote teleconnections, temporal lagged correlations, and the optimal precursor etc.***"*

The related references are shown as following and also added into the manuscript:

References

Dommenget, D., Semenov, V., and Latif, M.: Impacts of the tropical Indian and Atlantic Oceans on ENSO, Geophysical research letters, 33,2006.

Exarchou, E., Ortega, P., Rodríguez-Fonseca, B., Losada, T., Polo, I., and Prodhomme, C.: Impact of equatorial Atlantic variability on ENSO predictive skill, Nature communications, 12, 1–8, 2021.

Other typos corrections

When we improve our manuscript, we also find some typos and statement errors, which have been corrected as following:

Line 525: "little improvement" → "a little improvement"

Line 630: "an 18-month forecasts" → "long-term forecasts"

Line 655: "out" → "our"

Thank you again for your positive comments and valuable suggestions to improve the quality of our manuscript.

On behalf of all the co-authors, best regards,

Bo Qin