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 revisions. The point-by-point responses are as following:

Comment 1: In the ablation experiment, "The calculation of this variable contains SST, so the effect of the extra introduction of upper ocean heat content will be weakened" is at L533. I have a suggestion: if using upper ocean heat content to take place the SST in the model, how will the ENSO-ASC perform?

Response: Thank you so much for your professional attitude and insightful suggestion. This is indeed a valuable question for investigating the effects of different predictors on an ENSO deep learning forecast model. The upper ocean heat content is a very concerned variable, which can reflect the vertical and horizontal propagations of ocean waves and help interpret the dynamical mechanisms of ENSO. Therefore, as the comment says, we supplement a control experiments to investigate the model performance by replacing SST with upper ocean heat content in the model input.

We conduct the comparison by two modified ENSO-ASCs with the same output of SST + u-wind, v-wind, rain, cloud, and vapor, while with the different input. One is upper ocean heat content + u-wind, v-wind, rain, cloud, and vapor (**EXAM**), the other is SST + u-wind, v-wind, rain, cloud, and vapor (**CTRL**). We find that the forecast skill of **EXAM** is slightly lower than that of **CTRL** (depicted as Table 4). The upper ocean heat content is the average of the oceanic temperature from sea surface to upper 300m, which is crucial to represent the deeper sea temperature beyond sea surface. However, our model is designed to forecast SST. We think that using the upper ocean heat content as a predictor for our model inevitably introduces more noise, which extracts the features of oceanic temperature not only from sea surface but also from deeper ocean. Actually, according to our extensive experiments, we find it is a positive determination that the model should select the physical variable we want to forecast as one of predictors.

We also supplement the related statements from the start of **line 545** as the blue text below:

"Among the three extra added physical variables, the upper ocean heat content is a very concerned variable, which can reflect the vertical and horizontal propagations of ocean waves and help interpret the dynamical mechanisms. Therefore, we conduct the comparison via two modified ENSO-ASCs with the same output of SST + u-wind, v-wind, rain, cloud, and vapor, while with the different input. One uses upper ocean heat content + u-wind, v-wind, rain, cloud, and vapor, marked as EXAM, another uses SST + u-wind, v-wind, rain, cloud, and vapor, marked as CTRL. The results are shown in Table 4.

Table 1: Model performance comparison when using upper ocean heat content to replace SST in the input

Model paradigm	12-month	15-month	18-month
	SSIM / PSNR	SSIM / PSNR	SSIM / PSNR

CTRL: *SST + others →* *SST + others*	92.65 / 22.05	90.31 / 20.97	87.53 / 18.17
EXAM: *upper ocean heat content + others →* *SST + others*	90.96 / 20.87	88.45 / 18.23	84.76 / 14.90

Note: Model paradigm represents the input and the output for the ENSO-ASC, where → means "forecast". "Others" is five variables, including u-wind, v-wind, rain, cloud, and vapor. The first row is the control experiment, which is the same with the result in Table 3, and the second row is the examined experiment, which only replaces SST by upper ocean heat content in the model input.

The forecast skill of EXAM is slightly lower than CTRL. The upper ocean heat content is the average of the oceanic temperature from sea surface to upper 300m. When using it as a predictor to forecast SST, our model will extract the features of oceanic temperature not only from sea surface but also from deeper ocean, which inevitably introduces more noise. This may be a reason for the above result. Generally, the model should select the physical variable to be predicted as one of predictors to obtain higher forecast skill."

Comment 2: The initial letter of the sentence should be uppercase and some mistakes are found at line 103 and line 222.

Response: Thanks for your comment. We have read through the full text and corrected all misspelling and grammatical errors, including **Line 103** and **Line 222**.

Comment 3: L374, "N40°-S40°, E160°-W90°", should be expressed as the region of 40°N-40°S, 160°E-90°W.

Response: Thanks for your comment. We have corrected the related text in the **Line 374**. In addition, we also modify the statements in the legend of Figure1 as the following blue text:

"Figure 1: Most concerned regions in ENSO events. The blue rectangle covers the Niño3 region (5°N-5°S, 150°W-90°W), and the green rectangle covers the Niño4 region (5°N-5°S, 160°E-150°W)."

Comment 4: In Figure 6, the text looks too small.

Response: Thank you for your reminding, and it is really a good suggestion to improve the whole quality of our manuscript. We have enlarged the font size and image size of Figure6. In addition, we also check and enlarge the size of other figures in our manuscript to make them more clearly.

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