# *Supplementary Material*

## S1. Supplementary Content: Impact of the temporal interpolation of the training data

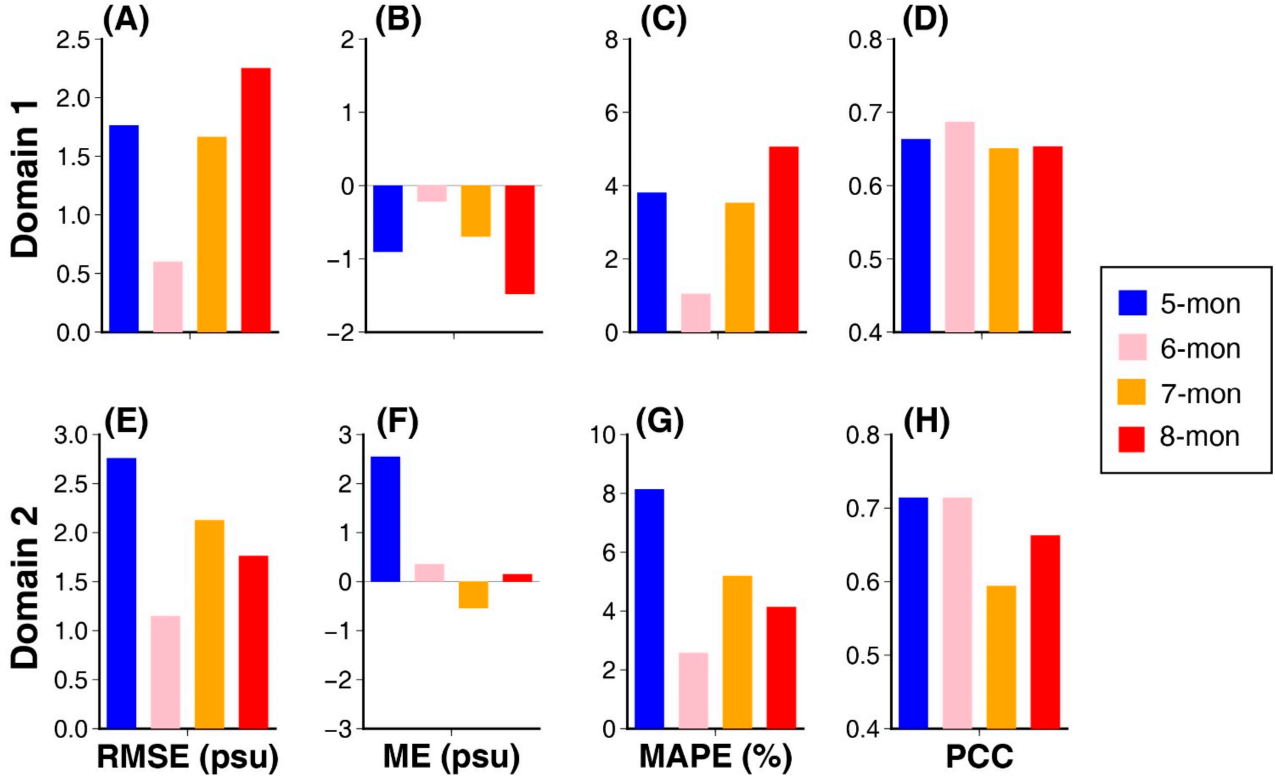
Due to the coarser temporal resolution of the sea surface salinity (SSS) dataset, it was a difficult task for our model to predict the summer low-salinity extension over the East China Sea and the Yellow Sea (ECS&YS). To enhance the model performance in predicting features that have relatively smaller temporal scales, the simplest way is to train the model with data with higher temporal resolution. However, that option may not always be available in practical cases. Therefore, in this supplementary section, we trained our model based on the semi-monthly dataset which was obtained by the linear interpolation of the monthly data. After that, we predicted the SSSs after 2021 based on the newly trained model following similar processes of the multi-step predictions shown in the main text.

Specifically, considering the practical situations, we 'could not' directly predict the SSS one month later at the first step due to the semi-monthly model has a time step of 0.5 month, and NO prediction was made from the interpolated time slot because we 'do not know' it until the next month. Following that line, the results of the first-, third-, and fifth-step prediction were compared to the interpolated true values, while the results of the second-and fourth-step prediction were compared to the true values each month. For example, when we start the prediction from January, the first-step result was compared to the 'true' SSSs interpolated between January to February, while the second-step prediction of the semi-monthly model could be directly validated by the true SSS in February.

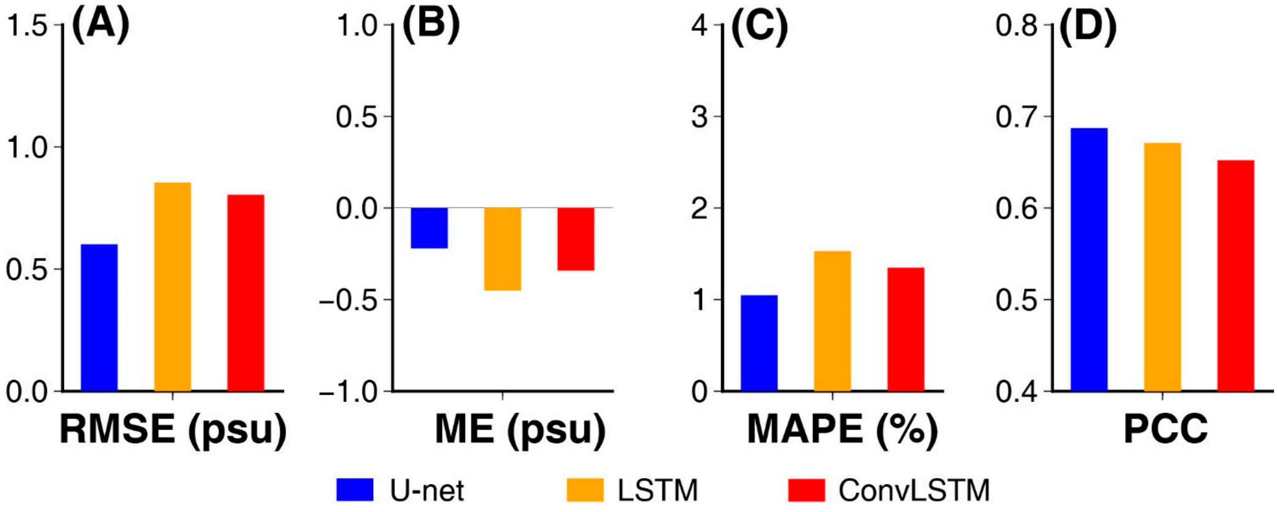
Figure S3 shows the results of the semi-monthly model. In general, the linear interpolation did not improve the performance of our Domain 1 mode, while all error indices remained at similar levels compared to the monthly model. Results also show that the performance of the Domain 1 model over the ECS&YS became worse, and prediction errors were even larger than in the previous settings. On the other hand, that was not the case in Domain 2, where the prediction errors were largely reduced. To find why the model became better, Figure S4 shows the error estimations of the second-step predictions in Domain 2. Compared to Figure 7, it is found that even the second step of the semi-monthly model showed a better performance than the model trained by monthly data. Improvements could be found in coastal regions, especially near the river mouth of the Yangtze River (122–124°E, 31–33°N). Moreover, the sudden increase of the errors in August and September (also see Figures 7 and 12), which was probably due to the failure in predicting the low-SSS tongue, was almost gone in this new model, suggesting the dataset with the higher temporal resolution is crucial in predicting such features.

Overall, these extra experiments provide a possible way to reduce the errors in predicting the phenomena with a shorter time scale when only relatively coarser datasets are available (e.g., monthly data). Moreover, it further confirmed the great potential of our U-net model in predicting oceanic variables, and much better performance could be expected if the model is trained by a high-frequency dataset.

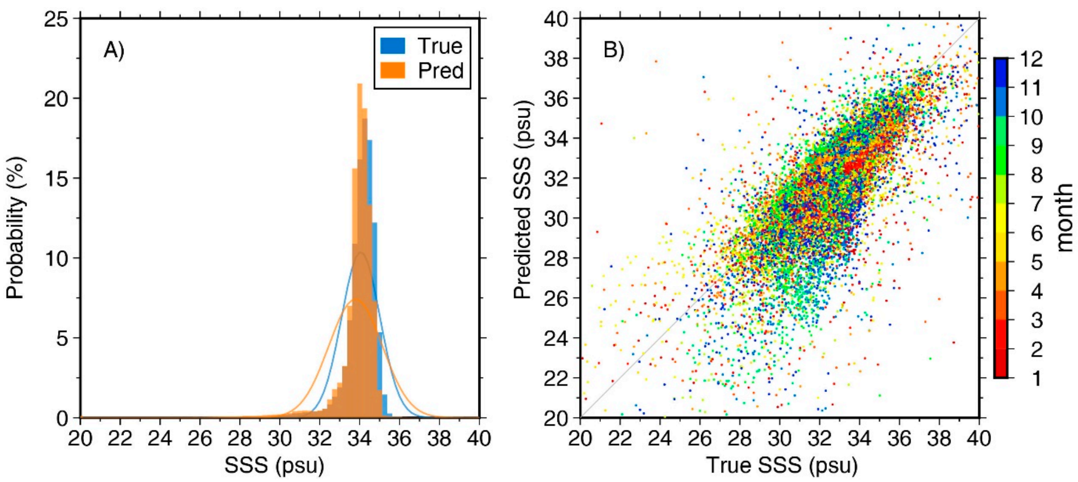
## S2. Supplementary Figures



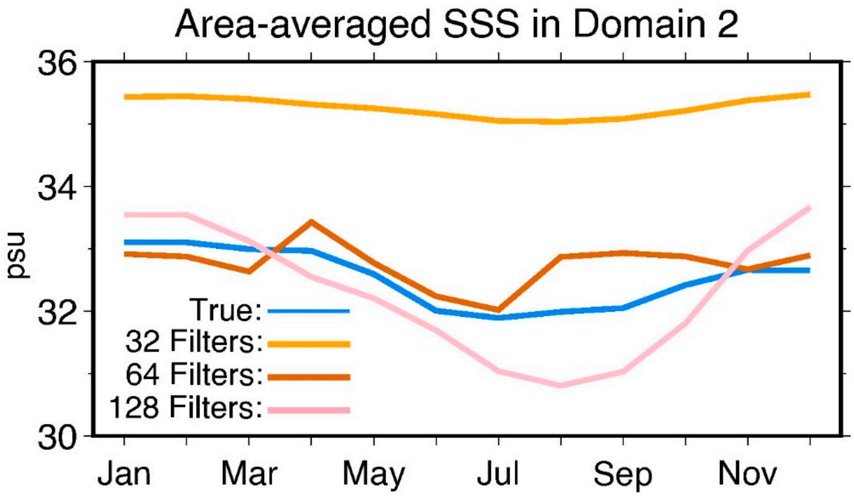

**Supplementary Figure S1.** Error indices calculated based on the results of models using previous five (blue), six (orange, used in the main text), seven, and eight consecutive months, which were averaged for 12 months in 2021 over Domain 1 (**A**–**D**) and Domain 2 (**E**–**H**) including the root-mean-square error (RMSE), the mean error (ME), the mean absolute percentage error (MAPE), and the pattern correlation coefficient (PCC).



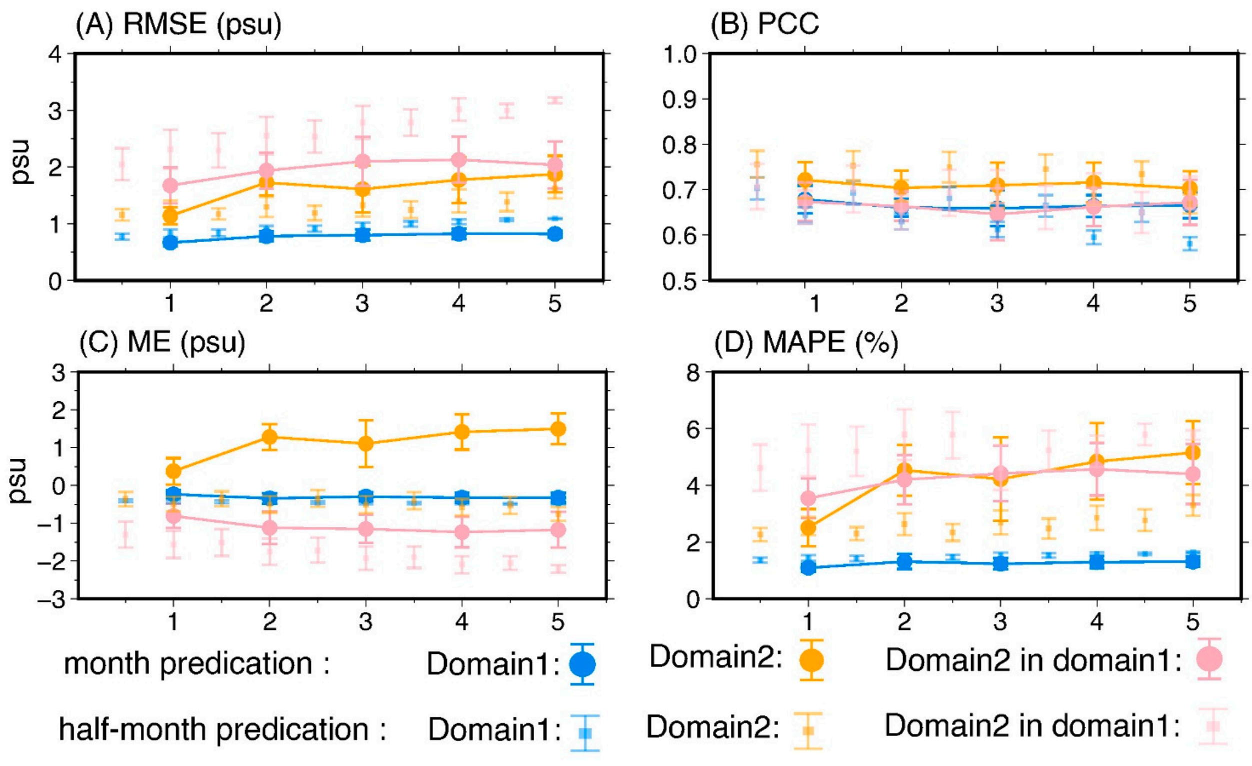

**Supplementary Figure S2.** Error indices for results using U-net, LSTM, and ConvLSTM models. Results were averaged over Domain 1 and 12 months in 2021. The LSTM and ConvLSTM models used the same filtter numbers (32 in the first layer), and all models were designed to predict one month future using six consecutive months.



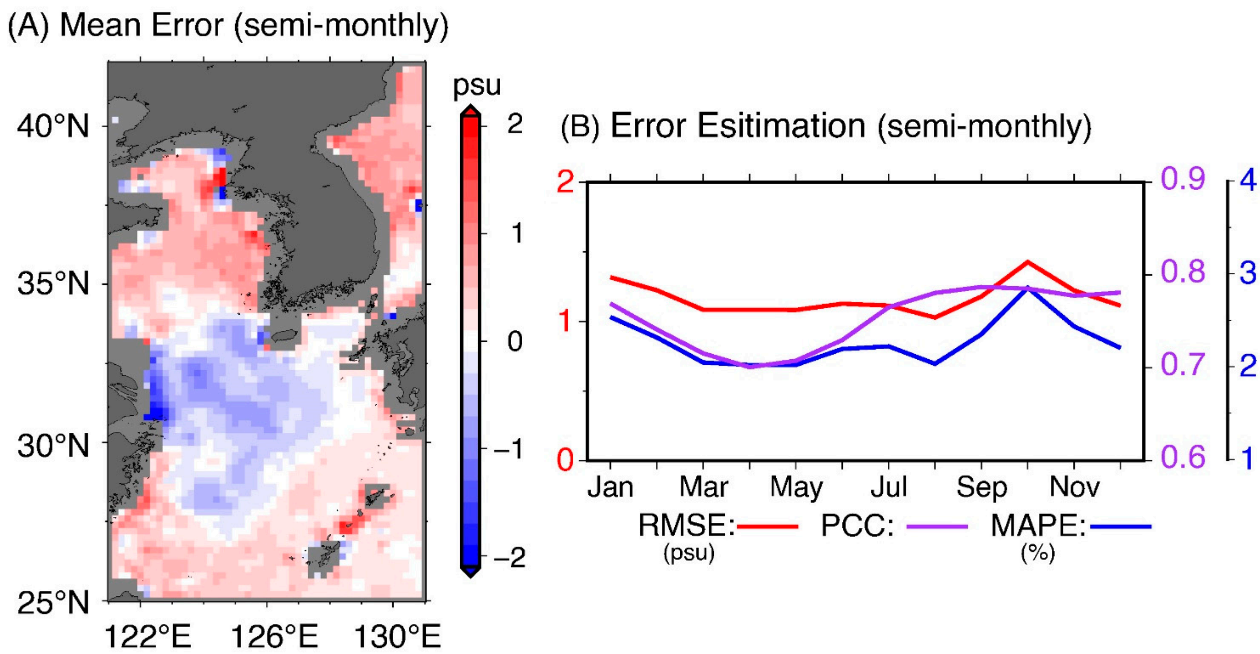

**Supplementary Figure S3.** (**A**) Probability of the true and predicted SSSs over Domain 1 in 2021 (bins with interval of 0.25 psu) and the regressed normalized distribution (line). (**B**) Scatter-plot of the true and predicted SSSs with colors representing the month in 2021.



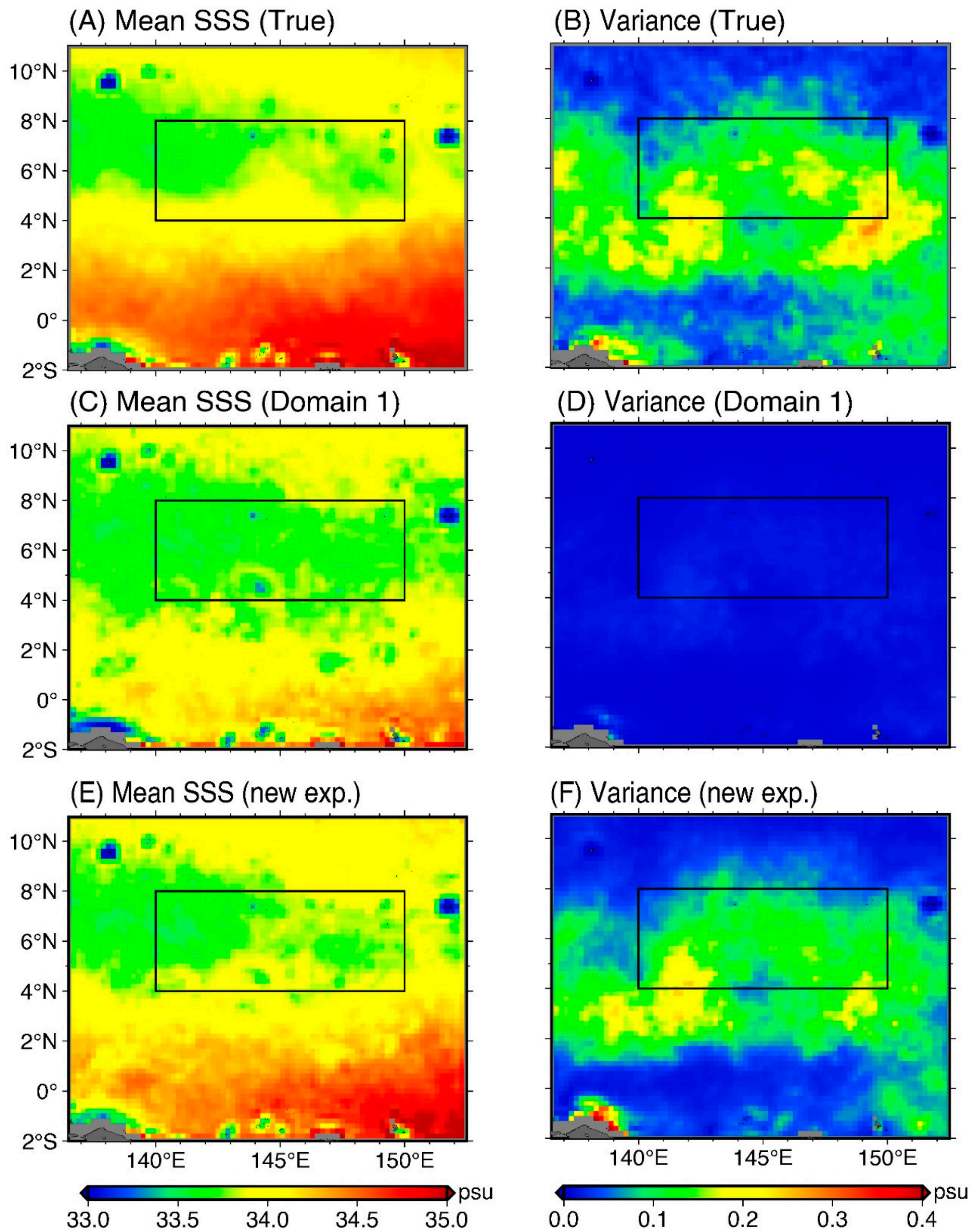

**Supplementary Figure S4.** Same as Figure 9 but for the true and predicted SSSs averaged over the entire Domain 2.



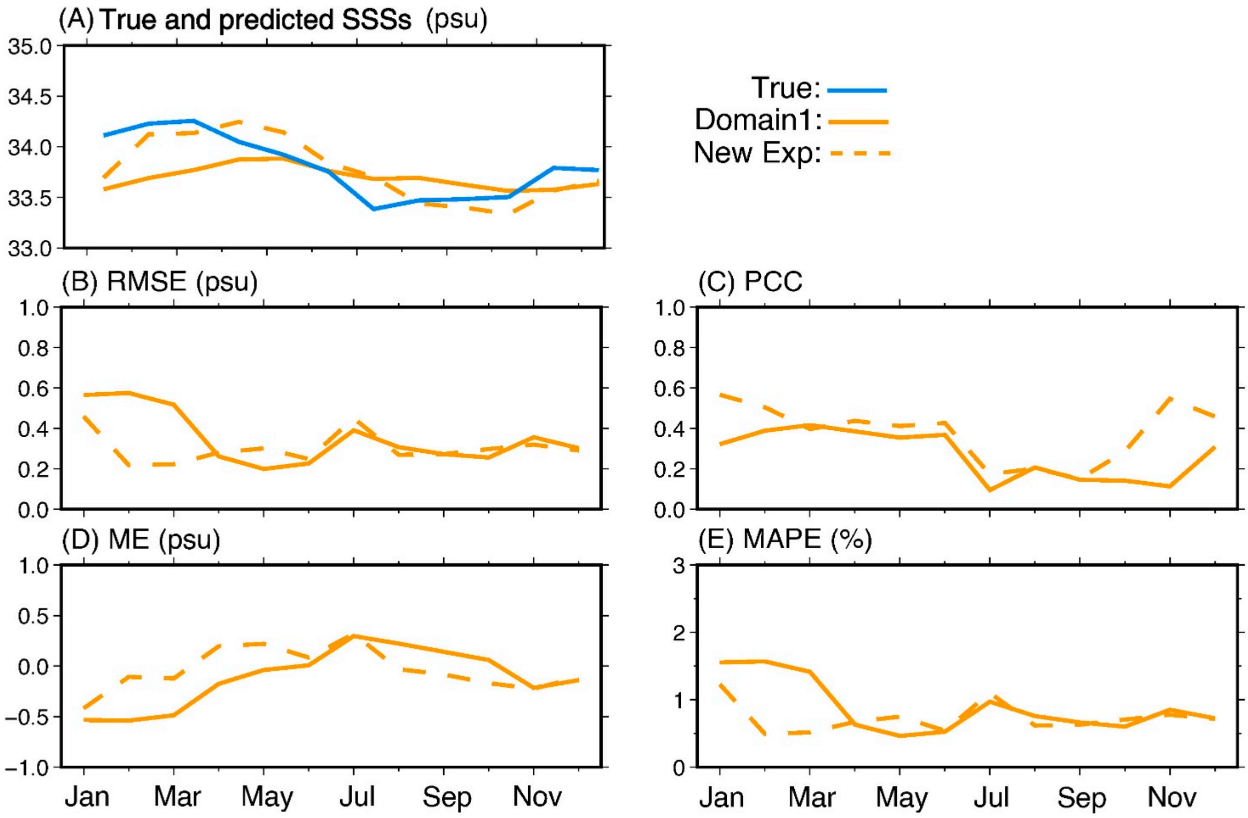

**Supplementary Figure S5.** Error indices for the results from the semi-monthly model.




**Supplementary Figure S6.** (**A**) Annual mean error of the predicted SSSs in 2021 over Domain 2 based on the semi-monthly experiment (**B**) the monthly variations of the error indices.




**Supplementary Figure S7.** Mean and the variance of the SSSs in 2021 over the tropical western Pacific region (136.5°~152.5°E, 2°S~11°N) based on the true SSSs (**A**,**B**), predicted SSSs by Domain 1 model (**C**,**D**), and the new U-net experiment with 16 filters in the first layer (**E**,**F**). The North Equatorial Counter-Current (NECC; 140~150°E, 4~8°N) region used for Figure S8 is marked as the black box in all panels.




**Supplementary Figure S8.** (**A**) Temporal variations of area-averaged true and predicted SSSs and (**B**–**E**) the error indices in 2021 over the NECC region (black box in Figure S7).

### S3. Supplementary Tables

**Supplementary Table S1.** Model performance during the three-time training based on the normalized SSS. All trials were based on same model settings.

| Model | Trial | Training Batches | | | Verification Batches | | |
|---|---|---|---|---|---|---|---|
| | | RMSE | MSE | Dice | RMSE | MSE | Dice |
| **Domain1** | 1 | 0.0474 | 0.0054 | 0.9834 | 0.0468 | 0.0053 | 0.9841 |
| | 2 | 0.0463 | 0.0052 | 0.9839 | 0.0479 | 0.0054 | 0.9838 |
| | 3 | 0.0479 | 0.0056 | 0.9824 | 0.0462 | 0.0052 | 0.9839 |
| **Domain2** | 1 | 0.0575 | 0.0078 | 0.9929 | 0..626 | 0.0085 | 0.9921 |
| | 2 | 0.0583 | 0.0076 | 0.9931 | 0.065 | 0.0089 | 0.992 |
| | 3 | 0.0591 | 0.0081 | 0.9926 | 0.0632 | 0.0085 | 0.9922 |