EGU General Assembly 2022

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Medium-to long-term prediction of sea surface temperature using EEMD-STEOF-LSTM hybrid model

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Sharing not permitted

OUTLINE

Part . 01

INTRODUCTION

- Typical Applications of Ocean Prediction

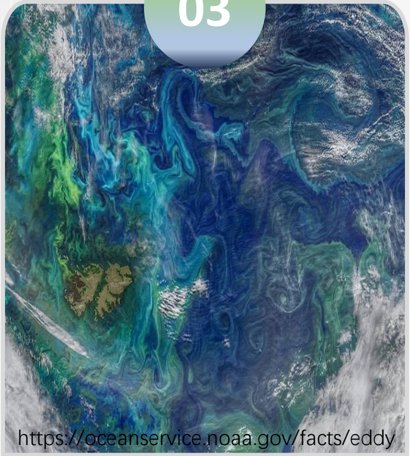
01

Military security

02

Resource exploitation

03



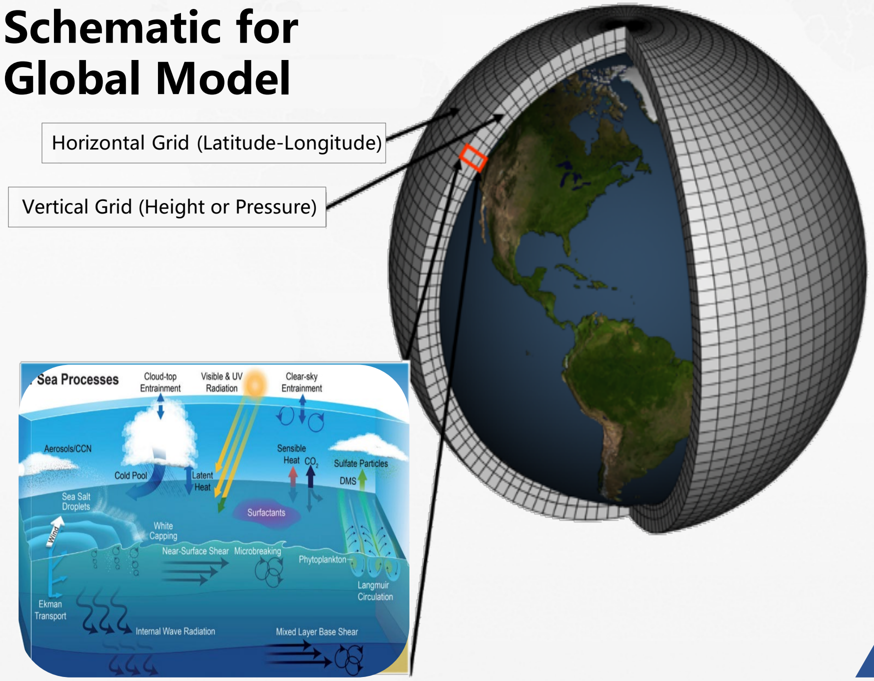
Disaster prevention

04

Ecological protection

● Shortcomings of numerical ocean prediction

Schematic for Global Model



https://en.wikipedia.org/wiki/Climate_model#/media/File:Global_Climate_Model.png

Models

- ➢ Uncertainty of initial state
- ➢ Inaccuracy of parameterization
- ➢ Instability of nonlinear systems

Computability

- ➢ Computational Complexity
- ➢ Parallel computing
- ➢ HPCs

Predictability

- ➢ Initial errors
- ➢ Mode errors
- ➢ Timeliness < 7 days

- Advantages of statistical methods

Deep Learning Methods	Statistical Learning Methods	Spatio-temporal Forecast
Long-term	**Spatiotemporal**	**Multi-scales**
Improving the predictive ability of seasonal prediction	Extract patterns / insights from the ever-increasing stream of ocean data	Modelling of long-range spatial connections across multiple timescales

- The **deep learning** and process understanding for data-driven ocean science.
- Inadequate for **multi-scale spatiotemporal** prediction.

Part . 02

DATA AND METHODS

General form of numerical ocean prediction

$$X_i = M_{(i-1)\to i}\left[X_{i-1}, F_{(i-1)\to i}\right]$$

$$X_i = X_i^{cl} + \widetilde{X}_i$$

$$F_{(i-1)\to i} = F^{cl}_{(i-1)\to i} + \widetilde{F}_{(i-1)\to i}$$

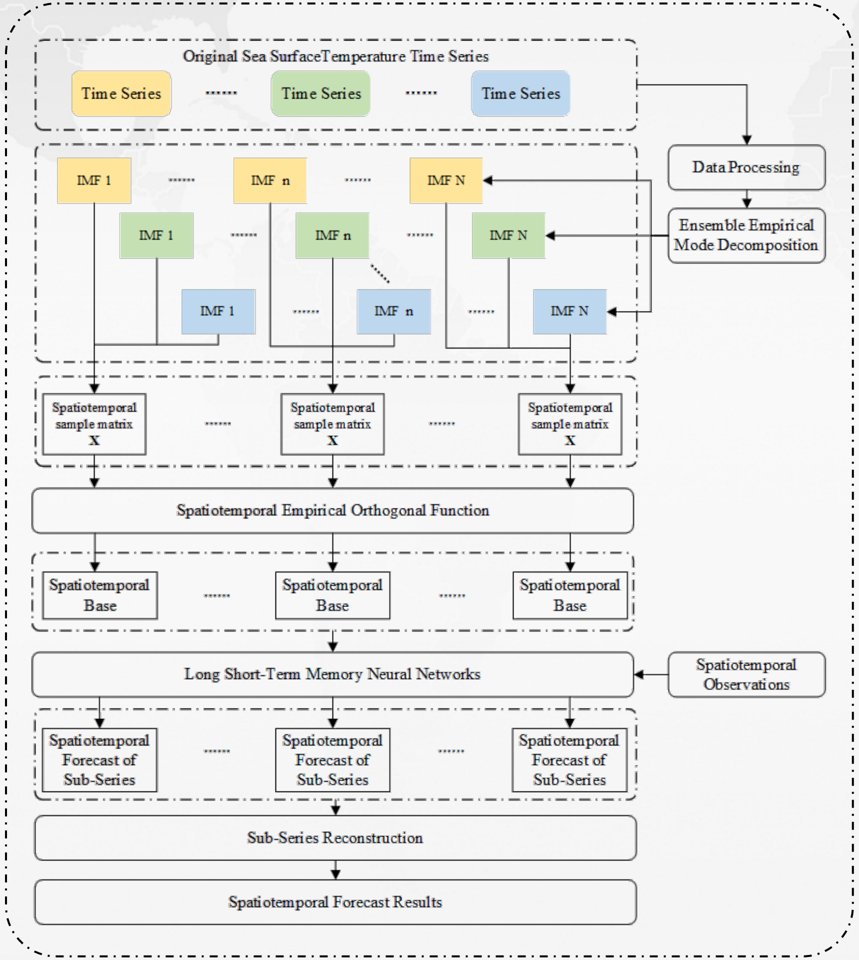
Expanded into climatic with disturbances

$$X_i^{cl} + \widetilde{X}_i = M_{(i-1)\to i}\left[X_{i-1}^{cl} + \widetilde{X}_{i-1}, F^{cl}_{(i-1)\to i} + \widetilde{F}_{(i-1)\to i}\right]$$

Disturbances satisfied with numerical models

Linearization part

$$\widetilde{X}_i = \boxed{M_{(i-1)\to i}\Big|_{X_{i-1}^{cl}, F^{cl}_{(i-1)\to i}} \widetilde{X}_{i-1} + M_{(i-1)\to i}\Big|_{X_{i-1}^{cl}, F^{cl}_{(i-1)\to i}} \widetilde{F}_{(i-1)\to i}}$$
$$+ G_{(i-1)\to i}\Big|_{X_{i-1}^{cl}, F^{cl}_{(i-1)\to i}}\left[\widetilde{X}_{i-1}, \widetilde{F}_{(i-1)\to i}\right]$$



Architecture of the EEMD-STEOF-LSTM model

KEY 1

Ensemble empirical mode decomposition

- Nonlinear & nonstationary
- False component & modal mixing
- Adaptive multi-scale analysis

KEY 2

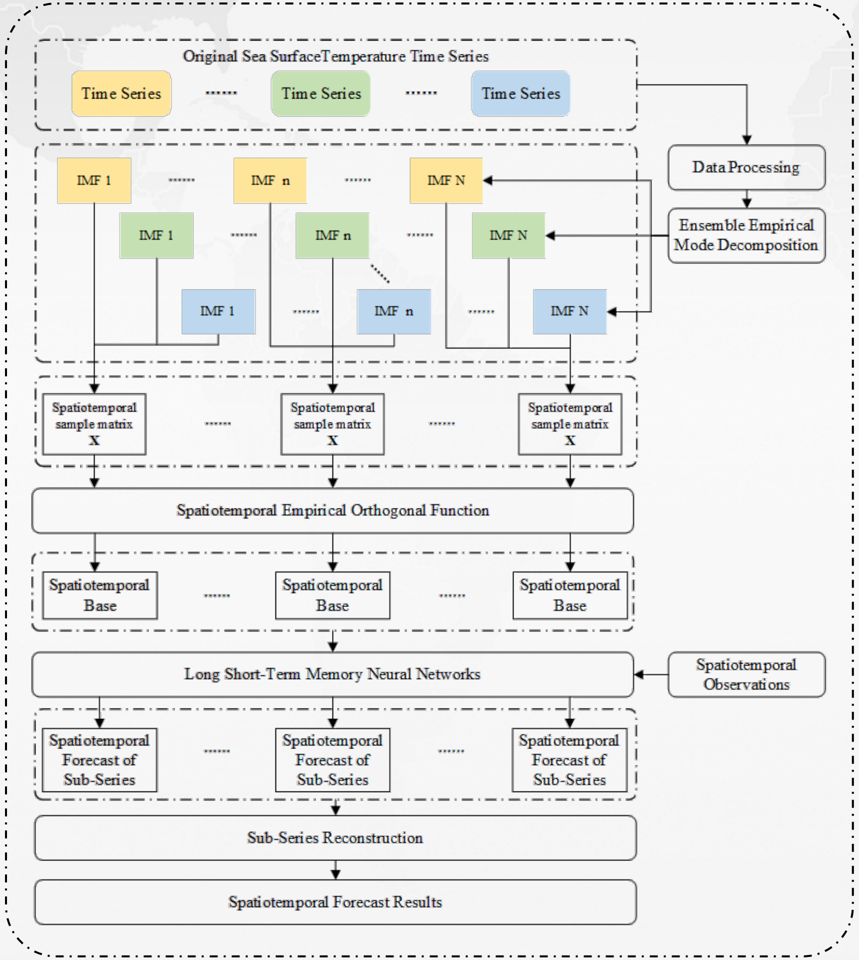
Spatiotemporal empirical orthogonal function

- Spatiotemporal analysis and forecast
- Embedding temporal information into spatial modes of EOFs
- Converting spatiotemporal forecast to time-series regression

KEY 3

Long Short Term Memory network

- Multiscale feature extraction
- Feature fusion prediction



Architecture of the EEMD-STEOF-LSTM model

Multivariate

- **Multivariate STEOF**
- Correlation analysis
- Dimensionality reduction
- Decoherence

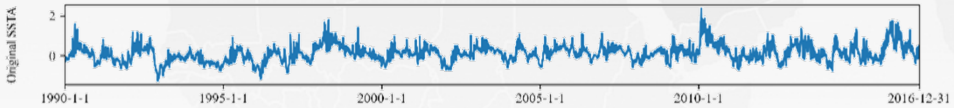
Completeness

- **Completeness of EEMD**
- Improving the predictability
- Extending prediction timeliness

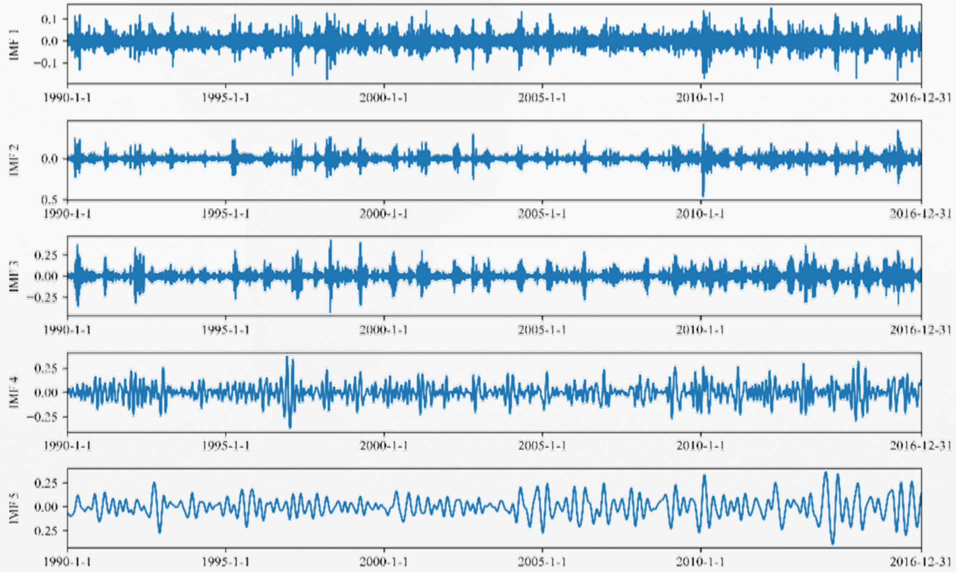
Part . 03

RESULTS

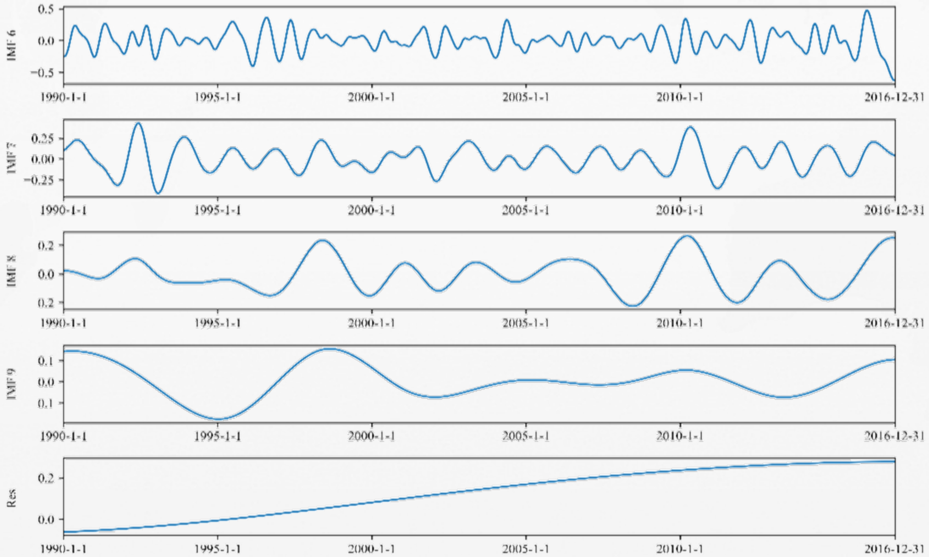
- IMFs of EEMD decomposition



Original series



IMF 1~5



IMF 6~10

- STEOF analysis towards IMFs

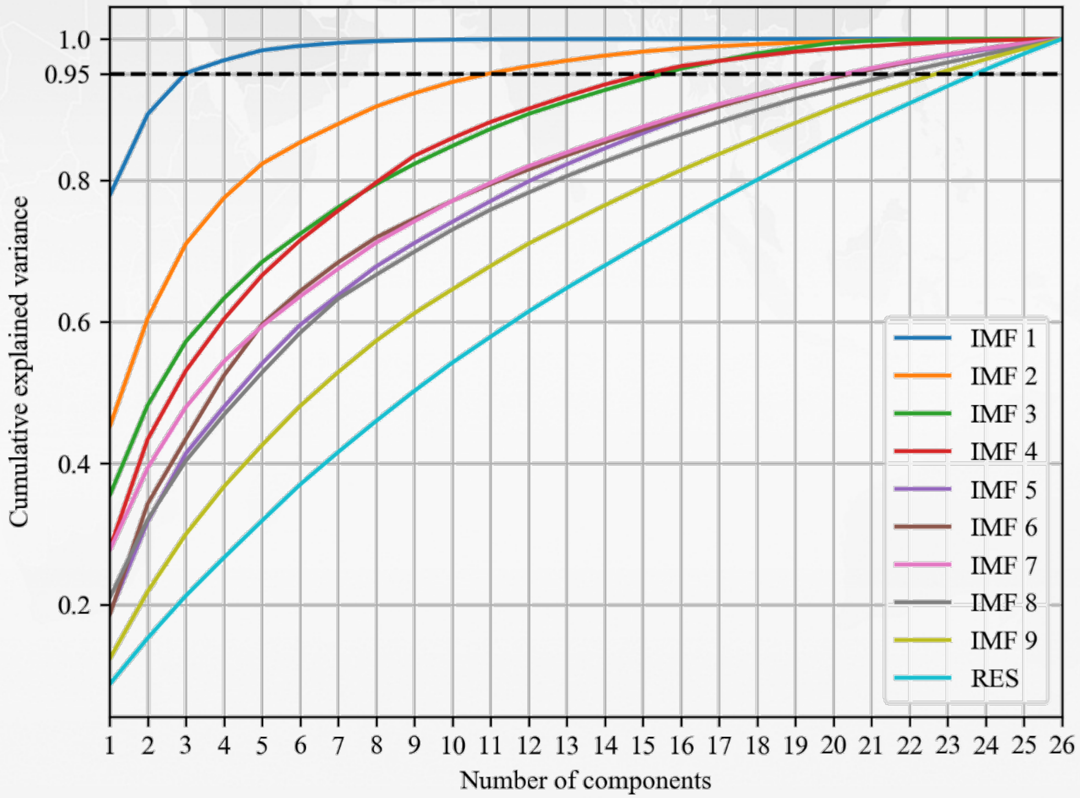
Reduce computational and dimensions

Cumulative explained variance

Confidence coefficient $\geq 95\%$

Significance test

SN of IMFs	IMF 1	IMF 2	IMF 3	IMF 4	IMF 5
Number	3	11	16	16	21
SN of IMFs	IMF 6	IMF 7	IMF 8	IMF 9	Res
Number	21	21	22	23	24

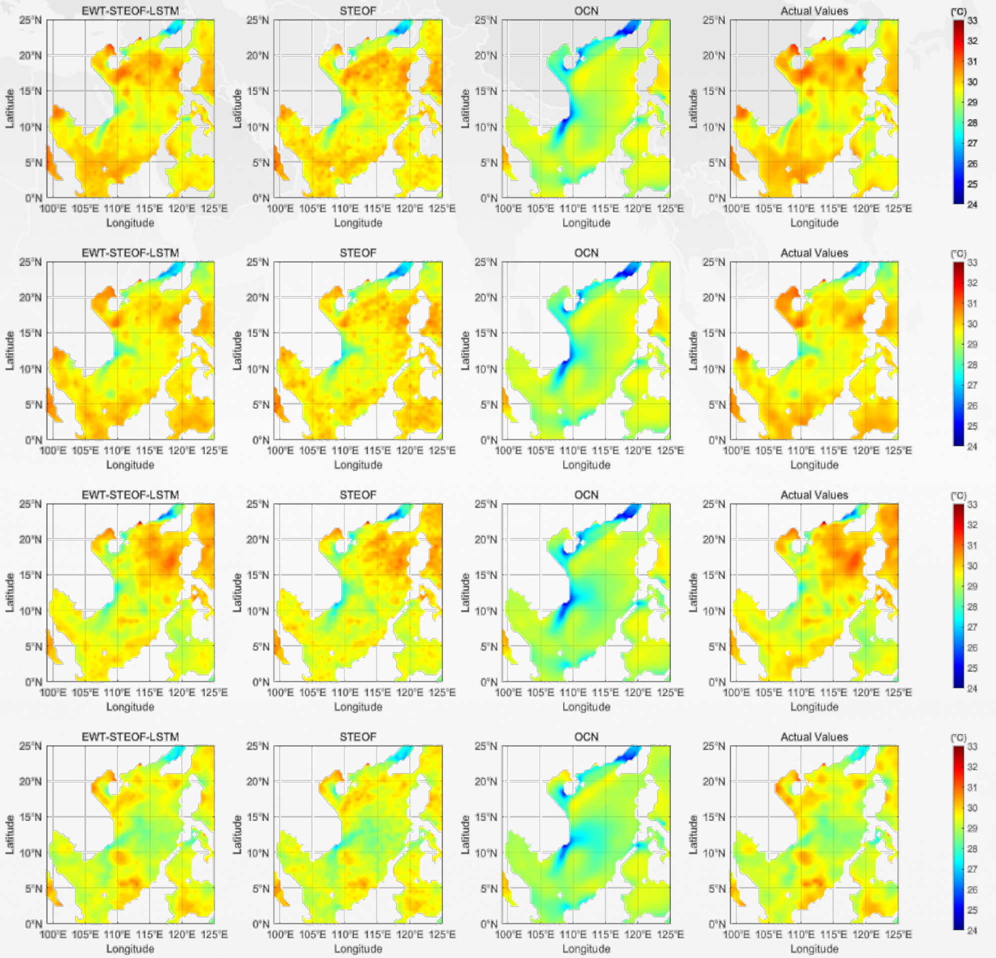


Percentage of STEOF principal components for different IMFs

RESULTS

- Model performance evaluation

  - **Train dataset**: January 1, 1990 to December 31, 2015
  - **Test dataset**: January 1, 2016 to December 31, 2016
  - **Period validity of model**: 7, 15, 30, and 60 day
  - **Benchmarks**: STEOF / OCN / Observations



Prediction performance among models. From left to right: EWT-STEOF-LSTM, STEOF, OCN and Observations. From top to bottom are the results for day 15, day 30, and day 60, respectively.

Model performance evaluation

- **Benchmarks**: STEOF / OCN / Observations
- **Period validity of model**: 7, 15, 30, and 60 day
- **Metrics**:

ACC $$ACC = \frac{cov(x,y)}{\sqrt{var[x]var[y]}}$$

RMSE $$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

MAE $$MAE = \frac{\sum_{i=1}^{n}|x_i - y_i|}{n}$$

TABLE I. *ACC* OF PREDICTION RESULTS OF DIFFERENT METHODS

Model \ Duration(day)	7	15	30	60
EWT-STEOF-LSTM	0.9858	0.9648	0.9405	0.9227
STEOF	0.9282	0.8863	0.7562	0.6808
OCN	0.5227	0.5035	0.4443	0.4248

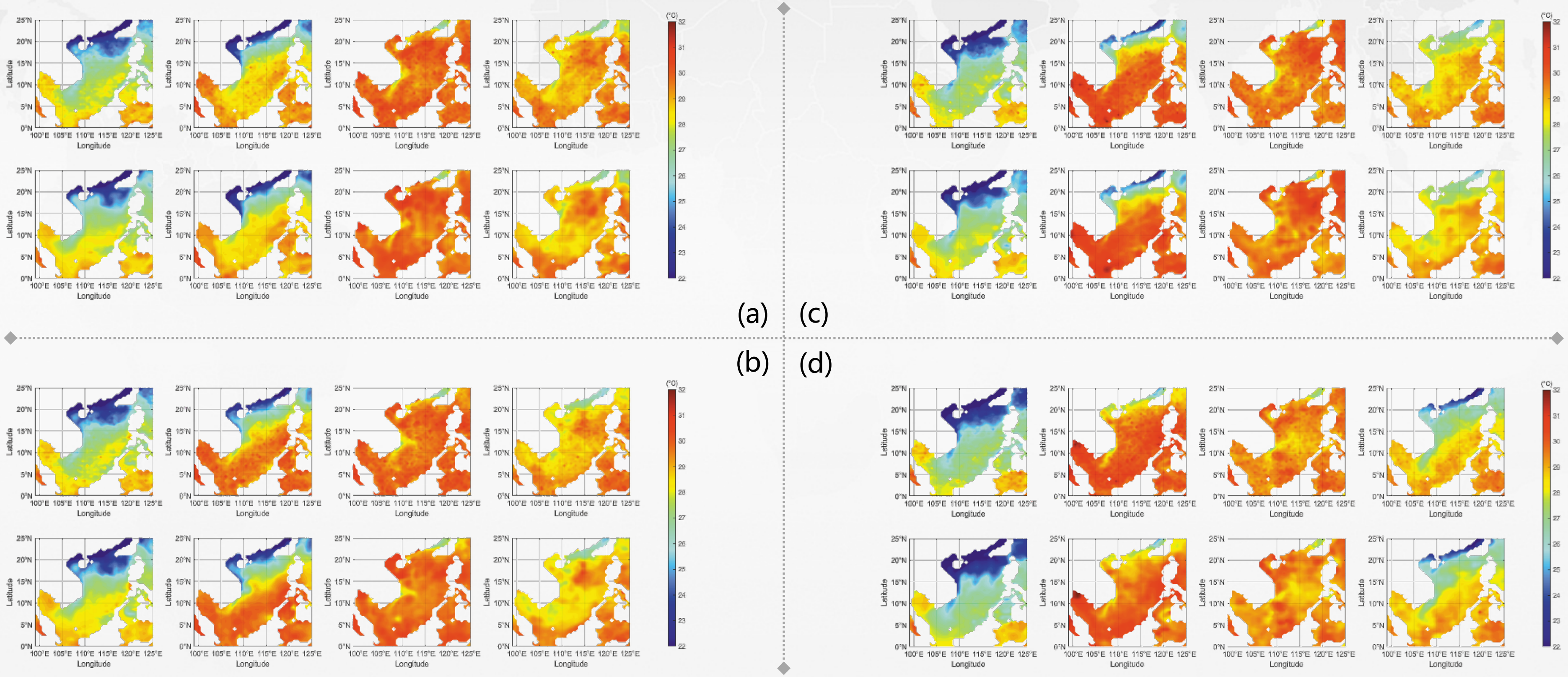
TABLE II. *RMSE* OF PREDICTION RESULTS OF DIFFERENT METHODS

Model \ Duration(day)	7	15	30	60
EWT-STEOF-LSTM	0.2369	0.2524	0.2640	0.2892
STEOF	0.6941	0.7322	0.7430	0.8091
OCN	0.9331	1.0411	1.1037	1.1365

TABLE III. *MAE OF PREDICTION RESULTS OF DIFFERENT METHODS*

Model \ Duration(day)	7	15	30	60
EWT-STEOF-LSTM	0.2039	0.2230	0.2306	0.2349
STEOF	0.5356	0.5629	0.5703	0.6355
OCN	0.6940	0.8194	0.8540	0.9465

- Seasonal performance



Prediction performance for different seasons. (a) (Top row) EEMD-STEOF-LSTM Forecast results of SST on day 7. (Bottom row) Day 7 SST observations. From left to right: winter, spring, summer, and autumn. (b), (c), (d) Same as (a) but for day 15, day 30 and day 60 results, respectively.

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Part . 04

CONCLUSION

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Model

01 Motivation

Aiming at the problem of **long-term spatiotemporal** prediction in **multiscale** background, a hybrid model based on deep learning is proposed to improves the **predictability**.

02 Architecture

EEMD realizes **adaptive multiscale** analysis; STEOF considers the **temporal and spatial correlation** of element states; LSTM for multiscale **feature fusion** prediction.

03 Evaluation

EEMD-STEOF-LSTM outperforms STEOF and OCN in medium-to long-term prediction with **applicability** among **seasons**. Moreover, **eddies** can be simulated well by this model.

04 Further study

Studying for more ocean variables, such as **SSH**, **SSS**, and **SSV**. And expanding model for **Nonlinear** system.

THANKS FOR LISTENING

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