Effective Ensemble Learning Approach for SST Field Prediction Using Attention-based PredRNN

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Problems & Ideas

- ***Problems of Sea Surface Temperature (SST) field prediction***

  ✓ SST field prediction problem is to forecast the most likely tensor of length k in the future, given the previous n observations, which is defined by the following equation.

$$\tilde{X}_{t+1},\dots,\tilde{X}_{t+k} = \underset{X_{t+1},\dots,X_{t+k}}{\operatorname{argmax}}\ P(X_{t+1},\dots,X_{t+k}|X_{t-n+1},X_{t-n+2},\dots,X_t)$$

Where $X_t \in R^{M\times N\times V}$ is a tensor, representing an observation of the SST field at time t, $M\times N$ represents a spatial region consisting of M rows and N columns. V is the temperature value.

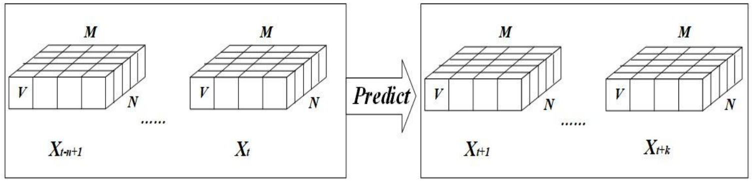


Fig.1 Illustration of SST field prediction problem

- ***Ideas: a novel ensemble learning approach for SST field prediction***

  The existing methods do not consider seasonal periodicity and abnormal fluctuation characteristics of SST, leading to low prediction accuracy. To solve the problems, we propose a novel ensemble learning approach (ELA-PredRNN-AT) that combines the PredRNN network and an attention mechanism for effective SST field prediction. The framework of ELA-PredRNN-AT approach is shown in Fig. 2.

  ✓ In the first stage, XGBoost and exponential smoothing models are used to extract the long-, medium-, and short-term time features of SST data at a single observation point.

  ✓ In the second phase, The PredRNN network is used to learn the spatiotemporal correlations of the SST field data from multiple observation points and predict the future SST.

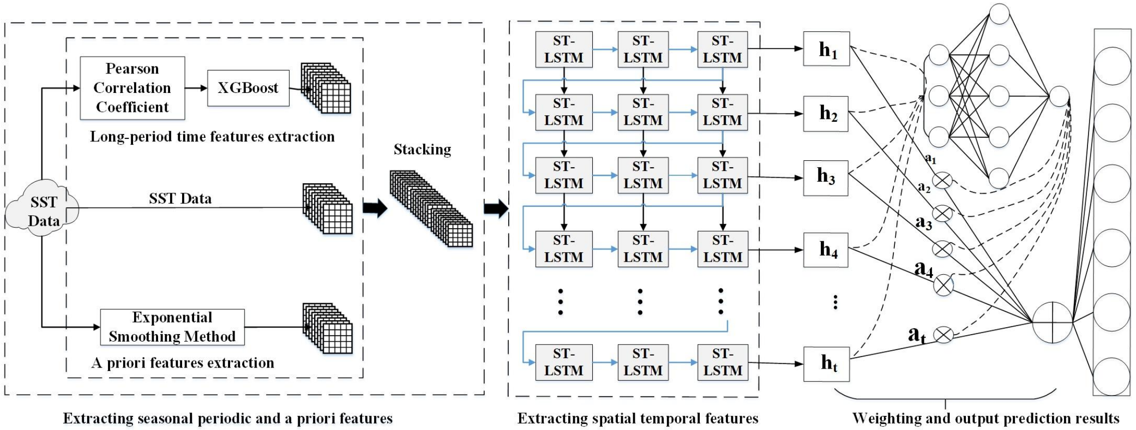


Fig.2 The framework of ELA-PredRNN-AT approach

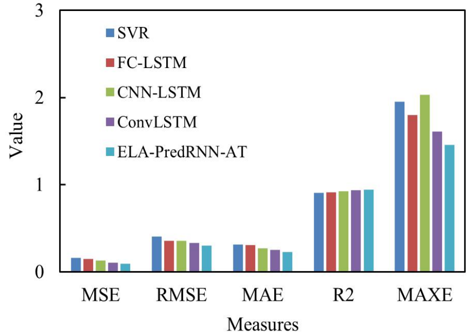
  ✓ An attention mechanism is used to weigh and fine-tune the output of each step of the PredRNN model to obtain a higher prediction accuracy in the last part

Results & Conclusions

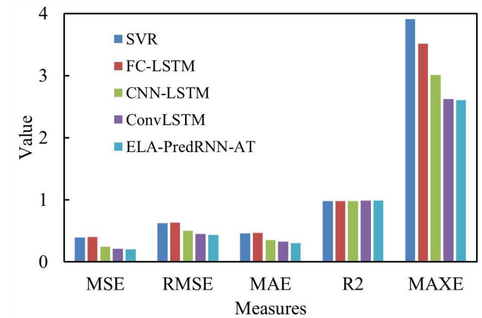
Results. SST field data from the Bohai and South China Seas were selected for training and testing the approaches. Experimental results on short-, medium-, and long-term SST predictions are as follows:

Dataset / Approaches	Bohai Sea Dataset				South China Sea Dataset			
	MSE	RMSE	MAE	R^2	MSE	RMSE	MAE	R^2
PredRNN	0.210	0.458	0.323	0.981	0.103	0.325	0.258	0.937
PredRNN-TF	0.208	0.457	0.316	0.981	0.092	0.303	0.229	0.946
PredRNN-ExpS	0.202	0.450	0.313	0.982	0.096	0.311	0.234	0.943
PredRNN-AT	0.198	0.445	0.318	0.982	0.090	0.299	0.226	0.947
ELA-PredRNN-AT	**0.183**	**0.425**	**0.315**	**0.982**	**0.081**	**0.285**	**0.215**	**0.952**

Fig. 3 Ablation Study

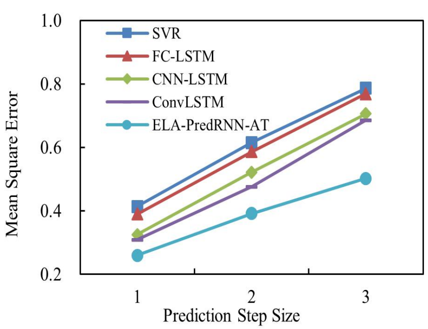


(a) South China Sea

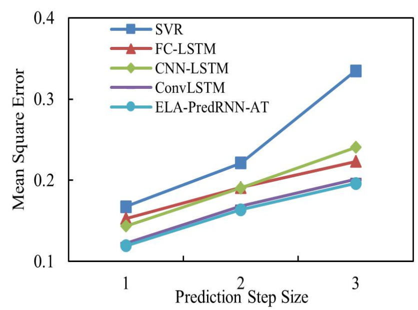


(b) Bohai Sea

Fig.4 Short-term prediction results

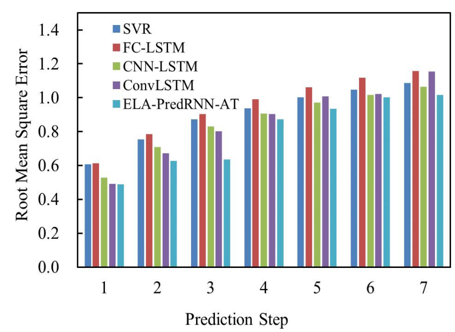


(a) South China Sea

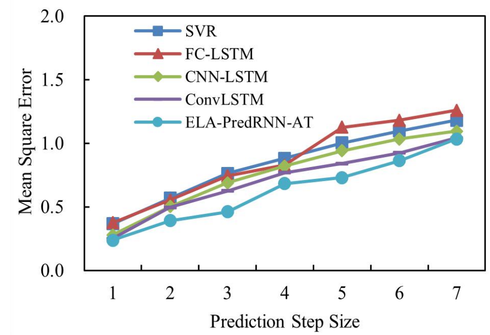


(b) Bohai Sea

Fig.5 Medium-term prediction results



(a) RMSE on the Bohai Sea



(b) MSE on the Bohai Sea

Fig.6 Long-term prediction results

Conclusions. We proposed an effective ensemble learning approach based on an attention-based PredRNN, which considers the correlations of SST across both space and time, as well as the importance of historical information. Moreover, the seasonal periodicity and non-stationarity in SST data were also considered in our approach. Experimental results showed that the proposed ELA-PredRNN-AT approach achieved an ideal effect and outperformed the other SST prediction approaches. In the future, we will further improve its prediction accuracy and efficiency.