PREDICTION OF SEA SURFACE TEMPERATURE IN THE SOUTH CHINA SEA BY ARTIFICIAL NEURAL NETWORKS

人工神经网络

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ABSTRACT

Sea surface temperature (SST) significantly affects the processes of air-sea interactions and thus forms an important indicator of climate changes. In SST predictions, the approach of artificial neural networks (ANNs) is data-driven, unlike that of the numerical models, which are physics-based. In this paper, Operational Sea Surface Temperature and Ice Analysis (OSTIA) dataset was used for training ANN models and verifying prediction results. To reduce the prediction error caused by SST variations, the authors propose to separate SST time series data into climatological monthly mean and monthly anomaly datasets, and construct two neural network models. The combination of these two models gives the final SST prediction results. This method was used to predict the SST in the South China Sea. The average bias and standard deviation between the predicted SST and OSTIA SST are -0.02 ℃ and 0.37 ℃, respectively. The results indicate that the proposed training method gives good prediction accuracy.

这个这里这个思路感觉挺好，为了减少SST变化带来的预测误差，提出将海温时间序列数据分解为气候月平均值和月异常数据集，并建立两个神经网络模型。这两个模型的结合给出了最终的海温预测结果。利用该方法对南海海温进行了预测

Index Terms— Artificial neural networks (ANNs), prediction, sea surface temperature (SST)

1. INTRODUCTION

The South China Sea, one of the largest tropical marginal seas in the western Pacific, plays a vital role in regulating the climate of Southeast Asia [1]. Sea surface temperature (SST), a physical attribute of the oceans, is crucial to climate system, and its prediction is fundamental to studying in many domains. However, the current system in the region is so complex with numerous mesoscale eddies [2] that SST anomalies can reach 1.5 ℃ at eddy cores [3]. Prediction of the SST in this kind of region is fraught with many uncertainties.

In recent years, artificial neural networks (ANNs), commonly referred to as "neural networks", are widely used in SST prediction studies, mainly because if correctly trained, they can outperform the traditional empirical, statistical linear methods [4]. The general form of artificial neural networks (ANNs) includes machines designed to simulate the brain that performs specifics tasks or functions of interest [5]. The neural network is massive with parallelly distributed processors, referred to as "neurons", which acquire knowledge through a learning algorithm and use interneuron connection strengths (synaptic weights) to store the acquired knowledge [5]. In neural network-based predictions, the factors that affect SST are usually taken as inputs, and the corresponding SST as targets. The input and target are connected by neurons. A learning algorithm trains the network by adjusting the weights of neurons in an orderly manner so that a particular input leads to a specific target, which is the learning process [6]. When the error between the output and the target reaches the desired value, the learning becomes complete, and the nonlinear relationship between the factor and SST is stored in a set of weights, which is called supervised learning. Some studies used meteorological and marine variables, such as mean sea level pressure, 2-m air temperature, 2-m dewpoint temperature, total cloud cover, wind stress, net surface heat flux, net radiation, and sea surface height, as predictors in constructing relationships with the SST. These include the prediction of SST in the western Mediterranean Sea [7], the prediction of SST anomaly in the equatorial Pacific [8], and the prediction of ocean subsurface thermal structure in the central Arabian Sea [9]. To predict the next stage SST by constructing the temporal relationships, the other studies used only the previous period SST values as predictors. These studies include the prediction of SST in the Bohai Sea and India Ocean [10] [11].

The above-mentioned studies, based on ANNs, generally use the original data to train the ANN models directly. The predicted results so obtained show where the data is turbulent and abnormal, the prediction accuracy is rather reduced [12]. These studies pay more attention to the impact of different ANNs on SST prediction accuracy, whereas the focus of this paper is on the impact of ANNs training data input mode.

而本文的研究重点是人工神经网络训练数据输入方式的影响。

The Multilayer perceptron (MLP) was adopted for this study. The original SST data was decomposed into monthly mean and monthly anomaly datasets and the corresponding ANNs were trained separately. The final SST prediction result is a combination of these two models. Compared with the direct training method, the separate training method aims at reducing the prediction error, caused by SST fluctuations in the South China Sea, and thereby improving the prediction accuracy. Hereafter, for convenience of description, the separate training method is referred to as STM, and the direct training method is referred to as DTM.

用的多层感知机，但是数据输入上进行了创新，本文提出的方式是把数据集分成平稳的和非平稳的两波，
然后分别用神经网络进行训练，然后把最后的结果进行整合。 这叫做STM
把这种方法与原始的方法DTM，也就是直接利用所有数据的这种进行对比

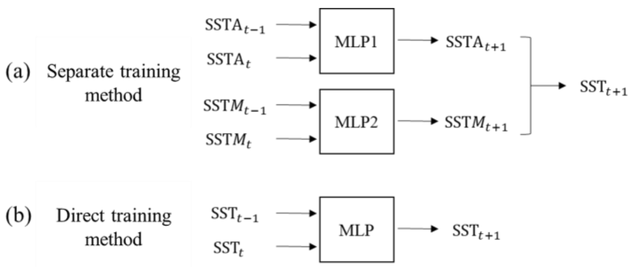

Fig. 1. (a) Process of separate training method; (b) process of direct training method.

2. DATA AND METHODOLOGY

2.1. Data

The SST data, used in this paper, was generated at the Met Office, using the Operational SST and Sea Ice Analysis (OSTIA) system, available at the Copernicus Marine Environment Monitoring Service (CMEMS) website (http://marine.copernicus.eu). The product SST-GLO-SST-L4-REP-OBSERVATIONS-010-011 contains SST daily data, from 1 January 1985 to 31 December 2007, on a global regular grid at 0.05° resolution.

Using the subset from the above data, with the spatial ranging from 0-25°N and 105-125°E (401×501 grid), the data from November 1985 to December 2006 was used as the training set, and the data from January 2007 to December 2007 as the test set. The subset data was preprocessed through two steps. The first step was

数据的预处理方式

generating the monthly average SST from the daily SST data and the second step was generating the mean value for each month (SSTM for short) for over 22 years. Then, the monthly anomaly (SSTA for short) was obtained by subtracting the mean value from the monthly SST. The SSTA and SSTM datasets were trained as shown in the flow-chart (see Fig. 1). For predicting t+1month SST, the SSTA and SSTM values, respectively of time step t and t-1, were used as input data. The final predicted value for t+1 month is the sum of $SSTA_{t+1}$ and $SSTM_{t+1}$.

2.2. Methodology

MLP is a standard feed forward network that is commonly used in meteorological and oceanographic studies. Its network structure includes neurons, arranged in an input layer, one or more hidden layers, and an output layer. The numbers of predictors and predictands determine the number of neurons in the input and output layers, and the complexity of the problem determines the number of neurons in the hidden layers [8]. The MLP can be trained using backpropagation algorithm in the supervised learning problem. For this study, gradient descent, with momentum and adaptive learning rate in the backpropagation algorithm, was adopted to train the MLP. The learning algorithm consists of a weight update rule and a learning update rule [13].

In the present work, we refer to the recommendations given in [14] to set the initial values, and the coordinate descent search method was used to determine the optimal values. The structure of the model consisted of an input layer, three hidden layers with 20 neurons, and one output layer. This MLP used a linear transfer function in the output layer and a hyperbolic tangent function in the hidden layer. The learning rate, momentum constant, ratio to increase learning rate and ratio to decrease learning rate were 0.01, 0.9, 1.07, 0.7, respectively. Small random values were used to initial the weights and bias. In each experiment, the ratios for training, testing and validation data are 0.7,0.15,0.15, respectively. The training was repeated several times to ensure good prediction accuracy.

3. RESULTS AND DISCUSSIONS

Both STM and DTM were used to train ANN models separately and predict the SSTs in 2007. To assess the performance of these two methods, the prediction results were compared with those of the OSTIA. The differences in SST between the predicted SST and OSTIA SST can be seen from Fig. 2. Most of the anomalies predicted by these two methods are found to occur near the coastal area, southeast of Taiwan and Vietnam. This finding is consistent with the SST standard deviation distribution pattern, shown in Fig. 3. The difference between the SST data of OSTIA and that predicted by STM is smaller than that predicted by DTM, especially in the coastal and the relatively high SST perturbation area. This improvement is obvious even from the statistics in Table I. The percentages of the SST difference within ±0.5 ℃ increased in each month, compared with the SST predicted by the DTM. The highest rise of 23.84% appeared in October. When SST variations were rather high, as in January, February, November and December, the improvements also are significant.

The biases, standard deviations and root mean square errors (RMSE) between the predicted and original OSTIA SST by these two models are also calculated and presented in Table I. For STM, the biases range from -0.65 ℃ to 0.3 ℃, the mean value being -0.02 ℃; the standard deviations range from 0.27℃ to 0.45 ℃, the mean value being 0.37 ℃. For DTM, the biases range from -0.64 ℃ to 0.43 ℃, the mean value being -0.01 ℃; the standard deviations range from 0.31 ℃ to 0.69 ℃, the mean value being 0.48 ℃. The standard deviation of STM results decreases by 0.11 ℃, unlike that of DTM results. This suggests that the STM mainly reduces the standard deviation of the SST differences between the predicted and OSTIA SST values. The SST values, predicted by STM (see Fig. 4), show that, in seasonal variability, the mean predicted SST has better agreement with the OSTIA SST and is within analysis error. Compared with the RMSE values obtained

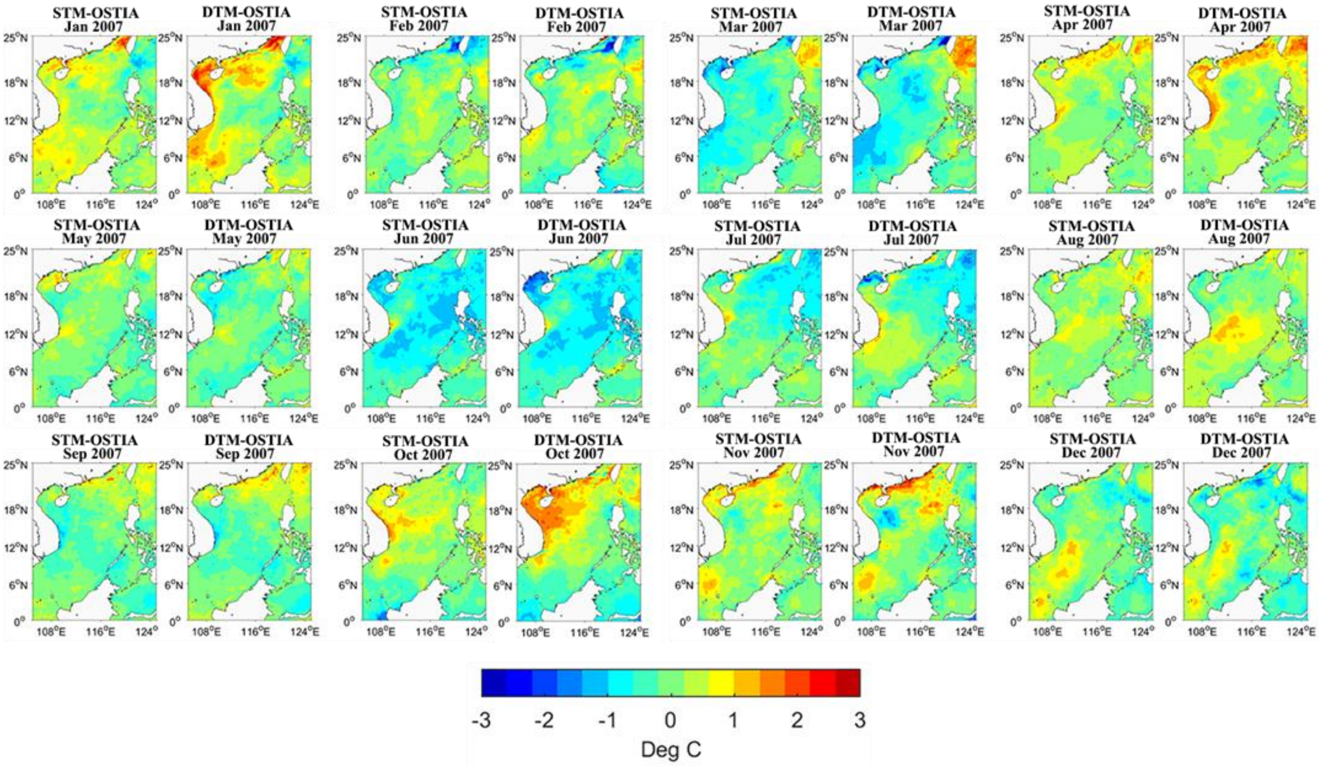

Fig. 3. Comparisons of SST differences in 2007.

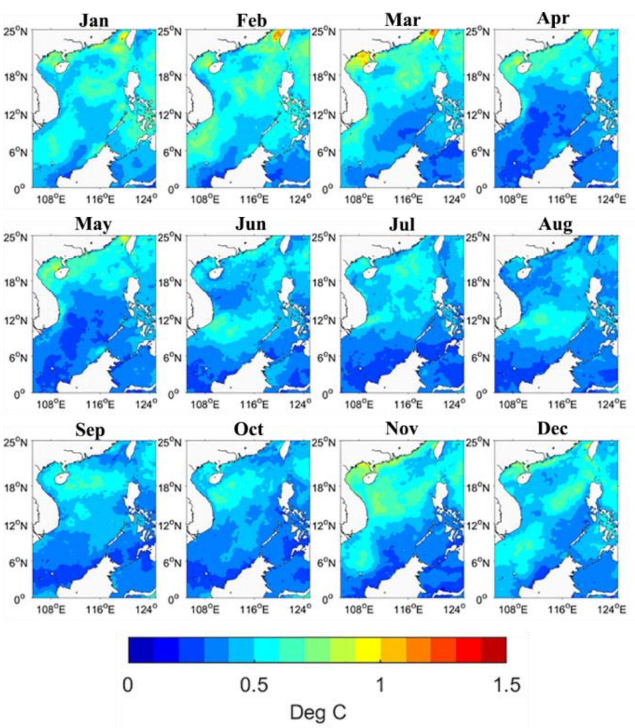

Fig. 3. Monthly SST standard deviations from 1985 to 2007.

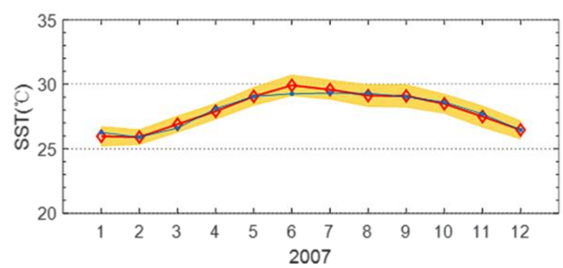

Fig. 4. The SST predicted with the STM (blue points and line); the SST of OSTIA (red diamonds and line) and its analysis error (yellow band).

for other months, the value obtained for June 2007 is larger, with a value of 0.74 °C. The bias and standard deviation obtained for June 2007 are -0.65 °C and 0.35 ℃, respectively. The monthly SST anomaly was calculated from the OSTIA SSTs between 1985 and 2007. In June 2007, the value is up to 0.64 ℃, the highest in 23 years. For the ANNs used for SST prediction, the SSTA data for the period 1985-2006 was used for model training. Obviously, this extremum information, which appears in the prediction period, was not included in the training data set of the model. As a result, the prediction result shows rather abnormal bias.

TABLE I
MONTHLY STATISTICS OF SST DIFFERENCES IN 2007

2007	Method	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Bias(℃)	STM	0.30	0.00	-0.29	0.21	-0.01	-0.65	-0.27	0.19	-0.07	0.13	0.21	-0.01
	DTM	0.43	-0.05	-0.28	0.33	-0.11	-0.64	-0.18	0.21	-0.01	0.20	0.14	-0.12
Std.Dev(℃)	STM	0.41	0.37	0.45	0.33	0.31	0.35	0.40	0.27	0.35	0.44	0.38	0.42
	DTM	0.57	0.46	0.62	0.45	0.31	0.39	0.49	0.33	0.42	0.69	0.56	0.47
RMSE(℃)	STM	0.51	0.37	0.53	0.39	0.31	0.74	0.48	0.33	0.36	0.45	0.43	0.42
	DTM	0.71	0.46	0.68	0.56	0.33	0.75	0.52	0.39	0.42	0.72	0.57	0.49
P(±0.5 ℃)(%)	STM	65.72	88.27	63.52	83.47	89.45	35.43	68.49	87.34	84.3	77.86	79.38	77.84
	DTM	56.47	78.69	58.76	72.88	86.77	33.73	67.76	83.63	78.57	54.02	69.21	67.13
P(±1 ℃)(%)	STM	96.37	97.63	94.67	96.57	99.48	82.74	96.69	99.51	99.17	96.11	96.06	97.96
	DTM	83.93	96.55	85.23	89.19	99.39	83.58	95.54	97.87	97.63	83.05	90.83	86.75
P(±1.5 ℃)(%)	STM	99.44	99.39	99.43	99.91	99.99	99.99	100	99.99	99.93	99.32	99.46	100
	DTM	96.27	99.08	97.41	98.01	99.98	98.5	99.55	100	99.89	94.06	97.8	99.73

4. CONCLUSIONS

The proposed model performs well in predicting SST in the South China Sea. The comparisons of the STM and DTM predicted SST show significant improvement by training the ANNs separately with mean SST and SST anomaly, particularly in the area with large SST variations. The proposed STM model reduces the degree of dispersion in the prediction results, caused by SST oscillations, thus reducing the standard deviation of the prediction results and thereby improving the prediction accuracy.

5. ACKNOWLEDGEMENTS

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