Contents lists available at ScienceDirect





Cold Regions Science and Technology

journal homepage: www.elsevier.com/locate/coldregions

Prediction of sea ice evolution in Liaodong Bay based on a back-propagation neural network model



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ARTICLE INFO

Keywords: Sea ice Spatial evolution BP model Wind direction Wind duration

ABSTRACT

In the present study, a back-propagation neural network model (BP model) was developed with the aim of predicting the sea ice spatial evolution in Liaodong Bay. In addition to air temperature and wind speed, two new variables wind direction and wind duration were used to train the BP model. Validation of the BP model with measurements showed that the BP model can effectively predict the spatial evolution of sea ice. The sensitivity studies indicated that wind direction and wind duration can obviously improve the prediction accuracy of sea ice edge in heavy ice years. Moreover, the BP model was easy to set up as it only used four yearlong periods, 2003–2004, 2005–2006, 2006–2007 and 2009–2010, and the results were not very sensitive to the training algorithms as well. By comparison with a least-square-based method (LSM), the BP model clearly outperformed the LSM during the period of ice melt with nonlinear characteristics caused by the frequent appearance of cold waves. Furthermore, the BP model had a higher accuracy in estimating the spatial evolution of sea ice compared with a logit model, especially for the ice edge, which is more easily affected by the complex ocean environment.

1. Introduction

The Bohai Sea is a seasonal sea ice area with different degrees of freezing every winter (Bai et al., 2011). There are three bays in the Bohai Sea, namely Liaodong Bay, Bohai Bay and Laizhou Bay. Liaodong Bay has the highest latitude and it is also the most serious ice area among the three bays, as can be seen from Fig. 1 (Ning et al., 2009; Shi and Wang, 2012a). Sea ice first appears in the northern top of Liaodong Bay at the beginning of December, and lasts until the end of mid-March next year. (Zhang et al., 2015). Heavy ice may lead to serious problems for offshore operations, ship navigation, port transportation and marine fisheries (Shi and Wang, 2012b; Su et al., 2013). In addition, sea ice is also hoped to be developed and used as a source of freshwater to alleviate the problem of freshwater shortages in coastal areas of northern China (Williams et al., 2013; Gu et al., 2013). Therefore, this study is important for reducing disasters due to sea ice and estimating the sea ice resources in Liaodong Bay.

Many studies have been carried out to perform sea ice estimations. They have included numerical models and empirical models (Gao et al., 2011; Zhang et al., 2016). Numerical simulation is a commonly used method for predicting sea ice parameters, such as coupled sea ice-ocean models based on thermodynamics and the dynamics of sea ice (Hibler, 1979; Rae et al., 2014). However, the fact that there are so many input variables in the ice-ocean models leads to high uncertainties in simulations; therefore, it is not surprising that the results of numerical model may not be in good agreement with the measurements.

An empirical model is another way to predict sea ice parameters based on the primary factors that influence sea ice cycles as derived from statistical methods. Previous studies about sea ice estimation have concentrated on sea ice thickness and sea ice area. For example, Dong and Liu (1989) indicated that sea ice thickness was mainly controlled by cumulative melting degree-days (CMDD) and cumulative freezing degree-days (CFDD). Zeng et al. (2016) estimated the ice thickness of Bohai Sea in 2010 based on the ice surface temperature from MODIS and meteorological data from ECMWF. Su et al. (2012) noted that the sea ice area was associated with CFDD highly based on statistical analysis in Liaodong Bay. In addition to CFDD and CMDD, Zhang et al. (2016) found that the wind was also an important factor influencing the prediction of sea ice, and they developed an empirical model to estimate the extent of sea ice using a non-linear least square method (LSM) and logit model based on measured wind speeds and air temperature. Compared to the data from MODIS, the predicted area and spatial evolution of sea ice area were able to account for 87% of the variability (Zhang et al., 2016). However, some limitations exist in the current

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http://dx.doi.org/10.1016/j.coldregions.2017.10.002

Received 9 May 2017; Received in revised form 30 September 2017; Accepted 4 October 2017 Available online 05 October 2017 0165-232X/ © 2017 Published by Elsevier B.V.

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List of symbols	
CFDD	cumulative freezing degree days, $CFDD = \sum_{Ds}^{D_E} T_{air} T_{air} \leq -5^{\circ}C$, [°C]
CMDD	cumulative melting degree days, $CMDD = \sum_{i=1}^{D_E} T_{air} T_{air} \ge -2.5^{\circ}C$, [°C]
T _{air}	daily average air temperature in Yingkou and Jinzhou, [C]
T _a	T_{air} with the effect of time lag. [C]
T_w	temperature integration over time with wind speeds higher than force 5, $T_w = T_a \times N$. [°C]
Ν	cumulative times of winds with speeds higher than force 5 that are accumulated over a winter.

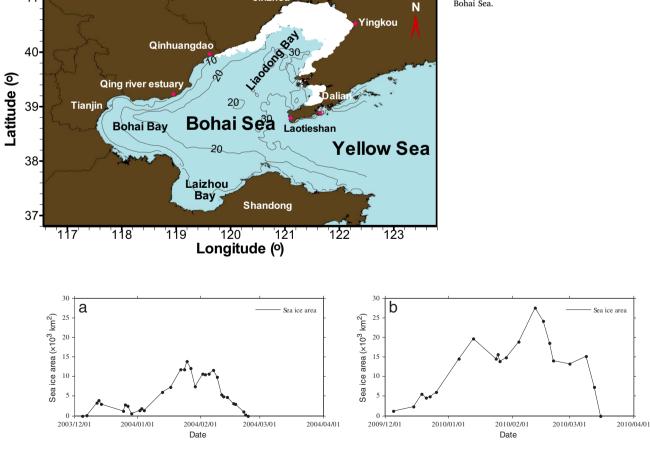
empirical model. For example, the nonlinear correlation between sea ice cover and meteorological data is not separable; therefore, it is hard to develop a simple empirical model to completely describe the complex nonlinear relationships. Further research is needed to improve the predictive precision of sea ice.

In this paper, a method known as a back-propagation neural network (BP) is applied to predict the spatial evolution of sea ice in Liaodong Bay. More meteorological elements such as wind direction and wind duration will be used for model development and prediction, in addition to the meteorological variables mentioned in Zhang et al. (2016). BP is able to find solutions under complex conditions and produce ideal results in solving non-linear issues (Hsieh, 2009). Because of these advantages, BP has been widely used in various research fields to improve the nonlinear relationships, for instance, predicting optics communication (Li and Zhao, 2017), tide levels (Lee, 2008; Salim et al., 2015), sand ripple geometry under waves (Yan et al., 2008), air pollutants concentrations (Bai et al., 2016), carbon dioxide emissions (Sun and Xu, 2016) and water temperature (Liu et al., 2016). The organization of the paper is as follows. Section 2 introduces the geographical location of the study area and the input data needed for model development. Section 3 describes the BP method. Section 4 discusses the sensitivity studies of the model input parameters. Model results are provided in Section 5. A comparison to other methods is discussed in Section 6. Finally, Section 7 presents the conclusion.

2. Data

The training data needed to develop the BP model are sea ice cover and meteorological data. The spatial cover of sea ice was extracted from MODIS images in Liaodong Bay using the Classification and Regression Tree (CART) method to reduce the error of sea ice due to suspended sediment (Zhang et al., 2015). We used 9 years' of data, from 2003 to 2012, to investigate the seasonal variation in sea ice in Liaodong Bay. For example, time-varying curves of the sea ice evolution in winter of 2003–2004 and 2009–2010 are plotted in Fig. 2(a) and Fig. 2(b), and the sea ice in 2010 was very serious with the maximum sea ice area of

Fig. 1. Geographical location and sea ice distribution in the Bohai Sea.



Jinzhou

Fig. 2. Time-varying curves of the sea ice area from MODIS in 2003–2004 (a) and 2009–2010 (b).

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