A New Approach to Predicting the Northern Hemisphere Sea Ice Extent

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Abstract

In this project, we developed a new simpler, less computationally expensive model using machine learning theories and algorithms. Specifically, the main machine learning algorithm is Time Lagged Neural Networks (TLNN), which is used in Time Series modeling and Forecasting. Inspired by the new development of Bayesian hierarchical models (BHM) to reconstruct the past temperature with adding external forcing, we added external forcing to TLNN (e.g. Solar radiation, Greenhouse Gas). We found this new model can capture the main features of Northern Hemisphere sea ice change as predicted by the complex numerical models with more physical meaning. We suggest that it could be widely used in ice forecasting in climate change community.

1 Introduction

1.1 Background

Sea level rises can considerably influence human economy in the coastal and island regions. There are two main mechanisms that contribute to the observed sea level rise [1]: (1) thermal expansion: ocean water expands as it warms, (2) the melting of land ice, like Greenland ice sheet. On the timescale of centuries to millennia, the melting of ice sheet could result higher sea level rise. Though the melting of Northern Hemisphere sea ice has little direct influence on the sea level rise, the biggest concern regarding Northern Hemisphere sea ice loss is the warmer average temperatures it will bring to the Arctic in coming years. Warmer temperatures will accelerate the melting of the Greenland ice sheet, which holds enough water to raise sea level 20 feet. Also it has impacts on the species living on the sea ice and global warming. Thus it is vital to have some insight into how the extent of Northern Hemisphere sea ice changes in the future.

Scientists in the climate change community have been used numerical models to predict how fast sea ice is expected to melt in coming decades[2,3]. These numerical modelings are typically based on many complex physical numerical models by solving numerous complex differential equations. It is very computationally expensive and time consuming.

1.2 Related Work

Machine learning has been recently used in the climate research. Haslett et al. (2006)[7] first proposed a Byesian reconstruction based on the fossil pollen data without considering external forcing. Lee et al. (2008)[8] proposed a Kalman filter approach to incorporate the external forcing. Li .et al (2010)[6] proposed a Bayesian hierarchical model (BHM) to reconstruct past temperature that integrates information from different sources with considering external forcing. Different proxies preserve the climate information in different ways and therefore are sensitive to climate at different time scales. In their approach, the authors used three proxies: tree rings, borehole temperature, and pollen abundances. They considered three external forcings: solar randiance, volcanism, and greenhouse gases. They showed that their method can avoid the possible attenuation effects caused by errors in explantory variables. Reid and Tarantino (2014)[9] developed a linear dynamic model based on the Support Vector Regression (SVR) to predict the Arctic Sea ice extent with historical data from remote sening sateliates data. The results shows that the prediciton made by the SVR model are within the range of results obtained by those complex climate model.

1.3 Potential novelty and Contribution

The novelty and contribution of our project is that we developed a new simpler, less computationally expensive model using machine learning theories and algorithms based on the Time Lagged Neural Networks (TLNN) [4] with considering external forcing (solar radiance and greenhouse gases). By the experiments, we show that this model could be used in ice forecasting in climate change community to save computer computing resource.

2 Dataset

2.1 North Hemisphere Sea Ice Data

The montly Arctic sea ice extent data set is from National Snow and Ice Data Center (`http://nsidc.org/data/seaice_index/archives.html`). An example of Arctic sea ice concentration of Jan 2016 is shown in Supplementary Section 5 (Fig. 7).

2.2 Solar radiation and CO2 Data

The monthly CO2 data set of period 1979-2014 is from Earth System Research Laboratory (`http://www.esrl.noaa.gov/gmd/ccgg/trends/data.html`). The monthly solar radiation of period 1979-2014 at the latitude of 80N is calculated based on Berger (1978)[11]. The monthly CO2 data set and solar radiation data set at the latitude of 80N of period 2006-2100 are from CCSM4 RCP8.5 Ensemble #1 (`http://www.cesm.ucar.edu/experiments/cesm1.0/`). RCP8.5 is a scenario of comparatively high greenhouse gas emissions. Fig.3 shows CO2 forcing in RCP8.5 changes from 400 ppm to 950 ppm from 2017 to 2100.

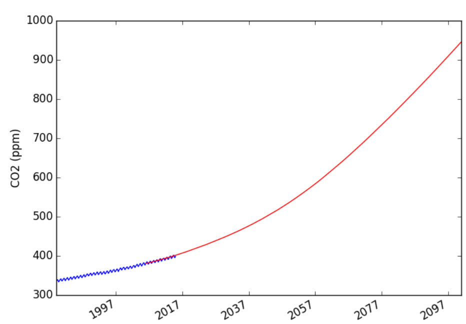

Figure 1: CO2 forcing (Red color shows CO2 change in RCP8.5)

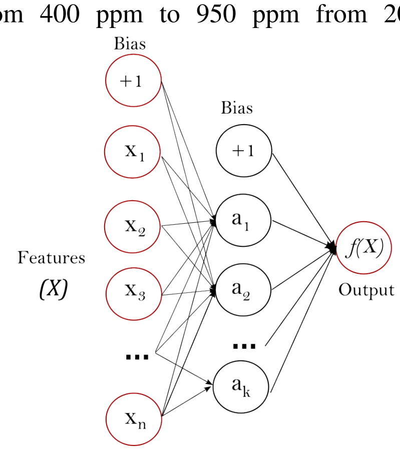

Figure 2: TLNN structure

3 Model

We would like to predict Northern Hemisphere sea ice extent using the time series data as well as adding external forcing (e.g. solar radiation, CO2). As mentioned in Adhikari and Agrawal's book[4], there are many methods developed to tackle the time series forecasting problem and one of them is Artificial neural networks (ANNs). ANNs approach has been suggested as an alternative technique to time series forecasting and it gained immense popularity in the past. Since ANNs are inherently non-linear, they can be more practical and accurate in modeling complex data patterns, as opposed to various traditional linear approaches. This is very important in our case because the pattern of Northern Hemisphere sea ice extent change is highly complex and dynamic, which makes it hard to model using the linear methods.

Our approach is to use Time Lagged Neural Networks (TLNN) and also modify it to fit our need of adding external forcing. Like TLNN, our model is characterized by a network of three layers, namely input, hidden and output layer, connected by acyclic links. The architecture of our model is depicted as Fig. 2.

We only have one node for the output layer, which is the target $\widehat{x}_t$, the predicted sea ice extent at time t. And the input nodes are composed of the successive observations of the time series, $x_{t-i}(i = 1, 2, \ldots, p)$ where p is the delay period we choose. Besides, the input nodes include the two external forcings we decide to add after considerations, solar radiation and CO2. It has been studied in many papers that solar radiation and CO2 are two main factors which affect the change of Northern Hemisphere sea ice extent. Thus, the number of input nodes is $n + 1 = p + 2 + 1$ (including a constant input term).

The prediction equation for computing a forecast can be written as follows:

$$\widehat{x}_t = \phi_0 \left\{ w_{c0} + \sum_k w_{k0} \phi_k \left(w_{ck} + \sum_{i=1}^{p} w_{ik} x_{t-i} + w_{sk} x_{sol} + w_{c2k} x_{co2} \right) \right\},$$

where $x_{t-1}, \ldots, x_{t-p}$ are the previous values, x_{sol}, x_{co2} is the solar radiation (W/m^2) and CO2(ppm) of time t, $\{w_{ck}\}$ are the weights for the connections between the constant input and hidden neurons and w_{c0} is the weight of the direct connection between the constant input and the output. Also $\{w_{ik}\}, w_{sk}, w_{c2k}$ denote the weights between the corresponding input and hidden neurons while w_{k0} denote the weights between the hidden and output neurons. ϕ_k and ϕ_0 the hidden and output layer activation functions respectively.

To estimate the connection weights, we set up the following optimization problem

$$\text{minimize} \sum_t (x_t - \widehat{x}_t)^2,$$

where $t - p \geq 0$, i.e. x_{t-p} exists. In our experiment, we solve the above problem using Limited-memory BFGS algorithm (L-BFGS) and choose the rectified linear unit function $\phi(x) = \max(0, x)$ as our activation function.

4 Experiments

4.1 Model parameters tuning

There are two parameters needed to be tuned. The first paramter of our model is the delay period, which is the number of the previous states to achieve the next output in the time series. In Reid and Tarantino (2014)[9], the Support Vector Regreession method suggests the delay period is about 10 years. We designed two experiments to set this parameter without external forcing. In one experiment, we set the delay period is 5 years. In the other experiment, we set the dealy period is 10 years. This means that in the first experiment there are 60 nodes for the first layer of out Nerual network. In the second experiment, there are 120 nodes. We create samples with previous 60 and 120 months sea ice extend values as the features and the current month sea ice extend as labels for each experiments. 70% of samples are used as the training set and the left 30% of sample are used as the testing set.

The second parameter is the size of the hidden layer. 10-fold cross validation is used to set the size of hidden layer. Mean absolute error is used to measure the risk. By testing, the smallest mean absolute error of 5-years delay model is 0.2268 with the hidden layer size of 5. The smallest mean absolute error of 10-years delay mdoel is 0.2478 with the hidden layer size of 10.

Fig. 3 and Fig.4 are the comparison of model predcitions to the observations. We can see that the model with 5-years delay performs as well as 10-years dealy. To have more training samples, in the following experiments we will use 5-years delay model.

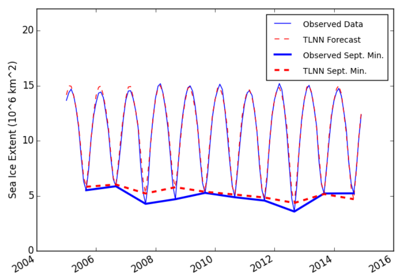

Figure 3: Comparion of model predcition to observation with 5-years delay without external forcing

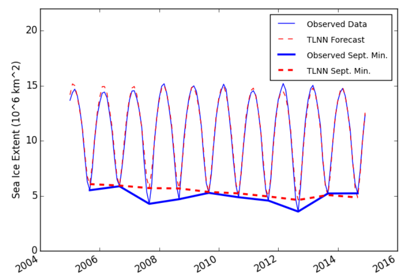

Figure 4: Comparion of model predcition to observation with 10-years delay without external forcing

4.2 Prediction for the future

With the confidence of the ability of the model to preditic the sea ice extent, we re-built the 5-year-delay model using all of the availabe sample data. Fig. 5 shows the prediction results beyond the known data into the future without the two external forcing. This represents both the full seasonal variation of the Arctic sea ice as well as the September minimum. The blue solid curve is the observed data and the red dashed line curve is the result obtained via forecasting with the model. The predicted September minimum sea ice extent (dashed red bold line) indicates that there will be sea ice free around 2037. This value is within the range of the results obtained by the complex physics based global climate models [10] (Fig. 8 in Supplementary 5).

Fig.6 shows the prediction results beyond the known data with the solar radiation and CO2 forcing. Two nodes are added in the first layer of TLNN to input the two forcings. The results show that even though the simulated ice-free time is quite same as the result of the experiment without the external forcing, the amplitude of the sea ice extent is significantly decreased with the external forcing. This result is reasonable. As we know that the CO2 forcing can increase the year-round temperature. The higher temperature in the winter time would lead less sea ice extent in the winter. Thus our model with the external forcing produces more physical meaning result.

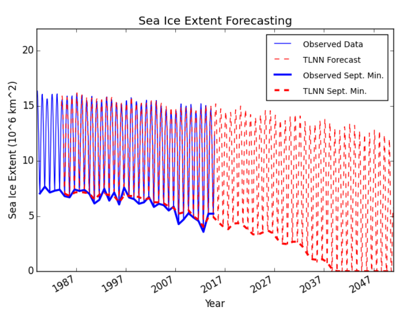

Figure 5: Prediction beyond known data without external forcing

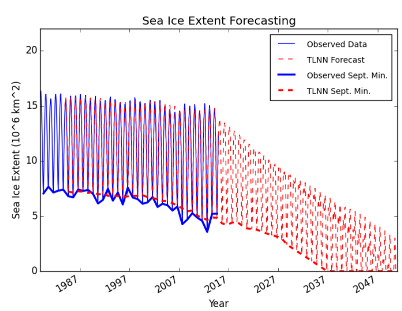

Figure 6: Prediction beyond known data with external forcing

5 Conclusion

We developed a new simpler, less computationally expensive model using Time Lagged Neural Networks (TLNN) with external forcings. We found this new model can capture the main features of Northern Hemisphere sea ice change as predicted by the complex numerical models. Compared with the result without the external forcing, our model resut has more phyiscal meaning. We suggest that it could be widely used in ice forecasting in climate change community.

References

[1] IPCC, FAQ 5.1 (2007) : Is Sea Level Rising?, *IPCC AR4 WG1*

[2] Chevallier, M., Salas y Melia, D., Voldoire, A., Deque, M., & Garric, G. (2013) Seasonal Forecasts of the Pan-Arctic Sea Ice Extent Using a GCM-Based Seasonal Prediction System, *Journal of Climate* , vol. 26, pp. 6092-6104.

[3] Stroeve, J. C., Kattsov, V., Barrett, A., Serreze, M., Pavlova, T., & Holland, M. (2012) Trends in Arctic sea ice extent from CMIP5, CMIP3 and observations, *Geophysical Research Letters*, **39**: L16502.

[4] Adhikari, R. & Agrawal, R. K. (2013) An Introductory Study on Time Series Modeling and Forecasting, *CoRR*, **1302**:6613.

[5] Faraway, J., & Chatfield, C. (1998) Time series forecasting with neural networks: a comparative study using the airline data, *Applied Statistics*, **47**: 231-250.

[6] Li,B., Nychka, D. W., & Ammann, C. M. (2010) The Value of Multiproxy Reconstruction of Past Climate, *Journal of the American Statistical Association*, **105**(491): 883-895, DOI:10.1198/jasa.2010.ap09379.

[7] Haslett, J., Whiley, M., Bhattacharya, S., Salter-Townshend, M., Wilson, S.P., Allen J. R. M., Huntely, B., & Mitchell, F.J.G. (2006) Bayesian Palaeo-cliamte Reconstruction, *Journal of the Royal Statistical Society, Ser. A*, **169**: 395-438.

[8] Lee, T. C. K., Zwiers, F. W., & Tsao, M. (2008) Evaluation of Proxy-Based Millennial Reconstruction Methods, *Climate Dynamics*, **31** (2-3):263, DOI:10.1007/s00382-007-0351-9.

[9] Reid, T. G. R., & Tarantino, P. M. (2014) Arctic Sea Ice Extent Forecasting using Support Vector Regression, *13th International Conference on Machine Learning and Applications*.

[10] Overland, J. E., & Wang, M. (2013) When will the summer Arctic be nearly sea ice free?, *Geophysical Research Letters*, **40** : 2097-2101.

[11] Berger, A.L. (1987) Long-term variations in daily insolation and Quaternary climate changes, *Journal of Atmospheric Science*, **35**:2362-2367.

Supplementary

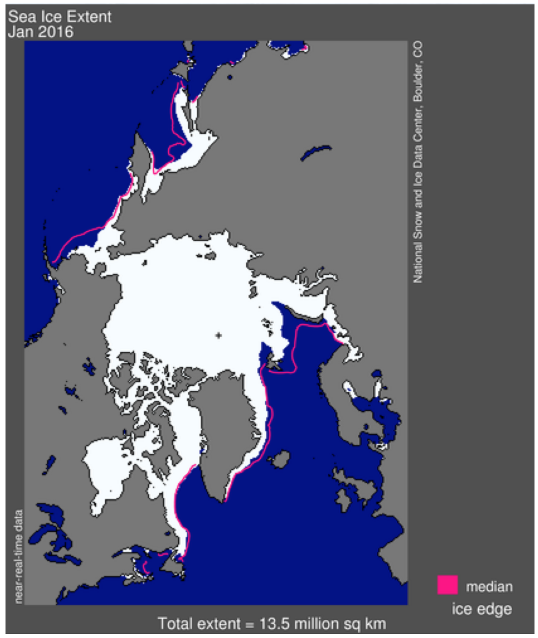

Figure 7: Arctic sea ice extent (white) of January 2016 (source: National Snow and Ice Data Center)

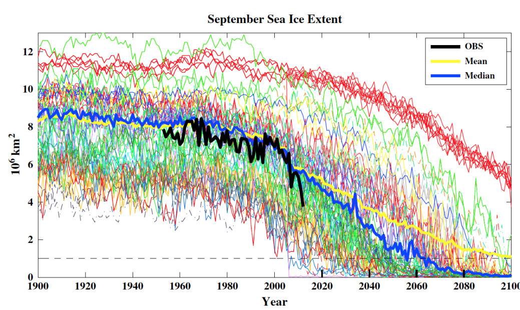

Figure 8: September Arctic Sea ice extent based on 89 ensemble members from 36 CMIP5 models under RCP8.5 (high) emission scenario (source: reference 10)