Deep learning analysis on impact of polar ice effects on Indian climate

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Abstract**—**Change in polar ice concentration affects the global climate variability in different scales. Many studies have explored the impact of polar sea ice parameters such as extent and concentration on various climatic factors like temperature, rainfall etc. But studies correlating the impact of polar ice effects on Indian climate are very few. The existing works too are statistical models which could not model the dynamics in sea ice extent, due to which their accuracy is limited. This work applies deep learning based analysis at different scales on the impact of polar ice effects over Indian climate at a fine grained level to solve the problems in statistical models. Due to larger area and multiple climatic zones, spatial fine grained analysis over different zones is necessary and it has not been investigated in any of earlier works. This work makes an important contribution of fine grained analysis of polar sea ice extent over Indian climate using deep learning model. Deep learning multivariate LSTM is used as tool for analyzing the impact of polar ice effects. The predictability of model is tested at fine grained level and it is found that model has good predictability of 75%.

I. Introduction

Global climate is regulated by exchange of energy between polar and tropical regions. This exchange process is significantly influenced by the polar ice. By altering the heat and momentum exchange between ocean and atmosphere, polar ice affects the amount of solar energy absorbed by earth[1].It also affects the evaporation and heat loss to atmosphere [2] by insulating the ocean surfaces. Decrease in polar ice extent influences the global radiative flux balance. This in turn increases the amount of heat absorption leading to climate change globally. Since 1970, the average temperature of land and sea has incremented by 0.85 ◦C[4]. This increase in temperature has increased the mean sea level by 0.2 m. Arctic ice extent decreases by 3.5 to 4.1% every decade. The sea ice extent in northern hemisphere has reduced by about 12.6% per decade during the years from 1985 to 2020. (Figure 1)

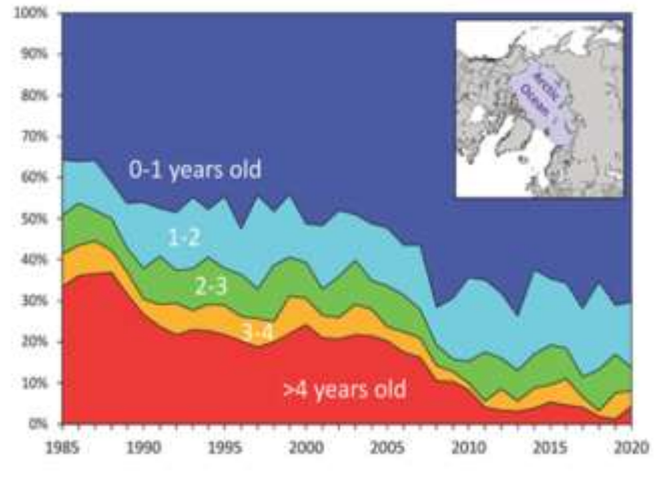

Figure 1Sea ice age percentage within the Arctic Ocean for the week of 11-18 March 1985-2020. Credit: NOAA

This rapid change in cryosphere impacts the climate, biology and socio economic activities negatively.

Polar ice affects the climate system in following ways. (i) limiting the heat exchange between ocean and atmosphere (ii) Loss of more heat to atmosphere through sea ice cover insulation reduction. The change in temperature is more noticeable in winter than summer. The effect of polar ice effects is both local and global. Compared to local, the remote effects are more complicated. It is very challenging to infer the correlation between polar ice change and global climate in presence of various other factors dominating the global climate.

The influence on polar ice effects on climate system has been analyzed in many existing works. Sandip et al [7] analyzed the monthly fractional sea ice over in the Antarctic (1999-2009) and its influence on climate in local regions. Author fitted a linear regression model and found sea ice cover has strong correlation to cooling trends locally. Kennel et al [8] analyzed the influence of sea ice extent in Arctic region on pacific area climate. Regression models was used for correlation analysis in this work.. Syairah et al [9]made a study correlating Indian ocean sea ice extent to average Indian rainfall. Various correlation techniques like partial, composite etc were explored in this work.. Works [10-12] analyzed the teleconnection between Antarctic sea ice extent to climate variability indexes. Linear correlation were used in these studies.Prabhu et al [13] analyzed the influence of Antarctic sea extent on south west monsoon rainfall through correlation tests. Though the study found strong correlation, the study is only short range. The influences of Arctic sea ice on earth's climate were investigated using observations and simulations in studies [14-20]. Among them statistical correlation with singular value decomposition was used in [20] to analyze the relationship between sea ice concentration in Arctic region to Chinese rainfall. Xue et al [21] used composite analysis to analyze the influence of sea ice oscillation in Antarctic region on monsoon over east Asian countries. Most of above works are based on deterministic coupled circulation models based on atmospheric air data. The works are statistical techniques at seasonal lead times of two months and beyond. Tripathi et al [22] analyzed the influence of sea ice concentration in Antarctic region on ocean surface temperature. Southern (400 S - 410 S and 820 E - 850 E) and the Central (220 S - 240 S and 790 E - 810 E) regions of Indian ocean was considered in this work. The sea ice concentration averaged over the Antarctic region (600 S - 890 S and 10 E - 890 E) has been used for identifying any relationship that may be present with the SST of these areas using artificial neural networks (ANN). Authors inferred that compared to these statistical techniques, machine learning based regression with ANN were found to better systems for analyzing impact of polar ice effects on climate over a long range. Recently deep learning techniques which are advancement of ANN have been used in many forecasting applications. Andersson et al [25] used a deep learning U-Net model to predict the sea ice extent from climate data collected around polar regions. Wei et al [26] used attention based LSTM network for sea ice extent prediction from past data.

Long Short term memory (LSTM) is a deep learning recurrent neural network which is being successfully applied in many long range prediction applications like stock markets. Mu et al [27] predicted sea ice extent using LSTM based transformer model from atmospheric and ocean variables. Liu et al [28] predicted sea ice concentration from atmospheric variables using LSTM. Kim et al [29] used convolutional neural network to predict sea ice concentration from satellite data. Chi et al [30] modified the loss function in LSTM to predict sea ice concentration. But in all these works [25-30], the predictor variable was sea ice concentration. But in this paper work, sea ice concentration is the input variable and climate is the predictor variable.

From the survey, it could be seen that exiting works on prediction of climate from sea ice extent are mostly statistical models. The existing deep learning models take climate only as input variable and don't consider it as predictor variable. Also there are not much works influence of polar sea ice extent on climate predictability. This work attempts to address these research gaps. This work uses multivariate LSTM to analyze the correlation between polar ice effect factors andrainfall at a fine grained level over Indian subcontinent. Though there are multiple polar ice effect factors, this work uses sea extent data as the input variable for the model.

II. Data

Antarctic sea ice extent data over monthly average is collected from year 1978 to 2019.The data collected using microwave radiometer and imaging was used for the experimentation. Sea ice extent was collected for Indian ocean sector (20°to 90°E) of Antarctic.

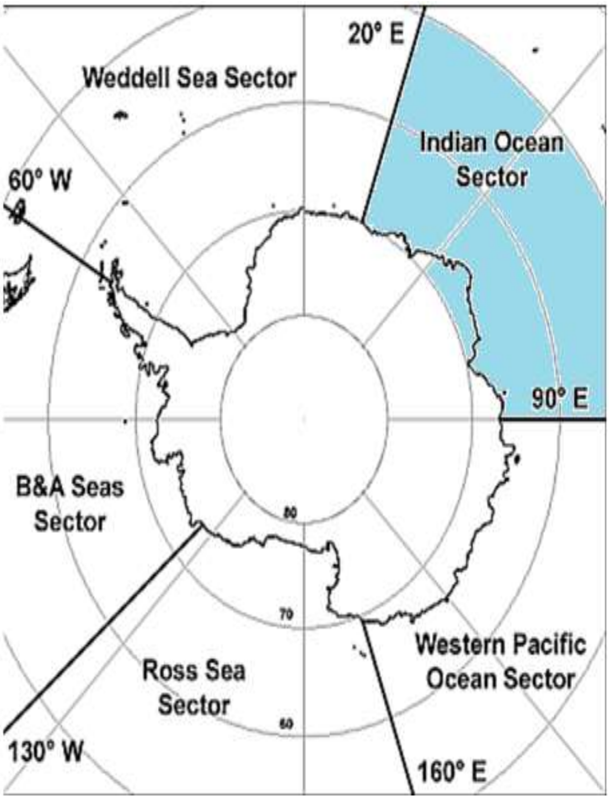

Figure 2 Indian ocean sector of Antarctic

In addition, monthly rainfall of meteorological stations located in western coastal regions of Indian subcontinent (Figure 3) was collected from Indian institute of Tropical meteorology.

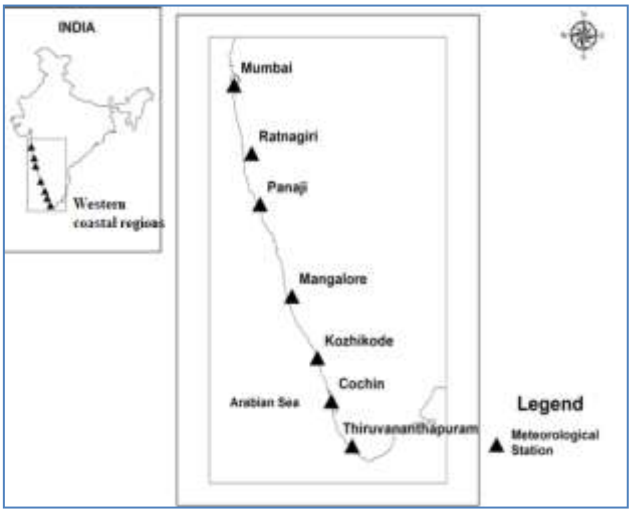

Figure 3 Indian western coastal region

The rainfall data collected from 1978 to 2019 from the eight meteorological stations were averaged monthly to construct the dataset of average rainfall in western coastal regions over the year 1978 to 2019.

The sea extent data and average rainfall data from 1978 to 2019 month wise is arranged as in table below and a dataset is created.

Table 1 Dataset fields

Year	Month	Sea extent	Average rainfall

III.Methodology

Multivariate LSTM deep learning model is used in this work to analyze the influence of Antarctic sea ice extent on Indian rainfall especially on the western coast. Recurrent neural network(RNN) is the base for LSTM[6]. It extends RNN by adding gate and cell activation state to the hidden states of RNN. Gating facilities losing or retaining information. Addition of cell activation provides control on level of activation needed in output layers. LSTM architecture is given in Figure 4. It is an sequential connection of LSTM nodes taking current input vector x and previous hidden state as input for processing. With this input, it calculates the cell activation as weighted sum of inputs($W_c x_t$)

along with the bias(b_c). The cell activation got as result is then processed with a hyperbolic tangent activation function($\emptyset_t$) as below

$$c_t = \emptyset_t(W_c x_t + U_c h_{t-1} + b_c)$$

In the above equation, h_{t-1} is the cell activation result of previous LSTM node in the sequence. The values W_c and U_c are the weights for input and the hidden state vector. The level of activation to be retained or forgot is done by controlling the gates.

The hidden state information is calculated at the final state. The level of activation to be retained or lost is controlled by the gates. While the level to retain is controlled by input gate, the level to forget is controlled by forget gate. Hidden state information is influenced by the final gate. The final gate takes two information, forgot vector (f_t) and input vector ((i_t) as input to provide the output vector (o_t).

$$f_t = \emptyset_s(I_{w_f} x_t + I_{U_f} h_{t-1} + bias_f)$$
$$i_t = \emptyset_s(I_{w_i} x_t + I_{U_i} h_{t-1} + bias_i)$$
$$o_t = \emptyset_s(I_{w_o} x_t + I_{U_o} h_{t-1} + bias_o)$$

In the above equation f_t represents the forgot vector, i_t represents the input gate vector and o_t represents the output gate vector.

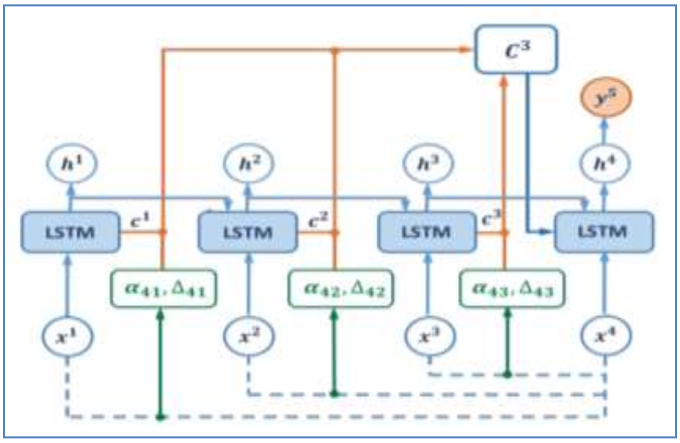

Figure 4 LSTM Architecture

The architecture of the multivariate LSTM used to predict the rainfall from the series of sea extent data is shown in Figure 4.

It takes the $Z = (Z_1, Z_2, \dots Z_T)$, where T sea extent observation are used to predict the rainfall at time T+1 and each Z_i is the input embedding of the transformed original sequence $X = (X_1, X_2, \dots X_T)$. The final LSTM layer output is passed to a Softmax classifier in regression setting [23]. In regression setting, softmax classifier the LSTM output to one of possible value of drought indicator. The output of the softmax classifier is the rainfall value prediction for the given T sea extent values. The loss function for training the softmax regression classifier is given as

$$L = -[\sum_{i=1}^{m}\sum_{k=0}^{1} 1\{y^{(i)} = k\} \log P(y^{(i)} = k|z^{(i)}; \theta)]$$

Where

$$P(y^{(i)} = k|z^{(i)}; \theta) = \frac{\exp(\theta^{(k)} z^{(i)})}{\sum_{j=1}^{K} \exp(\theta^{(k)} z^{(i)})}$$

Where $\theta^{(1)}, \theta^{(2)}, \dots \theta^{(k)}$ are the parameters of the model and $\exp(\theta^{(k)} z^{(i)})$ is the normalization of parameter with the input feature values.

The sea extent values are arranged in 6,12,24,36 past month values as input and rainfall in 7,13, 25,37 month as output. Four long range datasets S-6,S-12, S-24, S-36 are created. From these datasets, 80% were used for training and 20% were used for testing. Four different multivariate LSTM predictors were trained with 80% data of S-6,S-12, S-24 and S-36 dataset.

The prediction performance of the solutions is measured using following metrics: Mean absolute error (*MAE*), Nash–Sutcliffe model efficiency coefficient (*NSE*) [24], and coefficient of correlation (*R*). The metrics are calculated as follows. The metrics are calculated as below

$$NSE = 1 - \frac{\sum(P_j - A_j)^2}{\sum(\bar{A} - A_j)^2}$$

$$MAE = \frac{1}{n}\sum_{j=1}^{n} |A_j - P_j|$$

$$R = \frac{\sum_{j=1}^{n}(\bar{A} - A_j)((\bar{P} - P_j)}{\sqrt{\sum_{j=1}^{n}(\bar{A} - A_j)^2 \sum_{i=1}^{n}(\bar{P} - P_j)^2}}$$

In the above equations, n is the number of test observations, A is the actual value and P is the predicted value.

The proposed methodology was implemented in Python 3.8.2 in Windows OS environment. LSTM from tensorflow module is used.

IV. Results

The results of performance metric for four ranges are shown below

Table 2 Results for performance metrics

	NSE	**MAE**	**R**
S-6	0.58	200	0.56
S-12	0.63	150	0.61
S-24	0.75	92	0.73
S-36	0.76	88	0.75

The MAE in S-24 and S-36 are almost same and it is 66% lower compared to S-12 and 122% lower compared to S-6. From this, it can be inferred that long range of 24 and 36 months were found to have lower prediction error compared to S-6 and S-12. The error is higher in prediction based on 6 months and MAE is lowest in prediction based on 36 months. Over 24 months, there is not much difference in MAE.

The maximum correlation coefficient of 0.75 is achieved for prediction based on 36 months. But there is not much difference of it with prediction based on 24 months. The maximum value 0.75 indicates that prediction of western coast rainfall based on sea ice extract is almost 75% accurate.

The predicted average rainfall in S-36 and sea ice extent are normalized in range of -3 to 3 and plotted for year from 1985 to 2019. The plots for S-6,S-12,S-24 and S-36 are given in Figure 5-8. The results show a statistical correlation of 0.74.

The rainfall data of Mumbai, Mangalore and Cochin were individually fitted for S-6 to S-36 LSTM to check if the results are statically significant. ANOVA was used for testing the statistical significance between sea extent data over 6-36 months to the Indian western cost rainfall. The result is given in Table 3. From the results, the

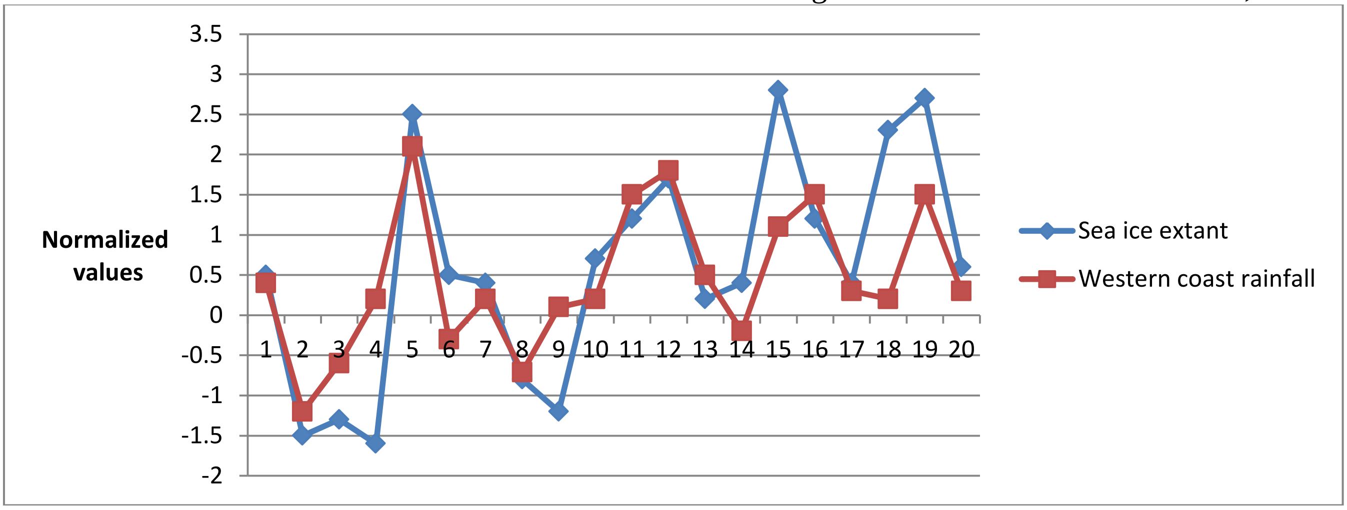

Figure 5 Correlation plot for S-36

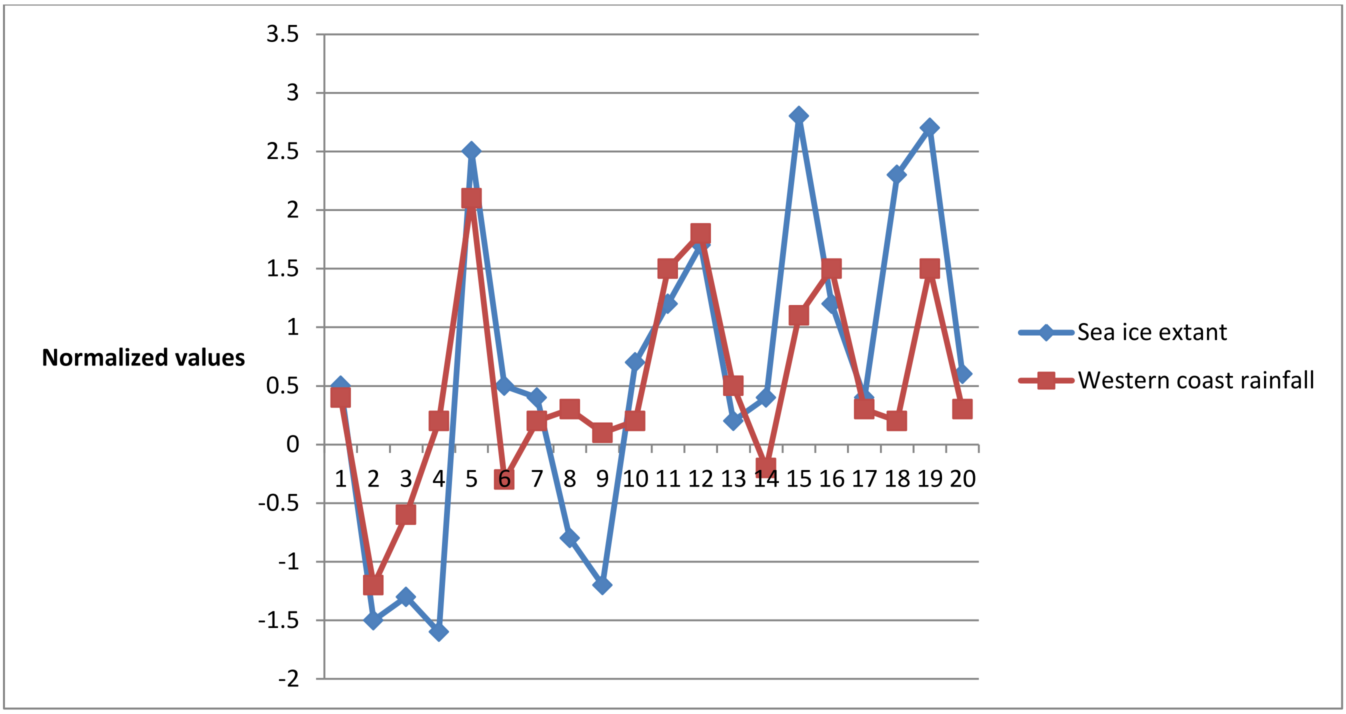

Figure 6 Correlation plot for S-24

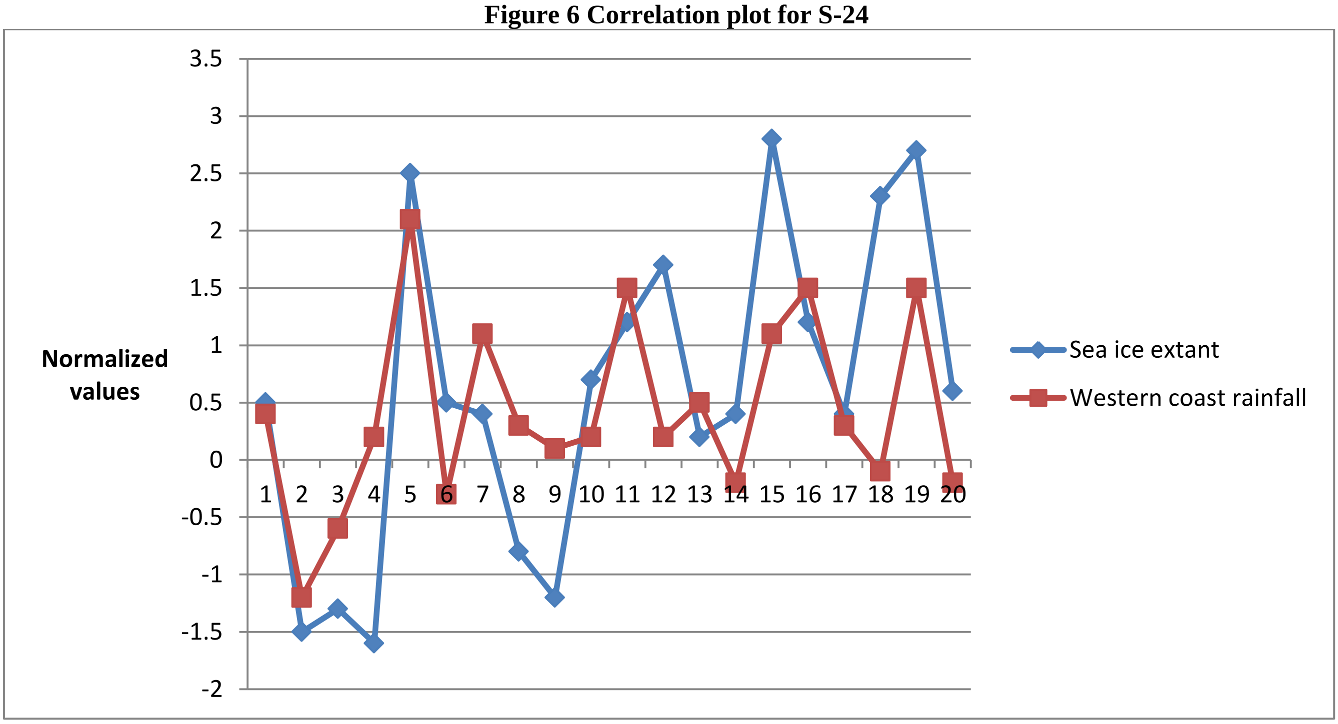

Figure 7 Correlation plot for S-12

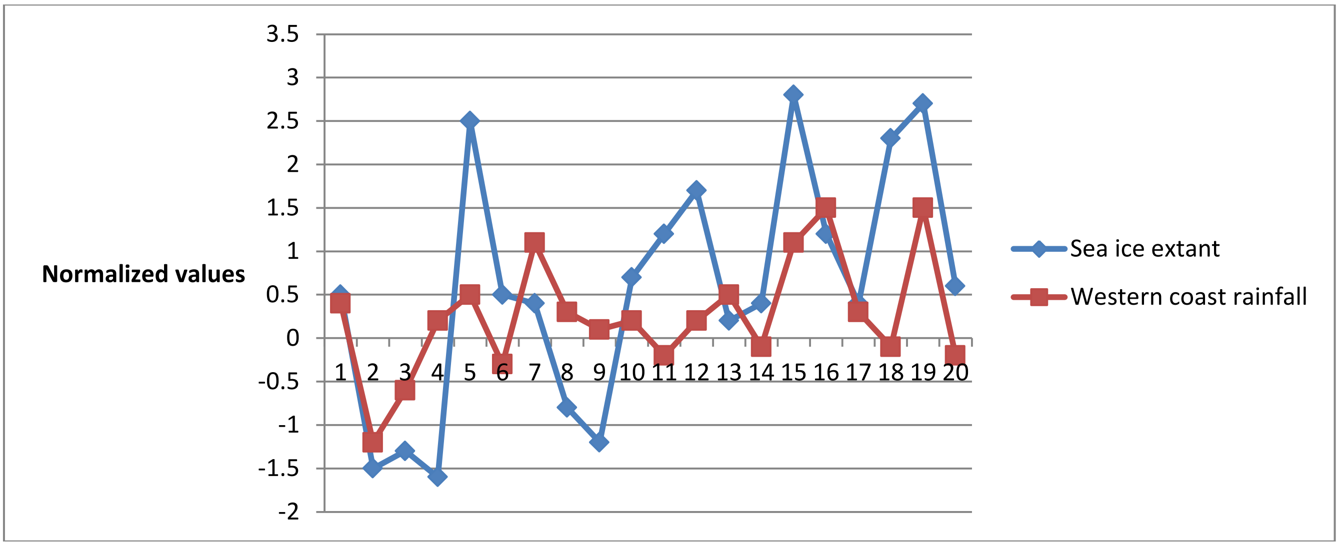

Figure 8 Correlation plot for S-6

Table 3 ANOVA Results

Range	Station	F-Value	P-Value
6 months (S-6)	Mumbai Mangalore Cochin	3.212 3.201 3.215	0.009 0.010 0.008
12 months (S-12)	Mumbai Mangalore Cochin	4.142 4.132 4.171	0.008 0.007 0.009
24 months (S-24)	Mumbai Mangalore Cochin	5.792 5.231 5.812	0.005 0.006 0.004
36 months (S-36)	Mumbai Mangalore Cochin	5.784 5.233 5.821	0.005 0.006 0.004

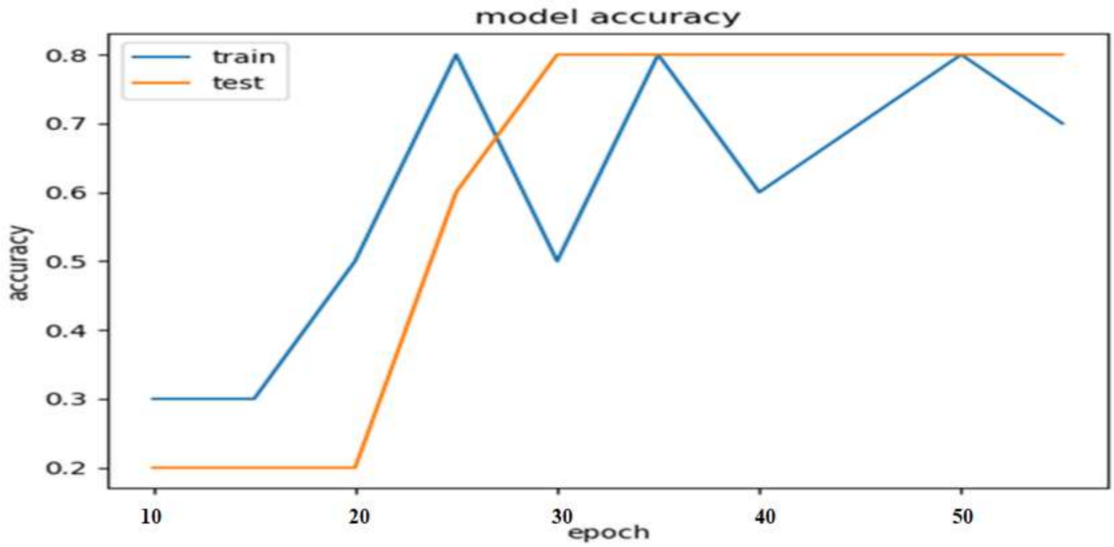

Figure 9 S-36 LSTM accuracy plot

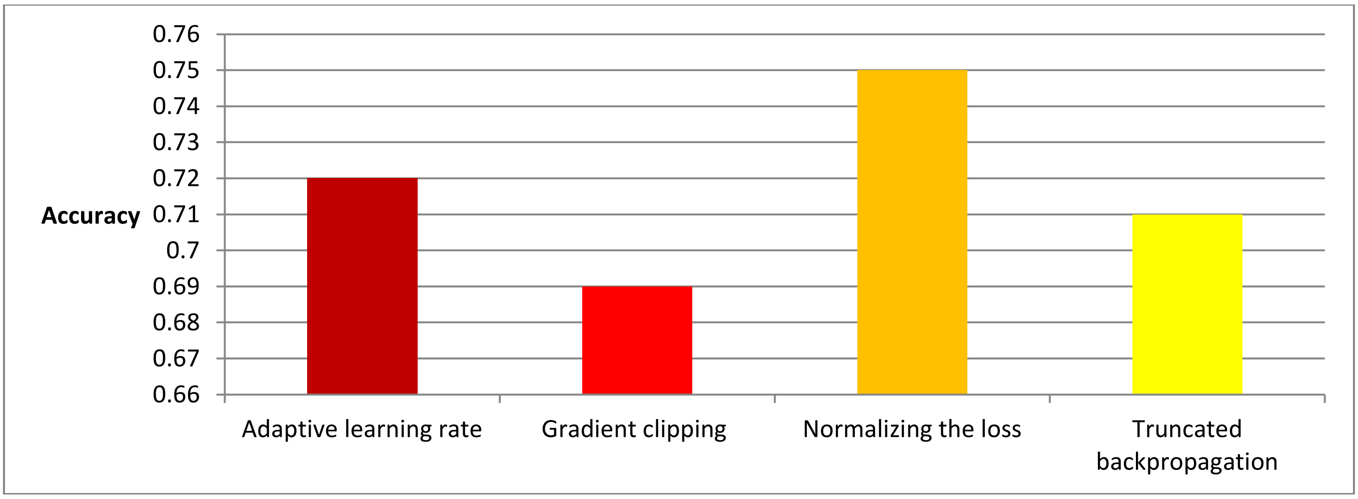

Figure 10 Accuracy across training functions

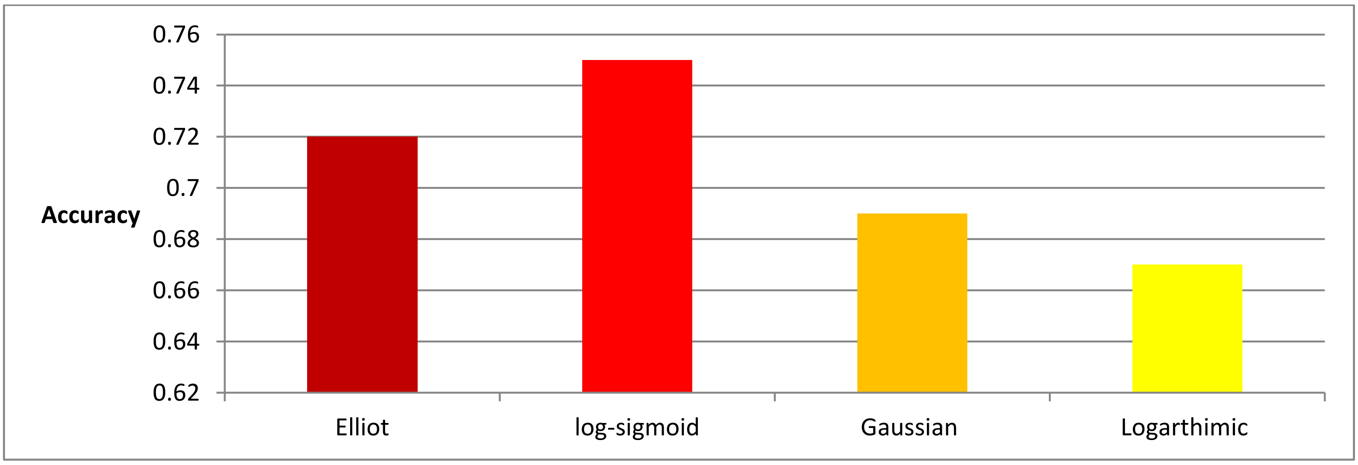

Figure 11 Accuracy across activation functions

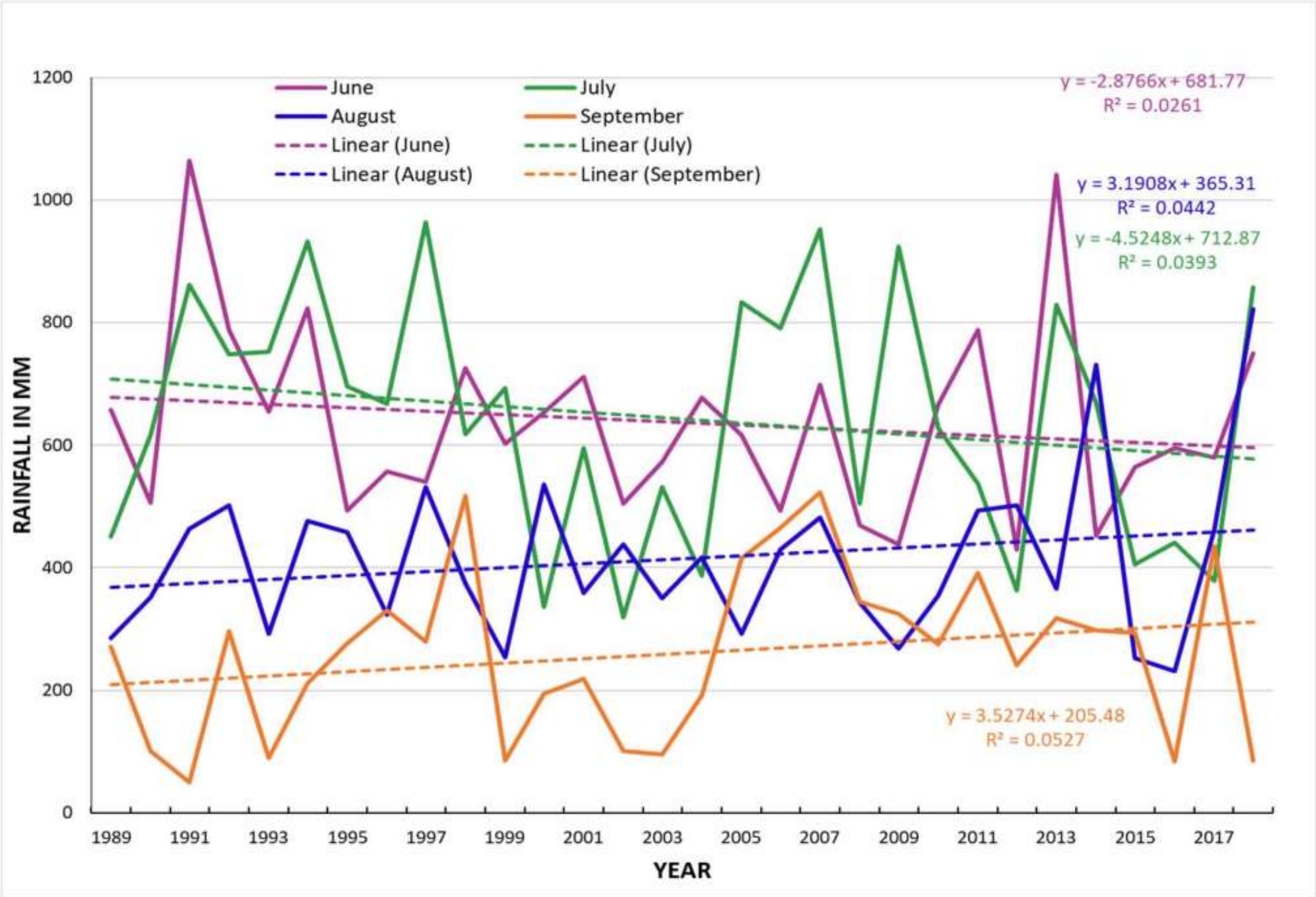

Figure 12 Month wise prediction

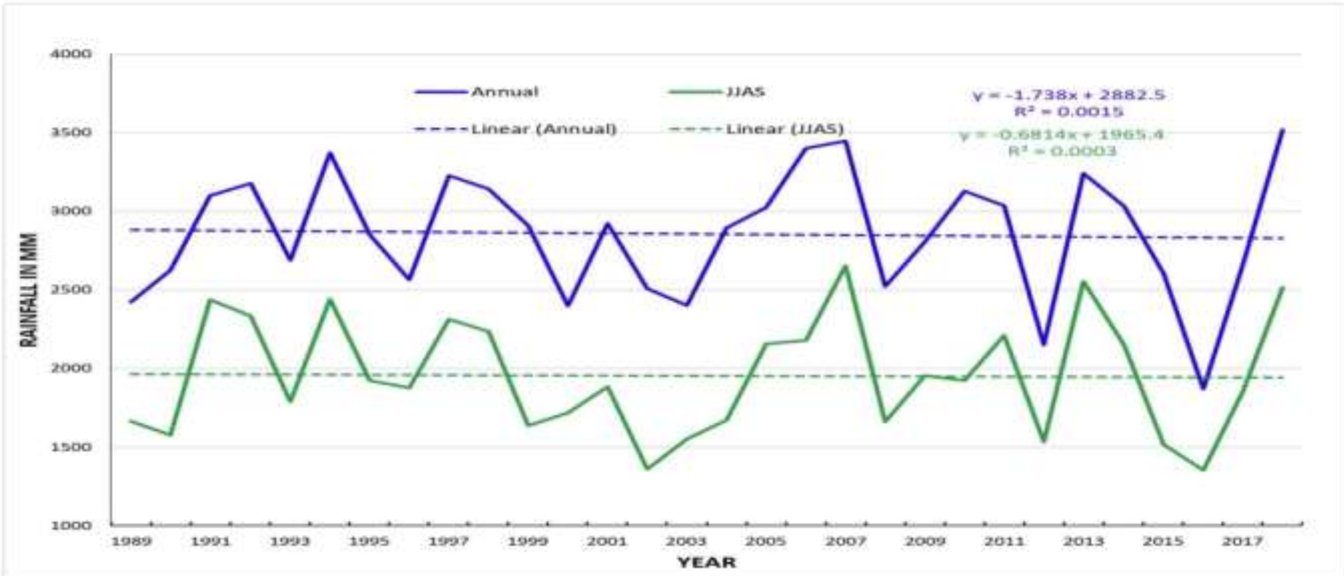

Figure 13 Annual rainfall prediction

average P value is 0.005 signifying the statistical significance at 95%. Also the results indicate that with increase in sea ice extent, the rainfall in Indian western coastal region also increases.

In Indian western coastal regions, the maximum rain fall is received in months of June, July, August and September. The prediction of rainfall using the S-36 LSTM model over these months for years 1989-2019 and the corresponding linear fit is plotted in Figure 12. The prediction of rainfall using the S-36 LSTM model over every year from 1989-2019 and the corresponding linear fit is plotted in Figure 13. The data is completely non linear as seen from low R value for linear fit. This justifies the use of LSTM model to model the rainfall dynamics instead of statistical models.

The multivariate LSTM S-36 accuracy is plotted for every epochs of training. In Figure 9. The maximum accuracy is achieved around 30 epochs. Thus the LSTM for S-36 configured for minimal 30 epochs to achieve maximal performance.

The LSTM configuration parameters used for experimentation are given in Table 4.

Table 4 LSTM configuration

Parameters	Values
Dropout	10%
Decay rate	0.2
Activation function	Log-sigmoid
Learning rate	0.5
Momentum	0.6
Number of epochs	50
Batch size	32

The accuracy of LSTM was measured for four different training functions and the results are given in Figure 10. The maximum accuracy of 0.75 is achieved by using loss normalization as training function. From the Figure 11 of plot of accuracy across the activation functions, maximum accuracy is achieved with log-sigmoid function and thus log-sigmoid is found to be better fit for prediction of rainfall.

Discussion

From the results, it can be inferred that there is high correlation between the polar sea extent especially the Antarctic and the Indian western coast rainfall. The Deep learning model especially the LSTM with sequence window as 36 months is found to have 75% correlation. Since there are no equivalent works correlating the influence of Antarctic sea ice extent on Indian climate especially Indian rainfall at fine grained level, the work could not compared to any works and thus comparison was made only against sequence window variations in LSTM.

Limitations

There has not been any earlier works designed to predict rainfall based on sea ice extent in Antarctic region. Though the work was able to achieve 75% prediction accuracy, it could be still improved. The predictability model proposed in this work can be still improved with attention mechanism, to increase the accuracy. The sea ice extent in different seasons can be correlated to analyze the impact of polar sea extent in different seasons on Indian climate.

V. CONCLUSION

This work explored the influence of Antarctic sea ice extent on Indian climate with use of deep learning model. Multivariate LSTM in 4 timescale of 6,12,24 and 36 months were fitted and tested for data from year 1979 to 2019. Maximal correlation 0.75 between sea ice extant in Indian sector to western coast monsoon rainfall was observed at range of 24 months. After 24 months there are not much significant difference in correlation. The model was found to be statistically significant at 95% using ANOVA test. The study correlated only sea ice extant to rainfall, but there are other factors like rapid reduction of green cover in Western ghats region, rapid urbanization etc. The effect of these mediating variables must also be considered in long time forecast of rainfall. Modeling the rainfall without considering these factors is a limitation of this work and can be considered as part of future work.

REFERENCES

[1] Z. Jin, K. Stamnes, W. F. Weeks, and S. C. Stay, “The affects of sea ice on the solar energy budget in the atmosphere–sea ice–ocean system: A model study,” J. Geophys. Res., vol. 99, no. C12, pp. 25 281–25 294, 1994.

[2] X. Yuan, “ENSO-related impacts on Antarctic sea ice: A synthesis of phenomenon and mechanisms,” Antarctic Sci., vol. 16, no. 4, pp. 415–425, Nov. 2004.

[3] Zahoor A. Khan, ShyamalaSivakumara, William Phillips, Bill Robertson, "A QOS-aware Routing Protocols for Reliability Sensitive Data in Hospital Body Area Networks", Trans. on ELSEVIER in proc. ANT, pp. 171-179, 2013.

[4] M. Dirscherl, A. J. Dietz, S. Dech, and C. Kuenzer, “Remote sensing of ice motion in Antarctica—A review,” Remote Sens. Environ., vol. 237, Feb. 2020, Art. no. 111595

[5] Andersson, T.R., Hosking, J.S., Pérez-Ortiz, M. et al. Seasonal Arctic sea ice forecasting with probabilistic deep learning. Nat Commun 12, 5124 (2021)

[6] Staudemeyer, Ralf & Morris, Eric. (2019). Understanding LSTM -- a tutorial into Long Short-Term Memory Recurrent Neural Networks

[7] Oza, Sandip & Singh, Rajkumar & Srivastava, Abhinav & Dash, Mihir & Das, I. & Vyas, Navrishi. (2011). Inter-annual variations observed in spring and summer Antarctic sea ice extent in recent decade. Mausam. 62. 633-640. 10.54302/mausam.v62i4.381.

[8] Kennel CF, Yulaeva E. Influence of Arctic sea-ice variability on Pacific trade winds. Proc Natl Acad Sci U S A. 2020 Feb 11;117(6):2824-2834.

[9] Atiqah, Syairah & Chenoli, Sheeba & Abu samah, Azizan & Kim, Seong-Joong. (2020). The linkages between Antarctic sea ice extent and Indian summer monsoon rainfall. Polar Science. 25. 100537. 10.1016/j.polar.2020.100537.

[10] Yuan and Martinson, 2000 X. Yuan, D.G. Martinson Antarctic sea ice extent variability and its global connectivity J. Clim., 13 (2000), pp. 1697-1717

[11] S. Rai, A.C. Pandey, "Antarctica sea ice variability in recent years and its relationship with Indian Ocean SST", J. Indian Geophys. Union, 10 (2006), pp. 219-229

[12] S. Rai, N. Khare, A.C. Pandey Possible relationship Antarctica sea ice variability and southeast Indian Ocean SST Indian J. Mar. Sci., 37 (1) (2008), pp. 35-39

[13] A. Prabhu, P. Mahajan, R. Khaladkar, S. Bawiskar Connection between Antarctic sea-ice extent and Indian summer monsoon rainfall Int. J. Rem. Sens., 30 (13) (2009), pp. 3485-3494

[14] Rigor, I. G., J. M. Wallace, and R. L. Colony (2002), Response of sea ice to the Arctic Oscillation, J. Clim., 15, 2648– 2663

[15] Alexander, M. A., et al. (2004), The atmospheric response to realistic sea ice anomalies in an AGCM during winter, J. Clim., 17, 890– 905

[16] Deser, C., J. E. Walsh, and M. S. Timlin (2000), Arctic sea ice variability in the context of recent atmospheric circulation trends, J. Clim., 13, 617– 633.

[17] Deser, C., G. Magnusdottir, R. Saravanan, and A. Phillips (2004), The effects of North Atlantic SST and sea ice anomalies on the winter circulation in CCM3. Part II: Direct and indirect components of the response, J. Clim., 17, 877– 889.

[18] Magnusdottir, G., C. Deser, and R. Saravanan (2004), The effects of North Atlantic SST and sea ice anomalies on the winter circulation in CCM3. Part I: Main features and storm track characteristics of the response, J. Clim., 17, 857– 876.

[19] Wu, B., J. Wang, and J. Walsh (2004), Possible feedback of winter sea ice in the Greenland and the Barents Sea on the local atmosphere, Mon. Weather Rev., 132, 1876– 1968.

[20] B. Wu, R. Zhang, B. Wang, R. D'Arrigo On the association between spring Arcticsea ice concentration and Chinese summer rainfall Geophys. Res. Lett., 36 (L09501) (2009), pp. 1-6

[21] F. Xue, H. Wang, J. He Interannual variability of Mascarene high and Australian high and their influences on east Asian summer monsoon J. Meteorol. Soc. Jpn., 82 (4) (2004), pp. 1173-1186

[22] Tripathi, K C; Das, I.M.L. Variability of Antarctic sea ice concentration as a prospective predictor for Indian summer monsoon rainfall, Proceedings of National Snow Science Workshop, SASE, Chandigarh, India, 229-232, 2008b

[23] A. Sangari and W. Sethares, "Convergence Analysis of Two Loss Functions in Soft-Max Regression," in IEEE Transactions on Signal Processing, vol. 64, no. 5, pp. 1280-1288, March1, 2016

[24] Nash, J. E.; Sutcliffe, J. V. (1970). "River flow forecasting through conceptual models part I — A discussion of principles". Journal of Hydrology. 10 (3): 282–290

[25] Andersson, T.R., Hosking, J.S., Pérez-Ortiz, M. et al. Seasonal Arctic sea ice forecasting with probabilistic deep learning. Nat Commun 12, 5124 (2021)

[26] Wei, Jianfen & Hang, Renlong & Luo, Jing-Jia. (2022). Prediction of Pan-Arctic Sea Ice Using Attention-Based LSTM Neural Networks. Frontiers in Marine Science. 9. 860403.

[27] Mu, B., Luo, X., Yuan, S., and Liang, X.: IceTFT v 1.0.0: Interpretable Long-Term Prediction of Arctic Sea Ice Extent with Deep Learning, Geosci. Model Dev. Discuss. [preprint], https://doi.org/10.5194/gmd-2022-293, in review, 2023.

[28] Liu, Q., Zhang, R., Wang, Y., Yan, H., and Hong, M.: Daily Prediction of the Arctic Sea Ice Concentration Using Reanalysis Data Based on a Convolutional LSTM Network, Journal of Marine Science and Engineering, 9,

330, 2021

[29] Kim, Y. J., Kim, H. C., Han, D., Lee, S., and Im, J.: Prediction of monthly Arctic sea ice concentrations using satellite and reanalysis data based on convolutional neural networks, The Cryosphere, 14, 1083–1104, 2020

[30] Chi, J., Bae, J., and Kwon, Y.-J.: Two-Stream Convolutional Long- and Short-Term Memory Model Using Perceptual Loss for Sequence-toSequence Arctic Sea Ice Prediction, Remote Sensing, 13, https://doi.org/10.3390/rs13173413, 2021