The Effects and Prognosis of Global Warming on Glacial Melt and Warming Trend on Earth

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Abstract— Global Warming is defined as a rise in global average temperatures. The chief reasons of such a rise in average global temperatures are assumed to be natural occurrences and human activity. Climate change, driven by increased carbon dioxide emissions from automobiles, industry, and power plants, will have an impact not just on the climate and the oceans, but also on the Earth's geology. The temperature is fast dropping, which might have a big impact on our society, both positive and negative. Increases in greenhouse gases such as carbon dioxide, nitrogen oxide, sulphur dioxide, hydrogen, and others are the primary cause of global warming. Climate change is caused by a warming planet, and this may have a detrimental influence on weather in a variety of ways. Despite substantial achievements in modelling sequential and geographical data for voice recognition and computer vision, remote sensing and climate research applications are rarely investigated. In this research, we demonstrate how to increase the accuracy of ice flow tracking in multi-spectral satellite photos by using unsupervised learning approaches for future video frame prediction. As the volume of cryosphere data expands in the next years, machine learning will have an exciting and critical chance to address a worldwide problem for climate change, flood risk management, and freshwater resource conservation.

Keywords—global warming, ice melting, deep learning; global warming; long and short-term memory; machine learning; multilayer perceptron; neural network; sea ice concentration; sea ice extent

1. INTRODUCTION

Recent developments in climate research, satellite remote sensing, and high-performance computing are allowing new advancements that can benefit from the most modern machine learning approaches. A new generation of Earth observation satellites is producing petabytes of data, and the commercialization of the space sector is cutting data collecting costs even more. Such huge geoscience datasets are now available for machine learning applications, when combined with the most current supercomputer simulation outputs from global climate model intercomparison efforts. Some of the most visible indications of global warming are as follows:

i. Land temperature

ii. Snow cover on hills

iii. Hills with Glaciers

iv. Heat content of the ocean

v. The Sea Ice

vi. The sea level

vii. Temperature at the sea's surface

viii. Ocean Temperature

viii. Humidity

The warmest period in the recent decade, according to experts from 48 nations, was reported on July 28, 2010, during a conference of the National Oceanic and Atmospheric Administration. Even though scientists and environmentalists have been warning for decades that our current use of Earth's resources is unsustainable. Alternative technologies have been constantly campaigned for, apparently falling on deaf ears or, more cynically, on those who do not want to make big changes since it would challenge their bottom line and lower existing earnings. Global warming is a threat to humanity's existence in the current circumstances. Marion King Hubert, a US-based Chief consultant and oil geologist, projected in 1956 that if oil consumption continues at its current rate, US oil output will peak in 1970 and subsequently fall. He also claimed that additional nations might hit peak oil over the next 20-30 years, and that many more could suffer an energy catastrophe during the next 40 years, when oil wells run dry. He visualised the projection using a bell-shaped Hubert Curve based on fossil fuel supply and use. Small fields are discovered initially, then large fields. Following exploration and early output growth, output plateaus and finally drops to zero.

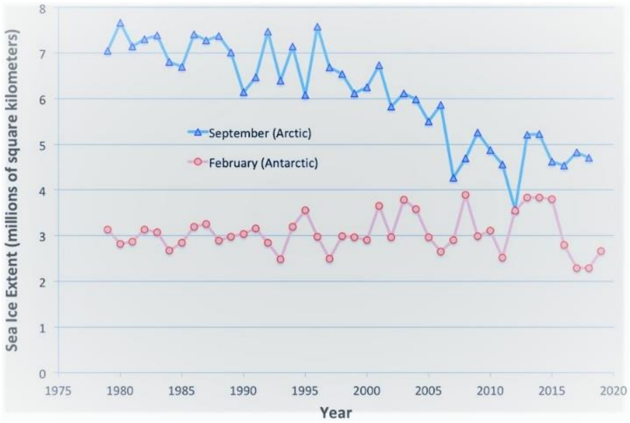

Fig 1. Ice melting Graph

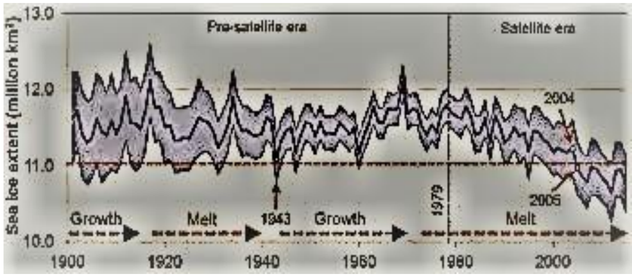

Fig 2. Ice melting graph in specific months (when heat is at its peak)

It is projected that traffic pollution in India has grown eightfold during the previous two decades. This source alone is estimated to account for nearly 70% of overall air pollution. India's contribution to global carbon emissions is predicted to climb in the future years due to the rapid pace of urbanisation, the move from non-commercial to commercial fuels, rising vehicle traffic, and the ongoing use of older and more inefficient coal-fired fossil fuel power plants. Thus, if self-sufficiency and energy sustainability are not prioritised, peak oil year might be a watershed event for humanity, signalling the end of a century of easy progress. This chapter describes efforts to investigate non-conventional energy resources such as solar energy, wind energy, biomass and biogas, hydrogen, and biodiesel, which may aid in the sustainability of fossil fuel reserves and reduce tail pipe emissions and other pollutants such as carbon dioxide and nitrogen oxide, among others. To preserve energy sustainability, a special emphasis is placed on energy storage, such as compressed air collected from solar, wind, or other resources such as climatic energy. This might also lead to a more environmentally and ecologically friendly future.

II. LITERATURE SURVEY

O'Gorman and Dwyer effectively mimicked physical processes from costly climate model outputs by parameterizing moist convection processes using random forests. Scher was also able to accurately replicate the dynamics of a basic climate model using deep learning after being supplied with adequate data in 2018. Sherwood et al. have demonstrated promise in addressing the main source of uncertainty in climate forecasts, cloud convection.

Rasp et al. and Gentine et al. in 2018 demonstrated the application of deep learning to mimic sub-grid processes in simplified climate models to resolve model clouds at a fraction of the computing cost of high-resolution physics models. These advances enable machine learning researchers to create models of ice flow and dynamics using satellite data, or to anticipate changes in glaciers and ice dynamics using novel video prediction approaches developed by Mathieu et al., Denton & Fergus in 2018.

Our main contributions to this work are:

(1) The development of an unsupervised learning model for tracking ice sheet and glacier dynamics.

(2) The introduction of IceNet, a dataset that we make available to the community as a first step toward bridging the gap between machine learning and cryosphere climate research.

III. MEHODOLOGY

Deep learning is a relatively new topic of machine learning that was inspired by the creation of artificial neural networks in the late 1980s. The advancement of faster computers, as well as the increasing availability of large datasets for training large neural networks, has resulted in an exponential growth in DL research, which has been accompanied by increased investment in the technology. Perceptron's or neurons in hidden layers, which are basic computational units, connect weighted input layers to output layers via an activation function.

The main difference between deep neural networks and standard neural networks is that deep neural networks include more than two hidden layers in the network, whereas classic neural networks only have one hidden layer. Neurons in the first hidden layer of a deep network design make simple judgments, such as weighing input variables, whereas neurons in the second hidden layer make more complicated and abstract decisions than neurons in the first hidden layer. As a result, a network with numerous hidden layers may make more difficult judgments theoretically. This article offers a deep learning based SIC prediction model based on a Convolutional Neural Network. Convolutional Neural Network is a sort of artificial neural network model introduced by LeCun et al. in 2013 and since developed with various architectures and methods by Deng et al. Browne and Ghidary in 2003 pioneered the use of Convolutional Neural Network - CNN techniques to handle picture recognition and classification challenges. By Wang et al. in 2017, Convolutional Neural Network learns visual characteristics and saves them as crucial information to extract outputs. This study investigated three models for forecasting SIC: basic climatology, RF-based models, and CNN-based models. To forecast SIC for each month, we constructed twelve distinct models. A hindcast validation technique was used to assess the performance of each model. Using historical data, each monthly model was trained to forecast SICs. These new RF variables are designed to bridge conceptual gaps between the two techniques by considering predictive spatial patterns such as features in the CNN model.

Because the enormous number of pixels in the open sea biassed most SIC samples to zero values, the training samples were balanced out by applying a monthly maximum sea ice extent mask, which depicts the widest sea ice extent for the whole research period for each month. The imbalance sampling problem continued, however, because the lower SIC samples were rather tiny. In the case of the basic prediction model, the SICs of each pixel were forecasted using simply yearly climatology. In this work, we employed a multilayer perceptron and a long and short-term memory to forecast monthly Arctic SIC values in a supervised way. A multilayer perceptron, often known as a feedforward neural network, is the most useful form of neural network. In a multilayer perceptron, the outputs anticipated by training the network with given inputs may not be equivalent to the desired values. Because there may be disparities between the actual and planned outputs, the training algorithm adjusts the network weights repeatedly. As a result, through an iterative process, the network can finally obtain optimal outcomes.

The stages involved in the implementation of a multilayer perceptron are as follows:

1. Configure the network weights.

2. To the weighted inputs, apply an activation function.

3. Calculate the difference in output between the network and the predicted output.

4. Recreate the mistake throughout the network.

5. Reduce overall inaccuracy by adjusting the weights.

6. Continue until the error is smaller than a user-specified threshold or the maximum number of repetitions is achieved.

Although a multilayer perceptron may be used to predict sequences, needing to specify the extent of temporal dependency between observations has significant downsides. Long and short-term memory is a sort of recurrent neural network, which is built for sequence issues and holds promise for time series data interpretation. Loops in the long and short-term memory feed prior time step network states as inputs to the network, influencing predictions at the present time step. Because each unit of long and short-term memory is built up of cells with gates containing input/forget/output information, it may maintain a longer-term temporal sequence than a typical feedforward. Perceptron network with several layers.

The fundamental processes of long and short-term memory are like multilayer perceptron's, however long and short-term memory feature an extra recurrent mechanism to transfer learning status to the next learning step.

Although multilayer perceptron outperforms long and short-term memory for long-term sequence predictions, the large computational burden is a worry. To get optimal performance, the parameters used in Deep Learning models must be properly adjusted. Many parameters must be established before models can be constructed in neural networks, and they are challenging to optimise. In practise, there are recommended setups for choosing certain algorithms and settings. In practise, small random numbers for weight initialization, a rectifier activation function, and an Adaptive Moment Estimation gradient descent optimization technique with a logarithmic loss function, for example, perform well. However, in iterative gradient descent, the batch size, number of rounds of exposing the whole training data set to the network during training, and number of layers and neurons utilised to define network topology should all be considered.

It is heavily reliant on the dataset utilised. All parameter combinations should be examined using a grid search, which is the classic and frequently used technique of parameter optimization, to discover the best combination of parameter values that maximise model scores. Parallel processing is utilised to determine the optimal parameter value combinations because grid searching might be time-consuming. Due to sensor faults, low spatial resolution, and sea ice movements in daily photos, near-real-time data is limited for practical use, but it is valuable for monitoring tiny changes in sea ice coverage or day-to-day shipping operations. A simple monthly average reduces some of the day-to-day noise in daily sea ice data.

IV. RESULT & ANALYSIS

A time series model's capacity to provide accurate forecasts is a measure of its performance. Split-sample studies, in which the model is fitted to the first portion of the data, are widely used to assess this capacity. projections for the latter half of the series are derived and the values are then compared to known observations of a known data sequence the objective is to minimise foresting mistakes such that anticipated future values are as near to real future values as feasible. The CNN model fared better than the others. The simple prediction and RF models outperform the simple prediction and RF models in all accuracy criteria.

When all SICs were considered, the basic prediction model had the lowest prediction performance. While both the RF and CNN models fared well in terms of prediction accuracy, with just a little difference in MAE and RMSE, the CNN model surpassed the RF model in terms of nRMSE. These data show that the error distribution of the CNN model was more stable than that of the simple prediction model and RF. The MAE rose when compared to low SIC values, although this was owing to the lower SIC values.

The RMSE and nRMSE of the basic prediction model have reduced, whereas the others have grown. It suggests that the RF and CNN models are less reliable in forecasting SICs in the marginal sea ice zone than in the core zone. The NSE values for all models declined when the SIC was low. Nonetheless, the CNN model consistently beat the other models in both circumstances. Typically, time series forecasting is done as a one-step prediction based on past data.

Two techniques are often used to handle multiple-step ahead prediction problems:

(1) Direct model re-training and

(2) Recursive approaches.

If we were projecting SIC for the following two months, we would develop a model for the first month and a different model for the second month. This method may provide more fitting models and surprising outcomes, but its extraordinarily high computational overhead is troublesome in practise, especially when training our enormous sea ice data. The recursive technique repeats the use of a single prediction model. We used the most popular initialization, activation, and optimization algorithms to tune the batch size, number of epochs, number of hidden layers, and number of neurons for fitting the network topologies, and we used a parallelized grid search to tune the batch size, number of epochs, number of hidden layers, and number of neurons.

However, if we used the network extensively and iterated many times, the DL models finally converged to a high accuracy result. Consequently, we picked three hidden layers, each with 32 neurons. Both the batch size and the number of epochs were limited. Then, on each layer, we employed the rectifier, also known as rectified linear unit activation function, which has demonstrated better performance in recent research, to initialise the network weights using tiny random values from a uniform distribution.

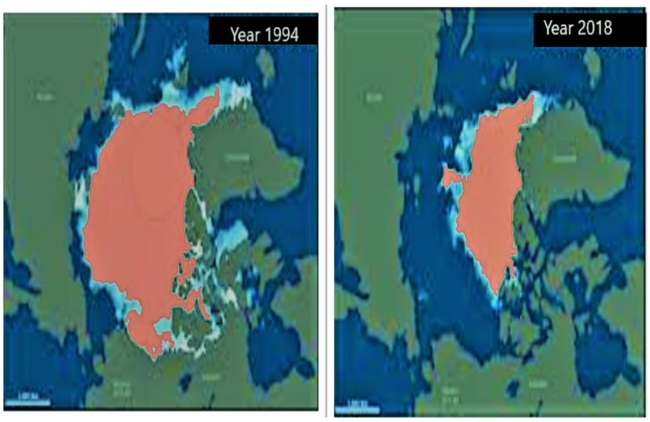

Fig 3. Output Image & Comparison

Dropout layers with a rate of 0.3 were added after each concealed layer to prevent overfitting. The Adam optimization approach was chosen because it is practical. To test the performance of the proposed DL-based prediction models statistically and qualitatively, we employed an autoregressive model, which is a basic and classic statistics-based time series model. To forecast the value at the next time step, an AR model uses prior time step observations as inputs to a regression equation. Because an AR model can address a wide range of time series problems, it is an ideal baseline model for evaluating the performance of our proposed DL-based models. Both AR and DL-based models require a certain number of previous observations. Additional tests were conducted using a recursive strategy to assess the efficacy of our DL-based model for multiple-step forward prediction. The anticipated values were utilised as inputs several times for the long-term forecasts, using the same single DL model as in the one-step forward predictions.

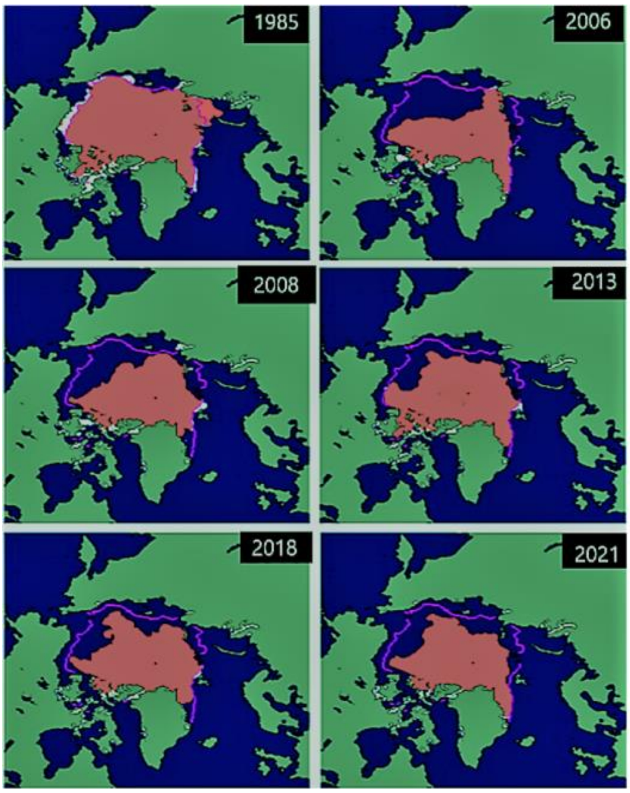

Fig 4. Output Image & Comparison between 6 years

V. CONCLUSION

The purpose of this study was to forecast Arctic SIC using a deep neural network, a technology that is being actively investigated in the machine learning field. In contrast to standard models, which employ a range of environmental or physical information as input, this study exclusively used actual sea ice data from remote sensing instruments. The findings demonstrate that DL-based prediction models can successfully fit long-term Arctic SIC datasets and estimate monthly SICs throughout the year, while prediction quality has degraded significantly as recent summer month sea ice melting rates have accelerated.

This work provides numerous substantial advances to Arctic sea ice prediction by integrating historical data with a cutting-edge approach. Our suggested technique beat a typical AR model statistically and aesthetically, notably during the summer months, when DL model errors in sea ice photos were much fewer than those predicted by the AR model. We were unable to directly recreate predictions based on a variety of different methodologies, such as statistical and numerical models, which rely on a variety of external elements for prediction. We were, however, able to compare our prediction findings based simply on remote sensing picture data. Both SIC and SIE were overstated because of the recent unexpected drop in Arctic sea ice. Although a wholly image-data-driven strategy that ignores physical characteristics may not capture this atypical tendency as well as other approaches, the study's findings give some insight into Arctic sea ice forecast. The major purpose of this study was to develop a unique one-month SIC prediction model based on the CNN method. In terms of prediction performance, the CNN model beat the basic prediction and RF models. The overall prediction accuracy has declined in recent years due to the increased melting of sea ice induced by global warming.

The CNN model gave good prediction results in terms of RMSE and SIC spatial distribution in two extreme scenarios. Prediction mistakes were most prevalent in the marginal ice zone, where sea ice anomalies were the greatest. In the variable sensitivity analysis utilising CNN, the SICs were found as the most important factor in forecasting sea ice changes one year prior. While SIC-related factors influenced SIC prediction over ice-covered regions, other meteorological and oceanographic variables were more sensitive in predicting SICs in marginal ice zones. More research on a range of subjects relating to this study should be undertaken.

Although we thought that the NSIDC SIC data was of assured data quality, there are certain uncertainties in it. Higher resolution datasets, such as the Moderate Resolution Imaging Spectroradiometer, or the use of alternative sensors, such as improved microwave scanning radiometers with varied retrieval techniques, will result in more accurate prediction models. The LSTM kept its promise of delivering accurate long-term forecasts, but it is computationally expensive. More sophisticated ways to eliminating and optimising redundant inputs would be good for future work. Including environmental or physical elements in our model or utilising our results as a baseline for other methodologies, might be a fascinating subject for further research. Finally, we feel that integrating our prediction findings in the SIPN would be beneficial as a fresh method.

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