Analyzing the Dynamics of Arctic Ice Extent: A Comparative Study of Regression and Time Series Forecasting Methods

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The rapid decline in Arctic ice extent poses critical challenges to the global climate system, necessitating accurate forecasting methodologies to inform mitigation and adaptation strategies. In this study, we present a comparative analysis of Arctic ice extent prediction using regression models and time series forecasting techniques. Our investigation focuses on the rate of change of Arctic ice extent and the global average tempeprature. We find that the best arctic ice extent prediction methods are time series forecasting techniques that can take into account parameters that affect Arctic ice extent. Finally, we propose a Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMA-X) model for this task.

Introduction.– Arctic ice extent is the total region in the Arctic covered by ice, measured in million square kilometres. It has a direct impact on the global climate and sea level regulation. It also provides a habitat for various species, including polar bears, seals, and numerous marine organisms. Therefore, the monitoring and forecasting of a declining Arctic ice extent is essential to inform mitigation and adaptation strategies. We use Artic ice extent data from NSIDC [1] which are collected through NASA SMMR and DMSP satellites [2]. Data is available from 1978 to 2023, where we see the yearly average Arctic ice extent decreasing linearly, at a rate of 5% per decade (FIG 1).

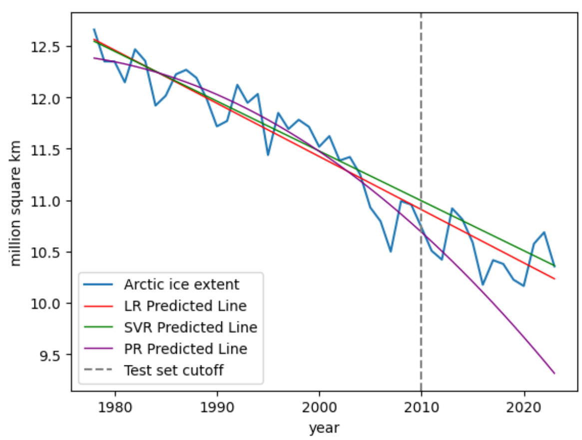

FIG. 1. Yearly averaged Arctic ice extent for the years 1979 to 2023. Right to the dotted vertical line (2010) are the years we used as our test set.

Both shallow and deep learning methods have been tried for Arctic ice predictions. In [3], CNNs are trained using climate simulations and satellite imagery to make predictions of Arctic ice extent on a scale of months. Support vector, random forest and multiple linear regression are tried in [4]. They find that multiple linear regression is the best predictor. However, these regression models fails to take into account the seasonal changes in Arctic ice extent.

Regression models.– We split the Arctic ice extent

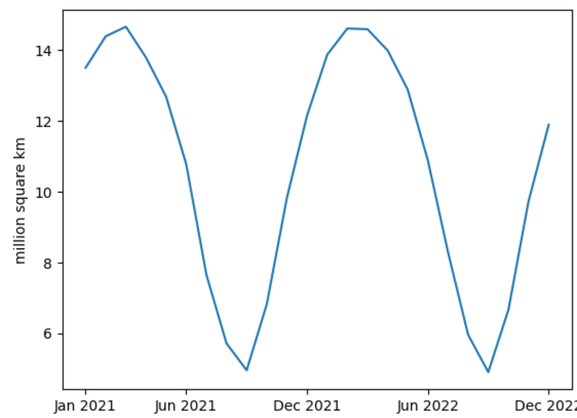

FIG. 2. Monthly change in Arctic ice extent for the years 2021-2022. Extent increases during the winter months following December, and decreases in the summer months following June.

data into train and test sets, using the first 70% of the years (1978-2009) for training and 30% of the years of testing (2010-2023). We then fit simple Linear Regression (LR), Polynomial Regression (PR) and a Support Vector Regression (SVR) model with linear kernel on the data (FIG 1). Coefficients of the models are provided as equations 1, 2 and 3 respectively.

$$\text{LR:} \quad \text{extent} = -0.052 \cdot \text{year} + 114.960 \tag{1}$$

$$\text{PR:} \quad \text{extent} = -0.001 \cdot \text{year}^2 + 4.62 \cdot \text{year} - 4542.619 \tag{2}$$

$$\text{SVR:} \quad \text{extent} = -0.049 \cdot \text{year} + 108.502 \tag{3}$$

Mean Squared Error (MSE) and Mean Absolute Error (MAE) are used as evaluation metrics. Evaluating the models on the test set, we see that Linear Regression performs slightly better (Table I) than Support Vector Regression. Polynomial Regression overfits the training data, performing poorly on the test set. By setting extent to 0 and using equations 1, 2 and 3, we also calculate the first ice free year according to the models.

Regression models that are linear are good at forecast-

TABLE I. Comparison of regression models for yearly averaged Arctic ice extent prediction

Metric	LR	SVR	PR
MSE ↓	**0.0628**	0.0871	0.3750
MAE ↓	**0.2221**	0.2489	0.4902
First ice free year	2221	2237	2074

ing the yearly averaged Arctic ice extent. However, they fail to model the seasonal changes. Even though (FIG 1) shows a decreasing trend of average extent over the years, when we look at monthly data 2, we see how extent is dependent on seasons. Arctic ice extent is seasonal in that it increases during Arctic winters following December, and decreases in Arctic summers following June. Therefore, we experiment with time series forecasting techniques to make predictions on a monthly scale.

Time series forecasting.– The arctic ice extent forecasting is a time series analysis data. Further, since the extent follows a seasonal pattern on monthly time scale, we need to factor in those patterns. Therefore, we implemented an ARIMA (full form) model on averaged yearly data and SARIMA (full form) on monthly data. For finding the paramters of the models, we used ACF (full form) and PACF (full form) plots. The ACF and PACF plots of monthly data, shown in figure 3, clearly indicates the seasonality in the data recurring every 12 months

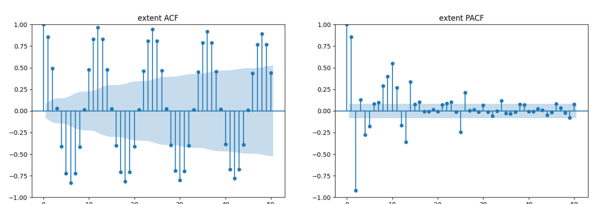

FIG. 3. Monthly data ACF and PACF

For ARIMA, we found the best fitting order to be (4,1,3) and for SARIMA, the best order is ((3, 1, 3),(2, 1, 2, 12)).

TABLE II. Metrics for Time-series models ARIMA on yearly data & SARIMA on monthly data

Metric	ARIMA	SARIMA
RMSE ↓	**0.2309**	0.355
MAE ↓	**0.1896**	0.2833
R^2 Score ↓	**0.8792**	0.9892

The metrics used are RMSE, MAE, R^2 . From the table II, we can see that the R^2 for sarima is 98.92 % whereas, for sarima, it is 87.92%. This tells us the dominance of the sarima in capturing the variabilty of the ice extent. Upon modelling it and forecasting it, we find using sarima that the first ice free year is in the year 2107,

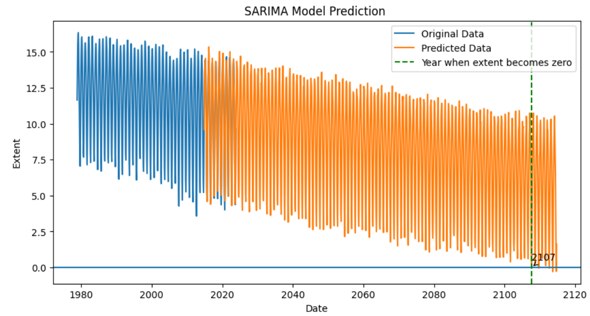

FIG. 4. SARIMA

which can be seen in Figure 4.

Conclusions.– Arctic ice extent has a direct impact on the global climate and sea level regulation. It also provides a habitat for various species, making it necessary to have accurate forecasting methods to inform mitigation and adaptation strategies. We find that linear regression can be used to make long term forecasts of yearly averaged Arctic ice extent. However, linear models fail to make short term predictions on a monthly scale since extent is seasonal. Time series forecasting methods are suitable for both short term and long term predictions. We find that a SARIMAx model which uses global average temperature is the best predictor of Arctic ice extent. Future works should investigate models with more parameters affecting Arctic ice extent such as Carbon Dioxide and Methane levels.

[1] F. Fetterer, K. Knowles, W. N. Meier, M. Savoie, and A. K. Windnagel, "Sea ice index, version 3," (2017).

[2] National Snow and Ice Data Center, "Quick facts about sea ice," `https://nsidc.org/learn/parts-cryosphere/sea-ice/quick-facts-about-sea-ice` (n.d.), accessed: January 16, 2024.

[3] T. R. Andersson, J. S. Hosking, M. Pérez-Ortiz, B. Paige, A. Elliott, C. Russell, S. Law, D. C. Jones, J. Wilkinson, T. Phillips, *et al.*, Nature communications **12**, 5124 (2021).

[4] S. Chen, K. Li, H. Fu, Y. C. Wu, and Y. Huang, Atmosphere **14**, 1023 (2023).