Prediction of Sea Ice Concentration using a U-Net

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The prediction of Sea Ice Concentration (SIC) in the Weddell Sea, Antarctic, has great importance for scientific logistics, e.g. logistical transport to the Neumayer II research station or fisheries management [1]. The aim of my project is the prediction of monthly SIC in the Weddell Sea, Antarctic. The parameter SIC is defined as the total area of sea ice in a region divided by the total area of that region [6]. It depends on air and ocean temperatures as well as wind speed. For this project, I therefore used Reanalysis data of spatial fields of air and sea surface temperatures, wind speed and SIC of the Weddell Sea. Three monthly averages of these variables were fed into an U-Net Convolutional Network to predict spatial fields of SIC with lead times of one, two and three months. I evaluated the performance of the model using the mean square error (MSE) between the predictions and the ground truth. To find out the two most important input variables, the MSE evaluation was used for different combinations of input variables for all lead times. The U-Net performed best for predicting SIC with one month lead time, followed by two and three months lead time. The model had difficulties predicting the correct position of the ice edge and the SIC in summer. Using only the two most important input variables, the U-Net showed comparable results to using all variables for one and two months lead time.

Data

SIC is dependent on the growth process and the drift of sea ice. The thermodynamic growth of sea ice depends on the temperatures at the ice-ocean and snow-air interfaces [5]. The drift of the sea ice is dependent on wind speed and direction, which influence the position of the ice edge [3]. To represent these influencing variables, I chose the parameters 2m air temperature (t2m), 10m u- and v-component of wind (u10, v10) and sea surface temperature (SST) of the ERA5 Reanalysis data [4] and SIC of the ORAS5 Reanalysis data [2] as input variables for the U-Net. The Network was trained with the ORAS5 SIC data.

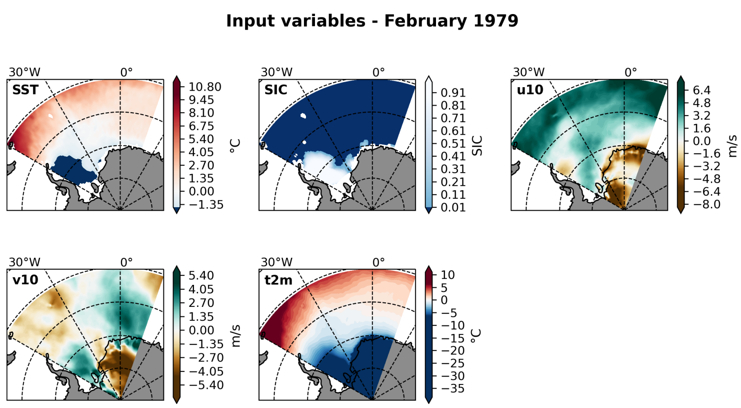

Figure 1: Spatial fields of input variables.

I processed the daily ERA5 data into monthly means using cdo [8]. The data used covers a period from January 1997 to December 2016. I chose the region of the Weddell Sea (60°W - 20°E, 50°S - 90°S) and scaled the resolution to a latitude $\times$ longitude grid of [$64° \times 128°$]. The SIC and SST data did not cover the Antarctic land area in the selected region and therefore had NaN values there. A mask of the NaN values was created to later apply it to the prediction. After normalization all NaN values for the input fields were set to the negative mean divided by the standard deviation of each variable. This was done to prevent feeding NaN-values into the U-Net, which would result in an erroneous output.

After processing, three months of each input variable were stacked together. This was done to predict one month, two months or three months ahead from the three month input fields. The data was split into training, validation and testing data sets. Data from January 1979 to December 2012 was split randomly with a batch size 50 into training and validation sets using a 75% to 25% split. The remaining data from January 2013 to December 2018 formed the test data set and was not split into batches or randomly permuted.

U-Net

For predictions of SIC, I used a U-Net Convolutional Network, developed by Ronneberger et al. (2015), following a tutorial by Tomar (2021). A U-Net is a Convolutional Neural Network (CNN) with a down-sampling and an up-sampling path and skip connections between the paths [11] (Fig 2). The down-sampling path consists of three convolutional blocks, each consisting of two 3x3 convolutions, followed by a batch normalization and a non-linear ReLU activation function. Between the convolution blocks are 2x2 max-pooling layers that reduce the dimensions by half and double the number of filters. The up-sampling path consists of the same convolution blocks as the down-sampling path, but contains a skip connection to the down-sampling path [10, 7]. Skip connections are used to reintroduce high-resolution information, that was filtered out in the down-sampling path to improve the accuracy of finer details in the output [6]. Between the convolutional layers of the up-sampling path are transposed convolutions, that divide the number of features by two i.e. the reverse process of the pooling layers in the down-sampling path [7, 10]. I set the input channel to 15 to enter three monthly means of every input variable. With a batch size of 50, this results in an input dimension of [50,15,64,128]. Only one or two variables reduce the channel dimension to three or six respectively.

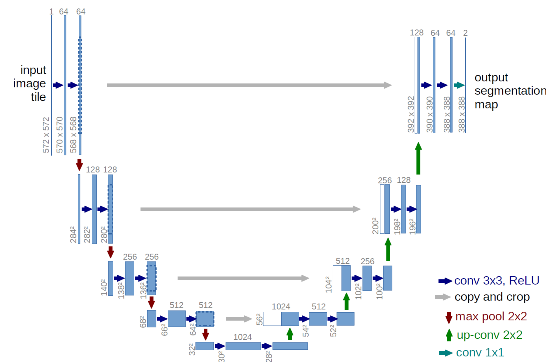

Figure 2: U-Net Architecture.

Lead	Opt	Loss	LR	Epoch	MSE
1	SGD	L1	0.005	795	0.0224
1	Adam	MSE	0.001	249	0.0226
2	SGD	MSE	0.001	335	0.0446
2	Adam	MSE	0.001	126	0.0447
3	SGD	MSE	0.001	691	0.0595
3	Adam	MSE	0.01	186	0.0660

Table 1: Results of Hyperparameter tuning.

Hyperparameter tuning resulted in the best proposed settings for the U-Net. Depending on this tuning, the best setting was chosen for each lead time, depending on MSE and computation time (Epoch). The model was tuned for optimizer (Opt), loss function (Loss) and learning rate (LR). During tuning, the best state of the model was stored at the point where the validation loss was the lowest to prevent overfitting by the U-Net. The period after how many epochs the validation loss had reached its minimum was used as the computation time. The setups with the two lowest MSEs for each lead time suggest the use of the Stochastic Gradient Descent (SGD) optimizer (Tab. 1). However, considering the computation time and the small degradation of the MSE, I decided to use the setups with the Adam optimizer. With these setups, the performance of the U-Net predicting SIC with lead times of one month, two months and three months was evaluated with the MSE, the spatial and the temporal distribution of absolute differences between the ground truth and the prediction using the testing data.

SIC predictions

Predictions of SIC with a lead time of one month show the best performance, i.e. the lowest MSE between the prediction and ground truth (MSE = 0.0223). This is followed by predictions with a lead time of two and predictions with a lead time of three months with MSEs of 0.0449 and 0.0501, respectively. For all lead times, the U-Net was not able to predict only SIC values between zero and one. Therefore, I set all predicted values above one to one and the negative values to zero. This did not change the spatial distribution of the absolute differences, nor the temporal evolution of the MSEs. After restricting the values, I calculated the MSE between prediction and ground truth

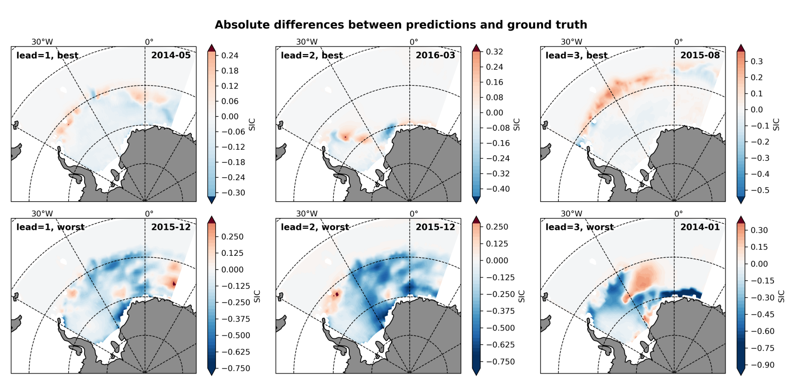

Figure 3: Absolute differences between predictions and ground truth for lead times of one, two and three months.

for each time step (Fig. 4, orange lines).
MSEs follow a seasonal pattern with highest values during Antarctic summer (Dec - Feb). In the other seasons, they tend to be lowest in summer, but fluctuate. This pattern can be observed for all lead times. The spatial distribution of absolute differences confirms this pattern. The best predictions with the lowest absolute differences are in May 2014, March 2016 and August 2015 for lead times one, two and three respectively. Here the largest differences occur at the marginal ice zones (Fig. 3). The highest absolute errors occur in December 2015 for lead times one and two and in January 2014 for lead time three. In this case, the distribution of differences is more irregular and not limited to a specific region. In the summer months and at the marginal ice zones, the sea ice system is very dynamic. Wave-ice interactions lead to a break-up of the ice in the marginal zones, resulting in a dynamic change of the SIC [9]. In the summer months, the sea ice melts, resulting in rapid changes in the SIC with spatially varying melt rates. Both highly variable processes are difficult for the U-Net to learn from monthly averages of three months. Incorporating forecasts of the rapidly changing parameters t2m, u10 and v10 as input variables improved the results, but still did not solve the problem of detecting fine details.

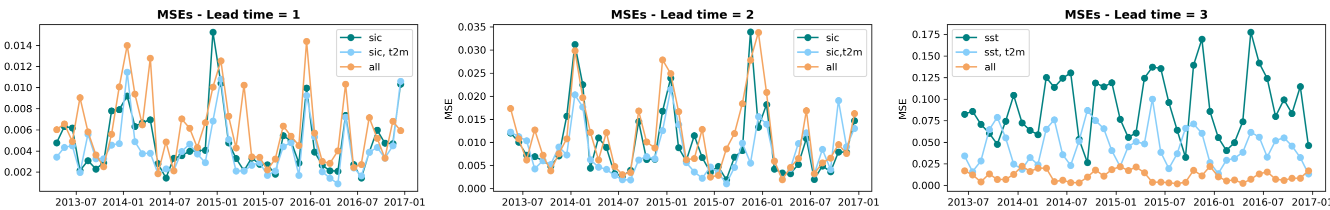

Figure 4: Temporal evolution of MSEs of prediction and actual SIC for lead times of one, two and three months.

Most important variables for SIC predictions

To identify the two most important input variables for the U-Net, combinations of two input variables were tested and evaluated using the MSE. Depending on the lead time, the most important first input variables were SIC for lead times one and two and SST for lead time three. The combinations of the two best input variables were SIC and t2m for lead times one and two and SST and t2m for lead time three. The temporal development of the MSEs follows the same pattern as the one for all variables: they also have highest values during Antarctic summer season and lower values in berween. MSEs of lead one and two have a comparable magnitude to the ones with all variables. However, the errors of lead time three are signigicantly higher than the ones for all variables. Also, an increase of the errors between lead times can be observed, with lowest MSEs for one month lead times. This suggests, that the input of one or two variables is sufficient for predicting SIC at lead times of one and two months. However, for three months lead time, more information is needed, i.e. more input variables.

Conclusion

The U-Net is capable of predicting SIC with lead times of one, two, and three months using three monthly means of the input variables 2m air temperature, SST, 10m u- and v-components of wind, and SIC. When using only the two most important input variables, SIC and 2m air temperature, comparable results were obtained for lead times of one and two months. Therefore, I suggest using only these variables for the mentioned lead times to save computational effort. However, for the three-month lead time prediction, more information is needed, and therefore all input variables should be used.
The largest errors in the predictions occur when the sea ice cover is variable, particularly in the marginal ice zones and during the melting season. Further hyperparameter tuning or a curriculum learning method, which introduces features in the training data step by step while slowly increasing their complexity, could help solve this problem, as suggested by Radhakrishnan (2021).
As a next step, I would try to train the model on the difficult regions of the marginal ice zones using a curriculum learning method. I would expect that the model could learn to better predict spatially highly varying SIC regions. Including not only monthly means but also daily values of rapidly changing variables such as air temperatures and winds could further improve the prediction of these regions. Additionally, I would explore predicting farther into the future. Trying different combinations of available variables, such as including ocean heat content, as well as conducting more hyperparameter tuning, could be helpful.

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