NEW HISTORIES OF ANTARCTIC SEA ICE FROM WEST ANTARCTIC ICE CORES

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ABSTRACT

New records of sea-ice edge in a portion of the Amundsen-Bellingshausen Sea (ABS), West Antarctica, have been developed using satellite-based remote sensing records of sea ice, ice-core glaciochemistry and artificial neural networks (ANNs). ANNs exploit the nonlinear relationship between sea-ice conditions and the chemical composition of snowfall on the nearby ice sheet, as recorded in high-resolution ice core records. Satellite remote sensing of sea ice provides calibration data for the period 1973 to present. ANNs are trained to predict sea-ice edge from ice core records developed under the US ITASE program and available up to 2001. The relatively small ANN training dataset resulting from the short overlap between sea ice observations and ice core data (less than 30 years) was expanded by adding small amounts of noise to the ice core data.

Results from a 110-year record of sea ice edge (28 years of observations and 82 years of ANN-based reconstruction) predominantly show long-term stability in this section of the ABS (140-115 °W) with no trend over the full record and only modest decadal-scale changes. Spectral analysis shows clear periodic behavior at ~8.5 and 3.3 years, suggesting that the Antarctic Circumpolar Wave has been active throughout this period.

1. INTRODUCTION

1.1 *Overview*

Comprehensive, spatially and temporally continuous records of Antarctic sea ice are limited to the period of satellite-based remote sensing (1973 onward). Fortunately, sea-ice conditions are a significant influence on ice-core chemistry, making the numerous high-resolution ice-core records on the adjacent West Antarctic ice sheet highly useful as proxies for sea ice. Unfortunately, sea ice is not the only influence and there is generally no simple linear relationship between sea- ice conditions and concentrations (or fluxes) of ice-core major ion chemistry. Artificial neural networks (ANNs) provide a solution to this problem through their ability to develop nonlinear relationships between predictors and targets (i.e., ice cores and sea ice, respectively).

2. DATA

2.1 *Sea ice*

We use sea-ice data from the monthly HadISST dataset (Rayner et al., 2003). Although this dataset extends into the 19th century, only the period since 1973 is based fully on observations year-round. Prior to that, it is essentially a climatology supplemented by occasional limited observations. HadISST data are global at 1 degree resolution with sea ice measured as percentage of grid box covered, i.e., gridded concentration. Antarctic sea-ice edge was derived by identifying the northernmost grid box at each longitude with a concentration greater than 15%. Annual sea-ice edge is the average of monthly values.

2.2 *Ice-core glaciochemistry*

The ice-core data used here are a subset of the many high-resolution cores now available in West Antarctica (e.g., Dixon et al., 2004). Annual averages of major ion chemistry were calculated from the original subannually sampled data available at the National Snow and Ice Data Center (NSIDC). Years with less than two samples were marked as missing. To better discriminate sources, data were also split into seasalt and nonseasalt fractions using the most conservative seasalt species in each sample and the relative ratios of these ions in seawater.

For our multisite reconstructions, we chose the newest (i.e., most recent) sites with complete records extending into the late 19th century. These criteria resulted in eight sites (Figure 1) covering 1890 to 2000, i.e., a 28-year overlap with the sea ice record. All of these records were developed under the US ITASE program after recovery in the 2000/2001 field season (Mayewski and Dixon, 2005).

Although nothing mathematical precludes using ANNs to predict sea ice conditions anywhere around the Antarctic continent, we thought it best to focus on regions close by the ice core data. Furthermore, we preferred to use a region free of trends during the calibration period to avoid bias and other potential problems in the reconstructions. That is, the calibration data need to be as representative as possible of the full reconstruction period. This criterion eliminated the region nearest the western Antarctic Peninsula due to the significant trend in sea-ice edge previously identifed there. Analysis of the full Ross-Amundsen-Bellingshausen Seas (ABS) showed the longitude range 140-115 °W to be free of statistically significant trends during the calibration period (Figure 2).

3. METHODS

3.1 *Linear correlations: ice cores to sea ice*

That sea ice conditions are but one influence on ice-core chemistry does not preclude there being a useful linear relationship between the two, particularly for chemical species with limited sources. A number of studies have successfully used this approach in the past for atmospheric circulation (e.g., Reusch et al., 1999; Kreutz et al., 2000) as well as sea ice (e.g., Curran et al., 2003; Abram et al., 2010). To test this hypothesis with our data, a series of linear correlations was done between the ice core chemistry data and the sea-ice edge data during the overlapping calibration period (1973-2000). With 14 variables per site (seven directly measured species and seven species derived from the seasalt-related species) and

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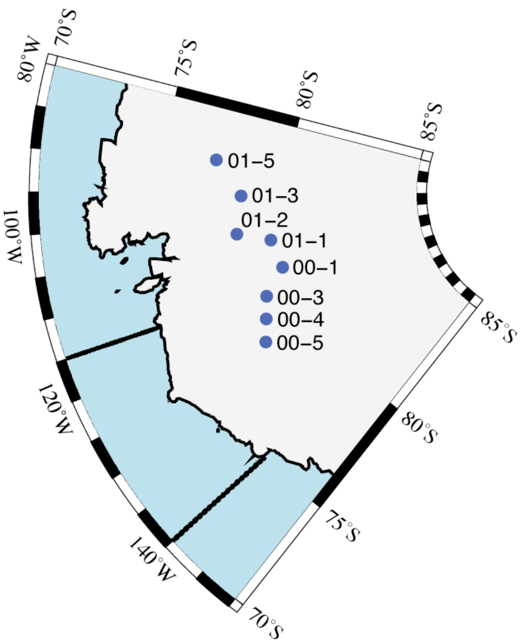

Figure 1. Location map for ice-core sites with U.S. ITASE identifiers. Black lines at 115° W and 140° W indicate longitude range of sea ice-edge data being predicted by ANNs.

eight sites, a total of 112 correlations were needed. Of these, only two had statistically significant r^2 values greater than 0.25, SO_4^{2-} and $nssSO_4^{2-}$ at site 00-1. Six of the 14 chemistry variables (Cl^-, Mg^{2+}, Na^+ and nonseasalt fractions of each) had no statistically significant correlations.

The linear relationship was further tested with stepwise linear regression of the individual ice core chemistry species with the sea-ice edge data, i.e., a total of 14 multivariable linear models. In this test, sites are added to the regression individually and kept or discarded based on whether they improve or reduce the quality of the regression. Of the 14 models tested, seven found no statistically useful relationship (Cl^-, K^+, Mg^{2+}, Na^+, $nssCl^-$, $nssMg^{2+}$, $ssNa^+$), six found a relationship with one site (Ca^{2+}, SO_4^{2-}, $nssCa^{2+}$, $nssK^+$, $nssNa^+$, $nssSO_4^{2-}$), and one model found a relationship for two sites and NO_3^-. In agreement with the basic linear regression results, even models indicating a relationship between ice-core chemistry at one or more sites and sea-ice edge were not predictively useful.

In addition to establishing a lack of useful linear relationships, the above tests also show that all ice core sites are effectively equal with respect to linear skill. That is, there do not appear to be any sites that would make noticeably better predictors versus the rest of the ice cores. In practical terms, this means any ice core site is as good as any other for predicting sea ice edge and we don't lose anything by focusing on the sites with the longest and/or most complete data. This is further supported by the lack of statistically significant single and multiple regressions within the ice-core datasets, i.e., correlations between ice cores.

3.2 *Artificial Neural Networks*

At the simplest level, artificial neural networks (ANNs) are a computer-based problem solving tool inspired by the original, biological neural network – the brain. Because of their ability to generate non-linear mappings during training, ANNs are particularly well-suited to complex, real-world problems such as understanding climate (Elsner and Tsonis, 1992; Tarassenko, 1998). Examples from the meteorological literature include an improved understanding of controls on precipitation in southern Mexico (Hewitson and Crane, 1994), prediction of summer rainfall over South Africa (Hastenrath et al., 1995) and northeast Brazil (Hastenrath and Greischar, 1993), and extreme event analysis in the Texas/Mexico border region (Cavazos, 1999). We have used the MATLAB® Neural Network Toolbox (Demuth and Beale, 2000).

Multilayer feed-forward ANNs were chosen to follow our previous ANN experiences with climate downscaling and in the literature (e.g., Cavazos, 1999). These ANNs consist of a large number of highly interconnected, simple processing nodes (a.k.a. neurons) organized into three layers. The input layer serves to receive input data and is sized according to the number of input predictors being used, with one node for each input variable. The hidden layer consists of nodes with inputs from each node in the input layer. Its size was varied to test this key parameter of ANN design. The number of hidden nodes is problem dependent and is a significant factor in how well the ANN works. The output layer receives intermediate results from the hidden layer and translates them to the desired output format and has one node for predicted sea ice edge.

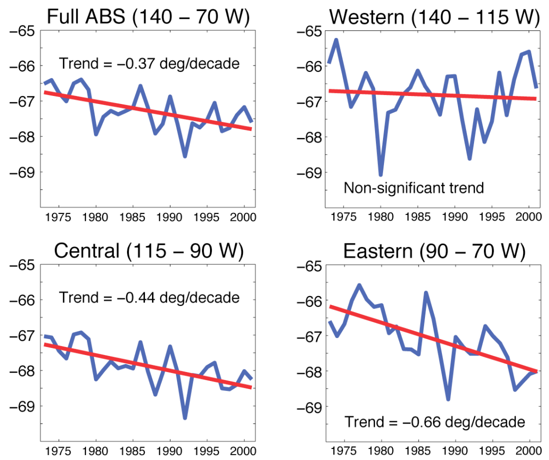

Figure 2. Observed sea-ice edge trends in the various parts of the Amundsen-Bellingshausen Sea (ABS). Vertical axis unit is degrees latitude.

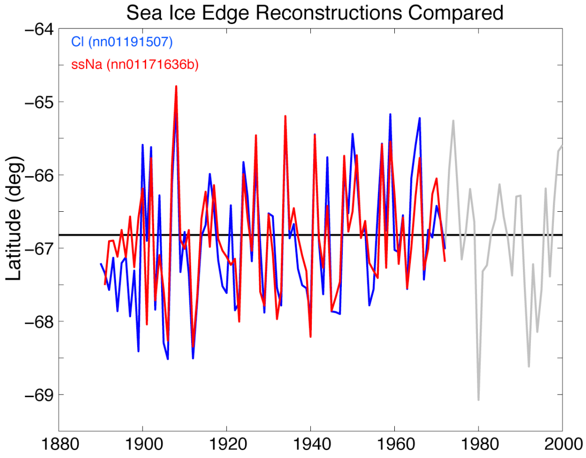

Figure 3. Sea-ice reconstructions for 1890-1972 using Cl^- (blue) and $ssNa^+$ (red) from sites in Figure 1. HadISST (Rayner et al., 2003) data in gray.

ANNs need to be taught to produce the desired outputs (sea-ice observations) from the inputs (ice-core data) before they can be used for predictions, a task done iteratively in three main phases: training, testing and validation. The training phase adjusts the connection weights using an optimization function that reduces the error in the network's results. The training error is calculated by comparing the network's output prediction to the sea-ice observations. Weights are adjusted based on the cumulative error from one pass through the complete training set (70% of the data). Testing uses a second subset (20%) of the data to evaluate training performance. Validation is used to avoid overfitting the training data and tests the network with data distinct from the training and testing samples (10%). The cycle then repeats until the desired output is achieved (or the error cannot be further reduced).

Rather than use just one particular ANN, or perhaps a few, for the long-term reconstruction, we opted to follow the model now often seen in numerical weather prediction and climate modeling, i.e., produce a large number of predictions (an ensemble) and average them to create the forecast (reconstruction). This approach has a further advantage of providing additional statistical data that can be used to evaluate confidence in the reconstruction. In this case, an ensemble of 50 independently trained ANNs is used to create the predictions of past sea-ice edge.

4. RESULTS

4.1 *Long-term Reconstructions*

Figure 3 shows reconstructed sea-ice edge from two "experiments" based on two different ice-core species, Cl^- and $ssNa^+$, both of which have been linked to sea-ice characteristics in other studies (e.g., Aristarain et al., 2004). Apart from the ice-core predictor, each experiment was essentially the same and used 50-member ANN ensembles to create the ensemble averages shown. Apart from the earliest section of the record and the period ca. 1920, the different predictors produced very similar estimates of past sea-ice edge.

With respect to basic analyses, interannual variability is (qualitatively) somewhat more pronounced through much of the reconstructions. The positive anomaly ca. 1910 is larger (by 0.5°) than all but the 1974 value in the observed record. There is also a possible trend in the annually-averaged minimum extent, though more extreme negative anomalies do appear in the observational period.

4.2 *Spectral Analysis: Antarctic Circumpolar Wave?*

Prompted by the visual appearance of a possible periodicity, spectral analysis using a range of windowing functions (e.g., split cosine bell, cosineZ, Welch) identified spectral peaks in both reconstructions around 8.5 and 3.3 years. These peaks are significant versus both red and white noise critical values. These are relatively close to the periods attributed to the Antarctic Circumpolar Wave (White and Peterson, 1996). If an actual manifestation of the ACW, and not an artifiact of the ANN training process, then this is evidence of at least a local persistence of the ACW throughout the 20th century, a topic of some controversy.

5. FUTURE WORK

Additional work will be proceeding along a number of tracks with the goals of expanding spatial coverage and length of record, improving understanding of the methodology's strengths and weaknesses, adding robust confidence estimates for the new time series, and integrating new results with existing reconstructions from the literature.

6. SUMMARY

Through advanced usage of ANNs, extended reconstructions of ABS sea-ice edge have been developed from West Antarctic ice cores. The overall picture is of relative stability with interannual and decadal variability not strongly different from the modern observational record. Although awaiting confirmation, it appears that the ACW has been influencing this region throughout the 20th century.

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