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[1] Several continuous observational datasets of Artic sea-ice concentration are currently available that cover the period since the advent of routine satellite observations. We report on a comparison of three sea-ice concentration datasets. These are the National Ice Center charts, and two passive microwave radiometer datasets derived using different approaches: the NASA team and Bootstrap algorithms. Empirical orthogonal function (EOF) analyses were employed to compare modes of variability and their consistency between the datasets. The analysis was motivated by the need for a reliable, realistic sea ice climatology for use in climate model simulations, for which both the variability and absolute values of extent and concentration are important. We found that, while there are significant discrepancies in absolute concentrations, the major modes of variability derived from all records were essentially the same. *INDEX TERMS:* 9315 Information Related to Geographic Region: Arctic region; 1863 Hydrology: Snow and ice (1827); 4540 Oceanography: Physical: Ice mechanics and air/sea/ice exchange processes; 3360 Meteorology and Atmospheric Dynamics: Remote sensing; *KEYWORDS:* sea-ice, passive microwave, algorithms, EOF analysis. **Citation:** Singarayer, J. S., and J. L. Bamber, EOF analysis of three records of sea-ice concentration spanning the last 30 years, *Geophys. Res. Lett.*, *30*(5), 1251, doi:10.1029/2002GL016640, 2003.

1. Introduction

[2] Changes in Polar sea-ice strongly influence surface albedo and air-sea fluxes, making it an important component of climate variability on seasonal to decadal time scales. There is now substantial evidence that the extent of Arctic sea-ice is decreasing at a rate of roughly 3% per decade, and thinning [*Johannessen et al.*, 1999]. The precise cause of this decline is unknown, as is its influence on ocean-atmosphere feedbacks, due to a relatively poor understanding of the interaction of sea-ice with the rest of the climate system. In an attempt to address this gap in understanding, simulations with a GCM will be undertaken using observational data of Arctic sea ice coverage as an input.

[3] For such a study it is essential to employ reliable datasets that provide consistent coverage over the longest available time period. We have examined three datasets that provide multi-decadal estimates of sea ice concentration. The US National Ice Center (NIC) has released weekly operational charts of sea-ice concentrations spanning 1972–1994, providing complete coverage of the Arctic for latitudes above 45°N, digitized from original hardcopy onto grids of resolution, 25 km [*Arctic Climatology Project*, 2000]. Several sources of information were used to produce each chart, largely from satellite data (AVHRR and OLS, complemented with passive microwave radiometer (PMR) data from SMMR and SSM/I), ship and aerial reconnaissance data. Having been manually compiled from several sources by experienced analysts, this dataset may arguably be one of the highest quality records over the satellite era. However, changes in data sources and expertise may have created biases that are difficult to quantify.

[4] In an attempt to obtain a long temporal record, it was believed, initially, that the NIC data could be extended to the present day using one of the two other datasets, both derived purely from satellite PMR data. Nimbus-7 SMMR and DMSP SSM/I data were combined using two different algorithms to provide daily sea-ice concentration. One dataset uses the NASA team algorithm for the period Oct. 1978 to Dec. 2000 [*Cavalieri et al.*, 2002]. The second uses the Bootstrap algorithm from Oct. 1978 to Sept. 2001 [*Comiso*, 2002].

[5] The two algorithms use different combinations of sensor channels, reference brightness temperatures and weather filters, and have different sensitivities to physical temperature [*Comiso et al.*, 1997]. The NASA team algorithm derives radiance ratios from brightness temperatures to calculate ice concentrations, using 19V, 19H and 37V GHz channels provided by SSM/I. The NASA team use of ratios reduces errors from surface temperature flucations. The Bootstrap algorithm uses 37V, 37H and 19V GHz channels to derive ice concentrations. The differences in NASA team and Bootstrap processing of PMR data result in large differences in ice concentrations. Consequently, although ice extent is similar (max. 1% difference, calculated by *Comiso et al.* [1997]) there are considerable differences in total ice covered area between the two datasets.

[6] Here, we present the results of time-series and EOF analyses used to investigate differences in the three records in terms of absolute values and variability, both of which may have significant effects on simulation results, when used in a GCM. It is necessary, therefore, to examine how the datasets differ and how crucial these differences are for their use in modeling studies.

2. Initial Dataset Comparisons

[7] In Figure 1, example monthly mean concentrations for September 1994 for each of the sea-ice records are compared. The NIC and Bootstrap records show high concentrations with little deviation in the high Arctic, whereas there is much more variation in the NASA team dataset. The NIC data include some PMR data using, mainly, the CAL/VAL algorithm [*Hollinger et al.*, 1991]. This algorithm is optimized for the ice edge and is especially effective for thin ice. However, application in the high Arctic tends to produce artificial saturation due to the inability of the algorithm to detect small changes in con-

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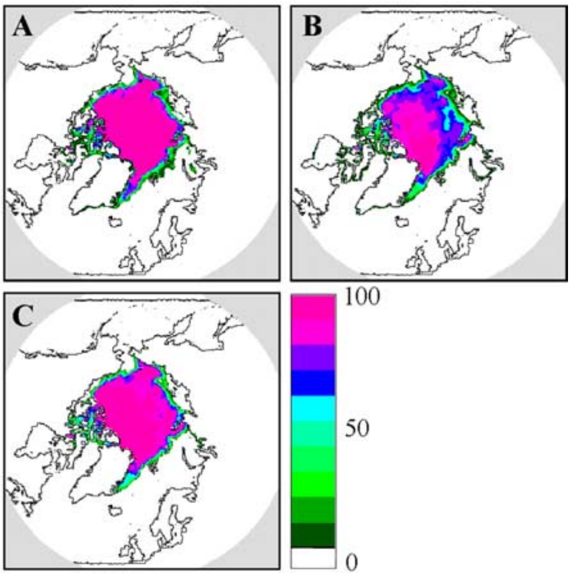

Figure 1. Maps of percentage sea-ice concentration averaged for September 1994 for three datasets: (A) NIC charts, (B) NASA team record and (C) Bootstrap record. For the satellite PMR data, the gap over 84° lat. is filled with 95% ice concentration, similar to the NIC records at high latitudes. All data have been converted to EASE grid projection.

centration in regions of near complete ice cover [*Meier et al.*, 2001]. As a result, the spatial variability of the NIC record in the high Arctic may be unrealistic.

[8] The NASA team algorithm conversely has considerable drawbacks in the marginal ice zone, being insensitive to thin ice. Additional biases are introduced from the inability to distinguish summer surface melt from open water, for example. In the summer months the NIC total ice-covered area is ~23% higher than the NASA team data due to the influence of ice melt areas being interpreted as low concentrations in the NASA team algorithm. This difference is large enough to have a measurable impact on ocean-atmosphere exchanges in GCM simulations [*Parkinson et al.*, 2001]. A new NASA team algorithm is being developed (the NT2 [*Markus and Cavalieri*, 2000]) that overcomes the problems of low ice concentration biases whilst not saturating at high concentrations. No NT2 time series is currently available, however.

[9] An inherent assumption in the Bootstrap algorithm is that there are large regions in the Central Arctic during winter with ice concentrations of 100%. It produces high concentrations in the inner ice pack similar to the NIC data. The Bootstrap algorithm is more sensitive to thin ice than the NASA team, but less so than the CAL/VAL.

[10] Time-series of the summer mean, ice-covered area, (Figure 2a), illustrate the magnitude of the absolute differences between the datasets. Despite these differences, trends in the time-series are highly correlated (r^2 = 0.87 for NIC and NASA team, calculated with anomalies for 1979–1994; and r^2 = 0.9 for NIC and Bootstrap, both significant at the 99.9% level). The winter mean time series show proportionately less difference between the datasets (Figure 2b). The correlation is lower (r^2 = 0.6 for NIC/NASA, r^2 = 0.62 for Bootstrap/NIC), but still significant at the 99% level.

[11] That the largest differences occur during summer suggests that the effect of summer melt areas on PMR retrieval is one of the most important causes of the dataset discrepancies, particularly affecting NASA team concentrations. Given the differences seen in Figures 1 and 2, EOF analyses were used to assess how consistent spatial/temporal modes of variability were between the datasets.

3. EOF Analysis

[12] In EOF analysis, 3-dimensional data (varying in position and time) undergo orthogonal decomposition of the space-time matrix. The result is a set of 2D eigenvector elements that can be plotted on a map (EOF) in the same locations as the original data, and corresponding 1D principal components (PC) that are a function of time. The spatial EOFs depict locations contributing most strongly to the respective PC. The highest EOFs are sometimes interpreted as uncorrelated physical modes of variability of the field under examination, although, care should be taken to avoid misinterpreting noise for variability. The datasets span a relatively short time period, which may limit identification of lower frequency modes (quasi-decadal oscillations such as the NAO). However, one of the motivations for using an EOF analysis is to allow a comparison of variability between the datasets rather than assigning a physical meaning to the PCs.

[13] EOF analysis was performed on monthly sea-ice concentration anomalies. The method was applied to the datasets for the period of overlap (Jan 1979– Dec 1994). The leading four EOFs are displayed in Figure 3 (positive anomalies in orange, negative anomalies in blue, when the PC time series is positive), as are the percentages of the total variance explained by each. Only ~20% of the total variance is explained by the first four EOFs from the NIC dataset,

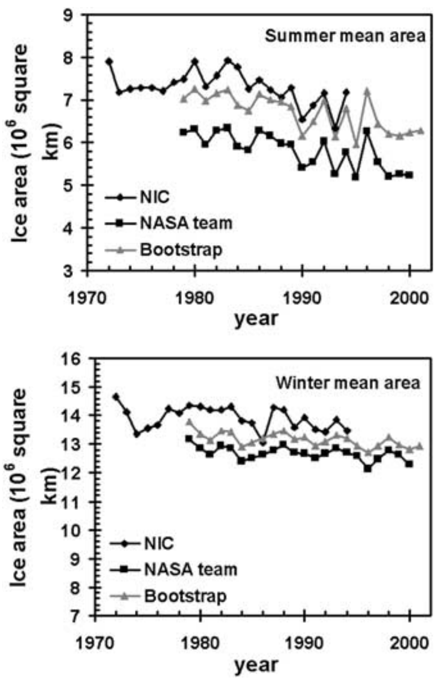

Figure 2. (A) Times series of summer (JAS) mean total ice-covered area for each of the datasets, and (B), time series of winter (JFM) mean ice-covered area. Ice-covered area is defined as integrated ice concentration.

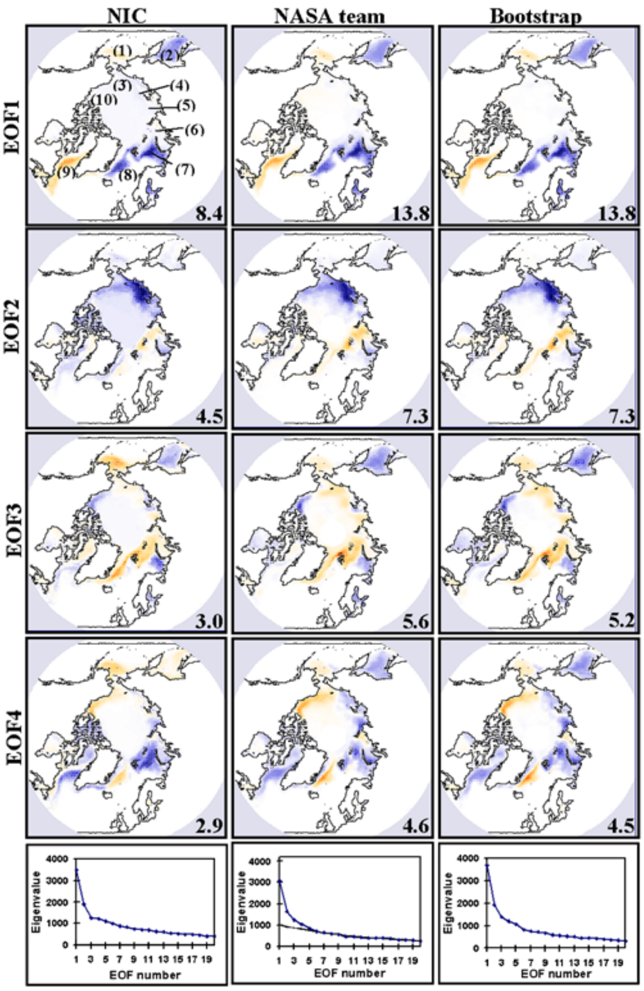

Figure 3. The first four EOF patterns for the three sea-ice datasets. The percentage variance described by each EOF is given in the corner of each sub-plot. Eigenvalue vs. EOF no. is plotted (lower) for each dataset. In NIC EOF1 numbers given indicate locations of: (1) Bering Sea (2) Sea of Okhotsk (3) Chukchi Sea (4) East Siberian Sea (5) Laptev Sea (6) Kara Sea (7) Barents Sea (8) Greenland Sea (9) Labrador Sea (10) Beaufort Sea.

compared to ~31% in the PMR records. The majority of the variance is not explained in the four leading modes. Since daily and weekly variations have been averaged out it is suggested that there is substantial variation in spring and autumn anomalies not associated with the most significant EOFs (K. Partington et al., The late twentieth century Northern Hemisphere sea-ice record from US National Ice Center ice charts, submitted to Journal of Geophysical Research, 2002, hereinafter referred to as Partington et al., submitted manuscript, 2002). Higher variance is explained by the EOFs in the PMR data compared with the NIC. Possibly this is due to the single data source, as opposed to the various sources compiled in the NIC over time that may produce additional uncorrelated noise.

[14] In the determination of the number of principal components to retain in order to separate meaningful signals (highest EOFs) from noise (lower EOFs) we examined scree plots [*Wilks*, 1995] of eigenvalues vs. EOF number (Figure 3, lower plots). Theory suggests that the steep slope represents signal and the shallow slope noise and that the latter will decay exponentially. An exponential fit to the shallow slope in the scree plot for the NASA data has been plotted and suggests that the first 4 EOFs contain meaningful variability.

4. Discussion

[15] Encouragingly, despite the large differences in absolute values examined in section 2, EOFs 1 to 4 (Figure 3) describe the same modes of variability, in each of the records. Small differences in the patterns are observed, however, which increase in their extent towards the lower EOFs.

[16] EOF1 describes the largest variance, and is the most similar in the datasets. There are strong negative centers of activity in the Greenland Sea, the Barents Sea and Sea of Okhotsk of opposite sign to those in the Labrador and Bering Seas (Figure 3 shows location of Seas). Figure 4 shows the corresponding PC1, which has a period of ~9 years (determined using an autocorrelation function). PC1 from the NIC and Bootstrap data, for their whole duration, are superimposed to demonstrate the persistence of this periodicity for the last 30 years. Standard deviations of PC1 for each month show EOF1 is a winter phenomenon. This is the time of year when concentration are closest in the datasets (Figure 2).

[17] Partington et al. (submitted manuscript, 2002) found a high correlation between EOF1 and the winter North Atlantic Oscillation (NAO) index from the previous year; a finding we confirm. They suggested the delay indicates the impact of NAO driven anomalies on multi-year ice, influencing marginal Arctic seas after one year. Advection of sea-ice anomalies in the Greenland and Barents Seas into the Labrador Sea takes ~4 years (half the period of this mode), resulting in the opposing sign in this area in the EOF pattern.

[18] The EOF2 patterns are similar in the three records, but display small differences (e.g. magnitude in the Labrador Sea). Based on the standard deviation of PC2, this component is a predominantly summer phenomenon, the time of year when the datasets show the largest discrepancies. In spite of this, the spatial variability of this mode is not significantly affected. The PC2 time series shows periodicity of over 10 years. Partington et al. (submitted manuscript, 2002) found that this EOF also related to the NAO from the previous year and suggested that winter sea

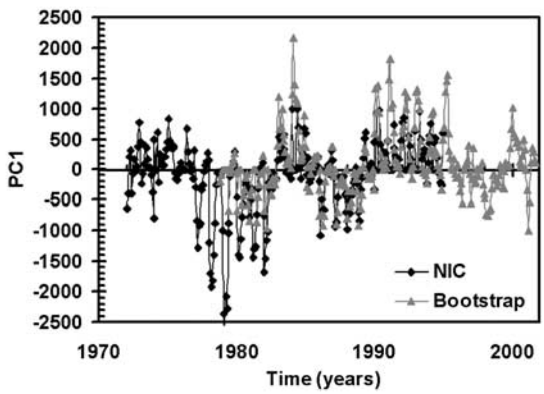

Figure 4. PC1 time series for the NIC and Bootstrap data.

level pressure anomalies cause ice export from the East Siberian and Laptev Seas (during positive NAO phase) and import/build-up of ice in the Kara Sea, preconditioning summer ice anomalies. Analysis of sea-ice motion data by *Rigor et al.* [2002] has directly shown stronger advection away from the East Siberian and Laptev seas during high-index phase Arctic Oscillation (related to the NAO), which opens up leads in winter, enhancing formation of thin ice. The winter advection pattern resulted in lower sea-ice concentrations and thinner ice-cover in the East Arctic in the subsequent summer.

[19] The EOF3 patterns are similar in areas of strongest activity, but there are more differences between the records than in the higher EOFs, especially in the East Siberian Sea, where the spatial extent of the pattern is larger in the PMR records than the NIC.

[20] In EOF4, larger differences were observed, the sign of the EOF pattern in the Sea of Okhotsk and the magnitude in East Siberian Sea being the main discrepancies. EOF4 has been related to centers of freshwater inflow/outflow in the Arctic (EOF2 in Partington et al. (submitted manuscript, 2002)), which have a significant effect on circulation.

5. Conclusions

[21] The analysis presented here was intended to assess the similarity of three Arctic sea-ice concentration records that will potentially be used in conjunction with GCM simulations. A dataset that describes the real variability is essential. Significant differences rise in the datasets due to differences in source and processing methodologies. In general, the NASA team data produce lower ice concentrations than the Bootstrap, and the NIC record shows higher concentrations than both of these. In the high Arctic large areas of near-saturated concentrations are observed in the NIC and Bootstrap records, whereas the NASA team shows more variation.

[22] The magnitude of absolute differences implies that combination of the datasets to obtain a consistent 30-year record will not be straightforward. Nevertheless, given that the major modes of variability, derived from EOF analysis, show relatively long periodicities, a dataset of at least this length would be preferable. Despite the differences in sea ice area equivalent modes of variability are obtained from all three datasets. Small discrepancies occur in the less significant modes. In general the PMR datasets produce more widespread EOF patterns when compared with the NIC record.

[23] The coincidence of the most significant modes of variability makes the choice of dataset for modeling studies less critical if variability is more important than absolute magnitude. It has not been possible to identify one dataset as being more reliable or realistic than another, although the strengths and weaknesses of the algorithms used to generate them are well known. For example, *Comiso et al.* [1997] compared Bootstrap and NASA team with SAR and AVHRR data, but neither proved to be "better" than the other overall.

[24] Ice concentration and ice area are important variables in climate modeling since areas of open water are of major significance for the ocean-atmosphere exchange of heat and moisture. Heat flux from the ocean to the atmosphere within leads and thin ice can be two orders of magnitude greater than through the ice cover, even though being only a few percent of the surface area of ice [*Maykut*, 1978]. Therefore, the differences between the datasets may have a measurable effect on simulation results. In a study to examine the sensitivity of climate simulations (GISS GCM) to prescribed sea-ice concentrations *Parkinson et al.* [2001] found that uniform biases of ±7% could affect regional temperatures by over 6°C, and global surface air temperatures by 0.27°C. However, open water is most important for heat exchange during winter, which is when the datasets display the greatest similarity (5–10% difference in ice-covered area between NIC and NASA team data compared with up to 23% in summer). Thickness of sea-ice, which has not been considered here, is an equally important parameter. Rapid decreases in exchange rates occur as ice forms in open water, but even 0.5m ice allows net heat loss an order of magnitude larger than thick multi-year ice [*Maykut*, 1978]. Consequently, the insensitivity of the NASA team algorithm to thin ice, partly responsible for the lower ice-covered area obtained from this algorithm, may be less important given the similarity of exchanges through thin ice and open water.

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