JP2.24 A TIME SERIES ANALYSIS OF MULTIYEAR SEA ICE IN THE CENTRAL ARCTIC

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1. Introduction

Global climate change is one of the most controversial issues in the scientific community. Why does climate change? What causes climate change? How often does climate change? Are the processes that regulate climate natural or synthetic? How do the activities of humans affect climate? These questions cannot reasonably be considered without examining a tremendous quantity of scientific data. Some of the most important scientific data associated with global climate change is sea ice concentration in the Polar Regions.

There are two types of ice in the Arctic and Antarctic regions. First-year ice is ice that does not survive the melting period during the summer months, while multiyear ice is the ice that survives at least one complete summer (Gloersen et al., 1993). However, total sea ice concentration in the Arctic region at the September minimum is not representative of multiyear sea ice concentration the following winter. (Gloersen et al., 1993). Total ice concentration is the combined concentration of both first-year and multiyear sea ice (Gloersen et al., 1993). Sea ice concentration, which is a common measure of surface ice in the Polar Regions, is the percent of each individual grid point covered by ice. This paper will investigate how the concentration and distribution of multiyear sea ice changes in the central Arctic region over time.

Satellites are the primary tools used to measure sea ice in the Polar Regions. Four satellites have collected the data used in this study: the Nimbus 7 satellite with the Scanning Multichannel Microwave Radiometer (SMMR) and three Defense Meteorological Satellites with Special Sensor Microwave Imagers (SSMI) (Gloersen and Huang, 2003). These satellites obtained data by examining the brightness temperature (or radiance) of each individual grid point in the area of interest using microwave radiation, which greatly reduces contamination of the data by clouds (Gloersen et al., 1993). Basic radiative transfer equations and algorithms are used to extract several different variables from the satellite data, including sea surface temperature and sea ice concentration (Gloersen et al., 1993). The radiance in each individual grid point is used to calculate the sea ice concentration that specific grid point.

Multiyear sea ice can be distinguished from first-year sea ice by using an algorithm when examining the satellite data; however, this algorithm is not effective during the summer months. Multiyear sea ice has a characteristic signature in the satellite data during the winter, fall, and spring months that can be used to distinguish it from first-year ice; this signature disappears during the summer months due to summer melting and the algorithm cannot discriminate between multiyear sea ice and first-year sea ice (Gloersen et al., 1993). Therefore, we have more confidence in our data during the fall, winter, and spring months than during the summer months.

One aspect of this research is to investigate three known types of sea ice advection: the Beaufort Sea Gyre, the Transpolar Drift Stream, and the Fram Strait Exit Current. The Beaufort Sea Gyre is characterized by cyclonic rotation of sea ice in the Beaufort Sea, while the Transpolar Drift Stream is the general advection of sea ice from Siberia to Greenland. The Fram Strait Exit Current is the exiting of sea ice from the Arctic through the Fram Strait, which is located between Greenland and Svalbard (Spitsbergen). These three types of sea ice advection will be identified and examined in our investigation of multiyear sea ice in the central Arctic.

2. Data and Methodology

The multiyear sea ice data span October 1978 through December 2002 with spatial resolution of approximately 50 km, but a sampling interval of 25 km due to over sampling. We have decimated the data so that observations occur at four-day increments. These data have been quality-controlled and any data problems, including missing data, have been fixed through the use of linear interpolation and fits to a modeled seasonal cycle. The data are also limited to the central Arctic region only. Since we are not considering oscillations in the data with frequencies greater than or equal to the seasonal cycle, the data must be decomposed into individual, elementary oscillatory modes, which may be used to filter the original data by selecting relevant modes and reconstructing. Traditionally, a Fourier Transformation has been used to separate the data, which consist of a time-series of sea ice concentration at each individual grid point, into its elementary modes. However, these data are non-stationary and non-linear and a Fourier Transformation is not appropriate (Huang et al., 1998). Non-stationary data are data that are frequency and/or amplitude modulated. Empirical Mode Decomposition (EMD) (Huang et al., 1998) is used to separate the signal into its intrinsic modes, which will allow the data to be filtered.

Empirical Mode Decomposition is a recently developed process that is specifically designed to analyze non-stationary and/or non-linear data (Huang et al., 1998; Gloersen and Huang, 2003). There is only one straightforward assumption for EMD: all data must consist of simple intrinsic modes of oscillations. An intrinsic mode function (IMF) is defined as the following:

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1. The number of extrema and the number of zero-crossings in the data must be either equal or differ by no more than one.
2. The mean value of the envelope defined by the local maxima and the envelope defined by the local minima at any point must be equal to zero.

Empirical Mode Decomposition begins by identifying all of the local extrema in the signal, $X(t)$, and connecting all of the local maxima by a cubic spline; this is the upper envelope. This procedure is repeated for the local minima to produce the lower envelope. The mean of the upper and lower envelopes is equal to m_1 and the following equation can be developed:

$$h_1(t) = X(t) - m_1(t) \tag{1}$$

Ideally, $h_1(t)$ will be an IMF satisfying the two criterion above; however, if $h_1(t)$ is not an IMF, then the "sifting" process that is described in equation (1) will continue:

$$h_{11}(t) = h_1(t) – m_{11}(t) \tag{2}$$

where $h_1(t)$ is treated as the new signal and $m_{11}(t)$ is the new mean. This sifting process will continue until the first IMF is produced, which is represented by $c_1(t)$. The first IMF will have the highest frequency; all subsequent IMFs will have smaller frequencies. After $c_1(t)$ has been determined, the first residual, $r_1(t)$ can be calculated:

$$r_1(t) = X(t) – c_1(t) \tag{3}$$

This residual can be treated as the new signal and equations (1) through (3) can be used to determine additional IMFs and subsequent residuals. Empirical Mode Decomposition ends when the final residual contains one of the following properties:

1. The residual becomes a constant.
2. The residual becomes a monotonic function.
3. The residual becomes a function with only one cycle from which no more IMFs can be extracted.

In summary, the IMFs and the residuals sum to the original signal within machine error:

$$X(t) = \sum_{j=1}^{n} c_j + r_n \tag{4}$$

As described by equation (4), EMD separates a signal into several intrinsic modes and a residual, all of which are used when filtering the signal (Figure 1). For example, removing the intrinsic modes with frequencies higher than a specific threshold and reconstructing the signal with the remaining IMFs and the residual would complete a low-pass filter, which is used in this study. A high-pass filter is accomplished by removing the intrinsic modes with frequencies lower than a specific threshold and removing the residual before reconstructing the signal with the remaining IMFs. A band-pass filter consists of removing certain IMFs and reconstructing the signal with only select IMFs. These filters on non-stationary and/or non-linear data are only possible when EMD is used to separate the signal into its intrinsic modal frequencies. More information about Empirical Mode Decomposition can be found in Huang et al. (1998).

Before EMD can be applied to a time series of grid points, the data must be separated into temporal and spatial parts because, in its parent form, EMD is only applicable to a time-series analysis of one variable. Application of EMD to one grid point at a time is intractable, since it would involve individual analyses of over 17,000 grid points. Singular value decomposition (SVD) is used to separate the data into two parts: spatial and temporal (Gloersen and Huang, 2003). Three matrices result from the singular value decomposition: U (spatial, principle component (PC) number), S (PC#, PC#), and V (temporal, PC#). The eigenvalues of the original matrix are located along the main diagonal of S, which is a diagonal matrix. These eigenvalues are weights for the individual principle components and, therefore, if the first few eigenvalues decrease sufficiently rapidly, then only a few principle components need be considered, which significantly reduces the effort needed to complete the EMD filtering process.

Since the main goal of this process is to filter the original data, one would believe that it is necessary to complete EMD on a time series of each spatial component. However, using matrix algebra and the properties of the matrices produced by SVD, one can avoid the spatial variable aspect and only filter the temporal components of the PCs, which greatly simplifies the application of EMD (Gloersen and Huang, 2003). The U and V matrices that are produced by SVD are unitary matrices and the product of a unitary matrix and its transpose is an identity matrix. Therefore, starting with equation (5):

$$A = U * S * V' \tag{5}$$

where A represents the original data matrix and U, S, and V are the products of SVD, one can derive the following:

$$U * S = A * V \tag{6}$$

Since EMD can presently handle only one dimension:

$$V_{filt(t,\ pc\ i)} = EMD(V_{(t,pc\ i)}) \tag{7}$$

Therefore, to determine the filtered data matrix A_{filt}, we

Intrinsic Modes of the Temporal Part of the Second Principle Component of Multiyear Sea Ice Concentration in the Central Arctic

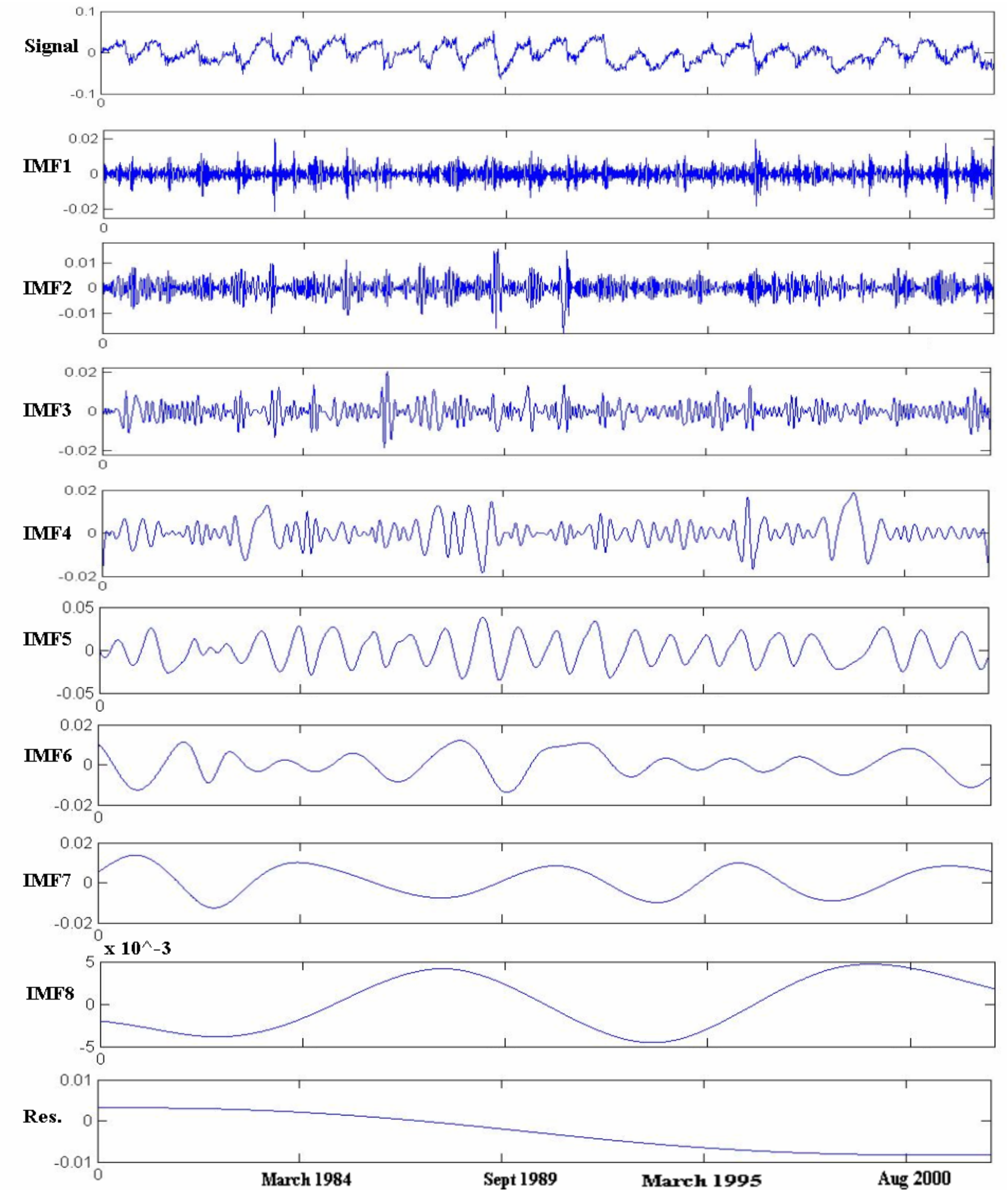

Figure 1. Signal and IMFs, including the residual, for the second principle component of multiyear sea ice concentration in the central Arctic. The signal is a time series of the temporal part of a given PC. EMD breaks a non-linear and/or non-stationary signal into its IMFs and a residual, which are used to filter the original data. This signal may be exactly reconstructed by summing the IMFs and the residual.

use the following:

$$A_{filt} = U * S * V_{filt}' \quad (8)$$

Finally, using equations (6) and (8), $\mathbf{A}_{filt}$ can also be written as:

$$A_{filt} = A * V * V_{filt}' \quad (9)$$

After the data have been filtered, movies can be made that show the changes in the low-pass filtered multiyear sea ice concentration over time. These movies provide a straightforward means of investigating the filtered data and examining potential trends. One application of these movies is to investigate the three types of sea ice advection described earlier. In addition, the IMFs that are calculated in the filtering process can be used to compare the multiyear sea ice concentration to different meteorological and/or oceanic variables, including sea level pressure (SLP) in the central Arctic to investigate a possible correlation. SLP data have been obtained from Trenberth's Northern Hemisphere Monthly Sea Level Pressure Grids through the National Center for Atmospheric Research (NCAR). SLP data span October 1978 through December 2002 with monthly temporal resolution and focus on the central Arctic with 5° spatial resolution. Since we will consider trends within the temporal variable only, this coarse spatial resolution is sufficient. EMD is used to separate the SLP PC data into its IMFs, which, when compared to the IMFs with similar average periods for the multiyear sea ice concentration data, can be used to identify possible correlations.

EMD is also used to explore multiyear sea ice area, which is the product of multiyear sea ice concentration and area summed over all grid points. Since multiyear sea ice area is one-dimensional, SVD is not necessary. Using the same technique described earlier, multiyear sea ice area can be compared to SLP to identify possible correlations.

3. Results

The three types of sea ice advection described earlier (Beaufort Sea Gyre, Transpolar Drift Stream, and the Fram Strait Exit Current) were investigated using three of the seven ice movies with the following minimum oscillatory periods: 1.60 years, 2.00 years, and 2.67 years. The other four ice movies were not used because we found no evidence of the three types of sea ice advection in the movies with higher frequency low-pass filters. After examining these movies, it was determined that though these three types of sea ice advection can be identified in certain intervals during the movies, they could not be identified in continuous, unbroken intervals throughout the movies (Table 1). It was quite difficult to visually identify these forcing mechanisms (especially the Beaufort Sea Gyre and the Transpolar Drift Stream) at certain intervals and a significant degree of uncertainty remains as to the exact times of the intervals and if there are other, shorter intervals not identified during our examination.

After the data were filtered and the movies were made, the individual IMFs were investigated to determine which are most important to the filtered data, i.e., the IMFs that provide the greatest variability to the filtered data. To determine the most important IMFs, two variables were examined: PC eigenvalue and amplitude of the IMF. Since the eigenvalues are weights for each individual PC and each IMF corresponds to a specific principle component, then the product of the eigenvalue and the amplitude of a specific IMF is the relative importance of that IMF. It would be expected that, since the eigenvalues decrease nearly exponentially, IMFs corresponding to the first principle component would be the most important; however, this is not always true. In fact, among the top five most important IMFs, only the most important and the fifth-most important IMFs correspond to the first principle component (Table 2). Also, many of the most important IMFs have different average periods, including an average period of 10.00 $\pm$ 2.00 years for the third-most important IMF.

The individual IMFs for the multiyear sea ice concentration data are also used to investigate a possible relationship between multiyear sea ice concentration and SLP. First, EMD is applied to the PCs of the SLP data to obtain the individual IMFs; after examining the eigenvalues, it was determined that only five principle components were necessary for a suitable description. By contrast, 50 principle components were used when examining the multiyear sea ice concentration data. Next, the individual IMFs

Table 1. Intervals where the Beaufort Sea Gyre, the Transpolar Drift Stream and the Fram Strait Exit Current are identified on the low-pass filtered multiyear sea ice movies. Only three of the seven movies were used (minimum oscillatory periods 1.60 years, 2.00 years, and 2.67 years)

Type of Sea Ice Advection	Interval Identified on Movie
Beaufort Sea Gyre	February 1980 – June 1983
Transpolar Drift Stream	November 1981 – August 1985
Transpolar Drift Stream	January 1990 – March 1991
Transpolar Drift Stream	February 1993 – July 1996
Fram Strait Exit Current	October 1978 – December 1980
Fram Strait Exit Current	September 1982 – April 1985
Fram Strait Exit Current	January 1989 – July 1990
Fram Strait Exit Current	September 1991 – March 1993
Fram Strait Exit Current	August 1995 – July 1997
Fram Strait Exit Current	February 2002 – December 2002

Table 2. Ranking the IMFs for multiyear sea ice concentration in the central Arctic by relative importance.

Rank	Principle Component	IMF Number	Amplitude*PC Eigenvalue	Period(years)
1	1	6	6416.772	1.80 ± 0.20
2	4	6	3248.487	1.80 ± 0.20
3	5	8	2762.460	10.00 ± 2.00
4	3	7	2528.955	5.00 ± 1.00
5	1	7	2284.576	3.33 ± 0.67
6	1	8	1989.792	7.00 ± 1.00
7	6	7	1924.936	2.17 ± 0.17
8	2	7	1845.624	5.00 ± 1.00
9	2	6	1810.664	2.17 ± 0.17
10	9	7	1737.120	5.00 ± 1.00

Table 3. Ranking the IMFs for sea level pressure in the central Arctic by relative importance.

Rank	Principle Component	IMF Number	Amplitude*PC Eigenvalue	Period(years)
1	1	7	308.360	> 12.00
2	1	4	220.084	2.17 ± 0.17
3	1	6	214.253	10.00 ± 2.00
4	1	5	179.229	5.00 ± 1.00
5	2	4	61.263	3.33 ± 0.67
6	3	4	55.711	3.33 ± 0.67
7	4	4	45.998	2.17 ± 0.17
8	5	4	36.439	2.17 ± 0.17
9	2	5	26.071	5.00 ± 1.00
10	4	5	22.576	5.00 ± 1.00

for SLP are arranged according to importance (Table 3). Finally, we compare the respective IMFs with similar average periods and look for the following characteristics:

1. The periods should be identical or very nearly identical. This is the most important characteristic.
2. There should be no varying phase shifts in the data. This will always be satisfied if the periods are identical.

After comparing the respective IMFs for both variables, we found no identifiable correlation (Figure 2).

Our next step is to investigate multiyear sea ice area. EMD is applied to the data to obtain the individual IMFs that are necessary to investigate a possible correlation with SLP. Since there is only a one-dimensional time series for multiyear sea ice area, it is neither necessary to employ SVD nor rank the IMFs according to importance. Using the technique described earlier, the appropriate IMFs for multiyear sea ice area and SLP are compared to identify a possible correlation; however, no correlation was found (Figure 3). It is interesting to note that the residual of multiyear sea ice area in the central Arctic trends downward; however, there is a hint of a long-period cycle (Figure 4).

4. Conclusion

The seven ice movies that are created provide an excellent means of examining long-term changes in the concentration and distribution of multiyear sea ice in the central Arctic. Advection of this ice can be seen in movies with minimum oscillatory periods shorter than four years; however, much of this movement appears random and unassociated with known forcing mechanisms in the Arctic. In addition, advection of multiyear sea ice is difficult to recognize in the movies with longer minimum oscillatory period filters; these movies are characterized by general, stationary increases and decreases in extent. Even though these movies provide visual insight into long-term changes in multiyear sea ice in the central Arctic, much of the motion of the ice is unexplained by known types of sea ice advection in the Arctic.

There are, however, short intervals in the movies with minimum oscillatory periods of less than three years where the three types of sea ice advection described earlier can be identified. This brings up an important question: why are these motions not apparent over the entire span of the data? It is quite surprising that the ice tends to move according to these forcing mechanisms during certain intervals, but not during others. Are the forcing mechanisms stronger in certain years and weaker in others? How can one explain the rest of the motion of the multiyear sea ice in the central Arctic?

We approached this final question by examining a possible correlation between SLP and multiyear sea ice concentration. However, it quickly became apparent that there is no identifiable correlation between SLP and multiyear sea ice concentration.

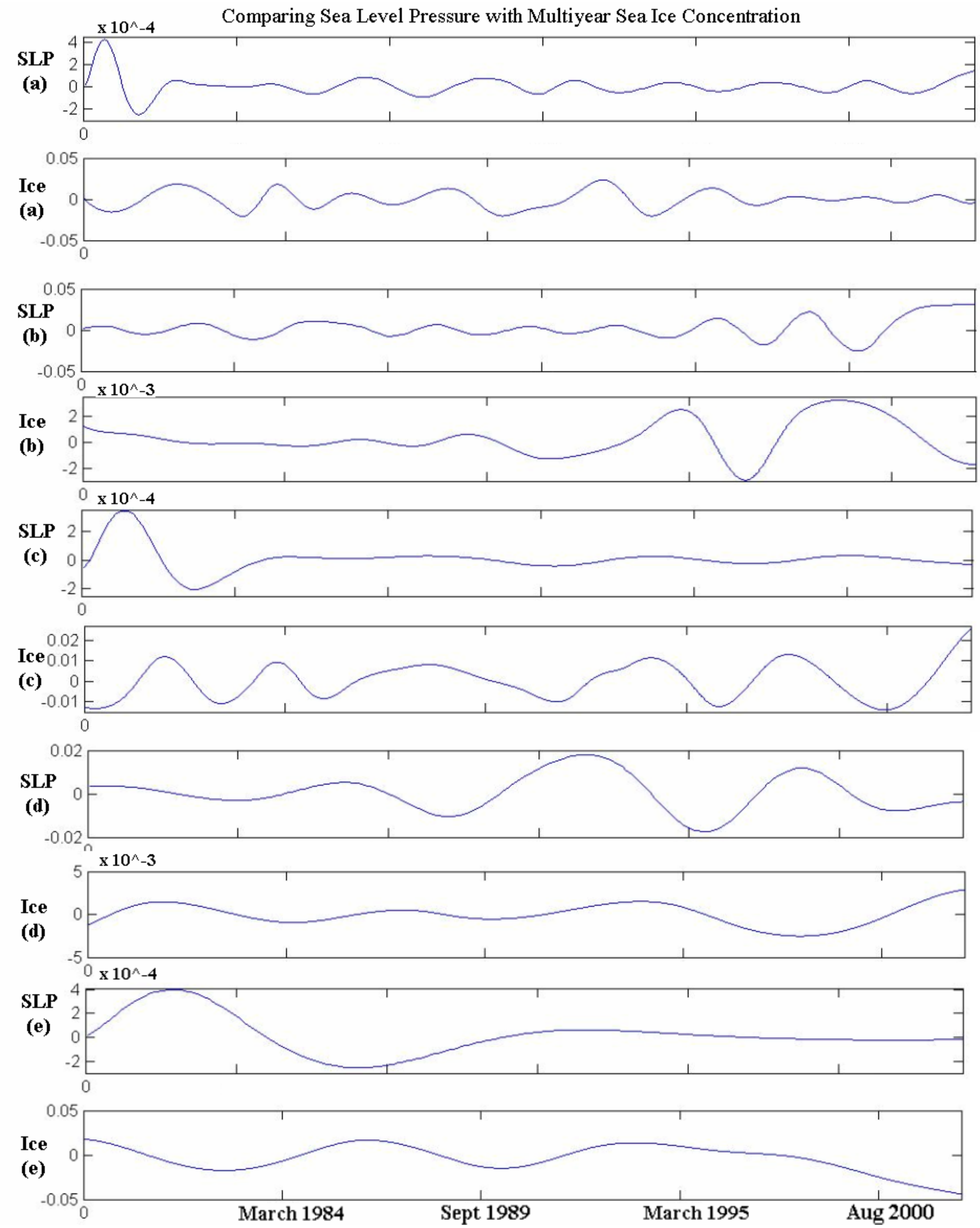

Figure 2. Select IMFs for SLP (upper IMF) and multiyear sea ice concentration (lower IMF) for the following average periods: (a). 2.17 ± 0.17 years. (b). 3.33 ± 0.67 years. (c). 5.00 ± 1.00 years. (d). 7.00 ± 1.00 years. (e). 10.00 ± 2.00 years

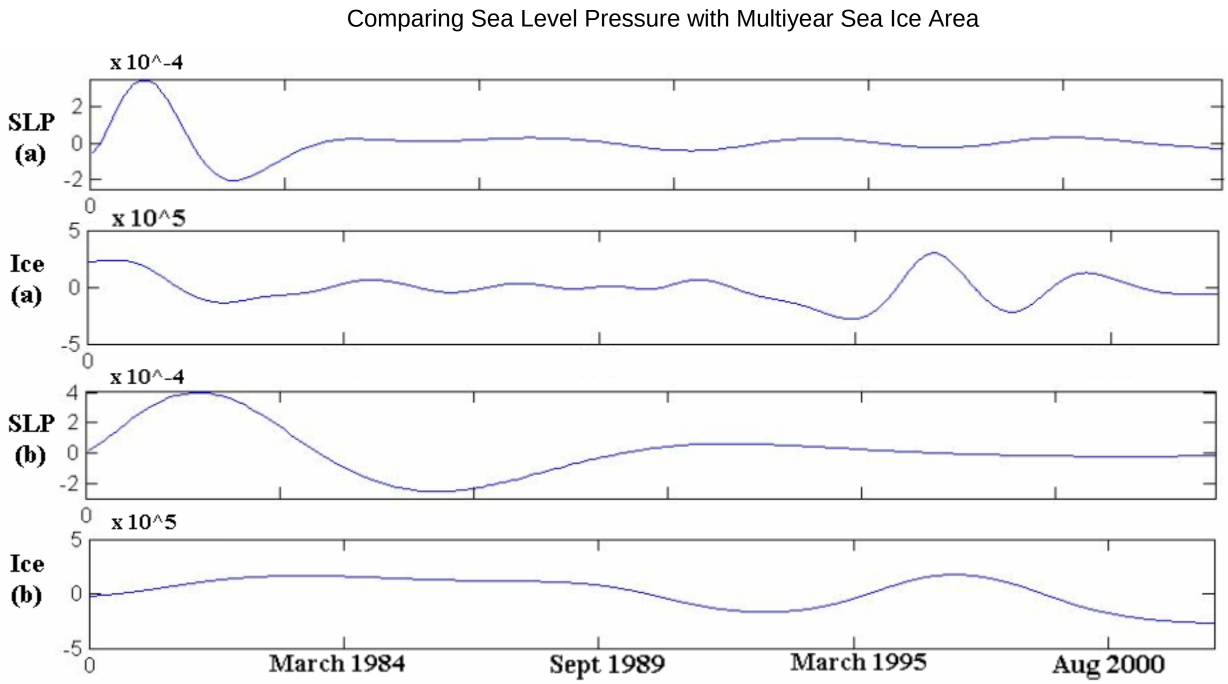

Figure 3. Select IMFs for SLP (upper IMF) and multiyear sea ice area (lower IMF) for the following average periods: (a). 5.00 ± 1.00 years. (b). 10.00 ± 2.00 years.

Hence, it is not likely that any of the motion in the movies may be explained by comparing it with correlations in sea level pressure. Is it possible that other meteorological or oceanic variables may be examined to help explain changes in multiyear sea ice in the Arctic? There are several variables that could be examined, including air temperature, near-surface winds (*u* and *v* components), and unknown or unexamined ocean currents. In fact, prior research has shown a correlation between near-surface winds and the advection of total sea ice (e.g., Wadhams, 2003). Investigations into possible relationships between any of these variables and multiyear sea ice concentration may provide exciting insight into possible explanations for the changes in the concentration and distribution of multiyear sea ice concentration.

As mentioned above, an investigation into a possible relationship between near-surface winds and multiyear sea ice concentration may yield interesting results. However, there are several problems that must be resolved before these investigations may occur. Most importantly, wind data are quite sparse in the Arctic. While gridded data sets of air temperature spanning the 1970's through the present are available, data sets containing near-surface winds that span this same time interval are not available. Because the amount of wind data available for the last quarter century in the Arctic is quite sparse, they are not an appropriate representation of the near surface wind patterns over the entire sea ice. Hence, as far as we can tell, a reliable data set for near surface winds in the central Arctic over the last quarter century does not exist.

Therefore, we propose the use of a model to obtain the desired data set. This model would be based on several meteorological and oceanic variables, most notably sea level pressure. This model would also contain both spatial and temporal resolution that is similar to the resolution of the multiyear sea ice data. Since the Arctic, and especially the sea ice, has terrain that is much less complex than that of the surrounding land, we believe that a model could be developed with a reasonable degree of accuracy. Even though it is preferred to have a data set of *measured* near surface winds over the sea ice in the central Arctic, we believe that the development of a model-derived data set would provide an excellent opportunity to examine and understand multiyear sea ice in the central Arctic.

Several additional questions have been raised by this research. Why aren't the three types of sea ice advection clearly identifiable for longer intervals? What governs the motion of multiyear sea ice? What are the major forcing mechanisms that determine the concentration and distribution of multiyear sea ice? Future research investigating possible relationships between different meteorological and/or oceanic variables may provide insight into these questions; however, data collection may be the most difficult problem to resolve in subsequent investigations.

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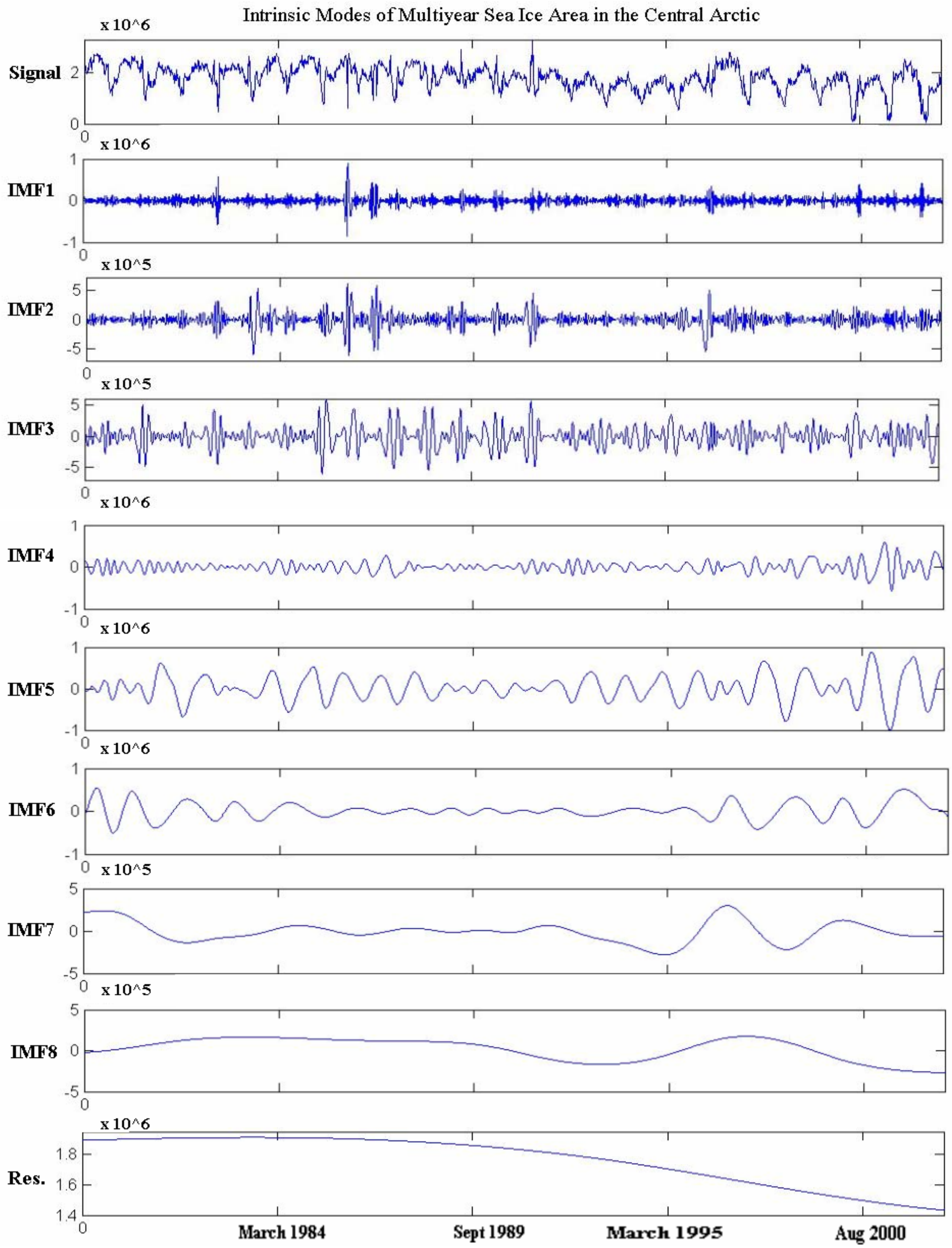

Figure 4. Signal and IMFs, including the residual, for multiyear sea ice area in the central Arctic.

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6. References

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