Quantifying Temporal Variance in High-Latitude Air–Sea Interactions

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ABSTRACT

A novel way of quantifying the variance of a time series is presented. The method first involves filtering the time series using filters with different temporal characteristics, and then using a moving window to calculate the variances in each filtered time series. The use of a moving window allows the original temporal resolution to be retained, as well as allowing one to study how the variance changes with time. Air–sea interaction time series from Ocean Weather Station (OWS) Bravo in the Labrador Sea are analyzed as an example. High-pass, bandpass, and low-pass filters are used to isolate the diurnal signal, the storm/cyclone signature, and the weather regime transition signal, respectively. The variance during the winter months is found to be strongly influenced by weather systems in the bandpass and the low-pass frequency range. The variance during the summer months, on the other hand, is dominated by the shortwave radiation in the high-pass frequency range.

1. Introduction

Studies of high-latitude air–sea interactions pose a challenge to researchers in that the sparsity of high-quality data with sufficiently good temporal and spatial coverage makes analysis difficult. However, due to the importance of these regions in the world climate system, it is important that we devise innovative ways of extracting information and conclusions from what data are available to us. Here, we present a novel way of quantifying the temporal variance from a high-latitude time series of air–sea fluxes. We demonstrate this method by way of an example.

Our study is based on data collected at Ocean Weather Station (OWS) Bravo, located in the middle of the Labrador Sea at 56°N, 51°W. The Labrador Sea is an important region of the World Ocean because deep-water formation occurs there (LabSea Group 1998). Deep-water formation occurs in a few select locations in the World Ocean and is accepted to be the forcing agent for the thermohaline circulation (Marshall and Schott 1999). The atmosphere plays an important role in this process. Air–sea coupling results in a transfer of heat and moisture between the atmosphere and ocean, leading to densification of the surface waters and subsequent convective overturning of the water column.

OWS Bravo was commissioned to collect data between 1945 and 1974. As a result, we have a relatively long time series of high-quality data (24 yr had continuous record collecting) at a high temporal resolution (data was collected every 3 h). Several authors have made use of this dataset, though most have used monthly means. For example, Smith and Dobson (1984) looked at the heat budget at OWS Bravo using monthly mean data, and Lazier (1980) looked at the oceanographic conditions, again using monthly mean data. Esbensen and Reynolds (1981) calculated the heat and momentum fluxes at several ocean weather stations, including Bravo, but again, their focus was on monthly means. Sathiyamoorthy and Moore (2002), however, used the full 3-hourly dataset to do a comprehensive study of the buoyancy flux at Bravo. Based on the years from 1949 to 1972, they found significant high-frequency variability as well as low-frequency modulation. We continue their analysis here by quantifying the temporal variability in the air–sea interaction that occurs in the Labrador Sea.

The motivation for this work comes from Fig. 1. The figure shows the 3-hourly time series as well as the monthly means for the buoyancy flux during 1962. As Sathiyamoorthy and Moore (2002) pointed out, there appears to be a difference in the nature of the variability between the summer and winter months. During the period from about March to August, the extrema occur closer together, while during the remainder of the year, they are farther apart. The contrast is sharpest between the summer (June–July–August) and the winter (December–January–February), though there is also a marked difference between the spring (March–April–May) and the fall (September–October–November); we will see more evidence of this latter asymmetry below. While it is clear from Fig. 1 that the variability changes
between the seasons, it is not obvious what the nature of the change is, nor what causes it. Our purpose in this paper is to quantify this difference in the variability in more concrete terms. The year 1962 was selected at random, but the change in the nature of the variability from season to season occurs for every year in the time series.

Variability occurs on many different timescales in the atmosphere over the North Atlantic. At the high end of the frequency range, there are the intraday and diurnal signals. Examples in this range include the changes in the air–sea fluxes as a storm passes by (Sathiyamoorthy and Moore 2002) and the diurnal solar forcing. The range from 2 to 6 or 8 days is generally associated with the passage of extratropical cyclones (Rogers 1997). Other phenomena in this range include polar lows (Moore et al., 1996), cold air outbreaks (Renfrew and Moore 1999), and the development of frontal waves and cold air cyclogenesis (Ayrault et al., 1995).

The range from about a week to 30 days has signals that are classified as weather regimes, and that some authors use as the background when studying higher-frequency signals (e.g., Ayrault et al., 1995). It is recognized that there are different regimes in the path that cyclones take in transiting the North Atlantic. Blender et al. (1997), for example, identifies three tracks—stationary, northeasterly oriented, and zonally oriented tracks. While different authors have looked at the variability of the storm track in terms of its intensity and location (Rogers 1997; Blender et al., 1997), no one has looked at the transitions between storm track regimes. There is evidence of such a transition in LabSea Group (1998), where mean sea level pressure maps for the Labrador Sea during January and February of 1997 are shown, and the large difference in the flow regimes (from a blocking to a zonal flow regime) and the associated difference in fluxes between the two months are noted. Also, Sathiyamoorthy and Moore (2002) suggested there may be a 10–20-day signal in the OWS Bravo data that represents this transition between regimes. They based their suggestion on a negative anticorrelation that was visible at those periods in the lagged autocorrelations for the sensible heat flux and the buoyancy flux time series. These regimes appear to last from about a week to a month, and are marked by the storm track moving northward or southward bringing it either closer to or farther from Bravo’s location. This results in the fluxes at Bravo increasing or decreasing as the weather regime shifts.

Beyond the 30-day range are the annual, decadal, and other longer period signals, including the quasi-biennial oscillation, North Atlantic Oscillation, and the El Niño–Southern Oscillation. Sathiyamoorthy and Moore (2002) identified statistically significant power in this frequency range in the air–sea flux time series from OWS Bravo. In this paper, we will focus on the sub-30-day ranges.

Our method is a multistep process that involves filtering the original time series using several filters, and then examining the variances in each filtered time series. This method in itself is not new: for example, Sawyer (1970), Blackmon (1976), and Blackmon et al. (1977) have studied variances in filtered geopotential height fields. What is different in our methodology is that we use a moving window for the variance calculations, whereas previous investigators used the entire period of study to calculate the variance. Our use of a moving window for the calculation retains the temporal resolution of the time series and affords us the advantage of being able to study the time evolution of the variance, both on intra-annual and interannual timescales. In section 2, we describe the steps we took in our analysis in detail, while in section 3, we present a discussion of the results. Finally, section 4 contains a summary.

2. Methodology

The data used in this study were collected at OWS Bravo from 1949 to 1972. OWS Bravo was located at 56°N, 51°W in the center of the Labrador Sea and collected data for a greater span of years; however, the range cited above provided the most continuous length of surface records. Sathiyamoorthy and Moore (2002) detail the processing that was performed on the data prior to the analysis.

For this study, we will be looking at the buoyancy flux and its components. The term buoyancy flux might be misleading because there is no actual flux of buoyancy. Instead, there are fluxes of heat and moisture, and the buoyancy flux is a convenient way of expressing the combined effects of both on the density of the surface waters. The buoyancy flux can be defined as

\[
B = \left[ \frac{g\alpha}{C_w} (Q_r + Q_s + Q_v) + [gS\beta(P - E)] \right],
\]

Fig. 1. Buoyancy flux for 1962 with monthly means superimposed.

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\]
where $\alpha = -(1/\rho)(\partial \rho / \partial T)$ and $\beta = (1/\rho)(\partial \rho / \partial S)$ are the thermal and saline expansion coefficients; $g$ is the gravitational acceleration; $S$ is the surface salinity; $T$ is the sea surface temperature; $Q_s$ is the sensible heat flux; $Q_l$ is the latent heat flux; $Q_i$ is the net outgoing longwave radiation; $Q_r$ is the net incoming solar radiation at the sea surface; $Q_p$ is the heat flux contribution from the precipitation; $E = Q_p/L_v$ is the evaporation; $P$ is the precipitation; $c_w$ is the specific heat capacity of water; and $L_v$ is the latent heat of vaporization. The component fields were calculated using bulk formulas on basic variables measured at OWS Bravo (such as air temperature, wind speed, and present weather codes). More details can be found in Sathiyamoorthy and Moore (2002). Note that this is the buoyancy flux for the ocean; that is, a positive buoyancy flux indicates that the buoyancy of the ocean is increasing.

The buoyancy flux cannot only be separated into its subcomponents, it can also be separated into a thermal contribution part and a saline contribution part. The two terms in square brackets in Eq. (1) represent these two parts. The former include terms that result in changes to the surface temperature, while the latter include terms that impact the salinity. In this study, we will examine the interannual and intra-annual variances in the buoyancy flux, the component fields, and the thermal and saline contribution parts.

Our method requires two sets of parameters: the temporal characteristics of the filters and the window size used for the variance calculations. The choice of the former is guided by an examination of the power spectrum, and the choice of the latter is guided by an examination of both the autocorrelations and the actual effect of using different window sizes to calculate the variances.

First, the multitaper method of Mann and Lees (1996) was used to obtain the power spectrum of the buoyancy flux for the period from 1949 to 1972. Daily averaged values were used to calculate the power spectrum in order to eliminate the strong diurnal cycle. The full time series, however, was used in the rest of the analysis. A magnification of the high-frequency portion of the spectrum (from 3 months to 1 day) is shown in Fig. 2, together with the 99% significance estimate that was based on an assumed red noise background fit to the data (Mann and Lees 1996). Examining the power spectrum, we see that the buoyancy flux has significant power (above the 99% significance level) in this portion of the spectrum.

The first part of the analysis is then to examine the power spectrum qualitatively and choose suitable filtering bands. Long gaps between the peaks or a change in the density of peaks are some examples of suitable places to stop one band and start another. This selection can, to some extent, be influenced by a priori knowledge or suspicion of what phenomena are being sought out. In our case, we picked three bands for our filters: from 0 to 3 days (high pass), from 3 to 6 days (bandpass), and from 6 to 30 days (low pass). Our band selections were partly influenced by our intent to separate the diurnal signature in the first band, the storm/cyclone signature in the second band, and changes in the storm track regime in the third band. Figure 2 shows the band selections as well (indicated by the alternating shaded regions). From this figure, one can see that these choices of bands fit the above requirements.

The data were then filtered so that we had three (high passed, bandpassed, and low passed) time series to work with. These refer respectively to time series that have been filtered to contain periods between 0–3, 3–6, and 6–30 days. The second parameter that needs to be determined is the window size to be used for the variance calculations. It is possible to use a different window size for each of the three filters, and we considered this, but in the end, for the sake of simplicity and to keep the number of degrees of freedom small, we settled on one window size for all three filters.

A visual examination of the lagged autocorrelations was used as a starting point for the choice of window size. Figure 3 shows the autocorrelations for the high-pass-, bandpass-, and low-pass-filtered time series of the buoyancy flux. From this figure, we selected 30 days for the window size. This is justified because the autocorrelations for all three filtered time series asymptote to zero.

To see how robust this value is, we calculated the variances from the filtered buoyancy flux using windows

\[\text{Note that traditionally, the low-pass filter extends to infinity. We decided to have a low-frequency cutoff at 30 days to diminish the effect of the strong annual cycle. Blackmon (1976) addressed this issue by removing the first four harmonics of the annual cycle to effectively have a low-frequency cutoff at 90 days.}\]
ranging in size from 1 to 60 days. We calculated the variance as a function of window size and time of year. Since the variation did not change appreciably over the year, we averaged along the time axis to obtain annual values. We present the results from 1 to 30 days as a function of the window size in Fig. 4. We display the results only up to 30 days since the values asymptote to their long-term values by then. We can see from this figure that for Figs. 4a–c, 30 days is a robust window size to use.

As a final note in this section, there are two important points to mention. First, we have referred above only to the buoyancy flux time series being split into the high-pass-, bandpass-, and low-pass-filtered time series. However, all the component fields as well as the saline and thermal contribution parts were also separated using the same filters. Second, our choice of frequency bands for the filtering and the window size for the variance calculations were chosen from an examination of the buoyancy flux data, yet the same parameters were applied when analyzing all the fields.

3. Results and discussion

We now present and discuss our results. The positive and negative peaks in the buoyancy flux such as those in Fig. 1 represent actual events such as the passage of cyclones and cold air outbreaks (Sathiyamoorthy and Moore 2002). Individual events have a finite time span over which they contribute to the buoyancy flux and its components, as shown by the composites and autocorrelations in Sathiyamoorthy and Moore (2002). Because these variables will return close to their background values after an event, there is a strong correlation between a variable and its variance. In other words, when a variable increases, its variance also increases. This will be apparent in the variance figures that we discuss below.

Figure 5 shows the mean annual cycle in the buoy-
ancy flux at Bravo. Twenty-four years of data were averaged to obtain this figure. The maximum and minimum values are approximately $1 \times 10^{-4}$ N m$^{-2}$ s$^{-1}$ and $-7 \times 10^{-5}$ N m$^{-2}$ s$^{-1}$. Contrasting this to Fig. 1, we see that the figure for the individual year has larger extrema (the maximum and minimum values are $2 \times 10^{-4}$ N m$^{-2}$ s$^{-1}$ and $-2 \times 10^{-4}$ N m$^{-2}$ s$^{-1}$ respectively). In Fig. 5, the averaging process has suppressed the extreme values. When averaging across the years, positive and negative peaks will only be represented in the mean figure if they occur at the same time each year. Since there is no a priori reason for a storm system (represented by a negative peak) to occur at the same time each year, any overlap from year to year is coincidental. This is especially noticeable for the larger positive peaks, visible in Fig. 1 throughout the year, but greatly muted in Fig. 5. These positive peaks are caused by precipitation events, and as shown in Sathiyamoorthy and Moore (2002), the autocorrelation for the precipitation drops off rapidly, greatly decreasing the likelihood of precipitation events overlapping from one year to another.

The mean filtered buoyancy flux (Fig. 6) shows a different picture for each of the filters. In Fig. 6a, we see that the high-pass figure has significant high-frequency variability that increases in magnitude during the summer months. In Fig. 6b, the bandpass figure shows that the variations occurring on this timescale are more predominant during the winter months. The fluctuations in Fig. 6a are due mainly to the diurnal forcing from the shortwave radiation, while the fluctuations in Fig. 6b are due to extratropical cyclones passing by Bravo’s location. As expected, the cyclones have a greater signature during the winter months. Figure 6c is similar to Fig. 6b, but the low-pass filter is meant to capture the changes in the storm track regime rather than individual systems. As mentioned in the introduction, the regimes may last from about a week to a month (LabSea Group 1998), but the actual change from one regime to another often occurs much faster (a couple of days). Hence, evidence of the transition between regimes may not appear in the low-pass-filtered variance.

The next six figures (Figs. 7–12) show the mean annual variance for the buoyancy flux and its subcomponents after being processed by the different filters. In each panel, the ± one standard deviation curves for the interannual variation in the respective variable are also displayed. This represents how much the average variance changes from year to year at a given time of the year. Note that the main curve is the variance in the respective variable calculated over a moving 30-day window, while the standard deviation is the interannual variation in the variance for a given time of the year. Though we are presenting the high-pass-, bandpass-, and low-pass-filtered variances, we are most interested in the 0–3 and 3–6-day-filtered variances. Thus, we will focus most of our discussion on the first two panels for the next six figures.

Comparing Figs. 7a,b, we can see that the 0–3-day variability in the buoyancy flux peaks in summer and is low in winter, while the 3–6-day variability has the opposite pattern. As well, the interannual variability is higher when the variance itself is high (i.e., during the summer for Fig. 7a and during the winter for Fig. 7b). The 6–30-day figure is similar to the 3–6-day figure except that the magnitudes are slightly larger. As well, the peak that occurs in late February may be an indication of the shift in storm track regime mentioned earlier. Comparing Figs. 7a–c, we note that the interannual variability is largest during summer for the 0–3-day high-pass-filtered variance, and during winter for the other filtered time series.

We now examine the component fields that make up the buoyancy flux, starting with the sensible heat flux. It is interesting to note that in Figs. 8a–c, the interannual variability is very low during the summer months and considerably larger during the winter months. Coincident with this, the variance itself is large only during the winter months and is close to zero during the summer months for Figs. 8a–c. This is consistent with the majority of storms occurring during the winter months (Sathiyamoorthy and Moore 2002). The unusual bump that occurs in June for this and the next figure is due to two years when the variance was high resulting in a large standard deviation at those points.

Figure 9, which shows the variances for the latent heat flux is similar in form to the previous figure. Again,
Fig. 7. Mean variance of the bandpass-filtered buoyancy flux (thick line) and ± one interannual std dev (thin lines): (a) 0–3, (b) 3–6, and (c) 6–30 days.

Fig. 8. Mean variance of the bandpass-filtered sensible heat (thick line) and ± one interannual std dev (thin lines): (a) 0–3, (b) 3–6, and (c) 6–30 days.

Fig. 9. Mean variance of the bandpass-filtered latent heat (thick line) and ± one interannual std dev (thin lines): (a) 0–3, (b) 3–6, and (c) 6–30 days.

like for the sensible heat flux, the variance in the latent heat flux is high during the winter and low during the summer for Figs. 9a–c. However, there are some important differences compared with the sensible heat flux. Though there is a decrease in the interannual variance when going from the winter to the summer months, it is not as drastic as it was for the sensible heat flux. It was seen in Sathiyamoorthy and Moore (2002) that the sensible heat flux was larger than the latent heat flux. Comparing the variances of these two fields in Figs. 8 and 9, we see that generally, the sensible heat flux variance is larger during the winter and spring (December–May) while the latent heat flux variance is larger during the summer and fall (June–November). As a result, the point of symmetry in the variance graphs is different for both the heat fluxes. For the sensible heat flux, it occurs approximately at the end of July, while for the latent heat flux, it occurs approximately at the end of June. Looked at another way, the latent heat flux picks up after the summer as early as August and September, while the sensible heat flux only starts to rise in October and November. This effect, which was observed in Sathiyamoorthy and Moore (2002) but not explored in detail, is caused by two things. First, during the summers, the warmer air temperatures allow the latent heat flux variance to be larger due to the increased moisture capacity of warm air. Second, the air temperature peaks during the summer when the solar cycle peaks while...
the sea surface temperature (see Fig. 13), peaks in late August because of the higher heat capacity of water. Thus, there will be reduced air–sea temperature differences in the fall, which will diminish the sensible heat fluxes. Concurrent with this, storms (which start to increase in frequency over the fall) draw dry air from the north allowing the latent heat fluxes to be larger.

Finally, note that for both the sensible and latent heat fluxes, the low-pass-filtered variance values are higher by a factor of 2 than the bandpass-filtered variance values. This is likely due to changes in the storm track regime. As we mentioned in the introduction, certain storm track regimes will lead to greater heat fluxes at OWS Bravo’s location. For instance, when the path of the storms crossing the North Atlantic are northeasterly, the resulting air circulation over the Labrador Sea will be conducive to drawing out cold dry air from the north and over the relatively warmer ocean. The net effect will be both higher sensible and latent heat fluxes, and along with this, a larger variability in those fluxes. Since the low-pass-filtered variances capture the net effect of several storms passing by OWS Bravo (i.e., a regime), that time series has the larger variance values. In other words, the variance in the fluxes due to changes from one regime to another is larger than variances in the fluxes arising from individual storms.

Unlike the fluxes in the previous two figures, the shortwave radiation is predominantly a diurnal cycle. This is clear from Fig. 10, where the variance values in Fig. 10a is one to two orders of magnitude larger than the values in Figs. 10b,c. There is also a significant amount of interannual variability during the summer when the shortwave radiation peaks.

Figure 11 shows the variances for the longwave radiation. Unlike all the other fields, the interannual variability for the longwave radiation is fairly uniform over the year (i.e., there is no seasonality in the year to year variance). While the low-pass-filtered variance does not have any trends, the bandpass- and high-pass-filtered variances have an upward trend that peaks in early winter (November–December). This trend, which starts in the summer, is likely due to the mixed layer being shallow and hence relatively sensitive to the forcing by individual storms. This sensitivity will be reflected in terms of enhanced variability in the sea surface temperature and hence in the longwave radiation. Furthermore, in early winter, as storms bring cool, dry air down from the north, the cooling of the sea surface temperature will cause the variance in the mean net longwave fluxes to peak.

Finally, Fig. 12a shows the variances for the precipitation. The high-pass-filtered time series has the largest variability in the precipitation consistent with the rapid drop off in the precipitation autocorrelations that Satyamoorthy and Moore (2002) found; the values in Figs. 12b,c are one or two magnitudes smaller. Though precipitation can and does occur throughout the year, much of the precipitation is associated with the passage
Figures 14 and 15 show the filtered variances for the thermal and saline contributions respectively, in the same vein as Figs. 7–12. It is interesting that the thermal contribution variances peak in the summer for the high-pass-filtered time series, and in the winter for the others. The shortwave radiation causes this difference. Because the shortwave radiation occurs more strongly in summer and for short frequencies, it is the dominant contributor to the high-pass-filtered variances for the thermal contribution. The interannual variance also follows a similar pattern of being larger in the summer for the high-pass-filtered time series and larger in the winter for the other filtered time series. In Fig. 15, the variances and the interannual variances reach their lowest values during the summer months for all the filtered time series. We saw earlier that the latent heat flux variances picked up sharply in the fall. Since the latent heat flux enters both the thermal and saline contribution parts, it affects both. It enters the thermal side directly, and causes the peak in the high-pass-filtered variance graph in Fig. 14 to be shifted. It enters the saline contribution indirectly through the evaporation term, and causes the variance in the saline contribution to rise more rapidly than it might otherwise have for the high-pass-filtered time series. Also note that comparing the thermal contribution graph and the saline contribution graph, the bandpass-filtered variances of both have similar magnitudes. As Figs. 14b and 15b cover the 3–6-day range which is representative of storms, this shows that as storm systems pass Bravo, both the thermal and saline variations contribute to the variance in the buoyancy flux on equal
footings. This further illustrates a point raised in Moore et al. (2002) and Sathiyamoorthy and Moore (2002), namely, that precipitation cannot be neglected when calculating the buoyancy flux at high latitudes. This was due to a nonlinearity in the equation of state for seawater that makes the thermal expansion coefficient strongly dependent on the sea surface temperature.

4. Summary

We have presented a novel way of quantifying variance in a time series, by first filtering the time series, and then using a moving window to calculate the variances. The use of the moving window has the advantage of not only allowing one to retain the original temporal resolution, but also allowing one to study how the variance changes with time.

We applied the method to the specific example of analyzing the variance in time series of atmospheric and oceanic variables collected at OWS Bravo. Though it has been decommissioned, OWS Bravo’s location in the Labrador Sea makes it a valuable source of data, as that region of the World Ocean is one of the few locations where deep water is known to form.

We chose to use three filters, a high-pass filter (0–3 days), a bandpass filter (3–6 days), and a low-pass filter with a low-frequency cutoff (6–30 days). The filters were selected based on an examination of the power spectrum of the buoyancy flux, as well as our desire to separate the diurnal signal, the storm/cyclone signature and the signature of transitions in the storm track regimes. A window size of 30 days was used to calculate the variances. This choice was based on examining the autocorrelations of the buoyancy flux. Furthermore, the 30 days was tested to make sure it was a robust choice.

The filtered variances showed some interesting results. The interannual variance was generally higher when the variance was high, and low when the variance was low. The shortwave radiation was the only component field that had its maximum variance values during the summer months. The variance in the longwave radiation was for the most part flat, with perhaps a slight upward trend. The variance in all the other buoyancy flux component variables reached their maximum values during the winter months. Since storms occur with greater frequency during the winter months, this strongly suggests that the other components of the buoyancy flux are influenced by the storms. Though the shortwave radiation’s variance peaked during the summer months for all three filtered time series, only the high-pass-filtered time series had a noticeable effect on the buoyancy flux variances. In other words, for the buoyancy flux variances, the high-pass-filtered time series peak in the summer, as it is strongly dominated by the shortwave radiation variances. The bandpass- and low-pass-filtered time series, as expected, are influenced by the storms and hence follow the pattern of having the largest variances during the winter months.

The higher moisture capacity of warm air and the introduction of dry air by storms were found to cause the variance in the latent heat flux to pick up in August and September instead of later on. The effect of this is visible in the buoyancy flux variances as well. Finally, the low-pass-filtered variance in the buoyancy flux showed some evidence of transitions in the storm track regimes. We will explore this last point further in a future paper.

It was pointed out earlier that in Fig. 1, the nature of the variability between the summer and winter months was different. We can now address this issue in more concrete terms. The summer variability is dominated by the shortwave radiation in the high-pass-filtered time series. The winter variability, on the other hand, is influenced strongly by storm systems from the bandpass- and the low-pass-filtered time series. The variability in the sensible heat flux, the latent heat flux, and the precipitation are the main contributors to the variability in the buoyancy flux during the winter months. In all cases, the interannual variance was found to be higher when the 30-day moving variance was high.

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