2.2 STATISTICAL ANALYSIS OF SEA SURFACE TEMPERATURE IN THE NORTH ATLANTIC OCEAN

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1. INTRODUCTION

The importance of sea surface temperature anomalies (SSTA) for the climate of the North Atlantic region has been documented in previous studies (for instance, see Marshall et al., 2001; Sutton and Hodson, 2003, 2005; Desser et al., 2003). Over ocean regions, there is significant covariance between SSTA and the anomalies of air temperature at surface, in monthly, seasonal and annual average values. Such covariance is due to exchange of heat and momentum between the upper ocean layer and the air near surface (Desser et al., 2003). Oceans have significant thermal inertia and provide slow variations of the lower boundary of the atmosphere (Saravanan, 1998). This feature is useful in studies of climate predictability at time scales from season to decade.

SSTA variations have been linked to climate variations in North America and Europe. Such studies are supported by statistical analysis of observations as well as by recent modeling studies (Marshall et al., 2001). A notable phenomenon for the long term SST behavior in North Atlantic in the Atlantic Multidecadal Oscillation (AMO) which provides support for climate predictions at decadal time scale (Knight et al., 2005; 2006). It has been reported that some climate predictability might be possible at various scales, as long as strong SST signals or oscillations are identified (such as ENSO, events, for example) (Keller, 1999; Marshall et al., 2001; Andronache and Phillips, 2008). Research is underway to address the climate prediction at seasonal scale and develop practical applications, where such forecasts can have significant impact (Palmer, 2010; Timofeyeva, 2010; Tugrul Yilmaz, 2010). In the context of the climate predictability, we address the problem of SSTA persistence at seasonal scale in North Atlantic ocean. The data and methodology are presented in the next section.

2. SST DATA

There are complete global monthly SST analyses, used extensively in climate studies (Reynolds and Smith, 1994; Kaplan et al., 1998). Such data sets are constrained by quality, quantity and distribution of the original measurements (Hurrell and Trenberth, 1999).

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Before the satellite era, observations did not cover the whole ocean, and various techniques have been employed to produce global data sets. Since the 1980s satellites have been increasingly utilized to measure SST and have provided an enormous rise in the ability to view the spatial and temporal variation in SST. Such advances in observations contribute to improvement of model initial and boundary conditions specification, as well as in statistical analyses of climate variations (Marshall et al., 2001). In this study we use the NOAA SST monthly time series (1856 – 2008), and the NCEP/NCAR SST data sets (1948 – 2008) for the North Atlantic ocean.

3. METHOD

Three methods are used to obtain the monthly SST residuals of importance for seasonal climate variations at the time scale of interest. These methods aim to obtain approximately stationary yearly time series of the monthly SSTA. We are particularly interested in the correlation between SSTA between various months, in the stationary time series (Wilkis, 1995; von Storck and Zwiers, 1999). The presence of the long term trend and AMO type variations in the original SSTA time series tends to produce high correlations. We attempt to describe the SSTA correlations at short time scales (such as season), which might become more evident after achieving stationary conditions. These three methods are briefly described here.

1) For each month, from the yearly time series: a) remove the linear trend; b) remove the AMO type of oscillation (Andronache, 2009). The long term trend is largely attributed to increase of global temperature over the last century (Andronache and Phillips, 2008). The AMO phenomenon is an internal oscillation of the ocean circulation, driven by a natural mode of variability in the thermohaline circulation in the North Atlantic, with possible alterations due to climate change (Delworth and Mann 2000; Knight et al., 2005).

2) Remove the linear trend between breakpoints (BP) in the time series. This method does not make any assumptions about long term trend over the whole time interval, and does not consider explicitly any low-frequency oscillation. Instead, it finds the local min and max SST values over few decades, and does a linear regression between two such consecutive local extreme values. Thus, it removes

the linear trend established between such BP, as will be illustrated in Figure 4.

3) Remove a polynomial fit of the SST time series (Andronache et al., 2008). This method does a least squares (LS) fit with low order polynomials, as an approximation of the data over the whole observation period. The method works well for short time series, and for low order polynomials. High order polynomials tend to present too much detail of the original time series, and have large errors at the end of the time interval.

Notations used in this study:
y – the yearly time series of the monthly average SST for a given month;
y_{LT} – the linear trend of y;
y_{AMO} – the sine LS fit of the (y-y_{LT});
$r_1 = y - y_{LT} - y_{AMO}$ – the SST residual of y after removal of linear trend and AMO approximation.

For method 2, the residual r_2 is defined as
$r_2=y-y_{BP}$ (the difference between y and the LS linear fit between breaking points of y).

For method 3, the residual r_3 is
$r_3=y-y_P$ (the difference between y and the polynomial fit of y, where the order of the polynomial used in this study is n = 7).

The three methods provide similar results, and they were used to check the robustness of the first one which is illustrated here in detail. The time series of the SST residuals obtained by the above methods are stationary in weak sense (the mean and the variance are constant in time). We illustrate how SST residuals are obtained by removing the linear trend and the AMO type oscillation.

4. RESULTS AND DISCUSSION

Figure 1 shows the SST time series for each month. Due to the annual cycle, there are pairs of months with very similar variations. For instance, at the bottom of the plot, February and March SST have very similar behavior, and they seem highly correlated. These months correspond to the lowest SST values during the cold season in North Atlantic region. At the top of the plot, August and September SST have similar variations, corresponding to the highest values in the warm season. Few characteristics are evident: a) the long term positive trend; b) the multidecadal oscillation. We are interested to find out a statistical relationship between SST in various months, and we have to produce SST time series that are stationary. These conditions are illustrated in Figures 2 and 3 for the month of January. Figure 2 shows: (a) the time series of monthly SST for January, versus time in years. The LS linear trend is shown; (b) the monthly SST residual for January, which is the difference ($y - y_{LT}$), versus time, in years. This residual SST has no trend but exhibits a multidecadal oscillatory component. Figure 3 shows: (a) The January monthly SST residual ($y - y_{LT}$) and the least square of a sine function, versus time, in years; (b) The January monthly SST residual r_1, versus time, in years. This residual time series is approximately stationary.

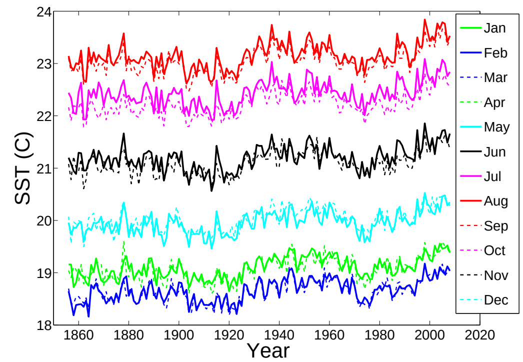

Fig. 1. Time series of the monthly SST versus time, in years.

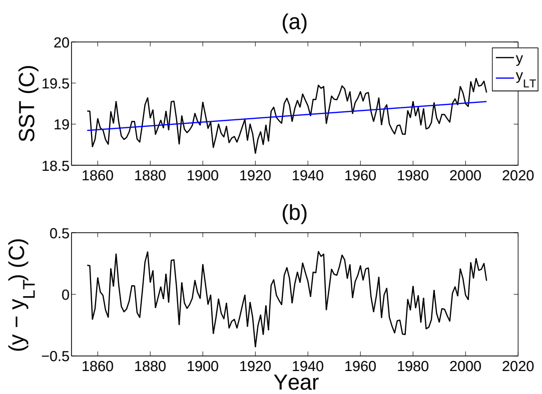

Fig. 2. (a) Time series of monthly SST for January, versus time in years. The linear trend in least square sense is shown; (b) The monthly SST residual for January, ($y - y_{LT}$), versus time, in years.

This procedure in applied for all months. We note that y_{AMO}, approximated by a sine function with three parameters (amplitude, period, and phase) is the first Fourier component of the time series, which correspond to a well defined physical phenomenon (AMO). By taking more Fourier series terms, we can obtain a better approximation of the ($y - y_{LT}$) data, at shorter time scales, but our purpose here is to remove only the dominant multidecadal oscillatory features (such as AMO). The application of this method for all twelve months produced some variability in the fitting parameters (amplitude, period, and phase), consistent with previous results.

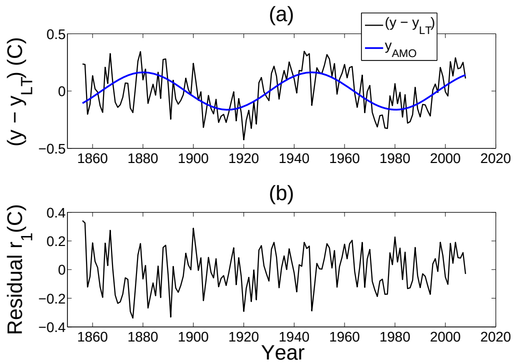

Fig. 3 (a) The January monthly SST residual ($y - y_{LT}$) and the least squares of a sine function, versus time, in years; (b) The January monthly SST residual r_1, versus time, in years.

Next subsection provides a brief account of AMO as a physical low-frequency oscillation in the North Atlantic ocean.

4.1 AMO

SST in North Atlantic show variations with a period of 65 – 80 years, a phenomenon called Atlantic Multidecadal Oscillation (Schlesinger and Ramankutty 1994; Delworth and Mann 2000). There is extensive literature on AMO and its effects on climate, and there is potential predictability at decadal time scales in the North Atlantic region based on this phenomenon.

AMO is associated with large scale precipitation changes in Sahel, US, and Brazil (Knight et al., 2005, 2006). It is also associated with the variations in the frequency of severe Atlantic hurricanes (Goldenberg et al., 2001). AMO is correlated with Arctic temperature changes (Chylek et al., 2009). Based on results from model simulations, AMO is considered a natural mode of oscillation of the Atlantic Ocean thermohaline circulation (Delworth and Mann 2000) and this conjecture is supported by available observations.

Some caveats need to be noted concerning the present state of AMO understanding. The observational SST time series are too short to infer oscillations with a quasi-period of 60 – 80 years with high degree of reliability. Longer time series, extending in the past, using proxy data, would be beneficial to investigate AMO in the North Atlantic region. The coupled ocean-atmosphere models need to reproduce the thermohaline circulation and its characteristics. For such aim, long term records of deep ocean data becomes paramount.

4.2 Correlation of SST residuals

We note first that the residuals obtained by the three methods are similar. Figure 4 a shows the SST and the linear regression between BP in the time series. Figure 4 b shows the polynomial fit (order = 7) of the same data. Figure 4c compares the three residuals obtain using these methods. More detailed tests (not shown) were performed to determine any significant variations between these methodologies, and we found that they produce similar stationary time series of the SST residuals.

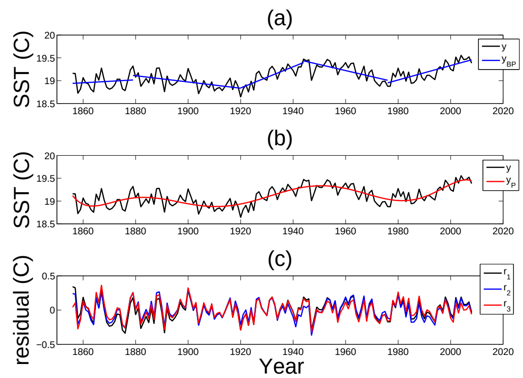

Figure 4. Residuals obtained by the three methods: a) BP; b) polynomial fit; c) comparison of residuals from the three methods.

Figure 5 shows the contour plot of the SST residual obtained above. For any given month, there are significant variations at time scales of several years, likely linked to ENSO events and teleconnections between Atlantic Ocean and other regions (Penland and Matrosova, 1998; Marshall et al., 2001; Andronache and Phillips, 2008). For any given year, we note some persistence of the SST anomaly. This is more visible if we take a smaller time interval such as that shown in Figure 6 for the period 1988 - 2008. It is apparent that SSTA persistence at few months is common, while does not seem to be a simple rule.

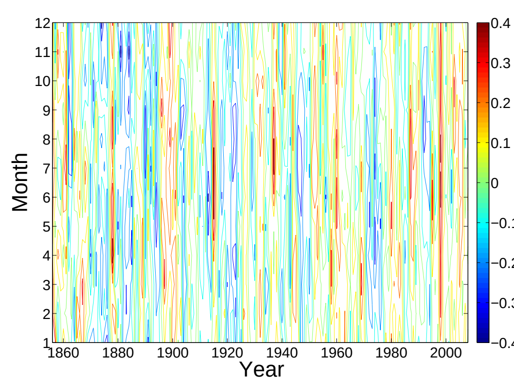

Fig 5. Contour plot of SST residual, r_1 for the time interval 1856 - 2008.

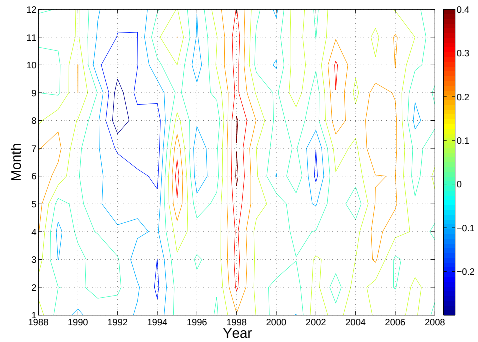

Fig. 6. Contour plot of the SST residual r_1 for the time interval 1988 – 2008.

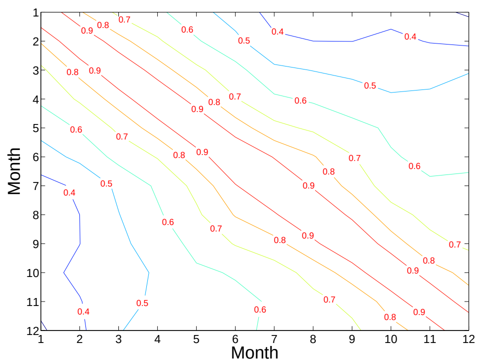

Fig. 7 Contour plot of the correlation coefficient for the matrix r_1 of the SST residuals.

We estimate the correlation coefficients between r_1 in various months. Figure 7 shows the contour plot of the correlation coefficients of the matrix r_1 of SST residuals. It illustrates that significant correlation exist between consecutive months. Thus, for example, February, March, and April correlate well with January. Generally, in most cases, each month correlates well with previous three to five months. This result confirms that in the monthly SSTA anomalies (after removal of decadal trend and oscillations), there is significant persistence at season time scale (few months up to about six months or so). While this result is applicable for the average SSTA for the whole North Atlantic, preliminary studies show the importance of spatial distribution, well illustrated and documented by previous studies (Penland C, and L. Matrosova, 1998; Marshall et al., 2001).

5. CONCLUSIONS

For the North Atlantic region, the monthly SST residuals obtained after removal of long term trend and AMO type oscillation, show significant persistence at seasonal time scale and beyond. The significant covariance in the SST residual matrix is valuable in studies of climate predictability at regional scale and will be explored in more details to account for the role of the spatial distribution of the SSTA.

Preliminary results show that the spatial distribution of SSTA provides a detailed structure of interactions between ocean and atmospheric circulation. Further work will address the connection between North Atlantic SSTA and tropical storms, the role of SST in Arctic climate variations, and the role of ENSO in North Atlantic region climate.

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7. REFERENCES

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