Surface Air Temperature Pattern Variability in the Canadian Maritimes

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INTRODUCTION

The reliable characterization of the surface air temperature (SAT) variability and of its change over time is particularly important for a better understanding of climate processes. A relevant assessment of climate change implications for ecosystems, human health, etc. (Nakashima et al. 2012) should also include knowledge of temperature variability. Nevertheless, information on SAT variability is modest compared to other aspects of weather and climate; moreover, the conclusions of studies dedicated to this subject are often inconsistent (Walsh et al. 2011). The aim of this paper is to address questions concerning SAT pattern variability using different methods applied to minimum and maximum daily temperature recorded in meteorological stations from the Maritime Provinces of Canada (Table 1). This region is interesting from the point of view of pattern variability, since it is subject to processes on different spatial and temporal scales including disturbances arriving from the Pacific, the Arctic, and the tropics, and is also influenced by the Atlantic Ocean with its warm and cold currents (Suteanu 2010). Long-term (> 100 years) homogenized (Vincent et al. 2002) daily records are used in this study.

METHODS

Three distinct ways of assessing pattern variability and pattern change are applied here:

(i) Statistical moments. Variability is thus characterized from the point of view of the value distribution, while the temporal succession is ignored.

(ii) Long-range correlations. Signal persistence is assessed over a range of temporal scales and quantified by the Hurst exponent *H*, which can be accomplished with different methods. Detrended fluctuations analysis (DFA – Kantelhardt et al. 2001) and Haar wavelet analysis (Lovejoy et al. 2012) are applied in this study. In both cases one starts from daily temperature time series with the seasonal trends removed by subtraction of the average temperature of the corresponding day of the year from each value. Both methods involve the division of the signal in sections of size *s*, with *s* spanning a range of time scale values (from days to months, years, and decades). In DFA, one finds for each segment the best fit polynomial of degree N (N = 1, 2, ..7), and the mean square differences between the polynomial and the actual signal are averaged for all segments, which leads to the average square difference *F(s)*. *H* is then found from the power law relation between *F* and *s*. Haar wavelet analysis relies on the computation, for each point *x* in the time series, of the difference between the mean of ($x + s/2$) and ($x - s/2$). Similarly, the power law resulting for these fluctuations leads to the exponent *H* (Fig. 1). The two methods produce similar outcomes, but Haar wavelets are faster to compute and lead to results that are easier to interpret, as well as to lower uncertainty intervals.

(iii) Distance from the average year. The latter is given by the mean temperature for each day of the year, calculated based on the whole dataset for every station. The Euclidian distance is then calculated for each analyzed window.

These time series analysis methods are applied to the whole available datasets, as well as to successive windows of different lengths (from 3 to 7 years). Both overlapping and non-overlapping windows are studied. The window size proves not to have a major influence on the outcomes of the analysis, which is in agreement with other studies (Walsh et al. 2005, Suteanu and Mandea 2012).

The results are used to assess (a) the degree to which the three different methods provide insights into distinct aspects of the analyzed patterns, and (b) the existence and the characteristics of spatio-temporal correlations among records from different stations in the region.

RESULTS

AST pattern variability assessed with the methods specified above proves to change significantly over time. While correlations among the different quantities

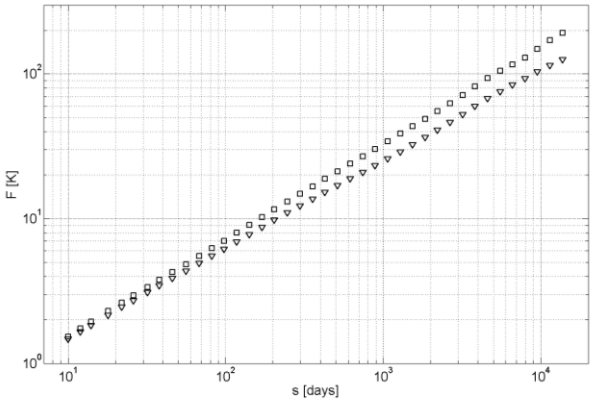

FIGURE 1. Haar wavelet analysis applied to daily SAT records from Fredericton: triangles – maximum temperature, squares – minimum temperature.

determined for the analyzed temporal windows (standard deviation *S*, Hurst exponent *H*, distance from the average year *D*) can be identified, their strength and even their sign changes over time. The temporal change in the mutual relationships among these quantities highlights the extent to which they grasp different aspects of the temperature patterns. Examples can be seen in Fig. 2 and Fig. 3: the analyzed windows, with a width of 7 years (as indicated by exponent subscripts), cover the time series with a step of one year. A positive correlation among *S*, *D*, and *H* can be consistently identified between the beginning of the records (end of the 19th century) and the 1940's, when correlation changes significantly in all cases. Interestingly, it is by analyzing together the different quantities reflecting variability that the pattern change can be clearly identified: no consistent signs of such a change are detected by temporal analysis performed separately with any of the three methods.

The correlation among the different perspectives upon pattern variability changes over time. Extreme values consistently obtained for most stations for *H* and *S* occur in many cases over different time intervals. For instance, there is a strong and consistent minimum for *H* in the early 1940's, and a strong minimum for *S* in the mid 1950's (Fig. 3). However, the way in which each of the determined quantities varies in time is comparable from station to station.

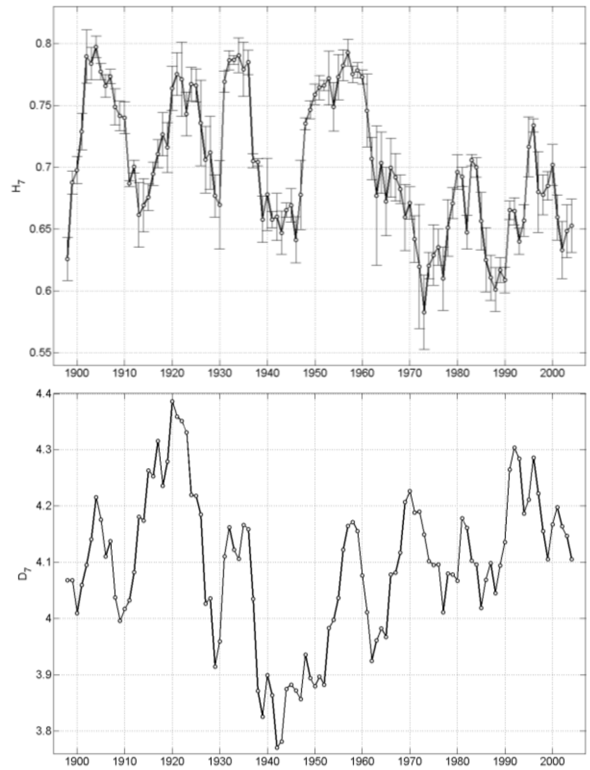

FIGURE 2. Examples for Sydney, daily minimum SAT; top: *H* exponent variation over time; error bars indicate 95% certainty intervals; bottom: distance *D* from the average year.

Minimum temperature values are found to be typically characterized by higher persistence and lower variability than maximum temperature records, in agreement with other studies (Suteanu 2010).

CONCLUSIONS

The lack of consensus concerning pattern variability and its temporal change can be partially explained by the fact that, like many natural patterns, SAT records cannot be exhaustively characterized by any time series analysis method. Each method only captures some aspects of pattern variability. Using not one, but a set of selected analysis methods may be

TABLE 1. Meteorological stations used in this study (data from Vincent et al. 2002)

Station	N Latitude	W Longitude	Start Year	End Year
Yarmouth, Nova Scotia	43.83	66.08	1895	2008
Sable Island, Nova Scotia	43.93	60.02	1895	2008
Saint John, New Brunswick	45.32	65.88	1895	2008
Fredericton, New Brunswick	45.87	66.53	1895	2008
Moncton, New Brunswick	46.12	64.68	1895	2008
Sydney, Nova Scotia	46.17	60.05	1895	2008
Charlottetown, Prince Edward Island	46.25	63.13	1895	2002
Miramichi, New Brunswick	47.02	65.47	1895	2005

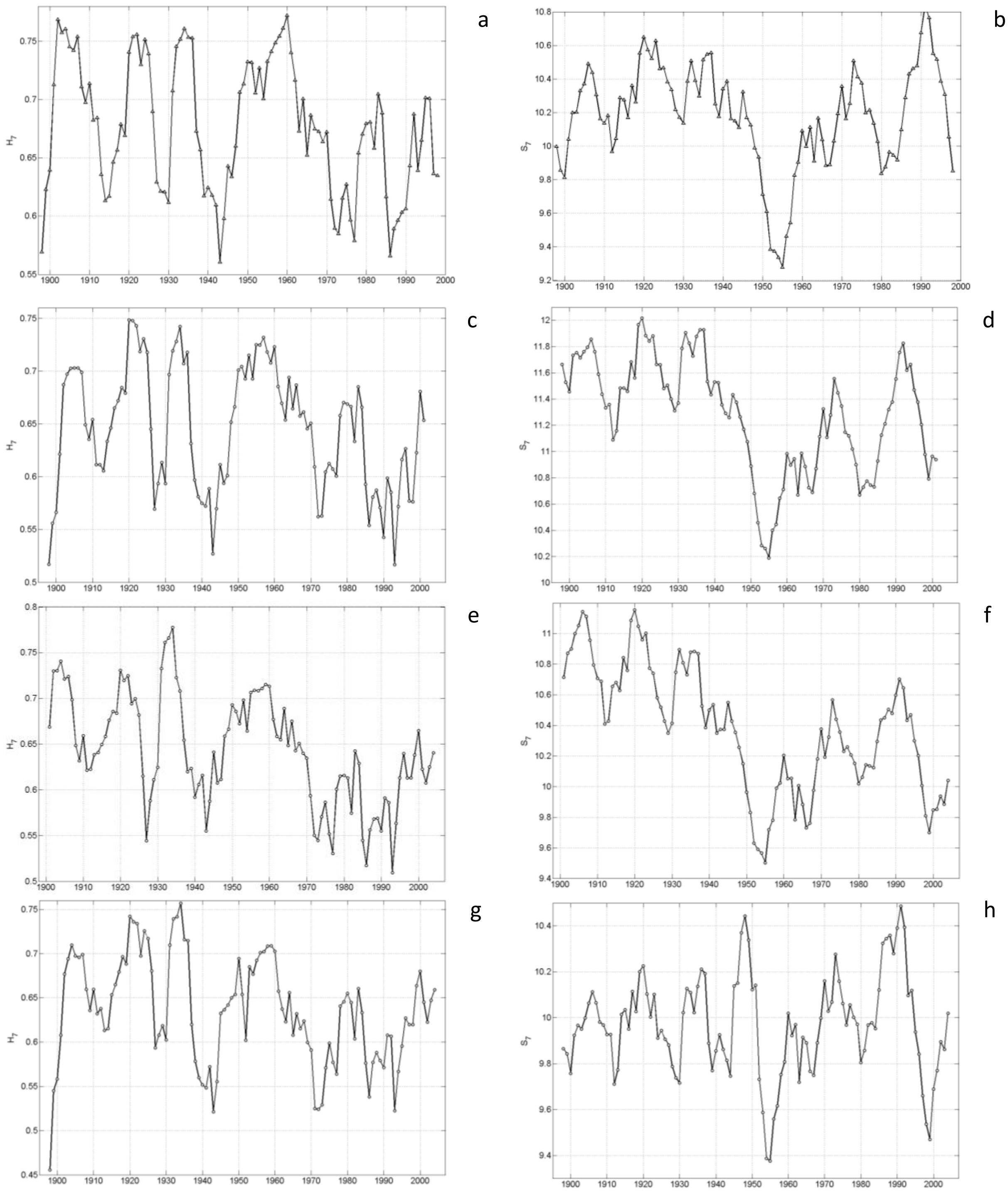

FIGURE 3. Examples of results obtained for *H* (left column) and *S* (right column): a, b: Charlottetown; c, d: Miramichi; e, f: Moncton; g, h: Saint John. Window width: 7 years, window step: 1 year.

more helpful for pattern characterization. Moreover, none of the methods applied in this study showed a simple trend in terms of variability change: on the contrary, we can identify in all cases irregular increases and decreases in variability. Variability is expressed in SAT time series in many ways and on many time scales. Therefore, the often asked question about variability increasing over the last decades or not cannot receive a simple answer; given the nature of variability, this situation is not expected to change, even if new, more powerful analysis tools will reveal novel and interesting aspects of pattern change.

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