Disruptions to global temperature patterns detected by multi-scale sample entropy

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Summary

Multi-scale sample entropy (MSE) is a method originally applied to the analysis of heartbeat data to detect heart disease. The authors recently applied the method to spatio-temporal global gridded temperature data. Previous research found that MSE can identify changes in the temporal behaviour of the climate system over Europe that are not identified by other analysis methods such as mean and variance at different scales of temporal aggregation. MSE estimates the sample entropy of the time-series after coarse-graining at different temporal scales. This paper presents the first application of MSE to variance-adjusted mean monthly air temperature anomalies (CRUTEM4v) at global scale.

KEYWORDS: entropy, information theory, multi-scale analysis, climate change, temperature.

1. Introduction

Global warming is influenced by increasing atmospheric greenhouse gas concentrations and other forcing factors. Not only are global average temperatures increasing, but extreme events are expected to become more frequent and more intense in some regions of the world (Coumou and Rahmstorf, 2012; Glądalski et al., 2014). The frequency of warm anomalies in the climate system is already changing (Robeson et al., 2014). Extremely hot days and nights are expected to become more frequent and extreme cold days and nights less frequent (Mika, 2013).

An open question is whether the temporal scales of variability of temperature anomalies have changed measurably in the recent past. Observing a process at the wrong temporal scale can overlook patterns in the data (Duttileul, 2011). Several climate indices have already shown a shift in the frequency of occurrence of extreme events from around 1970, including the Atlantic Multidecadal Oscillation (AMO), the North Atlantic Oscillation (NAO), the Northern Annular Mode (NAM), the Pacific Decadal Oscillation (PDO), the Southern Oscillation Index (SOI) and the Pacific-North-America teleconnection (PNA) (Rossi et al., 2011).

Multi-scale sample entropy (MSE) was developed for diagnostic purposes in cardiology (Costa et al., 2005). A loss of complexity at longer time-scales is apparent as lower entropy and is associated with ageing patients and certain types of heart disease (Costa et al., 2005). Balzter et al. (2015) applied MSE to spatial gridded temperature data for the first time, focusing on the European region.

This paper presents the first global analysis of temperature anomalies with MSE. MSE is based on the estimation of the sample entropy (Richman and Moorman, 2000) of the time-series after coarse-graining at multiple temporal scales. Systems of higher complexity appear 'more random' or 'less ordered' than simpler systems (Li and Zhang, 2008).

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2. Methods

Sample entropy is estimated for a time-series at different temporal granularity by successively coarse-graining the original time-series data into new coarser scale time-series using increasing scale factors. By plotting the entropy estimates against the temporal scale factor (the degree of coarse-graining), the effect of scale on the regularity of patterns in the data can be visualized. A detailed description of the MSE method can be found in Costa et al. (2005). A one-dimensional discrete time-series of N measurements [$x_1,\ldots,x_i,\ldots,x_N$] is consecutively coarse-grained into new time-series [$y(\tau)$] for different values of the temporal scale factor τ. The original times series is divided into non-overlapping chunks of length τ, omitting any residual $<\tau$ elements at the end of the time-series. All data points inside each chunk are then averaged:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i \tag{1}$$

for $1 \leq j \leq N/\tau$.

For τ=1, the coarse-grained time-series [y(1)] is the original time-series. For τ>1, each coarse-grained time-series contains N/τ data points. If we assume that the state of the parameter of interest at time t is partially determined by its previous values at times t-m, …, t-1 and can hence be described by a state vector of length m:

$$u_m(t-m) = \big(x(t-m), x(t-m+1), \ldots, x(t-1)\big) \tag{2}$$

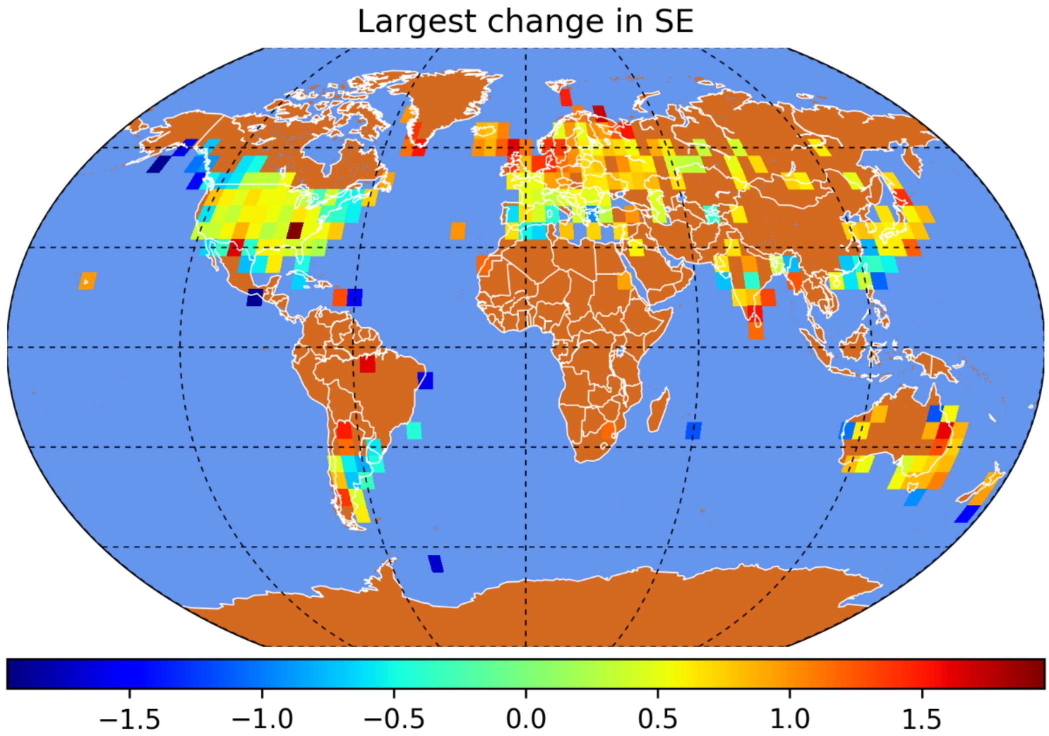
The algorithm now searches for the number of state vectors within a defined Euclidean distance from the reference state. For each vector $u_m(i)$ of length m, the algorithm counts the number of vectors in the time-series that meet the similarity criterion proportional to a tolerance parameter r scaled by the standard deviation of the original time-series. For a time-series of length N, the average number of such matching state vectors for all states $u_m(i)$, i=1, …, N-m+1, divided by the total number of vectors of that length in the time-series, is denoted by $U_m(r)$. Repeating this calculation for the vectors $u_{m+1}(i)$ leads to the average number of matching state vectors $U_{m+1}(r)$ of length m+1. The sample entropy SE (Richman and Moorman, 2000) is then defined as:

$$S_E(m,r,N) = -ln \frac{U^{m+1}(r)}{U^m(r)} \tag{3}$$

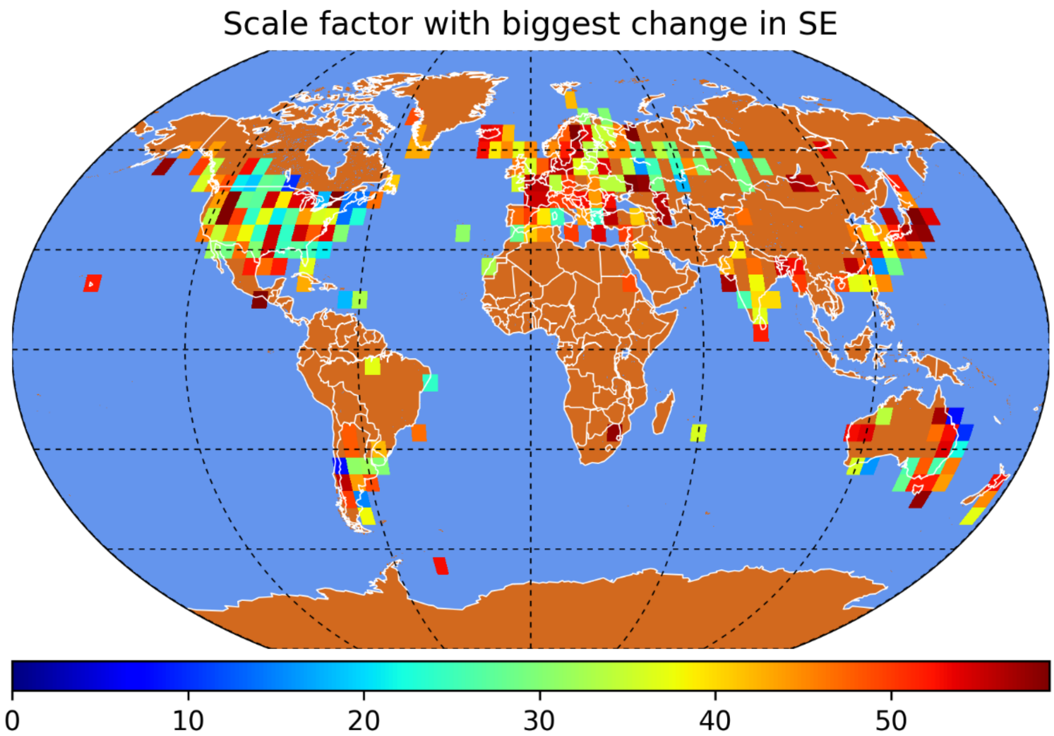
SE depends on the parameters m (length of the state vectors) and r (threshold for similarity of state vectors, scaled by the standard deviation of the time-series data). The MSE analysis was implemented in Python. Here, template length was set to m=3, and tolerance to r=0.4.
Variance-adjusted gridded air temperature anomaly data (CRUTEM4v, version 4.6.0.0) from a network of meteorological stations was obtained from the Climate Research Unit (CRU) at the University of East Anglia (UK). The dataset extends from 1850 to 2016 and is updated regularly (Brohan et al., 2006; Jones et al., 2012). CRUTEM4v is a dataset of temperatures on a 5° latitude/longitude grid, expressed as anomalies from the average climate during 1961-1990. The variance adjustment is applied to address the changing density of meteorological stations in each grid box over time (Jones et al., 2001). The MSE analysis was repeated for each grid box but time-series with <500 values were excluded. The data were split into two time periods from 1850-1960 and 1961-2016 in order to examine possible changes in the temporal scales of variability of recent temperature anomalies compared to the past.

3. Results

The results can be visualised by showing two main features: the magnitude of the largest change in sample entropy at any scale factor for each grid box, and the scale factor at which it occurred.



(a)



(b)

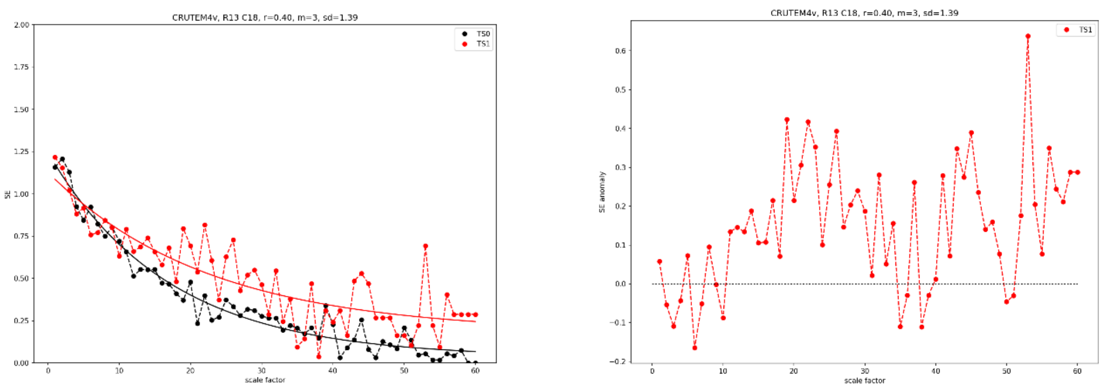
Figure 1 Global maps of (a) the magnitude of the largest change in sample entropy of the temperature anomaly data, and (b) the temporal scale factor at which the largest change in sample entropy occurred. Brown is the background colour for missing values over land and light blue shows the oceans.

Figure 1a shows a global map of the magnitude of the largest change in sample entropy of the temperature anomaly data. Figure 1b shows the corresponding temporal scale factor at which the largest change in sample entropy occurred. From Figure 1a it is evident that over the majority of grid boxes there was a positive change in sample entropy over time. An increased sample entropy indicates a greater complexity of the system.

We conclude that in many parts of the world for which long-term temperature observations exist, the complexity of the climate system has increased after 1960 compared to the historic record of 1850-1960. An alternative explanation could be that better and more frequent measurements may lead to greater entropy because of greater variability in the data.

Figure 1b shows that the temporal scale factor (in units of months) at which the greatest change in SE occurs, varies greatly over space. No clear pattern is discernable, but many grid boxes show scale factors >12 months as the scales at which the complexity of the climate system has increased. This is meaningful because it indicates that the temperature anomaly data represent the outcome of an increasingly complex set of processes at time scales longer than a year.

Figure 2 illustrates the underlying MSE analysis for one grid box. In Figure 2a, the black data points are the SE of the coarse-grained temperature anomaly data for 1850-1960 (TS0) and the red data points for 1961-2016 (TS1), along with fitted curves. The x axis shows the temporal scale factors up to 60 months. The comparison of TS0 and TS1 shows an example of a grid box where the SE has increased, indicating greater complexity of the system that produced the temperature anomaly data after 1960. Figure 2b shows the difference between SE for TS1 and TS0.



(a) (b)

Figure 2 (a) Multi-scale sample entropy (SE) at different scale factors (scales of temporal coarse-graining) for two chunks of the temperature time-series data for one grid box (row 13 column 18) for *m*=3. Curves are fitted models. TS0 = 1850-1960; TS1 = 1961-2016. (b) Difference between TS0 and TS1 by scale factor.

4. Conclusions

Multi-scale sample entropy analysis of global gridded temperature anomaly observations since 1850 revealed global patterns of an increase in complexity of the climate system after 1960 in many regions. The scale factors at which these changes occur vary between grid boxes and can be mapped using the spatialized algorithm presented in this paper.

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7. Biography

Heiko Balzter, Dipl. Ing. agr., Dr. agr., is research professor, Director of the Centre for Landscape and Climate Research and Earth Observation theme leader at the University of Leicester. He leads the Official Development Assistance Programme in the National Centre for Earth Observation and holds the Royal Society Wolfson Research Merit Award and the Royal Geographical Society's Cuthbert Peek Award.

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