

# Regime Change Detection in Irregularly Sampled Time Series

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**Abstract** Irregular sampling is a common problem in palaeoclimate studies. We propose a method that provides regularly sampled time series and at the same time a difference filtering of the data. The differences between successive time instances are derived by a transformation costs procedure. A subsequent recurrence analysis is used to investigate regime transitions. This approach is applied on speleothem-based palaeoclimate proxy data from the Indonesian–Australian monsoon region. We can clearly identify Heinrich events in the palaeoclimate as characteristic changes in dynamics.

**Keywords** Irregular sampling • Recurrence plot • Recurrence quantification analysis • Regime change • Indonesian–Australian monsoon • Heinrich events

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## 1 Introduction

In the last decades, palaeoclimate research has experienced an exciting progress with ever-higher resolution and better age control high-resolution records, innovative technologies and types of proxies, as well as new data series analysis approaches, such as speleothem-based proxies, fluid inclusion analysis and laser ablation techniques, and complex network-based data analysis. (Dennis et al., 2001; Kennett et al., 2012; McDermott, 2001; McRobie et al., 2015; Rehfeld et al., 2013). This progress helps greatly to increase our understanding of past climate variation and the mechanisms behind the climate system, but also to assess future climate-related vulnerability of our society. Of particular interest are critical transitions, such as tipping points or regime shifts, because they can bring the climate system into another mode of operation (Lenton et al., 2008; Scheffer et al., 2012). Identifying tipping points from measurements is no simple task. Several approaches have been proposed, such as testing for slowing down and increase of the autocorrelation (Scheffer et al., 2009), reconstructing potentials of the dynamics by using the modality of the data distribution (Livina et al., 2010), using a modified detrended fluctuation analysis (DFA) (Livina and Lenton, 2007), or the concept of stochastic resonance (Braun et al., 2011). While dynamical transitions are rather obvious when they appear in the first two moments (i.e. in mean or variance), they can be hidden when superimposed by signals of different time scales or by noise, issues frequently observed in palaeoclimate time series. For such problems, the application of methods from nonlinear time series analysis is a well-accepted perspective, e.g., by using the fluctuation of similarity (FLUS) (Malik et al., 2012). Another promising tool for the identification of subtle transitions is the framework of recurrence plots (Marwan et al., 2007). Recurrence plots and their quantification consider the evolution of neighbouring states in a phase space. Besides characterizing different classes of dynamics or testing for synchronization and nonlinear interrelationships and couplings of multiple systems, it allows to test for dynamical regime changes with respect to different properties, such as changes in the geometry of the attractor, in the predictability of states, or in the intermittency behaviour (Donner et al., 2011; Eroglu et al., 2014; Marwan et al., 2007). The recurrence plot framework has been successfully applied to investigate past transitions, e.g., in the Asian monsoon system (Marwan et al., 2013) and in the East African climate (Donges et al., 2011), and to uncover a seesaw effect within the East Asian and Indonesian–Australian summer monsoon system (Eroglu et al., 2016).

However, most palaeoclimate proxy records (independent of the actual archive) come with the challenge of irregular sampling. While sampling in the field or in the lab is often done on a regular depth/length axis, varying sedimentation or growth rates result in variable time–depth relationships and in time series with non-equidistant sampling points in the time-domain (Breitenbach et al., 2012). The most common procedure is data preprocessing using linear interpolation. However, interpolation can lead to a positive bias in autocorrelation estimation (and, thus, an overestimation of the persistence time) and a negative bias in cross correlation

analysis (Rehfeld et al., 2011). Therefore, several approaches have been suggested for analysing irregularly sampled time series (Ozken et al., 2015; Rehfeld and Kurths, 2014; Rehfeld et al., 2011; Scargle, 1982; Stoica and Sandgren, 2006).

In the following we will focus on a recently proposed technique that is based on a measure that compares spike trains by quantifying the effort it needs to transform one spike train to the other one (Hirata and Aihara, 2009; Victor and Purpura, 1997). This measure corresponds to a modified difference filter (a common practice to remove low-frequency variation and trends), where we determine the differences by a criterion of how close subsequent short segments of an unevenly sampled time series are by determining the cost needed to transform one segment into the following one (Ozken et al., 2015). Such comparison of successive segments has some similarity with the FLUS method (Malik et al., 2012), but instead uses the transformation cost as the similarity measure, and is thus directly applicable on irregularly sampled time series. We illustrate this approach by analysing a speleothem-based palaeoclimate record with respect to regime transitions.

## 2 Methods

### 2.1 Transformation Costs Time Series

Cumulative trends or low-frequency variations are common in palaeoclimate proxy records, but are often undesirable and can cause difficulties in the analysis. One frequently used solution is the difference filter, where the values of the proxy record are replaced by the differences of subsequent values,  $y(t - \Delta t/2) = x(t) - x(t - \Delta t)$ , with  $\Delta t$  the sampling time of a regularly sampled time series. Another, even more challenging problem is the irregular sampling frequently occurring in palaeoclimate proxy records. The *transformation costs time series* (TACTS) approach tries to overcome both problems by transforming irregularly sampled time series to regular ones and simultaneously using the transformation cost as the difference value. This procedure induces less loss of information compared to traditional interpolation procedures.

The core of the TACTS method is to measure the shortest distance (transformation cost) between two data segments by using two different processes: (1) *shifting points* in time which causes changes in the amplitude for marked data and (2) *adding-deleting* operations. The process starts with dividing the data into small and equally sized segments. These segments can have different number of points, because the points are not equally sampled. The transformation costs between all sequence windows are then calculated by

$$p(S_a, S_b) = \overbrace{\sum_{(\alpha, \beta) \in C} \{\lambda_0 |t_a(\alpha) - t_b(\beta)| + \lambda_k |L_a(\alpha) - L_b(\beta)|\}}^{\text{shifting}} + \underbrace{\lambda_S (|I| + |J| - 2|C|)}_{\text{adding/deleting}}. \quad (1)$$

The equation states two distinct operations for two essential processes. If the operation is *shifting*, then the first part of the equation involves, otherwise the *adding–deleting* operation involves as the second part. In the first part, the summation is over the pairs  $(\alpha, \beta) \in C$ , where  $C$  is the set of points that will be shifted in time and changed in amplitude.  $\alpha$  and  $\beta$  are the  $\alpha$ th event in the first segment ( $S_a$ ) and the  $\beta$ th event in the second segment ( $S_b$ ). The amplitude of points which are  $\alpha$ th and  $\beta$ th elements of  $S_a$  and  $S_b$  are denoted by  $L_a(\alpha)$  and  $L_b(\beta)$ , respectively. The data-adapted constants  $\lambda_0$  and  $\lambda_k$  are given by

$$\lambda_0 = \frac{M}{\text{total time}} \quad (2a)$$

$$\lambda_k = \frac{M - 1}{\sum_{i=1}^{M-1} |x_i - x_{i+1}|}. \quad (2b)$$

where  $M$  is the total number of events, and  $x_i$  is the amplitude of  $i$ th element in the time series.

In the second part of Eq. (1),  $I$  and  $J$  are sets of indices of the events in  $S_a$  and  $S_b$ , respectively. The parameter  $\lambda_S$  is the cost of deleting or adding processes and is used as an optimization parameter. The selection of optimum  $\lambda_S$  is the following: first we calculate total cost time series for the entire range of  $\lambda_S \in [0, 4]$  with step size  $\Delta\lambda_S = 0.01$ . Then we examine frequency distributions for each cost time series. Since each cost value is independent of the others, we expect to have a normal distributed histogram and choose the optimal  $\lambda_S$  according to the best fit on normal distribution.

Equation (1) is a metric distance function, satisfying the following three conditions:

- $p(S_a, S_b) \geq 0$  (positive)
- $p(S_a, S_b) = p(S_b, S_a)$  (symmetric)
- $p(S_a, S_c) \leq p(S_a, S_b) + p(S_b, S_c)$  (triangle inequality).

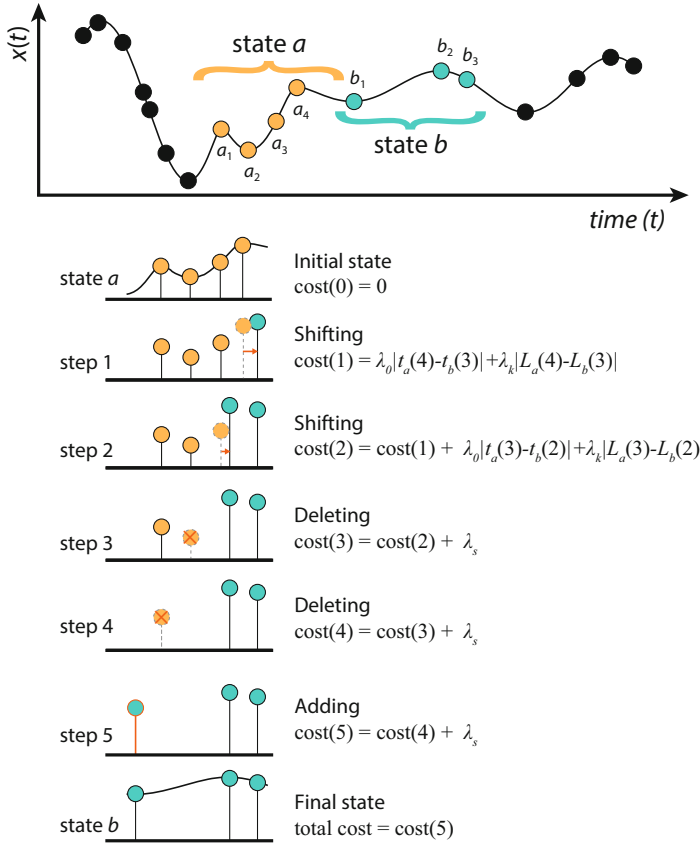
Now we illustrate the method for two consecutive segments. Irregularly sampled data is equally spaced into small windows which are given as state  $a$  ( $S_a = \{a_\alpha\}_{\alpha=1}^4$ ) and state  $b$  ( $S_b = \{b_\beta\}_{\beta=1}^3$ ). The costs computed between the states and all details are given in Fig. 1 step by step.

Note that the decision of which operation process to minimize costs is important. The transformation by shifting costs  $\lambda_0|t_a(\alpha) - t_b(\beta)| + \lambda_1|L_a(1) - L_b(1)|$  and deleting and adding a point costs  $2\lambda_S$ . Here we chose the least cost operation to either shift or delete/add. Therefore, in the algorithm, we consider all these possibilities and chose the operation carefully.

The final appearance of the cost time series is as follows: assume that we have an irregularly sampled time series  $\{u_i\}_{i=1}^N$ , where  $N$  is the number of points. The data is divided into a set of  $W$ -sized  $n$  segments and each segment has a minimum of a certain number of points, therefore,

$$TACTS = \{p(W_i, W_i + 1)\}_{i=1}^{n-1}$$

for all sequence windows. This leads to an equally sampled and detrended time series. The resulting cost values series can be considered as the difference filtered time series with a regularly sampled time axis and can be further analysed with standard or advanced time series analysis tools, e.g., in order to detect regime shifts (Fig. 1).



**Fig. 1** Illustration of the transformation cost time series method, which finds the minimum transformation cost between two data segments such as state  $a$  and state  $b$  in the *top panel*. In five steps state  $a$  is transformed into state  $b$ . At steps 1 and 2, we apply *shifting* a point in time and, as a consequence of shifting, changing the amplitude of the point. These operations cost regarding to first part of Eq. (1). Steps 3 and 4 are *deleting* and step 5 is *adding* a point; each of these operations costs a constant  $\lambda_s$ . The costs are written next to the related processes according to Eq. (1)

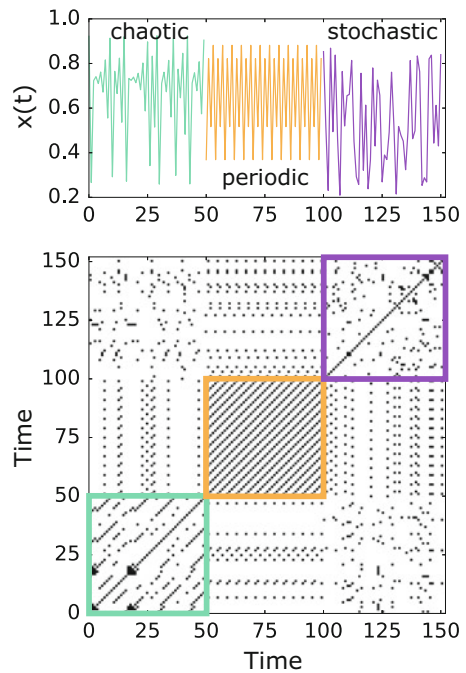
## 2.2 Recurrence Analysis

Recurrence is a ubiquitous property of many dynamical systems. Slight changes in observed recurrence behaviour allow to infer changes in the dynamics (Marwan, 2011; Marwan et al., 2007). In order to investigate recurrence properties, recurrence plots and recurrence quantification analysis have been developed (Marwan, 2008; Marwan et al., 2007). A recurrence plot is the graphical representation of those times  $j$  at which a system recurs to a previous state  $\mathbf{x}_i$ :

$$R_{i,j} = \Theta(\varepsilon - \|\mathbf{x}_i - \mathbf{x}_j\|), \quad i, j = 1, \dots, N \quad (3)$$

with  $\Theta$  the Heaviside function,  $\varepsilon$  a recurrence threshold,  $\|\mathbf{x}_i - \mathbf{x}_j\|$  the Euclidean distance between two states  $\mathbf{x}_i$  and  $\mathbf{x}_j$  in the phase space, and  $N$  the number of observations (or time series length). Such a recurrence plot consists of typical large-scale and small-scale features that can be used to interpret the dynamics visually. Important features are diagonal lines: similar evolving epochs of the phase space trajectory cause diagonal structures parallel to the main diagonal in the recurrence plot. The length  $l$  of such diagonal line structures of at least length  $l_{\min}$  depends on the dynamics of the system (periodic, chaotic, stochastic) (Fig. 2) and can be directly related with dynamically invariant properties, like  $K_2$  entropy (Marwan et al., 2007). Therefore, recurrence quantification analysis (RQA) uses the features

**Fig. 2** Example of a recurrence plot for changing dynamics from chaotic via periodic to stochastic dynamics, each lasting 50 time steps. In the periodic region, continuous long diagonal lines are observed, in the chaotic region, shorter diagonals and single points appear, and in the stochastic part, we find almost only single points



within the recurrence plots for defining measures of complexity. For example, the distribution  $P(l)$  of line lengths  $l$  is used by several measures of complexity in order to characterize the system's dynamics in terms of predictability/determinism or laminarity. The measure *determinism* DET is the fraction of recurrence points (i.e.  $R_{i,j} = 1$ ) that form diagonal lines and can be computed by

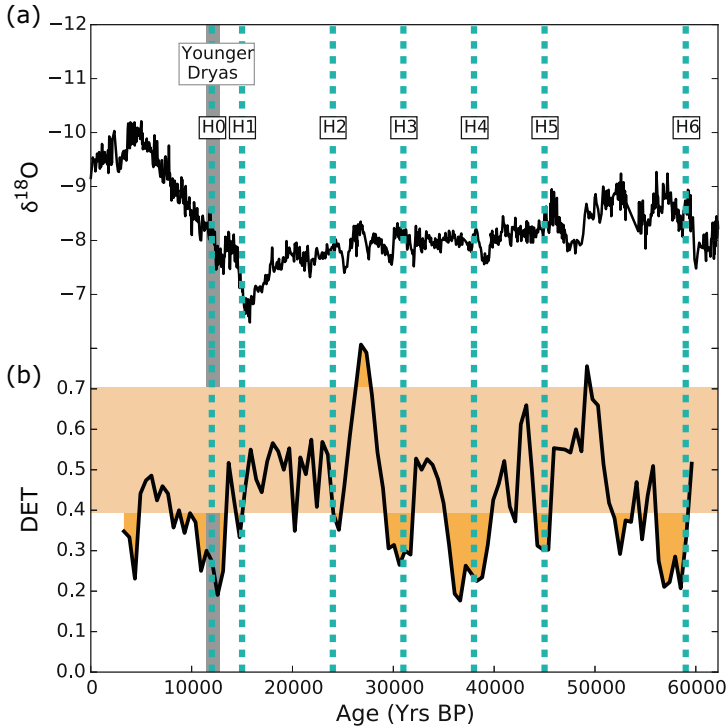
$$\text{DET} = \frac{\sum_{l_{\min}}^N l \cdot P(l)}{\sum_{i,j=1}^N R_{i,j}}. \quad (4)$$

In order to study the time-dependent behaviour of a system or time series, RQA measures can be computed within a moving window, applied on the time series. The window has size  $w$  and is moved with a step size  $s$  over the data in such a way that succeeding windows overlap with  $w - s$ . This technique can detect chaos-period and also more subtle chaos-chaos transitions (Marwan et al., 2007), or different kinds of transitions between strange non-chaotic behaviour and period or chaos (Ngamga et al., 2007). Moreover, the reliability of several RQA measures was investigated by their scaling properties with respect to critical points in the dynamics (Afsar et al., 2015).

### 3 Palaeoclimate Regime Transition

To illustrate the power of the techniques we advocate here, we choose as illustrating example a speleothem  $\delta^{18}\text{O}$  record from the Secret Cave at Gunung Mulu in Borneo/Indonesia (Carolyn et al., 2013). This particular record has been interpreted as a time series of the dynamics of the East Asian–Indonesian–northwest Australia monsoon. This monsoon regime provides a circulation regime that strongly links both hemispheres and serves as a major heat source, playing a significant role at planetary scale (Chang et al., 2006; McBride, 1987). Central to its geography is the Maritime Continent which provides a core region of monsoon activity (Chang et al., 2004; Ramage, 1968). A transect in regional precipitation patterns from the northern part of the Maritime Continent to the northern margin of Australia coincides with a change from the dominance of the boreal summer monsoon to the austral summer monsoon (Chang et al., 2004, 2006; Robertson et al., 2011). The transect captures key palaeoproxy monsoon records and has the potential to provide details of the function of the monsoon regime over Quaternary time scales (Ayliffe et al., 2013; Carolyn et al., 2013; Denniston et al., 2013; Partin et al., 2007). Imbedded in some of these records are short-lived millennial and centennial scale events, and, more general, relatively short-lived phases of climate instability.

While the full proxy record is around 100,000 years, we only analyse the last 62,000 years of the  $\delta^{18}\text{O}$  record (Fig. 3a). Before the 62,000 years many gaps appear and the data become too sparse to give any useful information about. The record used for the analysis contains about 1200 data points. Time intervals between measurements are irregular and follow a Gamma distribution with a skewness of



**Fig. 3** (a)  $\delta^{18}\text{O}$  record of Secrete Cave, Borneo. (b) RQA-determinism  $DET$ , Eq. (4), time series resulting from the transformation cost time series. The light orange band of the  $DET$  indicates the 90% confidence interval. The vertical lines H1–H6 give the six Heinrich events as well as H0, the Younger-Dryas

4.9. In our analysis we use a window length of  $\approx 210$  years to calculate the TACTS. While the parameters  $\lambda_{0,k}$  are determined by Eq. (2), we optimize  $\lambda_S = 1.07$ .

The next step is to analyse the regularly sampled TACTS with RQA using a sliding window method. We consider 30 data points (or 6200 years) of the TACTS as our window size. Given the average number of points in the proxy record, 30 data points of the TACTS correspond to approximately 100–140 points in the original proxy. Using an overlap of 90% of consecutive windows, we determine the  $DET$  [Eq. (4)] for each window with length of 6200 years (Fig. 3b). The recurrence threshold is selected to be  $\epsilon = 20\%$  of the standard deviation of the data in the particular window. The advantage of this  $\epsilon$  selection scheme is that it allows us to analyse proxy records with inherent non-stationarity. In addition, we determine the statistical significance of  $DET$  using the bootstrapping method as outlined in Marwan et al. (2013) (light red band in Fig. 3b).

The determinism  $DET$  indicates several distinct regime changes in the time series from less to more predictable (and vice versa) dynamics (Fig. 3b). Most minima of  $DET$ , signified as periods of decreased predictability, coincide with the so-called



Heinrich events (H1 to H6). Heinrich events are identified in the North Atlantic sediments as layers of ice-rafted debris, associated with the coldest phase just before the Dansgaard–Oeschger events, and result from episodic discharge of icebergs in the Hudson Bay region (Clement and Peterson, 2008; McNeall et al., 2011).

Heinrich events are well represented in the Chinese speleothem and loess record as periods of weakened summer monsoon and intensified winter monsoon (An, 2014). In their interactions with the Siberian Mongolian High of the East Asian Winter Monsoon they can be expected to trigger cold surges which leave their imprint in the proxy palaeoclimate record (Wyrwoll et al., 2016). During the East-Asian Winter Monsoon (EAWM), the Siberian High with its central pressure reaching in excess of 1035 hPa dominates much of the Eurasian continent. Strong northwesterly flows occur at its eastern margins, where one branch of the flow separates and first is directed eastward into the subtropical western Pacific and then tends southward in the direction of the South China Sea. These cold air ‘excursions’, also described as ‘cold surges’, are channeled by the trough southwards and are a characteristic feature of the EAWM (Lau and Chang, 1987). Their path is in part related to relief controls of the Tibetan Plateau. Cold surges transport absolute vorticity and water vapour up-stream of the South China Sea to the Equator (Koseki et al., 2013) and lead to the flare-up of convective activity over the Maritime Continent (Chan and Li, 2004). In the Borneo region, cold surges enhance surface cyclonic circulation triggering the Borneo Vortex, which leads to deep convection giving rise to heavy rainfall events (Koseki et al., 2013; Ooi et al., 2011).

It is noteworthy that in raw  $\delta^{18}\text{O}$  record from the Secret Cave the Heinrich events are almost indistinguishable from other variations in the time series. In the original work by Carolin et al., H1 to H6 were detected by visual comparison of the record to others (e.g. NGRIP), but the Younger Dryas (coinciding with the H0 event) was not detected (Carolin et al., 2013). However, our method clearly extracts these events, including the previously not detected Younger Dryas, and highlights the hidden impact of such distal forcing. Moreover, it allows an objective, quantitative analysis, while Carolin et al. rely on the subjective method of matching extreme proxy values with specific dates. At present, the Borneo Vortex leaves a strong climate signal on the regional precipitation patterns (Ooi et al., 2011). We propose that the prominence of the ‘instability climate phases’, coincident with the timing of Heinrich events in the Borneo record, is an expression of regional controls that are linked to the operation of the Borneo Vortex. The claim draws attention to the need to give more consideration to specific regional controls in explaining the palaeoclimate proxy record rather than simply appeal to global or hemispheric controls.

## 4 Conclusion

We have used the Secret Cave  $\delta^{18}\text{O}$  record from Borneo to illustrate the usefulness of the novel TACTS method for analysing palaeoclimate records. TACTS can transform irregularly sampled time series into a regularly sampled cost time series.

This is an important step, since most modern time series analysis methods—like the RQA used here—require a regular sampled time series as an input. Furthermore, the TACTS method is less biased than interpolation methods frequently used to transform irregularly sampled into regularly sampled data sets. This transformation only requires three parameters. The two parameters  $\lambda_{0,k}$  are given by the average amplitude and frequency of the record [see Eq. (2)], while  $\lambda_s$  needs to be optimized. Being a difference filter, the TACTS method lends itself naturally for palaeoclimate investigations, where proxy records often have some non-stationarity and usually need to be detrended. As we have shown the detrending is build into the TACTS method, therefore we do not need this additional step in our time series analysis.

Applying the TACTS and RQA approach on palaeoclimate data from the Secret Cave speleothem, we were able to identify regime changes in the monsoon activity during the last 62,000 years. We report on several distinct regime changes coinciding with the Heinrich events H1 to H6 and therefore add quantitative evidence of these impacts to previous, more qualitative studies (Carolin et al., 2013). Moreover, our analysis clearly unveils that also the Younger Dryas had an impact on the monsoon activity over the Maritime Continent.

Given that irregular sampling of proxy records is quite common in Earth science, the TACTS method has large potential in quantitative Earth science without prior modification or preprocessing the data.

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