Slowing down as an early warning signal for abrupt climate change

Vasilis Dakos*, Marten Scheffer*†, Egbert H. van Nes*, Victor Brovkin‡§, Vladimir Petoukhov‡, and Hermann Held‡

*Department of Aquatic Ecology and Water Quality Management, Wageningen University, P.O. Box 47, 6700 AA, Wageningen, The Netherlands; and
‡Potsdam Institute for Climate Impact Research, P.O. Box 601203, D-14412 Potsdam, Germany

In the Earth's history, periods of relatively stable climate have often been interrupted by sharp transitions to a contrasting state. One explanation for such events of abrupt change is that they happened when the earth system reached a critical tipping point. However, this remains hard to prove for events in the remote past, and it is even more difficult to predict if and when we might reach a tipping point for abrupt climate change in the future. Here, we analyze eight ancient abrupt climate shifts and show that they were all preceded by a characteristic slowing down of the fluctuations starting well before the actual shift. Such slowing down, measured as increased autocorrelation, can be mathematically shown to be a hallmark of tipping points. Therefore, our results imply independent empirical evidence for the idea that past abrupt shifts were associated with the passing of critical thresholds. Because the mechanism causing slowing down is fundamentally inherent to tipping points, it follows that our way to detect slowing down might be used as a universal early warning signal for upcoming catastrophic change. Because tipping points in ecosystems and other complex systems are notoriously hard to predict in other ways, this is a promising perspective.

catastrophic shifts | critical slowing down | autocorrelation | alternative stable states | tipping point

The relative constancy of the climate over the past 10,000 years is exceptional in view of the large variability found in reconstructions of almost all periods before. Particularly noteworthy in the records of past climate dynamics are occasional sharp transitions from one state to another. Such transitions happened at various time scales (1). For instance, ≈34 million years ago the earth changed suddenly from the tropical state in which it had been for hundreds of millions of years to a state with ice caps, a shift known as the greenhouse–icehouse transition (2, 3) (Fig. 1*A*). A prominent feature of the climate cycles that followed is the abrupt termination of most glacial periods (4) (Fig. 1 *C*, *E*, *G*, and *I*). Zooming in on a finer time scale shows that there are sharp shifts too. A well known example is the Younger Dryas period, when, just after the recovery from the last glacial maximum, the climate at Greenland relapsed to very cold conditions for many centuries and then suddenly jumped back to a >10° warmer state (5) (Fig. 1*M*). An even more recent abrupt climate shift is the sudden shift of North Africa from a savanna-like state with scattered lakes to a desert state ≈5,000 years ago (6) (Fig. 1*O*).

Proposed explanations for these and other examples of abrupt climate change usually invoke the existence of thresholds in external conditions where the climate system is particularly sensitive, or even has a tipping point (7), similar to that of a canoe where one leans over too much to one side. In models such tipping points correspond to bifurcations (8) where, at a critical value of a control parameter, an attractor becomes unstable, leading to a shift to an alternative attractor. The underlying mechanism causing such extreme sensitivity at particular thresholds is typically a positive feedback. The earth system is notoriously riddled with such positive feedbacks (9–11). Unfortunately, the explanations for abrupt climatic change in the past

remain rather hypothetical because they are difficult to test. Even if the proposed mechanisms seem plausible, our capacity to model these systems accurately is too limited to conclude with reasonable certainty that tipping points are involved. This is particularly worrisome in view of the possibility of hitting on a tipping point as current climate change proceeds. Although most climate scientists would acknowledge that possibility, we are simply unable to predict if and when future climate change might bring us to a critical threshold (1). Even though climate models are rapidly improving, the chances that we will soon be able to predict potential tipping points with sufficient accuracy seem negligible. A similar situation exists in ecology where the existence of thresholds for catastrophic shifts has been shown for a range of systems (12), but prediction of such shifts has remained elusive.

In the face of our limited mechanistic insight it would be invaluable to have another way to find out whether past abrupt climate change was related to the crossing of critical thresholds, and to know whether parts of our current climate system may be approaching such a threshold. A possible clue that we explore here is to use the theoretical finding that, as a rule, dynamical systems become "slow" when a critical point is approached as conditions are gradually changing. In technical terms, the mechanism is that the maximum real part of the eigenvalues of the Jacobian matrix tends to zero as a bifurcation point is approached (13). As a result the dynamical system becomes increasingly slow in recovering from small perturbations (13–15).

Although an ideal way to test whether a system is slowing down (15) would be to study its response to small experimental perturbations, this is obviously of little use for analyzing past climate change. An alternative is to interpret fluctuations in the state of a system as its responds to natural perturbations. Slowing down should then simply be reflected as a decrease in the rates of change in the system, and therefore, as an increase in the short-term autocorrelation in the time series (16). Various authors have elaborated methods to detect slowing down associated with a shift in model-generated time series of the thermohaline circulation (17–19). Kleinen *et al.* (17) analyzed spectral properties, and Held and Kleinen (18) focused on autocorrelation as a statistic to detect slowing down before the transition. Livina and Lenton (19) suggested an approach inspired by a technique for detecting long-term memory in a time series. Despite the interest in this field, so far, no significant signs of slowing down before a shift have been shown on real data.

Fig. 1. Eight reconstructed time series of abrupt climate shifts in the past. (*A*) The end of the greenhouse Earth, (*M*) the end of the Younger Dryas, (*K*) the Bølling-Alleröd transition, (*O*) the desertification of North Africa, (*I*) the end of the last glaciation, and (*G, E,* and *F*) the ends of earlier glaciations. In all cases the dynamics of the system slow down before the transition, as revealed by an increasing trend in autocorrelation (*B, D, F, H, J, L, N,* and *P*). The gray bands identify transition phases. The arrows mark the width of the moving window used to compute slowness. The smooth gray line through the time series is the Gaussian kernel function used to filter out slow trends. Data in *A* come from tropical Pacific sediment core records, data in *M* are from the Cariaco basin sediment, data in *K* come from the Greenland GISP2 ice core, data in *O* from the sediment core ODP Hole 658C off the west coast of Africa, and data presented in *C, E, G,* and *I* are from the Antarctica Vostok ice core (additional details are in supporting information (SI) Table S1 and Fig. S1).

Here, we analyze the change in autocorrelation in time series of eight ancient events of abrupt climate change reconstructed from geological records (Fig. 1; see *Methods*) to examine whether the climate system slows down when a critical threshold is approached. Because we are interested in the possibility of using such information as an early warning signal, we used only

data from before the actual transition (Fig. 1, shaded bands) to scan for slowing down. Details of the time series and the identification of the period before the shift can be found in Table S1. Techniques of data processing are described in *Methods*.

Results and Discussion

Evidence for Critical Slowing Down. In all examples of abrupt climate change we analyzed, autocorrelation showed an increase in the period before the shift (Fig. 1 *B*, *D*, *F*, *H*, *J*, *L*, *N*, and *P*), suggesting that these climate systems did indeed slow down before the abrupt change, as expected theoretically for systems approaching a tipping point. All of the trends were significant as measured by the Kendall rank correlation coefficient τ, but the strength of the correlation varied among cases. There was a marked increase in slowing down before the end of the greenhouse Earth (Fig. 1*B*), the end of the Younger Dryas (Fig. 1*N*), and the end of glaciation I (Fig. 1*J*). Autocorrelation moderately increased before the end of glaciation IV, glaciation III, and the desertification of North Africa (Fig. 1 *D*, *F*, and *P*), whereas the end of the Bølling-Allerød (Fig. 1*L*) and the end of glaciation II (Fig. 1*H*) showed weak signs of slowing down. We explored the likelihood that our method would find such results by chance, that is, without an underlying critical slowing down causing the pattern, by studying the occurrence of trends in computer-generated surrogate time series (see *Methods*). The approach was to generate large numbers of randomized time series with characteristics similar to the analyzed stretches of climate series before episodes of abrupt change, and see in how many cases our analysis would find an increase in autocorrelation by chance. These analyses (see *SI Text*, Table S2, and Fig. S3) indicated that the probability of finding the increase in autocorrelation detected in the data by chance is very low for the three transitions that showed the strongest slowing down (end of greenhouse Earth, end of Younger Dryas, and end of glaciation I). These records have the most detailed data (all >450 data points). The other time series are much less detailed (all <150 data points), and our surrogate data analyses suggest higher probabilities of finding the observed trends by chance in those cases. The lower number of points in some of the series obviously makes the results less reliable, not only because of the small number of points *per se*, but also because the resolution can be insufficient to capture the short-term autocorrelation. This is especially so in the case of the desertification of North Africa, where the points are spaced almost a century apart, which may well be too short to capture the interactive dynamics of vegetation and monsoon supposed to drive the dynamics. The scarcity of points in the record ($N_p = 30$ before the transition) results in residuals of alternating positive and negative values and in estimates of the autoregressive coefficient α_1 that show a negative autocorrelation (Fig. 1*P*).

To weigh the combined uncertainties, and look at the overall picture, we computed the probability of finding the complete set of *P* values by chance, by using Fisher's combined probability approach. This combined probability appears to be very small ($P < 0.003$) irrespective of the approach taken to generate surrogate data (Table S2).

Robustness of Results to the Choice of Methods. The results obviously depend on choices made in the data processing (see *Methods*). Two important parameters are the bandwidth used in the function for filtering and the size of the sliding window used to compute the autocorrelation. We performed an extensive analysis of the sensitivity of outcomes to the choice of these parameters for our three longest time series. The results indicate that the observed increase in autocorrelation before the climate shifts is a rather robust outcome. Actually, this analysis shows that we could have obtained more significant trends by tailoring these parameters for the specific series (Fig. S4). We also explored whether interpolation used to generate equidistant data for the time series analyses might have caused spurious trends in autocorrelation (*SI Text*, Fig. S1, Fig. S2). Estimates of autocorrelation on the noninterpolated data gave approximately similar results (Table S3) (see also *SI Text*).

Comparison to Model Results. Approaching the problem from a different angle, to check whether the theoretically predicted critical slowing down may indeed be expected to be visible from autoregressive coefficients in climate data, we also used our methods to analyze simulation results from climate models that were slowly driven across a known threshold (Fig. 2). The models deal with three quite different systems: the North African paleo-monsoon system, the thermo-haline circulation, and the earth temperature as affected by the ice-albedo feedback. Model details and references are given in *Methods* and in the *SI Text*. In all cases our indicator picked up an increase in slowness, comparable to that found in the geological records. Also, the results of bootstrap analyses and sensitivity analyses applied to model results are comparable to those from our climate datasets (Fig. S3, Fig. S4, Table S2). This lends further support to the idea that the patterns detected in the data do indeed correspond to critical slowing down as predicted by the theory.

Perspectives. It may seem rather surprising that all cases of sharp climate shifts we analyzed were announced well before they happened by changes in the pattern of fluctuations. Indeed, our bootstrap analysis shows that approximately half of the positive trends in autocorrelation may well have arisen by chance (the desertification of North Africa, the Bølling-Allerød transition and the end of glaciations II and III). Nonetheless, our analyses also show that the combined probability of finding these trends is extremely low. Furthermore, the close similarity to what can be shown in climate models suggests that the patterns in the data may indeed represent the slowing down of a system approaching a tipping point.

Our results have profound implications for climate science. So far, support for the idea that tipping points can be the explanation for dramatic climatic shifts in the past has been based on models of specific mechanisms. Although compelling cases have been built, there is always considerable uncertainty because it is simply very difficult to prove what had been the mechanism behind such events in the far past. The slowing down that our analysis suggests does not point to any specific mechanism. Rather, it is a universal property of systems approaching a tipping point. Therefore, it represents an independent line of evidence, complementing model-based approaches, suggesting that tipping points exist in the climate system. Clearly, this is an important insight because it implies that, in principle, internal feedback can propel the climate system through an episode of rapid change once a critical threshold is reached.

Obviously, detection of critical slowing down has two faces. In hindsight it may help to tease out whether past dynamics may be explained by the existence of critical thresholds. With respect to predicting future climate change, it may give us an indication of whether we are entering a situation in which the parts of the earth system may amplify rather than buffer human-induced climate change. Clearly, there are challenges and limitations. Long time series of sufficient quality are needed, and resolution needs to be sufficient to capture the characteristic time scale of the internal dynamics of the system. Similarly, good detrending is challenging but critically important, because unfiltered trends may lead to patterns in autocorrelation that are not related to the system's dynamical response to perturbations we wish to probe. An important fundamental limitation we should keep in mind is that slowing down will only occur if the system is moving gradually toward a threshold. Therefore, transitions caused by a sudden large disturbance without a preceding gradual loss of

Fig. 2. Three simulated abrupt climate transitions. Transition to an icehouse Earth (*A*), collapse of the thermo-haline circulation (*C*), and desertification of North Africa (*E*) (see *SI Text* for details on simulations). As in the reconstructed real dynamics, the transition is preceded by slowing down as revealed by increased autocorrelation (*B*, *D*, and *F*). The gray bands identify the transition phases. The arrows mark the width of the sliding window used to compute slowness. The smooth gray line through the time series is the Gaussian kernel function used to filter out slow trends. All models pass a fold bifurcation *F* as a control parameter is slowly changing (relative radiation, freshwater forcing, and insolation, respectively). In the case of the ocean circulation and desertification model (*C* and *E*), there are also alternative attractors present implying hysteresis (dashed line), if the change in the control variable would be reversed on the shift. Points F$_1$ and F$_2$ are saddle-node bifurcation points.

resilience will not be announced by slowing down. Certainly, current trends in atmospheric carbon are rather fast compared with the dynamics of ice caps and ocean heat contents, and fluctuations of such variables may therefore not show detectable slowing down on century scales. By contrast, slowing down could possibly be detected in faster subsystems that might have tipping points such as regional atmospheric circulation patterns. In view of our current inability to predict potential abrupt climate shifts (1), having slowing down as a clue for detecting whether such parts of the climate system may be approaching a threshold is a marked step forward in projecting future climatic changes.

Putting our results in an even wider perspective, it is important that slowing down is a universal property of systems approaching a tipping point. This implies that our techniques might in principle be used to construct operational early warning systems for critical transitions in a wider range of complex systems where tipping points are suspected to exist, ranging from disease dynamics and physiology to social and ecological systems.

Methods

Data Sources. We used examples of climatic transitions that have been widely interpreted as significant shifts in the climate record and for which underlying positive feedback has been suggested as mechanistic explanation. We have not preselected the examples on the basis of preliminary results from our own analyses. The time series used represent climate data proxies derived from different sources. All were downloaded from the World Data Center for Paleoclimatology, National Geophysical Data Center, Boulder, Colorado (http://www.ncdc.noaa.gov/paleo/data.html). The terrigenous dust record was accessed from the Lamont Doherty Earth Observatory Institute of Columbia University, New York (http://www.ldeo.columbia.edu/~peter/Resources/data.html). Full details on the data records used are given in Table S1.

Data Selection. We used only points in the record that correspond to the period before the transition (Table S1). The exact transition points were determined by eye and all were approximately equal to those cited in the original articles where the records appeared. We have chosen the transition points conservatively, in the sense that we avoided including points that were part of the transition itself. This is important, because, due to increased serial correlation, inclusion of such points would bias the estimate of our slowing-down indicator. In a few cases, double values for the same date occurred in the original files. Those were averaged to provide a single value for each chronology.

Interpolation. We used linear interpolation to transform the climate records to time series with equidistant data. This allows us to use the time series analysis approaches suggested earlier for detecting slowing down (17, 18, 20) on real reconstructed climate records.

Detrending. To filter out long trends and to achieve stationarity we subtracted a Gaussian kernel smoothing function from the data and used the remaining residuals for the estimation of the autoregressive coefficient at lag 1. We chose a bandwidth in such a way that we do not overfit while still removing the long-term trends visible in the records. The same treatment was applied also to the simulated time series and the original records without interpolated points (see Table S3). Fig. S2 shows the interpolated, filtered time series and the resulting residual time series of Fig. 1 *A*, *M*, and *I* for visual inspection.

Autocorrelation. The autocorrelation at lag 1 was computed by fitting an autoregressive model of order 1 (AR1 model of the form $x_{t+1} = \alpha_1 x_t + \varepsilon_t$, by an ordinary least-squares (OLS) fitting method) applied on the data points within a sliding window of fixed size up to the transition point. In each case we took a sliding window of half the size of the interpolated time series. We tested for evidence of slowing down by estimating the nonparametric Kendal rank-correlation τ statistic on the estimates of the autoregressive coefficients α_1 (details in *SI Text*).

Model-Generated Time Series. We used a stochastic 1D energy balance climate model forced by relative incoming radiation to simulate data of ocean temperature that reflect a transition to an icehouse earth (21) (Fig. 2*A*). The thermo-haline circulation dynamics is generated by the CLIMBER-2 climate model of intermediate complexity (Fig. 2*C*). The data series on desertification in Western North Africa (Fig. 2*E*) was produced by using a stochastic version

of the climate box model (22) forced by reconstructed solar irradiance and atmospheric CO_2 concentration. See *SI Text* for the model details.

Surrogate Data. For each time series we tested the likelihood of obtaining our computed trend statistics (Kendall's τ rank correlation) by chance by using 1,000 surrogate time series of the same length as the filtered simulated and real data in three different ways. First, we bootstrapped our datasets by shuffling the original residual time series and picking data with replacement to generate surrogate records of similar distribution (mean and variance). Second, we produced a surrogate time series that had the same Fourier spectrum and amplitudes as the original sets (23). Last, we created surrogate datasets produced by an autoregressive model of order 1 with the same variance, mean and autocorrelation at lag 1 with the residuals time series

starting from the same initial value as in the original series (23). For each surrogate set, we computed the trend detection statistic. We then calculated the probability that our estimates of the trend statistic would be observed by chance as the fraction of the 1,000 surrogate series scoring the same value or a higher one. The probability distributions for the model and data trend statistic as well as details on how we produced the surrogate sets are summarized in Table S2 and Fig. S3.

1. Alley RB, *et al.* (2003) Abrupt climate change. *Science* 299:2005–2010.
2. Tripati A, Backman J, Elderfield H, Ferretti P (2005) Eocene bipolar glaciation associated with global carbon cycle changes. *Nature* 436:341–346.
3. Kump LR (2005) Palaeoclimate—Foreshadowing the glacial era. *Nature* 436:333–334.
4. Petit JR, *et al.* (1999) Climate and atmospheric history of the past 420,000 years from the Vostok ice core, Antarctica. *Nature* 399:429–436.
5. Clark PU, Pisias NG, Stocker TF, Weaver AJ (2002) The role of the thermohaline circulation in abrupt climate change. *Nature* 415:863–869.
6. deMenocal P, Ortiz J, Guilderson T, Sarnthein M (2000) Coherent high- and low-latitude climate variability during the holocene warm period. *Science* 288:2198–2202.
7. Lenton TM, *et al.* (2008) Tipping elements in the Earth's climate system. *Proc Natl Acad Sci USA* 105:1786–1793.
8. Kuznetsov YA (1995) *Elements of Applied Bifurcation Theory* (Springer, New York).
9. Lawton J (2001) Earth system science. *Science* 292:1965.
10. Woodwell GM, *et al.* (1998) A simulation model to illustrate feedbacks among resource consumption, production, and factors of production in ecological-economic systems. *Climatic Change* 40:495–518.
11. Rial JA, *et al.* (2004) Nonlinearities, feedbacks and critical thresholds within the earth's climate system. *Climatic Change* 65:11–38.
12. Scheffer M, Carpenter SR, Foley JA, Folke C, Walker B (2001) Catastrophic shifts in ecosystems. *Nature* 413:591–596.
13. Strogatz SH (1994) *Nonlinear Dynamics and Chaos with Applications to Physics, Biology, Chemistry and Engineering* (Westview, Reading, MA).
14. Wissel C (1984) A universal law of the characteristic return time near thresholds. *Oecologia* 65:101–107.
15. van Nes EH, Scheffer M (2007) Slow recovery from perturbations as a generic indicator of a nearby catastrophic shift. *Am Nat* 169:738–747.
16. Ives AR (1995) Measuring resilience in stochastic-systems. *Ecol Monogr* 65:217–233.
17. Held H, Kleinen T (2004) Detection of climate system bifurcations by degenerate fingerprinting. *Geophys Res Lett* 31:L23207.
18. Kleinen T, Held H, Petschel-Held G (2003) The potential role of spectral properties in detecting thresholds in the Earth system: Application to the thermohaline circulation. *Ocean Dynam* 53:53–63.
19. Livina VN, Lenton TM (2007) A modified method for detecting incipient bifurcations in a dynamical system. *Geophys Res Lett* 34:L23207.
20. Ives AR, Dennis B, Cottingham KL, Carpenter SR (2003) Estimating community stability and ecological interactions from time-series data. *Ecol Monogr* 73:303–330.
21. Fraedrich K (1978) Structural and stochastic analysis of a zero-dimensional climate system. *Q J R Meteor Soc* 104:461–474.
22. Brovkin V, Claussen M, Petoukhov V, Ganopolski A (1998) On the stability of the atmosphere-vegetation system in the Sahara/Sahel region. *J Geophys Res* 103:31613–31624.
23. Theiler J, Eubank S, Longtin A, Galdrikian B, Farmer JD (1992) Testing for nonlinearity in time-series—The method of surrogate data. *Physica D* 58:77–94.