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Early warning of climate tipping points

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A climate 'tipping point' occurs when a small change in forcing triggers a strongly nonlinear response in the internal dynamics of part of the climate system, qualitatively changing its future state. Human-induced climate change could push several large-scale 'tipping elements' past a tipping point. Candidates include irreversible melt of the Greenland ice sheet, dieback of the Amazon rainforest and shift of the West African monsoon. Recent assessments give an increased probability of future tipping events, and the corresponding impacts are estimated to be large, making them significant risks. Recent work shows that early warning of an approaching climate tipping point is possible in principle, and could have considerable value in reducing the risk that they pose.

Elements of the climate system known as tipping elements[1] — which could pass a tipping point this century and undergo a qualitative change in state within this millennium — include the Atlantic thermohaline circulation (THC), West Antarctic ice sheet, Greenland ice sheet, Amazon rainforest, boreal forests, West African monsoon, Indian summer monsoon, and El Niño/Southern Oscillation (ENSO). Passing a tipping point (defined in Box 1) is typically viewed as a 'high-impact low-probability' event. However, recent (re)assessments give an increased likelihood of 'large-scale discontinuities' in the climate system under a given level of global warming[2], such that unmitigated climate change could result in some becoming 'high-impact high-probability' events[1,3], demanding early warning capability[4].

Early warning can take several forms, ranging from the knowledge that an event could occur, through qualitative assessment that it is becoming more likely, to a forecast of its timing. Recently, there has been growing interest in generic early warning signals[5] for critical transitions in complex systems, especially slowing down[6] as a bifurcation is approached. Furthermore, slowing down has been found in climate-model output[7–12] and palaeoclimate data[9,10,12] approaching abrupt transitions. This suggests probabilistic forecasting of some conceivable future climate tipping points may be feasible[1], especially if such statistical early warning indicators can be combined with dynamical modelling. However, critics have questioned the statistical robustness of proposed early warning signals[13], and have noted that some types of abrupt transition carry no early warning signals[13,14]. These potential problems are not unique to climate tipping points.

For several rapid-onset natural hazards, for example, hurricanes[15] and tsunamis[16], quite sophisticated early warning systems are already in place[17], whereas for some slower-onset hazards, for example, drought[18] and malaria outbreaks[19], seasonal climate-forecasting skill is beginning to be used in early warning. The United Nations has called for the development of a globally integrated early warning system for all natural hazards[20,21]. This should include climate tipping points, because they present significant risks in themselves, and they will affect shorter-term hazards. A tipping point can be seen as a nonlinear shift in the shape or location of the frequency distribution of events that represent the climate, in the tails of which are extreme events. For example, tipping of the Greenland or West Antarctic ice sheets would accelerate sea-level rise, in turn increasing the impact of hurricane-driven storm surges or tsunamis. Dieback of the Amazon or boreal forests would cause increased wildfires. Disruption of the West African monsoon would affect drought in the Sahel.

If early warning can be achieved for climate tipping points, it could have considerable value for societies, as hinted at by the value of shorter-term, seasonal, climate forecasting to agriculture[22–24]. For example, if El Niño increases in amplitude in a warming world, as some forecasts suggest[25], the resultant annual damages to the agricultural sector could exceed $1 billion (ref. 26), but these damages could be greatly reduced by effective response to seasonal early warning of El Niño[26]. Even earlier warning of, for example, potential future El Niño 'regime shifts' would add further value to adaptation efforts.

Here, recent scientific progress on the early warning of climate tipping points is reviewed, noting that successful early warning systems would rely on social and technological factors as well as on scientific capability[17,20,21]. In the first section, recent estimates of the proximity of climate tipping points are summarized, including a discussion of the structural weaknesses of present models. This leads to a focus on statistical methods of forecasting, as a complement to model-based approaches. In the second section, generic early warning indicators of approaching bifurcations are introduced and contrasted with the lack of forewarning of purely noise-induced transitions. The third section reviews recent tests of bifurcation early warning methods on climate model output and palaeoclimate data. The fourth section discusses the limitations of early warning methods, including false alarms and missed alarms. Finally, the research needed to improve scientific early warning capability and translate it into effective risk reduction is identified.

Proximity of tipping points

The proximity of different climate tipping points has been estimated from a variety of sources including process-based understanding, model projections and analysis of palaeoclimate data[1,27]. For those tipping points that can be related (albeit indirectly) to global mean temperature change, estimates of individual threshold levels differ and range[1] across 0.5 to 6 °C of global warming (above 1980–1999). Recent estimates of the corresponding aggregate risk of 'dangerous anthropogenic interference with the climate system' (due specifically to the crossing of large-scale thresholds) lie mostly in the range

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Box 1 | Defining climate tipping points

The phrase 'tipping point' captures the colloquial notion that 'little things can make a big difference'[81], that is, at a particular moment in time, a small change can have large, long-term consequences for a system. The term 'tipping element' was introduced[1] to describe large-scale subsystems (or components) of the Earth system that can be switched — under certain circumstances — into a qualitatively different state by small perturbations. These must be at least sub-continental in scale (length scale of order ~1,000 km). The tipping point is the corresponding critical point — in forcing and a feature of the system — at which the future state of the system is qualitatively altered. To define this, it must be possible to identify a single control parameter (ρ), for which there exists a critical control value (ρ_{crit}), from which a small perturbation ($\delta\rho > 0$) leads to a qualitative change ($\hat{F}$) in a crucial feature of the system (F), after some observation time ($T > 0$). The actual change (ΔF) is measured with respect to a reference state of the feature at the critical value:

$$|\Delta F| = |F(\rho \geq \rho_{crit} + \delta\rho|T) - F(\rho_{crit}|T)| \geq \hat{F} > 0$$

In this definition, the critical threshold (ρ_{crit}) is the tipping point, beyond which a qualitative change occurs, and the change may occur immediately after the cause or much later.

The subset of 'policy-relevant' tipping elements is defined[1] by the following (additional) conditions. (1) Human activities are interfering with the system such that decisions taken within a 'political time horizon' (T_P ~100 years) can determine whether the tipping point (ρ_{crit}) is crossed. If it is crossed, (2) the time to observe a qualitative change (including the time to trigger it) lies within an 'ethical time horizon' (T_E ~1,000 years). (3) A significant number of people care about the fate of the system because either it contributes significantly to the overall mode of operation of the Earth system, or it contributes significantly to human welfare, or it has great value in itself as a unique feature of the biosphere.

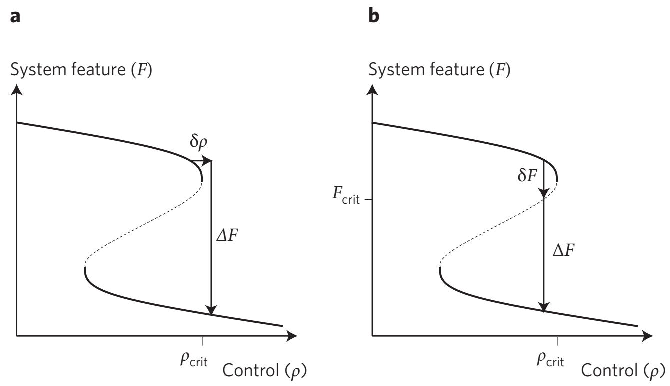

Figure 1 | Two sources of abrupt change. a, Bifurcation, where a small change in forcing ($\delta\rho$) past a critical threshold ρ_{crit} causes a large, nonlinear change in system state (ΔF) (thus meeting the tipping point definition in Box 1). **b**, Noise-induced transition, where internal short-term variability (δF) passing an unstable steady state F_{crit} causes a large, nonlinear change in system state (ΔF) without any change in forcing control (ρ). Solid lines are stable steady states, dashed lines are unstable steady states.

of 1–4 °C of global warming[2,28–30]. Given the large uncertainties, expert elicitation[1,3,31,32] has also been used to quantify and combine the subjective judgements of experts regarding the proximity of different climate tipping points. Even with the most conservative assumptions, the results[3] suggest it is more likely than not that at least one of five tipping points considered will be passed in a >4 °C warmer world.

So, can the proximity of individual thresholds be more accurately tied down? Without a precise past analogue of future climate change, predictive models are needed. However, weaknesses of recent global climate models limit their usefulness in this context. First, some potential tipping elements, for example, large ice sheets, have been missing from global coupled models. Second, even specific models of, for example, ice sheets, have been missing key processes and feedbacks that could generate nonlinear dynamics[33]. Third, at the regional scales of interest here, global models have been poor at capturing some tipping elements, for example, the West African monsoon[34], and even among those few models that have captured its present pattern, future predictions diverge in sign[34] (let alone magnitude). Fourth, for some well-studied tipping elements, for example, the Atlantic THC, models seem to be systematically biased with respect to data regarding its stability regime[35]. Also, where the joint uncertainties of a model and data have been formally combined, for example, for the Atlantic THC, the resulting uncertainty in tipping threshold (or lack of it) is large[36]. Finally, no model used for future projection has yet been able to simulate the most abrupt shifts in the palaeoclimate record. Although several of these issues are being addressed, given the current limitations of climate models, interest has grown in statistically based methods of directly diagnosing proximity to a tipping point.

Predictability and early warnings

The trigger of any future climate tipping point is likely to involve some combination of natural variability on top of an underlying forcing due to human activities. This suggests a probabilistic approach to forecasting is most appropriate, based on a paradigm where short-term variability in the climate system is characterized as a stochastic process ('noise') interacting with longer-term deterministic dynamics[37]. For a given abrupt change, the balance of deterministic and stochastic (random) processes driving it will determine its predictability. This can be highlighted by the following two, idealized, limiting cases (Fig. 1), although in reality, steady forcing and noise are both likely to play a role in tipping phenomena.

Bifurcations. Slow forcing past a bifurcation point (Fig. 1a) fits the definition[1] of a tipping point (Box 1) and shows greatest promise for early warning. In general (and nearly universally[38]), as a system approaches a bifurcation point where its current state (or mode of variability) becomes unstable, and it switches to some other state (or mode), one can expect to see it become more sluggish in its response to small perturbations[5,6,8,39,40]. This can be visualized for a system in a potential well that is getting shallower as it approaches a saddle-node bifurcation (Fig. 2); the ball representing the present state of the system, rolls back ever slower from perturbations, as bifurcation is approached. Mathematically, for systems that are gradually approaching a bifurcation point in their equilibrium solutions, the leading eigenvalue tends towards zero, indicating a tendency towards infinitely slow recovery from perturbations. This phenomenon — termed 'critical slowing down' in dynamical systems theory — is widely known[6,41], but has only recently been applied to climate dynamics[7,8].

Slowing down causes the intrinsic rates of change in a system to decrease, and therefore the state of the system at any given moment should become more like its past state. This increase in memory can be measured in a variety of ways. As slowing down occurs, time-series data becomes more correlated with itself from one point to the next, and this is measured by the (lag-1) autocorrelation function (ACF)[8,10]. Correlations over longer timescales also increase and this can be measured by de-trended fluctuation analysis (DFA)[9], which picks up the same slowing down signal as ACF (and is also sensitive to data becoming non-stationary and tending towards a random walk, for example, as a phase transition is approached). In the spectral (that is, frequency) domain, critical slowing down is expected to cause a shift of power to lower frequencies[7], meaning slower fluctuations of increased amplitude. Closely related phenomena are 'small-signal amplification'[41] and 'noise amplification'[42], in which small periodic perturbations or noise are amplified at particular frequencies that depend on the type of bifurcation being approached. Amplification occurs because of the decrease of damping and strengthening of positive feedback (or 'gain') in a system, just before bifurcation, which can lead to unlimited growth of fluctuations.

Other early warning indicators of approaching bifurcation have been suggested. First, for a given perturbation, a system will move further in a shallower potential well (Fig. 2), causing increased variance in data as a bifurcation point is approached[13,43–45]. Second, a system approaching a bifurcation may undergo greater amplitude deviations in the direction of the state it is destined to shift to, than in the opposite direction, with a trend that should show up as increasing skewness in its responses[44–46]. The spatial equivalents of increasing correlation[47], variance[16,17] and skewness[48] have also been proposed as early warning indicators of thresholds in systems where spatial information is available[47–49]. Finally, in systems with spatial patterning, for example, semi-arid vegetation, the nature of the pattern may change as a bifurcation is approached[50]. However, this can be an ambiguous indicator of change[51], and it is unclear how to make it quantitative.

Potentially the most robust early warning indicator of approaching bifurcation will be some combination of different statistical properties of the data[13]. Theory suggests that, for the simplest case at least, the ratio of variance to correlation time is a constant (determined by the noise amplitude) as a bifurcation point is approached[13]. Other studies have combined different indicators in pursuit of a robust early warning signal[48,52], but these combinations tend to be *ad hoc* and *a posteriori* (that is, once one knows a tipping point has been passed). What is needed is a generic *a priori* early warning indicator. Hence the recent focus on critical slowing down.

Noise-induced transitions. Purely noise-induced transitions between existing stable states (or modes) of a system (Fig. 1b), can also be described as tipping points[13], although they don't fit a definition[1] of forced changes (Box 1). The abrupt warming events during the last ice age, known as Dansgaard–Oeschger events, provide a likely real-world example[13]. In contrast to approaching bifurcations, noise-induced transitions are fundamentally unpredictable[13,14] and should show none of the early warning signals noted above, because there is no systematic change in the shape of the underlying potential[13]. However, if the slowest decay rate in a system can be diagnosed, this still provides some indicator of the (in this case, unchanging) stability of the present state. When combined with a diagnosis of the noise amplitude (for example, using wavelet de-noising), this can give some indication of the vulnerability of a system state to noise-induced transitions[53]. For systems experiencing a sufficient degree of noise — such that they are spending time in different states — given a long enough time window of data, one can build up a picture of the number and stability (or otherwise) of the underlying states, based on the frequency distribution of the data[54]. Furthermore, if a long time window is moved through an even longer time series, changes in the number and stability of states over time can be detected[55,56]. In cases where the number of states is increasing, 'flickering' may occur — representing sampling of a new state — before it becomes stable[5,56,57]. Corresponding changes in the frequency distribution of the data could be translated into an early warning signal of the emergence of a new state[56]. However, from society's point of view, the individual noise-induced switches between states would remain a key concern, and the timing of these individual events (in models at least) remains unpredictable, so one has to resort to vulnerability indicators (such as, a 'one-in-x-year' event).

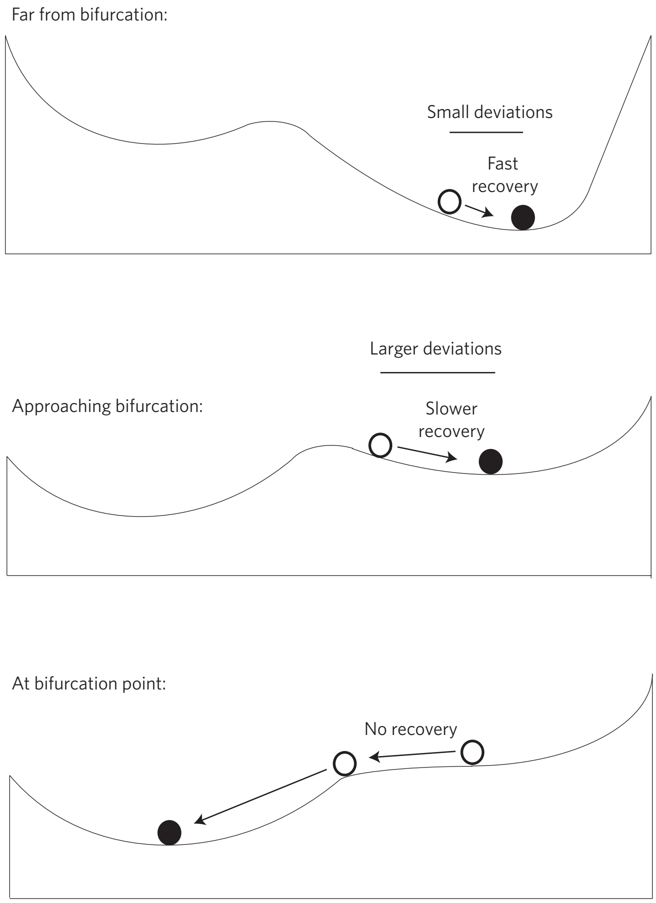

Figure 2 | Heuristic basis for early warning of an approaching bifurcation point. The valleys or potential wells represent stable attractors and the ball represents the state of the system. Under gradual forcing, the right potential well becomes shallower and finally vanishes (bifurcation) causing the ball to role abruptly to the left. Picture the system being nudged around by a short-term stochastic process (noise). The radius of the potential well is directly related to the system's response time to such small perturbations, which tends towards infinity as bifurcation is approached, that is, the system becomes more sluggish in response to perturbations ('critical slowing down'). Larger fluctuations are also expected as bifurcation is approached.

Other types of tipping point. Whether a tipping point exists should be considered in a time-dependent fashion[1] (Box 1), and there are potentially several other types, including reversible[1] and rate-dependent[58,59] tipping points. Strongly nonlinear but reversible transitions are expected to resemble bifurcation-type behaviour[1] so may carry similar early warnings, including slowing down. For rate-dependent tipping, rate of forcing and magnitude of noise should indicate vulnerability.

Tests of early warning indicators

At present, the best prospects for early warning are for bifurcation-type tipping points, even though noise will usually cause a system to exit

Table 1 | Early warning indicators of approaching bifurcation points and tests thereof.

Phenomenon	Indicator	System	Data Source	Signal	Reference(s)
Critical slowing down	Increasing autocorrelation, AR(1) coefficient	Climate	Models	+	8, 10, 12, 53
			Palaeorecord	+	10, 12, 53
				0	12, 13
		Ecological	Models	+	44
	Increasing return time from perturbations	Ecological	Models	+	39, 40, 45, 51
			Lab experiments	+	6, 52
	Increasing DFA exponent	Climate	Models	+	9, 11, 12
			Palaeorecord	+	9, 12
				−	12
	Spectral reddening	Climate	Models	+	7
		Ecological	Model	0	79
	Increasing spatial correlation	Ecological	Models	+	47
			Lab experiments	+	52
Increased variability	Increasing variance	Climate	Models	+	12
				0	12
			Palaeorecord	+	12
				0	13
				−	12
		Ecological	Models	+	43–45, 79
			Lab experiments	+	52
	Increasing spatial variance	Ecological	Model	+	48
			Data	+	49
			Lab experiments	+	52
Skewed responses	Increasing skewness	Climate	Palaeodata	0	46
		Ecological	Model	+	44–46
			Lab experiments	+	52
	Increasing spatial skewness	Ecological	Model	+	48

'+' means indicator increased as expected; '−' means indicator decreased, contrary to expectation; '0' means there was no significant change in the indicator.

its present state before a bifurcation is reached. Some of the proposed early warning indicators of bifurcation have been tested in climate models of varying complexity and in palaeoclimate data approaching abrupt transitions (Table 1, Figs 3 and 4). The absolute values of the indicators considered (Figs 3 and 4) are affected by the frequency of sampling; hence it is just any upwards trend that provides an early warning signal. The Kendall tau rank correlation coefficient is used here (insets in Figs 3 and 4) to measure the strength of the tendency of an indicator to increase (positive values) or decrease (negative values) with time, against the null hypothesis of randomness for a sequence of measurements against time[60] (value approximately zero).

Model tests. Climate model tests have shown that early warning methods based on detecting critical slowing down work in principle, in simple[7,10], intermediate complexity[8,9,12] (Fig. 3a) and fully three-dimensional (3D)[11,12] (Fig. 3b) models. Rising variance also provides early warning in intermediate complexity models[12] approaching thresholds (Fig. 3a), but is less clear in a 3D model[12] (Fig. 3b). Existing model tests focus largely on the example of a slowly forced collapse of the Atlantic THC, in which freshwater input to the North Atlantic Ocean is steadily increased by changing a forcing parameter. Either imposed white noise (Fig. 3a) or internal short-term variability (Fig. 3b) are used to diagnose decay rates in the model systems. The 3D model example (Fig. 3b) is most instructive for what may happen in real-world applications, as it couples dynamical components with very different internal timescales; the atmosphere and ocean. There is large interannual variability in overturning strength in the model ocean (as there is in observational data[61]), which primarily reflects coupling to the overlying atmosphere. If one inadvertently samples corresponding rapid decay modes that are not pertinent to bifurcation detection (for example, by de-trending with a short filtering bandwidth before examining autocorrelation), these actually speed up in the example, leading to a 'missed alarm'[12] (Fig. 3b, middle panel inset). However, consistent with the short memory of the atmosphere, using either a longer filtering bandwidth or aggregating data to a longer (for example, decadal) timescale is sufficient to reveal underlying slowing down in ocean dynamics[12]. This shows the importance of carefully selecting the parameters for statistical analysis.

Palaeorecord tests. Palaeoclimate data tests show mixed but encouraging results. Initial tests[9] detected critical slowing down during the ending of the last ice age in ice-core data from the Greenland Ice Sheet Project 2 (GISP2). Subsequent work[10] showed increasing autocorrelation in eight palaeoclimate time series' approaching transitions. However, there are no signs of slowing down or increased variability in North Greenland Ice Core Project (NGRIP) data approaching individual Dansgaard–Oeschger events during the last ice age[13]. The glacial Greenland climate can be characterized[54] by a stable, cold (stadial) climate state and a marginally stable, warm (interstadial) state, with the Dansgaard–Oeschger events representing unpredictable noise-induced switches between them[13,55]. However, the cold state became progressively more stable, and the warm state less stable, as the ice age progressed, until sometime before ~25 kyr BP the warm state passed a bifurcation point and

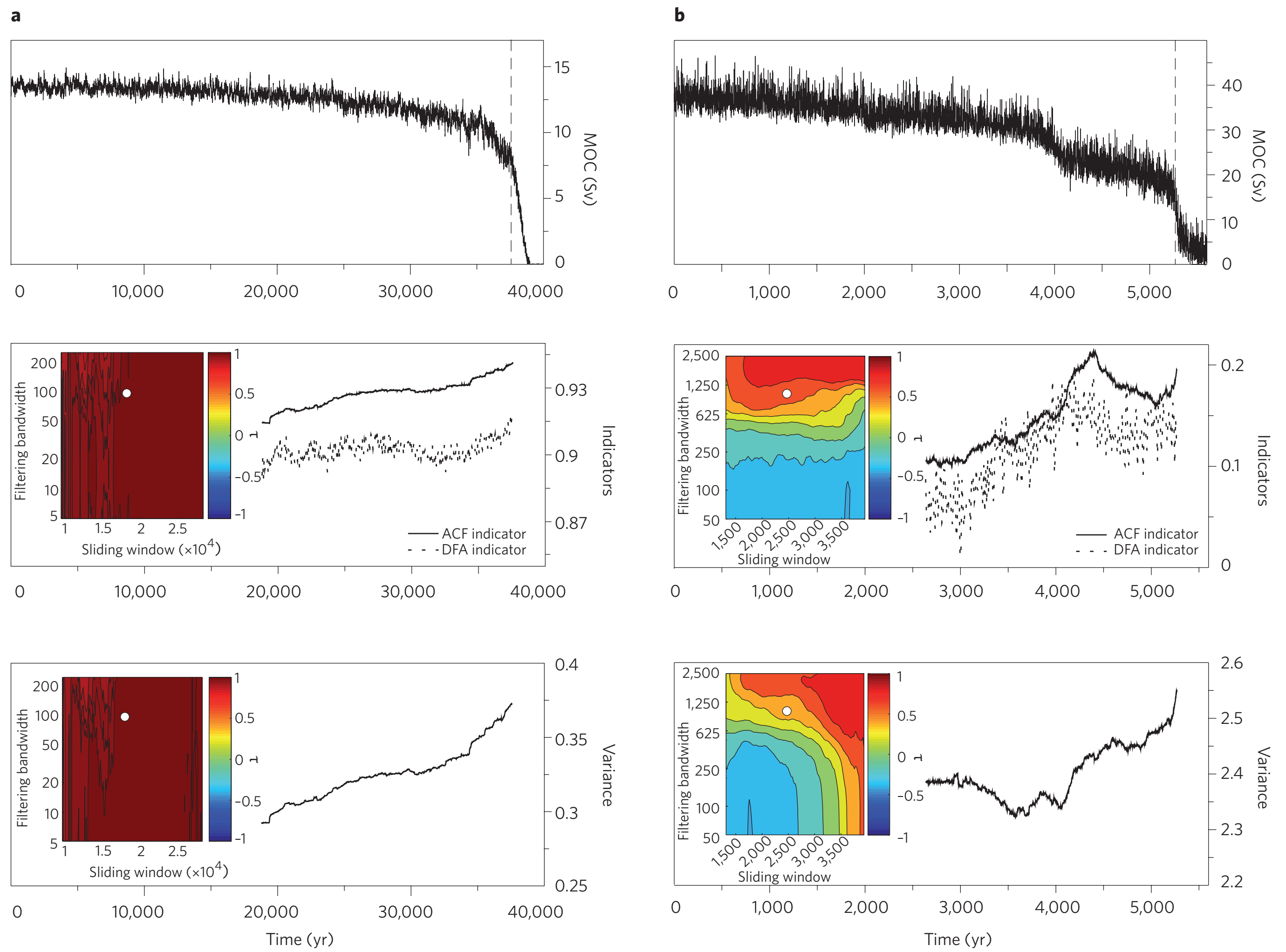

Figure 3 | Tests of early warning indicators in climate models. Slowly forced collapse of the Atlantic thermohaline circulation (data are maximum meridional overturning circulation (MOC)) in **a**, the GENIE-1 model (n = 37,600) and **b**, the GENIE-2 model (n = 5,270). Top: data (analysis stops at vertical dashed line before transition). Middle: example slowing down indicators from ACF (solid line) or DFA (dotted line). Bottom: example variance indicator. Insets: contour plots show Kendall rank correlation coefficient (τ) for the ACF indicator (middle) and variance (bottom) as a function of bandwidth used in Gaussian filtering to de-trend the original data, and sliding-window length (white dots correspond to example indicators). The Kendall τ coefficient measures the strength of the tendency of an indicator to increase (positive values) or decrease (negative values) with time, against the null hypothesis of randomness for a sequence of measurements against time (value approximately zero).

lost its stability[55]. During deglaciation, the warm state reappeared, but there is some disagreement over whether the Bølling–Allerød warming (Dansgaard–Oeschger event 1) in Greenland was preceded by slowing down[10] or not[13]. There is a weak signal[12] in GISP2 ice-core data, where variance is also increasing[12], but neither signal[13] appears in higher resolution NGRIP data. Slowing down in Antarctic (Vostok) ice-core data approaching the last glacial termination is ambiguous[12], as is any trend in variance[12] (Fig. 4a). However, robust signals[12] of critical slowing down are found in tropical Atlantic sediment-core data before the end of the Younger Dryas period (Fig. 4b), suggesting a bifurcation may underlie this transition (although variance robustly declines[12]). In the Holocene, a search for increased skewness[46] in data before Sahara desertification ~5 kyr BP showed no convincing signal (and the data are insufficient to test for critical slowing down).

Limitations of early warning

Existing tests show promise for early warning of bifurcation-type climate tipping points, but there are potential limitations of 'false alarms' (false positives) and 'missed alarms' (false negatives). These problems are common to other natural hazard early warning systems, and can undermine confidence in them[62,63]. However, societies can be quite tolerant of false alarms and still respond when a true alarm occurs[62].

False alarms. False alarms can arise because signals interpreted as indicative of approaching bifurcation are not statistically robust or have other causes[13]. Comparison of early warning methods being applied by different groups is limited[44,52], and some uncertainty remains over their sensitivity to parameter choices used in the statistical analyses (such as filtering bandwidth and sliding-window length), which can affect the significance, and even the sign, of any trend[10] (Figs 3 and 4).

A few guidelines can help guard against false alarms[12]. Before trying to extract warning indicators, where data is of sufficiently high temporal resolution to be sampling fast decay modes in the system in question, it can be aggregated such that the resulting time step is longer than the time it takes non-critical modes to decay, but still short enough to sample the slow decay of the critical mode[8,12]. Next the data should be de-trended, with a filtering bandwidth and

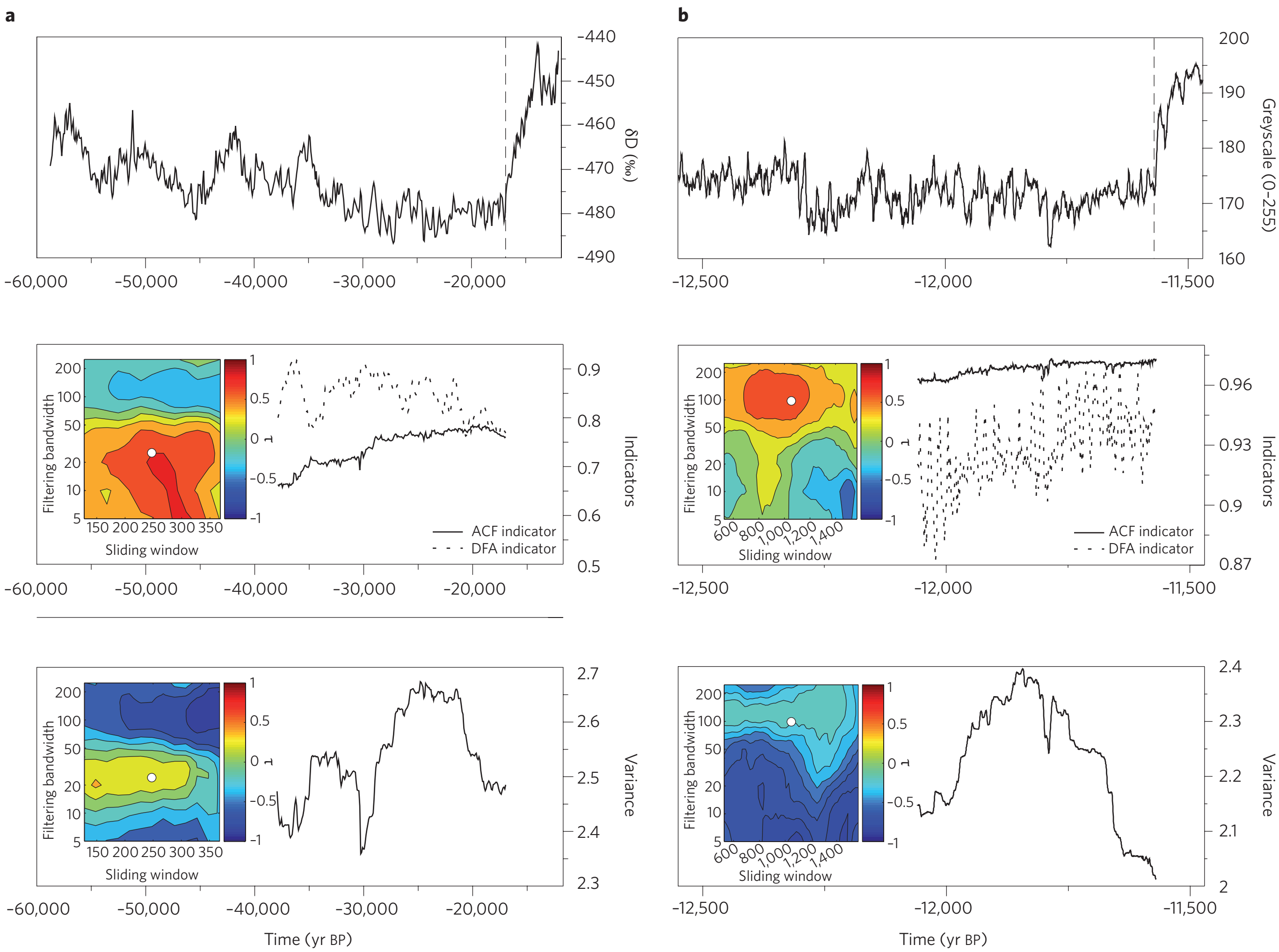

Figure 4 | Tests of early warning indicators in palaeoclimate data approaching abrupt transitions. a, Vostok ice-core deuterium proxy (‰) for local temperature 58.8–17 kyr BP (n = 513). **b**, Cariaco basin core PL07-58PC greyscale proxy (0–225) for local productivity in the tropical Atlantic, 12.5–11.6 kyr BP (n = 2,111). Top: data (analysis stops at vertical dashed line). Middle: example indicators from ACF (solid line) or DFA (dotted line). Bottom: example variance indicator. Insets: contour plots show Kendall rank correlation coefficient (τ) for the ACF indicator (middle) and variance (bottom) as a function of bandwidth used to de-trend the data, and sliding-window length (white dots correspond to example indicators). The Kendall τ coefficient is as described in Fig. 3.

sliding-window length carefully chosen (see insets in Figs 3 and 4) to remove any long-term trends whilst retaining the fluctuations pertinent to diagnosing slowing down. These method parameters should ideally be chosen based on theoretical guidelines[8,53] and the physics of the climate subsystem under consideration. Bandwidth should be much shorter than the time it takes the forcing parameter(s) to change, and much longer than the time it takes (initially) for small perturbations to decay[8,53]. The sliding-window length, when multiplied by the time step, should also be much shorter than the time it takes the forcing parameter(s) to change[8,53]. For the example of modelled Atlantic THC collapse (for example, Figure 3b), this means filtering bandwidth and window length should both be of the order of 1,000 yr. When analysing real data (for example, Fig. 4), the challenge is to estimate (or extract) the pertinent rates of forcing and decay in the system in question. Instead, some existing studies have come up with empirical guidelines, for example, a sliding-window length of half of the series[10]. In others, a wide range of values for bandwidth and window length have been experimented with to see how they affect the results[12] (Figs 3 and 4). Clearly more research is warranted to formulate and apply solid rules for the choice of method parameters.

Once one has a signal, for example, of rising autocorrelation, it could still be due to processes other than approaching bifurcation. To help guard against this, applying two different methods of detecting critical slowing down, can provide a useful cross-check[12]. In most examples[12] (Figs 3 and 4b), ACF and DFA methods give a similar signal, but in the case of Vostok ice-core data approaching the last glacial termination (Fig. 4a) the indicators give opposite trends, suggesting the signal is not robust. Alternatively, looking for rising variance as well as autocorrelation as a cross-check[13] works well in intermediate complexity models[12] (Fig. 3a). However, autocorrelation and variance may diverge, as seen in a 3D model known to be approaching a bifurcation[12] (Fig. 3b), and in palaeodata[12] (Fig. 4). This divergence can occur if slowing down causes fluctuations to decay more slowly, such that it reduces the ability of a system to track variable forcing, and thus reduces the variance (V. Dakos, personal communication). Alternatively, variance may decline in response to other drivers in the climate system, for example, the cold climate of the Younger Dryas (Fig. 4b) slowed Northern Hemisphere ice-sheet melt and this may have reduced the amplitude of freshwater fluctuations perturbing the Atlantic THC.

Missed alarms. Missed alarms can occur if abrupt transitions happen without underlying bifurcation (for example, noise-induced transitions[13]), but they can also occur even when bifurcation is approaching, for several reasons. First, to achieve an early warning, the time it takes to find out proximity to a threshold must be shorter than the time in which noise would be expected to cause a system to change state (the 'mean first exit time'[7]). Hence where internal variability in a system is high, it may exit its present state well before a bifurcation point is reached. The noise level can be taken account of, and early warning estimates adjusted accordingly[53]. However, in the worst case, a high noise level could prevent the detection of any early warning signals. Second, existing tests of bifurcation early warning (Table 1) are generally based on very gradual forcing of the systems in question, whereas human activities are forcing certain 'slow' parts of the climate system, for example, the ocean, ice sheets and biomes, faster than their internal dynamics allow them to respond. Hence they will be lagging their equilibrium solutions and may be committed to much greater changes than are observed at present[64]. This means a dynamical model simulating transient behaviour will be needed to establish proximity to a threshold. Also, for such 'slow' systems, a long record of their natural behaviour is needed to ascertain their slowest response timescale, but this demands longer palaeorecords than are available for, for example, the Atlantic THC.

Towards early warning systems

Despite these limitations, scientific tests show early warning signals exist for at least some climate tipping points, suggesting there is merit in building on them. Early warning systems should ultimately combine risk assessment, scientific prediction, careful warning formulation, effective communication and an appropriate response capability[17,20]. Here the research needed on risk assessment, improving scientific prediction and assessing response strategies is considered.

Risk assessment. The overall objective of any early warning system is to reduce risk[20], so the first step is to identify risks and assess their (relative) magnitude. Technically, risk is the product of the likelihood (or probability) of something happening and its negative impact (the magnitude of the potential loss). The focus above has been on improving information on the likelihood of passing a given tipping point, but ignorance regarding the corresponding impacts is arguably greater, and research on this is urgently needed[65]. Passing a climate tipping point is generally expected to have large negative impacts, but these have only begun to be quantified for some elements and scenarios[66], notably a collapse of the Atlantic THC[67–69]. The translation into societal impacts typically involves several intervening steps and variables, and underestimation problems arise because studies tend to only consider a subset of consequences or impacted sectors (for example, insurance[66]). For a collapse of the Atlantic THC[67,68], the magnitude and even sign of impacts has been contested[69], as have questionable extrapolations[70] to national security concerns[71]. Such disagreement[68–71] is to be expected, as impacts depend on human responses and are thus more epistemologically contested than assigning likelihoods to events[72].

With these caveats in mind, a 'straw man' tipping-point risk matrix is presented (Fig. 5). This illustrates some familiar dilemmas for the would-be risk manager: relatively high-impact low-probability events, such as West African monsoon shift, come out with a similar risk to relatively lower-impact high-probability events, such as Arctic summer sea-ice loss. However, what stands out are the high-impact high-probability scenarios as a priority for risk management effort — in this example, Greenland ice-sheet meltdown and West Antarctic ice-sheet collapse. To get a more scientifically credible and socially legitimate assessment of the

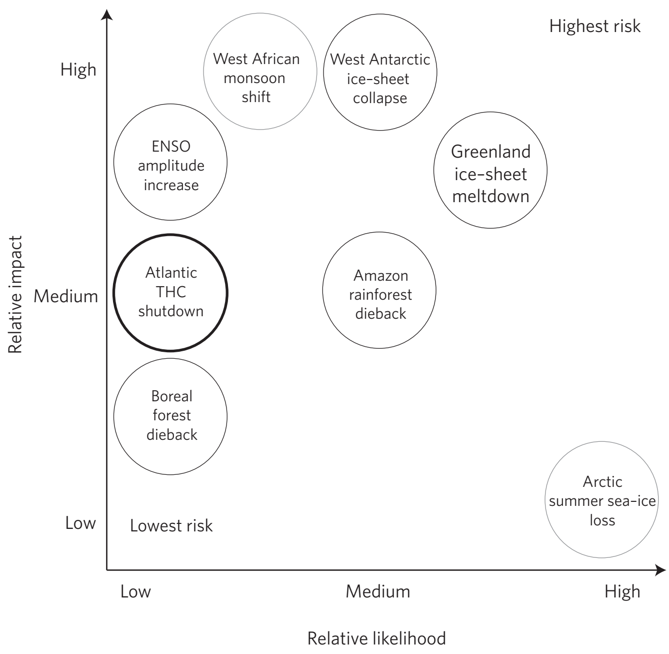

Figure 5 | A 'straw-man' risk matrix for climate tipping points. Relative likelihoods and impacts are assessed on a five-point scale: low, low-medium, medium, medium-high and high. Likelihood information comes from review of the literature[1,27,80] and expert elicitation[3] (feint rings indicate systems not considered in expert elicitation[3]). Impacts are based on limited research[66] and subjective judgment, and are relative to the one system (bold ring) with multiple impacts studies[66–69]. Impacts are considered on the full 'ethical time horizon' of 1,000 years (ref. 1; Box 1), assuming minimal discounting of impacts on future generations. (Note that most tipping point impacts would be high if placed on an absolute scale, compared with other climate eventualities.)

risks, a wider team of experts and relevant stakeholders should be engaged[72], including those likely to be most impacted, as well as those responsible for formulating and implementing policy. Such an assessment could then be used as a guide in prioritizing where to develop and deploy early warning systems.

Improving scientific prediction. The targets for early warning systems should also be guided by scientific considerations. In principle, the best prospects for bifurcation early warning should exist for relatively 'fast' systems with little internal memory, for example, monsoons, because anthropogenic forcing is slow relative to their internal timescales, and only relatively short records of their past behaviour should be needed. However, they demand relatively higher resolution data, which must reveal the underlying dynamics of the system. Models can be used to help identify direct indicators of vulnerability to tipping behaviour for specific systems (for example, indicators of bi-stability of the Atlantic THC[35]), which can then be sought in data. Also, models can be used to identify which variables already being monitored are best related to early warning indicators[65]. Where the connection is weak, theory could guide what data should be collected and where. In many cases, the duration and/or resolution of past data records will need to be improved. Real-time monitoring systems may also need to be improved (following the example of monitoring[61] of the Atlantic meridional overturning circulation at 26.5° N).

Generic early warning indicators warrant further development. Tests on ecological models[47] suggest it would be worth looking for increasing spatial correlation as an early warning indicator in climate data and models. Indicators that make combined use of spatial as well as temporal data should also be considered. Tests on both model output and palaeodata[65] should be extended, considering a larger variety of tipping points, with short response timescales as well as long ones. Independent evaluation of the statistical robustness of proposed methods is recommended, and if and when confidence is established, early warning methods should be applied to observational climate data leading up to the present. Future projections from the latest coupled models could also be systematically analysed for tipping behaviour, but there remain several critical model weaknesses.

An outstanding scientific challenge is to combine the generic statistical methods that have been the focus of this review, with process-based models, to produce a probabilistic forecasting framework. The fundamental issue remains whether current models are able to reproduce tipping behaviour, for example, as observed in the palaeorecord. But where the tipping element in question is at least represented in models, and data analysis reveals information on its stability and any underlying trends, then this should be used to improve the models. For example, the recently discovered systematic bias regarding the stability regime of the Atlantic THC in models[35] should inspire model revision.

Responding to early warnings. If an early warning can be obtained and effectively communicated, the challenge becomes to translate it into effective risk reduction, either by trying to minimize the likelihood of passing a tipping point or by trying to minimize the impacts of passing it. Corresponding risk-reduction strategies need to be evaluated[65]. For many tipping elements, warning is unlikely to be early enough to allow aversive action by mitigation of long-lived greenhouse gases, notably carbon dioxide. It is conceivable that faster climate intervention methods, such as mitigation of short-lived radiative forcing agents[73] or geoengineering to reduce incoming sunlight[74], could be more effective. However, the multiple sources of inertia in the climate system, and in human response systems, make this questionable. An analogous problem of avoiding an approaching tipping point in an ecological system such as a fishery[44] shows that once there is a reliable early warning of an approaching tipping point, it is too late for slow intervention methods to avoid it. Even when a tipping point is unavoidable, mitigation action may still help. For example, the rate of Greenland ice-sheet melt (and corresponding impacts through sea-level rise), even when committed to irreversible meltdown, depends on the extent to which this threshold has been exceeded[75].

When faced with most tipping point early warnings, adaptation to minimize impacts may be the most effective response, although maladaptive responses cannot be ruled out[4]. Appropriate adaptation action needs research and will depend on the particular tipping point, but always relies on the recipients of the warnings being empowered to act effectively on the information[76]. Deliberate efforts to counter tipping in ecological systems can also be envisaged, for example, reforestation in West Canadian boreal forests currently suffering mountain pine beetle infestation[77,78].

Conclusion

Early warning of climate tipping points may be feasible, at a level that could provide useful information to help manage the risks that they pose. Better assessments are needed of those risks, particularly of the impacts of crossing different tipping points, and of the response options available in reaction to early warning signals. Improvements to early warning methods should start with the formulation and application of objective guidelines for the choice of method parameters. Even if further research shows that early warning is unachievable in practice, it could still provide valuable information on the vulnerability of various tipping elements to noise-induced changes.

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Additional information

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