



Ideas for Creating Early Warning Systems in the Climate Sciences

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Abstract. A key concern with anthropogenic climate change is that continued warming may trigger transitions in tipping systems. These are Earth system components where small additional climate changes cause large, often irreversible, shifts in state. Such nonlinear transitions could have profound ecological and societal consequences, yet the global warming thresholds at which they occur remain highly uncertain. Current estimates rely mainly on Earth System Models (ESMs), but large inter-model differences undermine confidence in projected thresholds and complicate adaptation and mitigation planning.

Alternatively, Early Warning Systems (EWSs) infer proximity to tipping directly from observations, seeking statistical signatures that emerge before transitions. Most existing EWSs rely on generic indicators, such as critical slowing down, making limited use of process understanding. We argue that further progress, or refinement of existing EWSs, will require more process-informed rather than solely generic EWSs, where statistical indicators are guided by the dynamics of the Earth system component under investigation.

Earth Observation (EO) offers combining its extensive spatial coverage of, for instance, land ecosystem state with parallel observations of key environmental drivers. EO enables space-for-time approaches that exploit spatial variations and how they may change with proximity to a tipping point. Complementary datasets, such as meteorological records, describe the forcing behind observed EO variability, which may help explain the behaviour of candidate EWSs that incorporate satellite



measurements. Combined with reduced dynamical-system representations or ESM process descriptions, these datasets offer a foundation for more targeted and informative EWSs.

We review existing approaches to EWS development from climate science and related disciplines, then present theoretical hypotheses and conceptual frameworks for process-informed EWSs. Central to many suggestions is the proposition that the structure of an optimal EWS should reflect the governing dynamics of the underlying climate system component. We further argue that this relationship is bidirectional. Observations can enhance EWSs, which in turn could constrain ESM parameterisation and structure, improving projections by these models of future tipping behaviour. We propose that integrating EO, process understanding, dynamical systems theory, and ESM improvement offers a promising pathway to more robust EWSs and, ultimately, more reliable prediction of climate tipping risks.

1 Introduction

Climate change has long been recognised as a threat to society (e.g. Hansen et al., 1981), particularly if continued warming crosses climate Tipping Points (TPs), beyond which, with little additional warming, an Earth system component transitions to a new state. In some contexts, we use TP loosely to mean that a component has tipped, rather than that the climate has crossed the threshold causing it. Hysteresis may prevent a return to the original state even if warming reverses, and new states may exceed the adaptive capacity of social-ecological systems. Identifying TPs and the warming levels at which they may occur would therefore clarify which global warming thresholds, such as two degrees above preindustrial levels, must not be exceeded if society wishes to avoid their occurrence. Reviews (e.g. McKay et al., 2022; Lenton et al., 2008; Abrams et al., 2023) identify the components most likely to tip and the associated warming levels, but their large uncertainties hinder consensus on mitigation policies and, for terrestrial TPs, on land use policies that may modulate any TP timing and severity.

Earth System Models (ESMs) represent the atmosphere, oceans, land surface and cryosphere, and their couplings, as differential equations constrained by contemporary measurements, enabling numerical experiments on how changing Greenhouse Gas (GHG) concentrations alter climate (Flato, 2011; Bonan and Doney, 2018). ESMs strongly inform IPCC reports (e.g. IPCC, 2021). Atmospheric equations are well established, benefiting from decades of weather forecasting research associated with weather forecasts, but other components are arguably less well understood. Differences in equations and parameterisations (including subgrid) (e.g. Jones et al., 2024) cause considerable inter-ESM spread in projections, even at the same warming level, including in the warming levels for TP activation, complicating adaptation and mitigation planning. Major nonlinear changes predicted in some ESMs may be absent from others (Drijfhout et al., 2015), and current ensembles may not span all possible TP events. Such uncertainty has prompted efforts to develop Early Warning Systems (EWSs), calibrated with contemporary measurements, that ideally identify approaching TPs with less uncertainty (e.g. Dakos et al., 2024). While ESMs may indicate potential TPs, EWSs may more precisely estimate the distance to tipping (in further warming). Others call these early warning statistics, early warning indicators or TP signal detection.

Advances in nonlinear dynamics (e.g. Drazin, 1992) show that relatively simple equations can exhibit bifurcations and TPs, often triggered by slow changes in a bifurcation parameter (e.g. Kuznetsov, 2023), here related to a climate change metric such



as global warming or total GHG forcing since preindustrial times. Such conceptual models can be explored for a far broader range of forcings than computationally costly ESMs allow. Hence researchers have mapped climate components onto simpler equations, guided by ESMs or data (e.g. Dijkstra, 2013), valid provided the mapping does not degrade the simulation of the component behaviour.

5 Adding high-frequency “noise” to a reduced-complexity dynamical system model emulating a specific component reveals how statistics can represent its response. Such response to forcing fluctuations may evolve as a TP approaches, and finding these changes in measurements may indicate proximity to a TP through what is a process-aligned EWS. However, early analyses (Scheffer et al., 2009) suggest generic EWSs can still perform well, typically assessed on predicting critical transitions (e.g. Scheffer et al., 2012) (here synonymous with tipping). These studies, including the overview of Dakos et al. (2012), emphasise
 10 critical slowing down, namely changes in time series variance and AR(1). Generic or bespoke, such statistics reflect growing recognition that climate variability carries information beyond “noise”, including warnings of distance to tipping. We note, in a similar vein, how variability-based metrics are often the predictors in emergent constraints (Hall et al., 2019).

Earth Observation (EO) now provides unprecedented data across the Earth system, often with high spatial resolution and coverage but over short periods, seemingly limiting its use for characterising trends in temporal variability. Hence, there is growing
 15 interest in “space-for-time” substitution to investigate ecosystem resilience (Lenton et al., 2022) and tipping behaviours and their precursors (Lenton et al., 2024). EO is often available in parallel with measurements of key drivers, such as climatological forcings. Combining state and driver observations clarifies process responses, likely revealing system dynamics better than state data alone and potentially extending critical slowing down methods (Dakos et al., 2012).

We argue that next-generation EWSs should move beyond generic statistical indicators towards process-informed approaches
 20 integrating EO, dynamical systems theory and the process knowledge underpinning ESMs. These largely parallel fields offer complementary strengths for understanding and predicting TPs, and could refine, extend or replace current warning statistics. We discuss five considerations: the need for better TP timing predictions; the strengths and limitations of ESMs, including their often advanced process knowledge; reduced dynamical-system representations; EWS statistics; and EO datasets that can constrain them.

25 Section 2 reviews current approaches and their opportunities and limitations. Section 3 develops hypotheses and frameworks, many advocating integrating process knowledge into EWSs, to advance their predictive capacity. This integration is bidirectional, as observations used to develop EWSs may subsequently be used to assess ESM performance and so their internal process descriptions. Any EWS-based statistic capable of predicting proximity to a TP, we refer to as S .

2 Scientific problem and theory to date

30 We review existing EWS, emphasising statistics that may help predict large-scale changes in Earth system properties under a changing climate, and algorithms that may exploit the substantial high-resolution spatial coverage of EO datasets. We first describe the scientific problem (Section 2.1) and introduce mathematical notation (Section 2.3). We then present three frameworks reflecting increasing knowledge of processes and data, and their bearing on EWS selection (Sections 2.4, 2.5 and 2.6).



Next, we review existing EWS statistics, including from non-climatic disciplines (Section 2.7), before addressing the specific needs of evolving land surface properties and the application of EO (Section 2.8).

2.1 Overview of the scientific problem

Climate tipping elements are components of the Earth system that may change substantially following relatively small additional global warming. If a TP is a level of global warming or climate change that activates such elements, reaching it could have major consequences for society. Many tipping elements also exhibit hysteresis, so subsequent reductions in global temperature may not restore their original states. ESMs aim to represent all climate system components and their couplings, and to simulate their response to rising atmospheric GHG concentrations. However, models differ substantially in the global warming levels at which tipping elements may transition, contributing to wide uncertainty ranges for tipping thresholds (McKay et al., 2022). Given the potential severity of tipping implications and such model uncertainty, there is interest in complementary approaches that diagnose proximity to tipping directly from observations. For brevity, we sometimes refer to reaching a TP, meaning that climate change has reached a level that causes a major transition in a tipping element.

A central question is whether contemporary observations of large-scale environmental systems contain statistical signatures of how close a system is to a critical tipping threshold. In particular, temporal changes in the statistical properties of system variability may provide EWSs of approaching TPs. Many proposed EWS statistics are relatively generic, often based on theoretical expectations for dynamical systems approaching bifurcation (e.g. Scheffer et al., 2009). However, it remains unclear how such statistics can be refined when additional information is available on system forcings (rather than just their responses) or on underlying processes.

We review candidate EWS statistics while emphasising the potential benefits of jointly analysing system responses and their external drivers. We also consider how process-level understanding, expressed through dynamical equations, may inform the design and interpretation of EWS metrics. We emphasise EWS of land surface responses, for which high-resolution EO measurements provide extensive spatial information on terrestrial ecosystem properties. Complementary datasets describe key climatic drivers, including gridded near-surface meteorology (e.g. Hersbach et al., 2020). Land Surface Model (LSM) components of ESMs have been extensively developed, supported by decades of process research, such as on photosynthetic response (Beatty et al., 2005).

Conceptually, the land surface may appear simpler to model because many dominant transport processes are primarily vertical, for example soil moisture transport (e.g. Best et al., 2011) or vegetation demography across canopy heights (e.g. Argles et al., 2020), whereas atmospheric models usually require a full three-dimensional representation. Nevertheless, LSMs remain subject to substantial structural and parameter uncertainty, often with compensating errors between model components (Fawcett et al., 2022). For example, although LSMs broadly agree on total evapotranspiration, predicted partitioning between transpiration and evaporation is highly model dependent (Cui et al., 2025).

Structural differences in ESMs could undermine the reliability of EWS derived solely from them. In contrast, EWSs derived directly from observations, including EO datasets, offer potentially independent diagnostic constraints, and comparing them with model-derived EWS may help identify structural deficiencies in LSMs and ESMs. We therefore hypothesise that mappings



may exist between process dynamics and EWS characteristics, such that data-led development of EWS statistics may advance both the detection of TP proximity and ESM development. We explore this concept particularly in Section 3.1.

2.2 Desirable properties of an EWS

We outline the desirable properties of an optimal EWS, some of which, along with user-prescribed requirements that can be incorporated during its construction, are shown schematically on the left-hand side of Fig. 1. A skilful EWS should minimise both false positives (predicting a climate TP that does not result in a transition of a tipping element) and false negatives (failing to predict a climate TP that does). As this requirement is never fully achievable, an optimised EWS needs to balance their probabilities, for example using a Receiver Operating Characteristic (ROC) methodology (Fawcett, 2006). This balance depends on the costs and benefits of each error type, and thus on quantifying impacts on society, as well as the accuracy of the method. For a forced model, these probabilities can be determined if the natural variability and range of possible forcing profiles and rates can be quantified, although high model uncertainty may make this challenging.

Various features of an EWS may be closely aligned with the impact of interest. For example, a TP for some iconic vegetation types may be associated with complete forest loss, but policymakers may consider tipping to occur at, say, 50% loss. Similarly, in certain locations very substantial climate change may leave almost no vegetation types able to survive, resulting in a desert-like state, yet the path towards it might pass temporarily through many biome types. An EWS might then be designed to identify the termination of a particular biome type rather than complete loss. An EWS may also adapt to different forcing rates or formats. For example, some TPs may be avoided altogether if a climate change threshold that, in equilibrium, would correspond to tipping is only temporarily overshoot (Ritchie et al., 2021, 2025b), or a TP may exhibit substantially different features for different levels or rates of forcing (Ashwin et al., 2012). An optimal EWS incorporating the attributes in the left-hand boxes of Fig. 1 should skilfully estimate tipping risk in terms of the probability, timing, and impact of interest, producing calibrated predictions with confidence levels.

A more subtle but desirable EWS property is the ability to actively and autonomously manage where, when, and how ongoing observations are made. EO data could be complemented by dynamic in-situ measurements, with the EWS itself influencing the sampling strategy to reduce uncertainty. Optimal measurement locations for robust EWS development are starting to be considered, e.g. for projecting any potential collapse of the Atlantic Meridional Overturning Circulation (AMOC) (Smolders et al., 2025).

2.3 Mathematical notation

We define mathematical terminology to capture features of developing EWSs. Each observable process of interest is denoted by a state variable y , evolving over time, t . Our focus is on changes over decades to centuries driven by anthropogenic burning of fossil fuels. The concern is that y may exhibit, at some future time, rapid nonlinear change corresponding to a TP. If the process also varies with geographic position (e.g., “dieback” of a continental-scale biome occurring at different future times by location), this is expressed as a dependence on x , or $\mathbf{x}$ if space has more than one dimension.

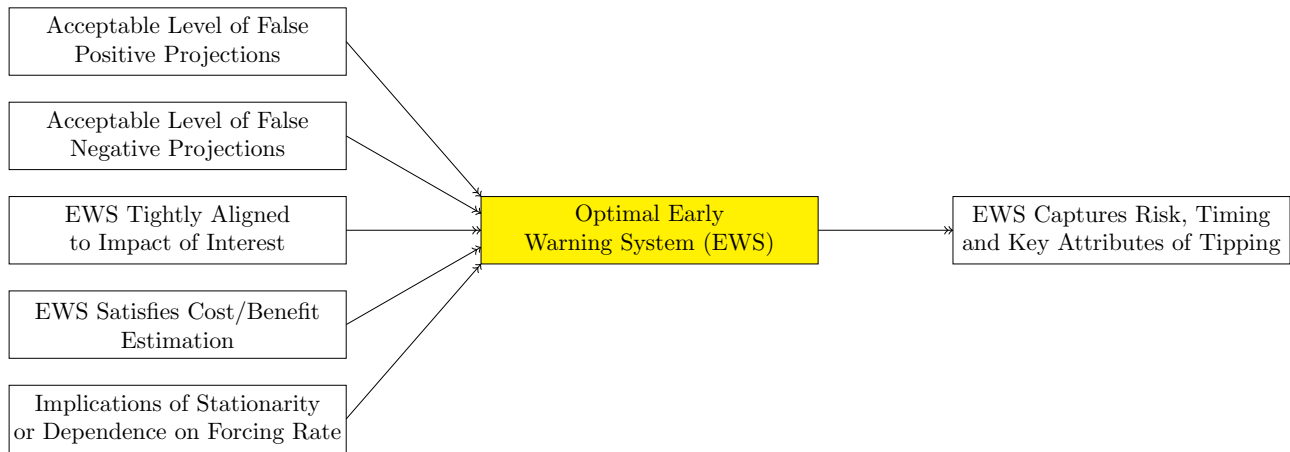


Figure 1. Desirable properties of an optimal EWS (yellow box), both in terms of its construction (left-hand boxes) and its outputs (right-hand box)

The system is assumed to be driven by climate change, represented by forcing $Q = Q(t)$, which in dynamical systems terms is the driver of our bifurcation parameter, $\mu = \mu(Q(t))$. This forcing is assumed well known historically, with policymakers able to set scenarios for its future value. $Q(t)$ could represent, for instance, rising local temperature, ΔT (K), or a change in another climate-related driving condition that aggregates the effects of different GHG changes, such as total radiative forcing.

5 EWSs mainly rely on interpreting fluctuations for clues to whether a TP is approaching. In early climate research, high-frequency variations were often dismissed as noise, with the focus instead on trends in models and measurements over the historical period. This dismissal has more recently been challenged by the growing use of emergent constraints in climate science (Hall et al., 2019). This technique seeks inter-ESM relationships between contemporary measurable climate attributes and key quantities describing future climate change. Combined with contemporary measurements, any such relationship con-
 10 strains estimates of those quantities. The method has refined assessments of fundamental climate quantities such as equilibrium climate sensitivity (Williamson et al., 2021), with the measured quantity often a statistic of climate fluctuations (e.g. Cox et al., 2018). Hence, it is already recognised that climate “noise” may inform on its longer-term behaviour. In Section 3.2, we suggest how emergent constraints might be combined with EWS refinement.

We distinguish two types of additional variation, treated as extra external forcings on our climate-system component of
 15 interest, y . These variations operate at higher frequencies than human-induced climate change, whose slower evolution is described by, for instance, ΔT . The higher-frequency variations may reveal internal system dynamics and serve as an EWS of any TP. The first, $\epsilon_1(t)$, acts on the system like the long-term forcing that may ultimately push it towards a TP. For example, $\epsilon_1(t)$ could represent interannual local temperature variations, whose impact may illustrate the effect of background changes in the bifurcation parameter μ , itself related to global warming, ΔT . Variable $\epsilon_1(t)$ could also represent other climate-related
 20 forcings expected locally to change more persistently under global warming, such as rainfall patterns (and where changes in



y could feed back onto $\epsilon_1(t)$). The second quantity, $\epsilon_2(t)$, arises from forcings distinct from those acting like the long-term climate forcing, and is better treated as independent random noise that does not affect μ . The system can also be considered to have an inertia, C .

Bringing these factors together, we assume an underlying dynamical system that captures the main features of a relatively complex climate process of interest. For variable $y(t)$, this system may be valid at a single point or represent a single timeseries of the spatially averaged behaviour of the full system. Setting global warming, ΔT , as the driver of the bifurcation parameter, μ , and describing the system with a nonlinear mapping function g , gives the generic equation:

$$C \frac{dy}{dt} = g(y, \mu(\Delta T, \epsilon_1), \epsilon_2). \quad (1)$$

Ideally, such an equation projects the existence and timing of any TP in the climate system of interest. A future TP may occur at warming above the present, $\Delta T = \Delta T^*$, at which (with no inertia, i.e. $C = 0$, and for a saddle-node bifurcation) $dy/d\mu \rightarrow \infty$. A common form for g is a polynomial in y , e.g. cubic (Huntingford et al., 2026), which can capture TPs with hysteresis for a bifurcation parameter that first increases and then decreases.

The problem is that, although ESMs would ideally guide the form of g , these complex models differ substantially between themselves. Sometimes ESMs do share the same functional form for g but with different parameterisations. Hence we cannot confidently use Eq. (1) to estimate ΔT^* . Instead, we aim to identify future tipping thresholds such as ΔT^* with an EWS based on a statistic

$$S = S(y(t); \epsilon_1, \epsilon_2; \Delta T) \quad (2)$$

that may be calibrated and tested against contemporary data on y . (As an aside, standard texts on nonlinear dynamical systems, e.g. Verhulst (1996), denote the variable of one-variable systems as x . We instead use y , retaining x as a spatial dimension. Areal variation (x or $\mathbf{x}$) is important in our suggested applications, where some EWS will incorporate, e.g., geographical EO data.)

ESM differences complicate our understanding of g in Eq. (1), and contemporary data may be too short to fully constrain g , so extrapolating it cannot reliably predict future behaviours, which may include tipping. Yet we suggest that process knowledge informing ESMs, or the functional form of g , may still help refine EWSs. We also propose the reverse, where knowledge from calibrating S in Eq. (2) against data may let features of the derived EWS give new insight into the structure of the underlying dynamical system, Eq. (1). Then, better knowledge of g could ultimately aid ESM development and parameterisation. We explore these concepts in Section 3. Fig. 2 illustrates Eqs. (1) and (2).

2.4 Underlying equations unknown and no forcing measurements

We first state what may be the simplest problem where only a single time series of the process of interest, $y(t)$, is available. Hence, there is no forcing time series and potentially no reliable mechanistic description of the underlying process, such as a dynamical system (g of Eq. (1)). Instead, statistics $S = S(y(t))$ (Eq. (2)) are constructed from historical and contemporary features of y alone, to infer whether its statistical structure is changing and whether this indicates an approaching TP. In

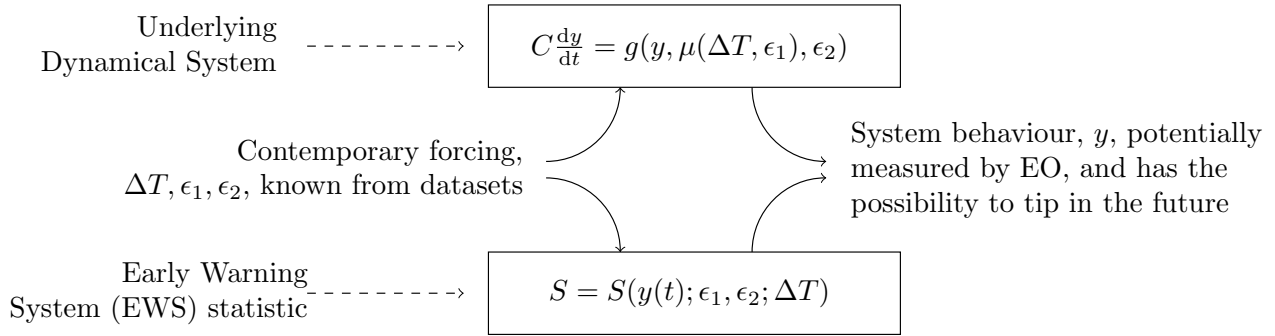


Figure 2. How global warming, ΔT , may trigger TPs can be explored through robust dynamical system models (which emulate key ESM-simulated climate components) or EWSs. Data, e.g. from EO, can potentially constrain both dynamical systems and EWSs designed to project future states, y , of key Earth system components. Changes in either can be characterised by climate forcing metrics such as ΔT . High-frequency forcing data, (additional to y) can further help calibrate dynamical systems and refine EWSs. We distinguish forcings that perturb a system in the direction of longer-term climate change (e.g. anomalously warm years), ϵ_1 , from general “noise” variability, ϵ_2 .

climate research, such analyses have most frequently focused on detecting critical slowing down (Section 2.7.2). Many of these methods explicitly assume that an approaching TP is generic, often a fold bifurcation, implying that the unknown g is locally quadratic in y at the tip.

2.5 Some knowledge of underlying equations and no forcing measurements

- 5 Probably, few important components of the climate system have very little process knowledge available. A major advantage of ESM development is that robust predictive capability requires representing all main climate-system components with equations, including their expected evolution and changing interactions under rising atmospheric GHG concentrations. Hence, ESM construction requires researchers to translate their knowledge, typically based on prior process understanding expressed as underlying equations, into a discretised numerical framework. In many examples, simpler and often nonlinear dynamical
- 10 systems, g , broadly represent the full component system (Dijkstra, 2013) as coded in ESMs. Thus, if g (Eq. (1)) is well understood (e.g. from ESMs), it can predict any warming associated with a TP, ΔT^* , questioning the need for statistically-based EWSs.

Unfortunately, ESM projections of many climate-system components still differ substantially (IPCC, 2021), for various reasons. For instance, many processes are initially characterised using local representative measurements or even controlled

- 15 laboratory experiments, then mapped onto equations assumed valid at larger scales, whereas real-world parameterisation may vary substantially geographically in ways not represented in ESM process equations. Yet it may be misguided to develop EWSs in isolation from the substantial financial and intellectual investment in building ESMs over recent decades. Can knowledge embedded in Eq. (1) inform the form of an optimal EWS statistic, S in Eq. (2)?



Section 3 suggests possible tight linkages between EWS format and the underlying equations of an Earth system component that could tip. Here, we take the general initial view that even partial knowledge of the functional form of g , potentially from fitting a dynamical system to ESM outputs, may guide EWS development. For example, numerical experiments could investigate different forms of g , even for the same process, by including simulated added noise. This activity would determine how the dynamical system translates high-frequency variations, ϵ_1 and ϵ_2 , into the statistical properties of y , as might be seen in S . Even if different dynamical systems behave similarly at tipping, knowledge of their differences before and after tipping may refine and extend EWSs beyond their current generic forms.

Information may also flow in the opposite direction, to enhance ESMs. For example, if different ESMs suggest alternative dynamical systems or parameters, an EWS derived from data on y may indicate which versions of g are more likely correct. Ranking candidate dynamical systems, g , or their parameterisations, may reveal which ESMs most reliably predict specific TP risks.

Ideally, both ESMs and EWSs accurately predict the distance from TPs, suggesting merit in developing them jointly. The broader non-climate literature already indicates that EWSs can reveal attributes of complex systems. For example, Dylewsky et al. (2024) asks “Can EWS detection applied to spatiotemporal measurements of the system offer any insight into the structure of the underlying bifurcation manifold?”, and Wang et al. (2016) argue that data can be used more routinely to identify underlying dynamical systems that describe processes. However, the range of possible bifurcations is potentially limited (e.g. Chapter 2 of Kuznetsov (2023) lists generic forms of tipping), whereas each Earth system component may contain much broader behaviours and attributes needed in equivalent reduced-form dynamical systems. Hence, more precise knowledge of an EWS for a particular Earth system component may only constrain combined clusters of ESM parameters, not their individual values. Even so, bounding their combined effects is still useful for evaluating different ESMs. Meanwhile, ESMs will continue to advance, with new datasets enabling the development of more accurate equations for solution within them. Novel methods may also support model improvements, for example, careful application of artificial intelligence may become a powerful tool for climate research (e.g. Huntingford et al., 2019), including equation discovery from data (Huntingford et al., 2025) to refine ESM formulas.

2.6 Some knowledge of underlying equations and forcing measurements available

EWS development largely depends on characterising variability, and changes in it, in a state variable y . In Section 2.5, we propose that knowledge of the underlying processes, potentially expressed through a dynamical system g , can help build accurate EWSs. Here, we argue that data on the forcings ϵ_1 and ϵ_2 that drive high-frequency variability will also help constrain the form of EWS. Here we place emphasis on identifying whether the land surface in key locations might be approaching a TP (e.g. Section 2.8). For the land surface, y may be measured by EO, and the underlying mechanisms of g are likely described by LSMs, often the terrestrial components of ESMs. Much of the forcing of changing land-surface responses arises from variations in meteorological conditions, which are also measured at high frequency in, for instance, reanalysis products. Such products provide spatio-temporal estimates of historical meteorological conditions by assimilating data into simulations of atmospheric dynamics. These calculations can be regarded as archived weather forecasts that also entrain meteorological measurements



to reduce biases and errors. An example is ERA5 (Hersbach et al., 2020), developed by the European Centre for Medium-Range Weather Forecasts (ECMWF). Quantity ϵ_1 could represent known interannual temperature variations that, when used to force the land surface, may inform the underlying system and its distance from any TP if temperatures rise more continuously. Quantity ϵ_2 may refer to other variables, such as some weather attributes, that are pure noise, carry no information on proximity to a TP, and can therefore be discounted in any statistic S .

Hence, for the land surface, information is available on the state variable response y , the underlying processes g (possibly including any inertia C), and both forcing types, ϵ_1 and ϵ_2 . This more complete set of diagnostics, guided by a better-constrained dynamical system (Eq. (1)) and differentiation between forcing types, may yield a more robust EWS statistic S (Eq. (2)), better constrained than one based on observing $y(t)$ in isolation.

2.7 Existing System Identification and EWSs, including from other scientific disciplines

2.7.1 Change point analysis

A closely related strand of work, developed largely outside the climate TP literature, is changepoint analysis (also termed changepoint detection, structural break, or regime shift detection), which detects statistically significant shifts in a time series, such as its mean, variance, autocorrelation structure, or higher-order moments without necessarily assuming proximity to a bifurcation. Its statistical foundations, dating from Page (1955), are well established, spanning classic non-parametric tests (e.g. Pettitt, 1979), Bayesian formulations (e.g. Barry and Hartigan, 1993), and model-selection approaches estimating the number and location of changepoints (e.g. Yao, 1988; Lavielle, 2005). More recent work has consolidated and extended these approaches to multivariate, high-dimensional, and non-stationary settings (Truong et al., 2020; Aminikhanghahi and Cook, 2017), and efficient methods such as PELT (Pruned Exact Linear Time) enable scalable multiple-changepoint inference on long temporal records (Killick et al., 2012).

In economics and finance, changepoint methods are central to analysing structural breaks in regression and time-series models, with rigorous frameworks for testing and estimating multiple breaks (Bai and Perron, 1998, 2003) as well as practical implementations for dating breakpoints (Zeileis et al., 2003). These approaches continue to be actively developed and applied in macroeconomics and finance, particularly to distinguish regime shifts from gradual parameter drift (e.g. Qu and Perron, 2007; Hansen, 2017). In climate and environmental applications, changepoint (or breakpoint) detection has been explicitly tailored to address the confounding effects of trends, autocorrelation, and seasonality. Reeves et al. (2007) review and compare techniques for climate data, Lund et al. (2007) develop methods for periodic and autocorrelated series, and Beaulieu et al. (2012) extend the approach to account for autocorrelation in climate time series, a critical advance since serial correlation can produce spurious shifts. Gallagher et al. (2013) examine changepoint testing under long-term trends, and recent assessments revisit these issues for modern climate datasets (e.g. Lund et al., 2023). Related approaches frame abrupt shifts as “regime changes” and target early detection in near-real-time monitoring (Rodionov, 2004).

For Earth System EWSs, changepoint detection, which has attracted much interest in ecology (e.g. Andersen et al., 2009), offers both opportunities and limitations. The method provides a flexible, data-driven way to identify when a system departs



from previously stable behaviour, potentially flagging the onset of rapid change in short or noisy records. However, changepoint detection alone cannot distinguish between externally forced shifts, stochastic fluctuations, and internally generated nonlinear transitions. Hence, the method may detect that a change has occurred or is underway, but not the remaining distance to a TP or the mechanisms driving the transition. Furthermore, although traditionally and predominantly applied retrospectively, related statistical approaches are increasingly being adapted to detect approaching transitions in a predictive or near-real-time manner (Islam et al., 2026; Beaulieu et al., 2012).

2.7.2 Critical slowing down

The most widely applied early warning indicators in climate science are based on Critical Slowing Down (CSD). As a system approaches certain classes of bifurcation, its recovery rate from small perturbations decreases, so a time series shows increasing variance, rising lag-1 autocorrelation, $AR(1)$, and spectral reddening. The theory and its broad applicability across complex systems are established by Scheffer et al. (2009) and operationalised for empirical time series by Dakos et al. (2012). Subsequent syntheses clarify when such indicators perform well and when they become ambiguous (e.g. Dakos et al., 2015; Rietkerk et al., 2025).

In climate science, CSD has been used to seek early warning signals for candidate tipping elements such as the AMOC. Early ESM studies show statistically significant increases in variance and $AR(1)$ prior to AMOC collapse (Boulton et al., 2014). More recent observation-based analyses report trends consistent with declining AMOC stability, while emphasising sensitivity to methodological choices and the limits of short, noisy records (Boers, 2021; Ditlevsen and Ditlevsen, 2023).

CSD indicators have also been applied to monsoon variability (Bochow and Boers, 2023), ice sheets (Boers and Rypdal, 2021; Bochow et al., 2023) and ecosystem transitions (Scheffer et al., 2015; Dakos et al., 2019; Boulton et al., 2022), using model, observational and reanalysis data. These studies show that generic indicators can detect signals before major transitions, but are highly sensitive to detrending, window length, noise structure and stationarity assumptions. Strong external forcing, time-varying parameters and high-dimensional dynamics can generate trends in variance or autocorrelation that are hard to distinguish from genuine proximity to a bifurcation.

These limitations have prompted a growing critical reassessment of statistical early warning indicators applied to real climate data, highlighting the risk of false positives and ambiguous signals in non-stationary systems under strong external forcing (Rietkerk et al., 2025). In response, work has expanded beyond univariate indicators to spatial early warning signals, multivariate approaches, and methods that account for evolving background conditions (e.g. spatial variance and correlation metrics; Clarke et al. (2026)). Other methods have been developed that need no detrending and can be applied to seasonal data (e.g. Smith et al., 2026). Collectively, these approaches are beginning to underscore both the promise of more advanced EWSs and the need for a stronger theoretical connection between observed statistical signals and the underlying dynamical processes that generate them.



2.7.3 Extensions of CSD

Beyond standard CSD approaches, a framework based on ergodic theory and linear response theory links the natural and forced variability of high-dimensional chaotic, possibly stochastic, systems such as the climate (Ghil and Lucarini, 2020; Lucarini and Chekroun, 2023, 2024). The theory explains how essential climate variables deviate from their stationary values under small, time-dependent perturbations, and offers a rigorous way to assess when critical slowing down first appears.

Under general conditions, the correlation function of any climate variable y decomposes into a sum of exponential terms Santos Gutiérrez and Lucarini (2022); Lucarini and Chekroun (2023); Chekroun et al. (2025):

$$c_y(t) = \sum_{k>0} y_k e^{-t/\tau_k} e^{i\omega_k t} \quad (3)$$

where τ_k and ω_k are the relaxation timescales and fundamental frequencies of the unperturbed dynamics, capturing the decay and oscillations of natural variability (Chekroun et al., 2025, 2020). Coefficients y_k are observable-dependent quantities. TPs arise when, as the bifurcation parameter μ approaches its critical value, one or more τ_k diverge, so correlation functions then decay sub-exponentially, giving the typical critical slowing down signature in observed signals.

Equivalently, sensitivity to perturbations is greatly enhanced near a TP, as illustrated by the fluctuation-dissipation theorem, which relates the statistics of natural variability to the response to perturbations Marconi et al. (2008). Central here is the Green's function $G_y(t)$, the linear response to small, time-dependent forcings. Introduced heuristically by Hasselmann and collaborators Maier-Reimer and Hasselmann (1987); Hasselmann et al. (1993), the Green's function methodology has since been used to study the climate response to rising CO₂ across many essential climate variables and timescales in a global climate model (Lembo et al., 2020), and provides a rigorous framework for detection and attribution (Lucarini and Chekroun, 2024).

The fluctuation-dissipation theorem illustrates that $G_y(t)$ decomposes into the unperturbed modes, as in Eq. (3) (Santos Gutiérrez and Lucarini, 2022; Chekroun et al., 2025), with coefficients y_k that depend on both the observable and the perturbation. Forced variability is thus a weighted average of the natural modes, with observable- and perturbation-dependent weights. Estimating the triple (y_k, τ_k, ω_k) for the leading modes of variability is therefore key to assessing the resilience of climate subsystems, and especially the slowly decaying eigenvalues that are the rigorous counterpart of neutral climate modes (Palmer, 1999; Hassanzadeh and Kuang, 2016; Lu et al., 2020) and characterise the degenerate dynamics near TPs (Held and Kleinen, 2004).

With climate simulations, the Green's function can be estimated by Monte Carlo comparison of suitably designed perturbed runs Lembo et al. (2020), but not resolved into individual modes. Alternative methods extract modes for non-oscillatory systems, i.e. $\omega_k = 0$ (Torres Mendonça et al., 2021a, b).

More fruitfully, the natural modes of variability can be related to the spectra of the Koopman and Kolmogorov operators describing the unperturbed dynamics (Chekroun et al., 2025, 2020; Santšić et al., 2012). Such spectral methods effectively capture modes of climate variability from high-dimensional models and observations (Froyland et al., 2021; Navarra et al., 2021, 2024), and have revealed rough parameter dependence and high sensitivity of these statistics near TPs in an intermediate-complexity ENSO model (Chekroun et al., 2014).



Combining linear response theory and Koopman analysis has been shown to reconstruct the full triple (y_k, τ_k, ω_k) in a fully data-driven manner from trajectory data for paradigmatic low-dimensional systems (Zagli et al., 2026; Lucarini et al., 2026). Rigorous data-driven Koopman methods for high-dimensional data (Colbrook, 2024) and machine learning of Koopman spectra from data (Lusch et al., 2018) offer a promising route to estimating natural and forced variability of the climate system.

- 5 Algorithms detecting anomalous gradient changes in a time series can also detect abrupt changes (Boulton and Lenton, 2019). For gridded observations or model output, spatially clustering the timing and intensity of these shifts can identify regions that behave similarly and quantifies the size and extent of a tipping event (Harteg et al., 2026). Section 3.3 considers how spatial information may refine EWSs.

2.8 EWS specific to the land surface and potential use of EO data

- 10 One focus of this manuscript is how EO data may improve understanding of future tipping risks at the land surface. Over recent decades, EO has enabled the Earth system to be studied in unprecedented detail (e.g. Tatem et al., 2008), and its substantial potential for integration into EWS is already recognised (e.g. Swingedouw et al., 2020). Although EO records are often relatively short, satellite measurements provide exceptionally high levels of spatial information.

- Several factors aid the assessment of actual or expected land surface change. First, alongside EO data (providing timeseries of state variable y in Eq. (1) at locations x), there are substantial parallel measurements of forcing data, notably near-surface meteorology, and relatively long records of atmospheric CO₂ concentration from about 1960 onwards (Keeling, 1960). These data allow ϵ_1, ϵ_2 and ΔT in Eq. (1) to be quantified. Second, substantial efforts to simulate the land surface have produced LSMs that embody process understanding, helping to constrain the functional form g in Eq. (1). Knowledge of g may in turn bring this process understanding into an EWS (i.e. Eq. (2)), potentially making it more accurate than generic methods. The land surface therefore falls into the case described in Section 2.6, where both process knowledge and forcing conditions exist.

- LSMs have three broad requirements: (1) determining land-atmosphere exchanges of momentum, heat and moisture, which are important, for instance, in weather forecast models; (2) estimating evolving land-atmosphere CO₂ exchanges, which often depend on the same forcings and (3) translating changes in CO₂ fluxes into changes in land carbon stores, which often relate to EO measurements. The third task is achieved through Dynamic Global Vegetation Models (DGVMs) subcomponents, a more recent development in LSMs, whose differences have been quantified in several studies (e.g. Sitch et al., 2008, 2024). One example LSM is the Joint UK Land Environment Simulator (JULES), whose equations are fully documented (Best et al., 2011; Clark et al., 2011), along with recent updates (Oliver et al., 2022). We note that biological ecosystems, in particular, have also been considered for representation by summary dynamical systems capable of simulating hysteresis (e.g. Hao et al., 2026).

- 30 We now consider three land surface regions believed capable of rapid nonlinear change under future climate change.

2.8.1 Tropical forests

Tropical forests, such as the Amazon, are key components of the Earth system, covering nearly two billion hectares and storing about 55% of global forest carbon (Pan et al., 2011). These systems host exceptional biodiversity (e.g. Pillay et al.,



2022), support numerous indigenous communities (Ellis et al., 2021), and regulate regional climates by providing moisture and cooling (Lawrence et al., 2022). However, climate change is believed to be increasing the risk of crossing forest TPs, with deforestation and degradation amplifying this vulnerability (Singh et al., 2024). The Amazon is the most notable example of a forest that may be approaching such a threshold (Boulton et al., 2022). Dieback would cause extensive biodiversity loss, substantial regional rainfall reduction, including downstream (Cui et al., 2026), additional carbon emissions, and changes to global rainfall patterns, with many associated societal impacts (e.g. Ritchie et al., 2026). Consequently, substantial recent effort has gone into quantifying resilience loss and developing EWSs (e.g. Forzieri et al., 2022).

Expanding satellite remote sensing has transformed Earth system observation, providing extensive datasets increasingly used to study ecosystem resilience. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), a measure of greenness, are commonly employed to calculate resilience metrics (e.g. AR(1), variance, recovery rate), particularly for tropical forests and especially the Amazon (e.g. Wang et al., 2024; Boulton et al., 2022). Current satellite observations include optical (visible, near-infrared (NIR), and short-wave infrared (SWIR)), thermal infrared, Synthetic Aperture Radar (SAR), passive microwave, and Light Detection and Ranging (LiDAR) data, which together inform on forest cover, structure, productivity, and vegetation health.

Optical observations (e.g. Sentinel-2; Drusch et al. (2012), Landsat; Crawford et al. (2023), MODIS; Justice et al. (2002)) yield vegetation indices (e.g. NDVI, EVI, kNDVI, FAPAR, LAI) and productivity indicators (Gross Primary Productivity (GPP), Solar Induced Fluorescence (SIF)), supporting assessment of forest cover, vegetation health, indirect biomass estimation, and disturbance detection. Optical sensors offer moderate to high spatial resolution (tens to hundreds of metres), global coverage, revisit times of a few days, and multi-decadal time series, but are affected by clouds. Thermal infrared sensors (e.g. Landsat, ECOSTRESS (Fisher et al., 2020), MODIS) observe land surface temperature and emissivity, enabling detection of water stress (soil moisture), evapotranspiration (ET) and fire, though they are also often obscured by clouds.

Passive microwave (e.g. SMAP; Entekhabi et al. (2010), SMOS; Kerr et al. (2010), AMSR-E; Kawanishi et al. (2003)) and SAR (e.g. Sentinel-1; Torres et al. (2012), ALOS-2 PALSAR-2; Tadono et al. (2025), TerraSAR-X; Buckreuss et al. (2018)) instruments are sensitive to plant and soil water content, used to derive Vegetation Optical Depth (VOD) and soil moisture products, and provide all-weather, day-and-night observations. SAR and LiDAR (e.g. GEDI; Dubayah et al. (2020)) observations also capture forest structure and canopy density, supporting estimation of Above Ground Biomass (AGB) and carbon storage. The BIOMASS satellite, launched in April 2025 with the first P-band SAR in space, will map global AGB in unprecedented detail (Le Toan et al., 2011).

Despite cloud cover, retrieval uncertainties, short records for some instruments, and inter-sensor biases, EO remains highly valuable for developing EWSs and constraining model predictions of TPs (Abrams et al., 2025). Combining dataset types (e.g. optical and SAR), exploiting long-term observations and high-resolution products, and applying approaches such as space-for-time substitution are effective ways to maximise the value of available EO data for resilience assessment and EWSs.



2.8.2 Drylands

Drylands are biomes characterised by chronic water scarcity, classified by Aridity Index (AI) into hyper-arid, arid, semi-arid, and dry subhumid subtypes. This land type covers over 40% of Earth's land surface and supports about 38% of the human population (Cherlet et al., 2018). Climate and land use change increasingly put drylands at risk of degradation and abrupt shifts in vegetation functioning, which can cause further aridification, biodiversity loss, groundwater depletion, shifts in species composition, and impacts on vegetation recruitment (Lenton et al., 2023).

As for early-warning signals of TPs in tropical forests, satellite observations of vegetation and soil help constrain understanding of dryland dynamics. However, whereas tropical forest assessments focus on vegetation structure and biomass, dryland studies typically centre on vegetation cover dynamics, spatial patterns, and soil moisture and texture. Satellite-derived vegetation indices such as NDVI and EVI remain widely used to analyse dryland vegetation resilience (e.g. Bernardino et al., 2025; Abel et al., 2024), and productivity metrics such as SIF have also proved effective (Wen et al., 2025). Increasingly available high-resolution imagery (e.g. Sentinel-2 (Drusch et al., 2012), PlanetScope (Planet Labs, 2021)) has enabled detection and analysis of fine-scale dryland vegetation properties, such as morphological features and spatial self-organisation patterns, which may contain early warning signals of critical transitions (Buxton et al., 2022; Kefi et al., 2014).

2.8.3 Permafrost

Permafrost covers approximately 15% of Northern Hemisphere land and stores roughly twice as much carbon as the atmosphere and terrestrial vegetation combined (Obu et al., 2019; Schuur et al., 2022). Rapid Arctic warming (e.g. Rantanen et al., 2022) has accelerated permafrost degradation, raising the risk of abrupt thaw and local TPs that could release large carbon reservoirs and amplify climate change beyond current model projections (Yokohata et al., 2020; Schädel et al., 2024). Early warning of such thresholds is therefore important, yet no operational permafrost EWS exists.

Recent geopolitical tensions have increased reliance on satellite observations of remote permafrost regions, where direct measurements may be impossible (Schuur et al., 2024). Permafrost cannot be observed directly from space, and its extent and degradation are instead inferred from satellite-monitored land-surface characteristics and processes. However, high-latitude remote sensing is hampered by persistent cloud cover, limited light (especially during the polar night), steep solar angles, and technical limitations such as decorrelation between Synthetic Aperture Radar (SAR) acquisitions used to measure ground-surface changes such as deformation (Philipp et al., 2021).

3 Conjectures and hypotheses on EWSs and potential related benefits

Various articles review the application of EWS to identify climate TPs, at which Earth system components may tip to a new state (e.g. Dakos et al., 2024; Beaulieu et al., 2012). Section 2 adds a focus on the land surface and the use of EO data. This Section 3 instead presents conjectures and hypotheses on EWS development that we hope will improve predictions of the timing of any approaching tipping in the climate system.



3.1 Creating a bespoke EWS

A bespoke EWS ideally optimises predictive features such as those in Fig. 1. Our first hypothesis is that if the governing nonlinear equations of a process are known, their features would be reflected in the structure of any optimal EWS statistic S . Equation terms and parameters would thus shape the form and parameters of the EWS, making it more targeted to the process than a generic EWS formula. Process-informed EWSs may also pass information in the other direction, helping to refine ESM projections. For instance, if an EWS is structured around a fundamental equation in ESMs whose key parameter is substantially uncertain, comparing the same EWS statistic to measurements of the state variable y may help constrain that parameter.

We represent information exchange between ESMs and EWSs as the “Potential Mapping” annotation in Fig. 3. Should such mappings be valid, their implications can be described by pathways formed by combining the lettered arrows in Fig. 3. However, we first consider the existing pathways pursued by researchers. “Pathway One”, of arrow A then arrow B (i.e. $A \rightarrow B$) represents the conventional approach to climate simulation. Available datasets constrain the form and parameters of the equations representing the ESM components. Diagnostics from the complete ESM, simulating future levels of climate forcing, are then analysed for evidence of expected future TPs. No use is made of an EWS. “Pathway Two” ($E \rightarrow F$) describes the conventional approach to developing an EWS. Here, the EWS does not draw on knowledge encoded in ESMs or their diagnostics. Instead, S is based solely on features of the measurements of the quantity of interest, y , derived using methods such as CSD (Section 2.7.2). This pathway thus links data directly to TP timing and attributes via an EWS.

If the “potential mapping” hypothesis is valid, a “Pathway Three” is possible. Once arrow A has been used to build ESMs (and possibly derive related dynamical systems, g , mirroring ESM components), arrow C may convey this information to a more theory-led EWS, rather than one built purely from data (arrow E). This new pathway for estimating TP risk, $A \rightarrow C \rightarrow F$, develops an EWS guided by the research used to build ESMs. Such an EWS may have better predictive capability than generic forms, and may more easily entrain forcing data, i.e. ϵ_1, ϵ_2 and ΔT (Eq. 2).

If the hypothesis holds, a “Pathway Four” is possible. Substantial ongoing uncertainty in the parameterisation of ESMs may limit their ability to estimate TP timing. If the timeseries of y yields well-defined statistics that support EWS development, these may be related, via arrow D, to the equations and parameters of ESMs. A data-led EWS may thus help constrain ESM parameter uncertainty and improve their projections of TP timing, via the new pathway $E \rightarrow D \rightarrow B$. Section 3.2 develops these ideas within the emergent constraint framework.

Directly linking the development of EWSs and ESMs is powerful, but we raise a couple of cautions. Many TPs exhibit a generic form at their tip (the point of occurrence), although the underlying equations likely vary, so any mapping from ESMs (and related dynamical systems) to EWSs may be closer to “many-to-one” than “many-to-many”. Before any tipping, behaviour may be broader and process-specific, reflected in a range of features of statistic S . However, even away from the generic tip forms, many EWSs effectively rely on local linearisation, with a single restoring rate parameter in response to perturbation. An EWS fitted to data therefore determines this local (in time) relaxation parameter and its time evolution, as two degrees of freedom. For data-calibrated EWSs informing climate models, these may not fully constrain the many uncertain ESM parameters, but could usefully constrain two parameter combinations. Particularly strong observed fluctuations during

the historical period could take the system temporarily beyond linearisation and exponential relaxation, revealing more of the underlying nonlinear structure.

An alternative approach defines EWSs using edge states, which are unstable states lying on the boundary between the basins of the reference attractor and the competing state (Lucarini and Bódai, 2017; Börner et al., 2026). Tipping phenomena, such as AMOC collapse, are related to the collision between the reference state and the edge state, which in turn lies on the boundary of the basin of the competing state (Lucarini and Bódai, 2017; Börner et al., 2026). The existence of CSD flags the nearing of such a collision, and so observables taking into account the relative position of the edge state relative to the reference state are well suited to constructing accurate EWSs (Lohmann et al., 2025). EWSs have also been defined from a dynamics-based description of tipping, using network theory to study the statistical and dynamical properties of the climate system (Dijkstra et al., 2019). Locating the edge state in a complex ESM is possible but computationally demanding. In an ESM-based network representation of the ocean circulation, the system fluctuates near the edge state, and very clear signals of a major structural shift emerge. These anomaly signals are proposed as a novel EWS of approaching AMOC collapse (Moinat et al., 2026).

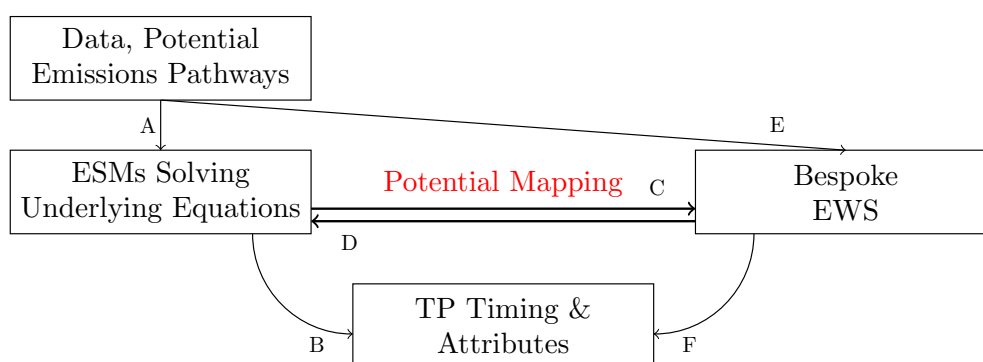


Figure 3. Schematic of the hypothesis that, if the equations describing an Earth system component predict a TP for future climatic forcings, a related bespoke EWS can be constructed. Such an EWS implicitly contains features specific to the large-scale environmental system of interest, which we suggest may give it better predictive capability than generic forms. When fitted to measurements, an EWS containing process information may also support ESM calibration. This may occur by data constraining EWS free parameters that are linked back to such ESMs. This Figure is ideally read alongside Fig. 1, which explores design constraints and considerations for optimising a bespoke EWS. The top rectangle is offset to the left to highlight the conventional approach to climate prediction, which merges potential emissions pathways with ESMs.

3.2 The method of emergent constraints may support EWS refinement

The Emergent Constraint (EC) method (Hall et al., 2019) exploits relationships, found inter-ESMs, between a quantity relevant to the prediction of future climate change and one measurable today. Measuring the second quantity then constrains the first via the EC regression (method in the Appendix of Cox et al. (2018)). Most ECs found so far are linear regressions, with each ESM a data point. The future-change quantity is often a key invariant “bulk parameter”, regressed against a statistic of a



high-frequency quantity measured today, where Huntingford et al. (2023) illustrate the concept mathematically. ECs therefore show that, in climate science, analysing only decadal-to-century trends while discarding high-frequency variability may mean ignoring valuable information (e.g. Hall et al., 2019; Ragone and Lucarini, 2026), including on key parameters such as the equilibrium climate sensitivity of Earth (Cox et al., 2018). As EWSs are also statistics of variability in data records, they may be commonalities with ECs. We propose this link even though EWSs are by definition associated with nonlinear tipping risk, whereas most existing ECs concern more linear changes expected in the climate system as GHGs rise (ECs can be interpreted as a form of linear response theory (Ragone and Lucarini, 2026), and such theory may provide key information in developing EWSs of TPs).

Our second hypothesis is that the equations representing a nonlinear process of interest are broadly common across all ESMs. If the hypothesis of Section 3.1 is valid, there also exists a process-specific form of EWS, S , that projects the distance of the current climate state to tipping through a function we name h , assumed invertible (likely requiring small C). Setting $S = S^*$ and $\mu = \mu^*$ when the system tips, the EWS tracks the distance from tipping as $S^* - S = h(\mu^* - \mu)$. ESMs informing the form of h would be an example of arrow C in Fig. 3, and h may also be linked to a dynamical system g in Eq. (1).

The known contemporary (“c”) level of climate change is $\mu = \mu_c$, and each ESM, indexed by i , projects tipping at $\mu = \mu_i^*$. These values can differ substantially, which is the fundamental problem of uncertainty when estimating the distance to a TP using ESMs. An EWS statistic S can be constructed from ESM diagnostics. EWS value at tipping, S^* , is considered invariant across ESMs and equal to the value that would actually be observed at tipping. However, each ESM estimates a different contemporary value of S , labelled $S_{c,i}$. The function h then serves as an EC linking contemporary S to the distance to tipping across ESMs, as $\mu_i^* - \mu_c = h^{-1}(S^* - S_{c,i})$. Since μ_c and S^* are known and h is identified from theory, calculating the contemporary EWS value, S_c , from observations would yield a more refined estimate of the distance to tipping, $\mu^* - \mu_c$.

Fig. 4 shows the EC in standard form. The “ x ” axis is the contemporary EWS statistic, S_c , available both as data and as ESM diagnostics. The “ y ” axis is the distance to tipping from the present day, in terms of the bifurcation parameter μ (black font) or global warming (red font). A negative “ y ” value (below the horizontal dashed zero line) indicates that, for a given ESM, the tipping point has not yet been reached (i.e. $\mu_i^* > \mu_c$). Thus, in temperature terms, a value of minus two implies that, for that ESM, a further two degrees of global warming is needed before a TP is reached at $\Delta T = \Delta T^*$. An ESM on the dashed line would project tipping at the present day. Critically, via the EC, the contemporary data for S (yellow range) may better constrain $\mu^* - \mu_c$. For a robust EC, this constrained estimate would be less uncertain than the raw range of ESM tipping estimates. Hence, the vertical spread of the horizontal orange bar would be smaller than that of the blue dots in Fig. 4.

Fig. 4 depicts an emergent property that is linear, as shown by the representative straight line, making the function h^{-1} a simple linear transformation. If a robust regression is found across different ESMs, this may act as verification of the process understanding leading to the construction of the EWS statistic S , and potentially also explain the shape and parameters associated with the function h . It is also possible that using existing, more generic statistical EWS forms for S , when plotted in the form of Fig. 4, may reveal a regression and thus an EC. Such a finding remains valuable, but as noted in Hall et al. (2019), ECs are ideally associated with process understanding. Hence, in such circumstances, mapping of mechanistic understanding onto a new statistic S may also create an EC in the form of Fig. 4, but where the regression is more tightly constrained (i.e., less



variability around the linear fit). This process-led statistic S , within the EC framework, would then create a smaller range of uncertainty in $\mu_i^* - \mu_c$ than that initially found with a standard generic form for the EWS.

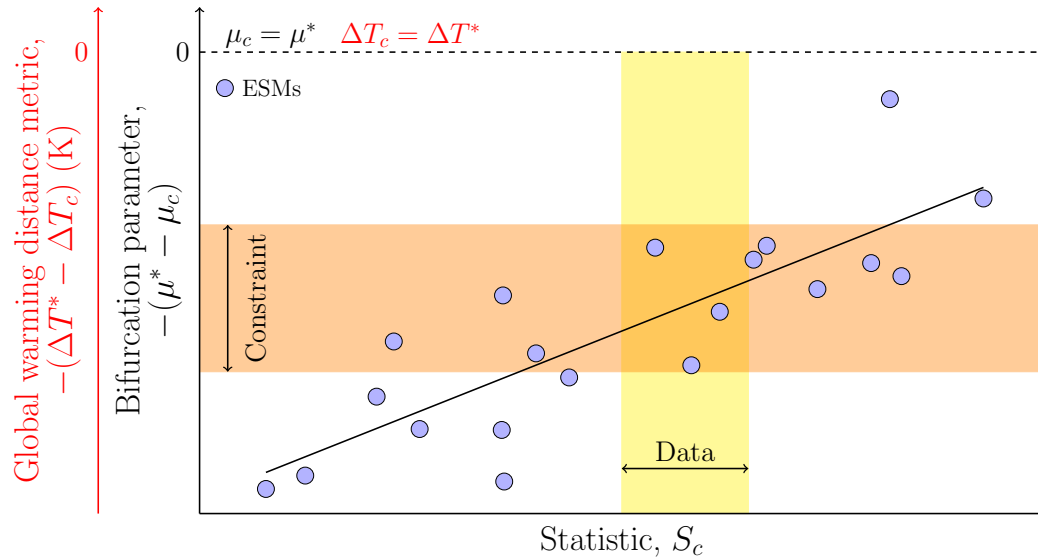


Figure 4. Schematic illustrating the potential of the EC method to develop an EWS for an approaching TP. For a large-scale environmental process, an EWS statistic, S , is derived. Its contemporary (“c”) value, S_c , is calculated from diagnostics of each ESM. For each ESM, the remaining distance from the present day to tipping is also calculated in parameter μ , a climate-change metric such as global warming (also in red). Tipping occurs at $\mu = \mu^*$ or $\Delta T = \Delta T^*$ (and, not illustrated, at a known $S = S^*$ off the diagram to the right). Each blue circle is a different ESM, and the EC is the fitted straight line. Here, all ESMs predict tipping at higher global warming than present, so an ESM estimating a TP after a further two degrees of warming would plot at minus two on the “y” axis. S may be informed by process knowledge (see Fig. 3). The data (yellow) show S_c , with uncertainties, from available process measurements. The vertical spread (orange) is the refined projection of distance to tipping, derivable using the statistical methodology of Cox et al. (2018).

3.3 Space for time substitution to advance EWS predictions

EO brings unprecedented spatial detail and coverage. However, many satellite records are short compared to the timescales over which the stability of tipping elements changes, making it difficult to derive, calibrate, or test any proposed EWS S fitted to time series at single points (van der Bolt et al., 2021). A more complete assessment of tipping risk may instead come from considering the full spatial field of the quantity of interest across, for example, a land biome. A “space for time substitution” may yield a refined S giving more accurate early warning of tipping. The appropriate approach depends on the spatial scales over which the system is coupled and the geographical variation of environmental forcing. We consider five cases.

- 10 In the first case, *Edge First Tipping*, we assume that environmental conditions vary strongly across the biome. EWS S can be calculated for each point in the biome and reflects local environmental conditions. Assuming smooth spatial variation in



environmental forcing, critical values of S (e.g. S^*), representative of those expected near TPs and thereby distinguishing between system states, are most likely found towards the current edges of the domain. Hence, the first parts of the biome most likely to tip are its edges, as shown in the schematic Fig. 5. Further from the edges, a vegetation type may have far greater resilience and so can cope with larger climatic changes before tipping. At these inner locations, S may differ substantially from S^* . Taken collectively, these varying S values can indicate how S will change over time in different places as the vegetation approaches tipping. That is, the spatial variation in S can populate different parts of the expected time-evolution of S at a single location (Fig. 6).

In detail, assuming the relationship between spatial variations in environmental conditions and S holds in the future, under climate change, the relationship presented in Fig. 6 can be converted into a space-for-time substitution. In a changing climate, the horizontal axis can instead represent the level of climate change, showing the time remaining until tipping rather than the spatial distance to the biome edge used to populate the curve. S can then warn of system changes as human-induced climate change increases. (Changing environmental conditions may also shift the boundary of a biome by altering where it can exist. For example, global warming is moving some ecosystems poleward or to higher elevations (Parmesan et al., 2022), towards more favourable temperatures. The speed with which the boundary moves may provide a measure of the level of future resilience.)

We distinguish four further classes of spatial tipping (Fig. 5): *Macro Tipping*, *Clustered Tipping* and *Propagating Tipping*, introduced by Lenton et al. (2024), and *Pattern Tipping*.

Macro tipping is a transition that is coherent over large spatial scales. Here we expect the mean environmental forcing to vary little in space, despite local fluctuations, so data from across the domain can be combined into a domain-wide value of S . Clarke et al. (2026) found that spatial variance and autocorrelation can then give skilful early warning of tipping, particularly when the forcing changes rapidly, building on evidence that summary spatial statistics evolving over time can better reveal an approaching tipping event (e.g. Dakos et al., 2010, 2011).

Where spatial coupling is weak but nonlinear behaviour is expected, clustered (or fragmented) tipping may occur (Bastiaansen et al., 2022), with smaller-scale clusters tipping at different times. Domain-wide spatial variance is likely to increase as a critical threshold is approached and the clusters emerge and become more distinct. Critically, local within-cluster calculations of S could warn of individual cluster transitions towards tipping.

Some tipping elements may be understood as coupled components of the same quantity at different locations, such that destabilising one component can destabilise another, leading to propagating tipping. The overall qualitative behaviour depends strongly on the inter-component coupling and the timescale of each component (Ritchie et al., 2025a).

With sufficiently strong spatial coupling, individual clusters may tip coherently, creating large-scale spatial or spatiotemporal patterns (Bastiaansen et al., 2020; Moreno-Spiegelberg et al., 2025), termed pattern tipping. Unlike clustered (or fragmented) tipping, where the mean domain-wide spatial variance is expected to increase gradually with increasing environmental forcing, in pattern tipping the mean spatial variance increases suddenly once a critical forcing threshold is crossed. Beyond this threshold, patterns form as a biome response to additional climate forcing (Meron, 2016), even before a full TP is reached, and may involve changes in ecosystem properties or type (e.g., forest to grassland or vegetation cover to bare land). During

this interim period, these pattern changes can therefore serve as a spatially explicit EWS. If environmental conditions across the biome are approximately uniform, the emerging spatial pattern can be relatively regular, e.g., consisting of approximately equidistant patches or stripes (Rietkerk et al., 2004; Zelnik et al., 2015). However, this regularity can be masked by strong spatially uncorrelated noise (Sieber et al., 2010) or transformed into an irregular pattern by complex internal dynamics of the system (Marick and Bairagi, 2026).

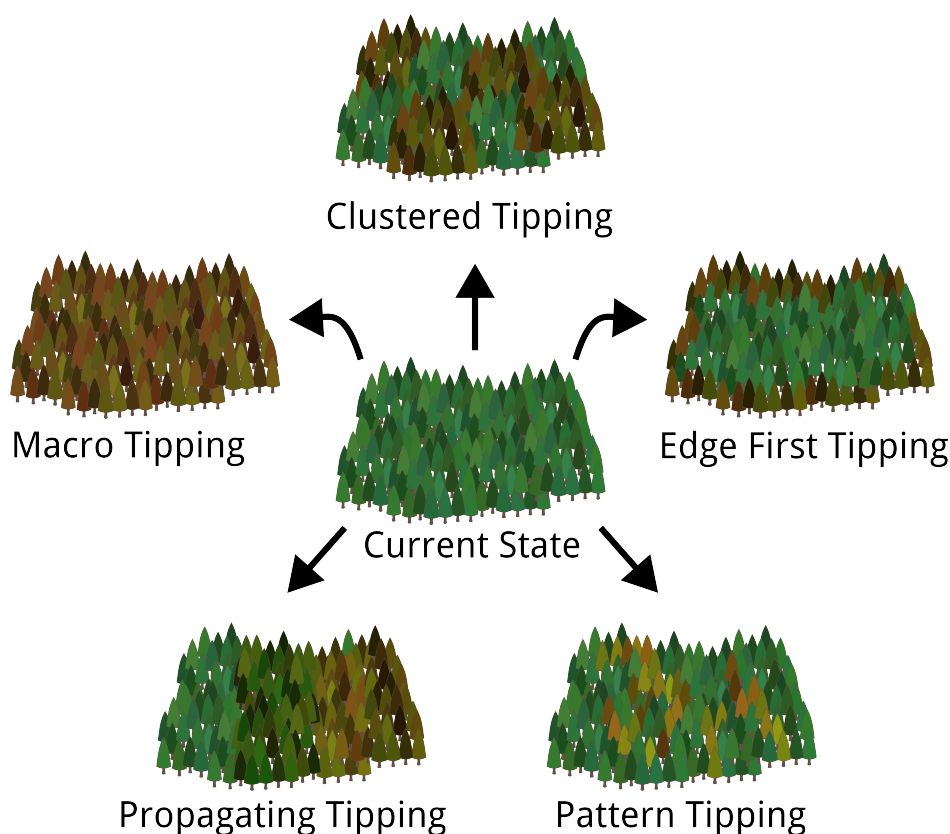


Figure 5. Classes of spatial tipping that may occur across a major forest biome vulnerable to collapse under climate change. At the centre is a current lush, green biome with extensive tree cover. Surrounding it, clockwise, are potential degraded, brown, future tipping states for each class (all described in Section 3.3). *Edge first tipping* is where the vulnerable edges tip under only a small amount of climate change while the more resilient centre persists. *Pattern tipping* is where parts of the biome degrade in a spatially correlated way. *Propagating tipping* corresponds to one region tipping, causing other connected parts of the domain to tip as well. *Macro tipping* is where broadly similar climatic drivers across the domain cause simultaneous tipping throughout. *Clustered tipping* is where tipping occurs within localised patches.

3.4 Some TPs have a related EWS that depends only on temperature rise, irrespective of warming trajectory

In this hypothesis, we suggest that some components of the climate system susceptible to tipping evolve towards a change in state depending solely on the level of background climate change (e.g. global warming, ΔT), with no additional dependence

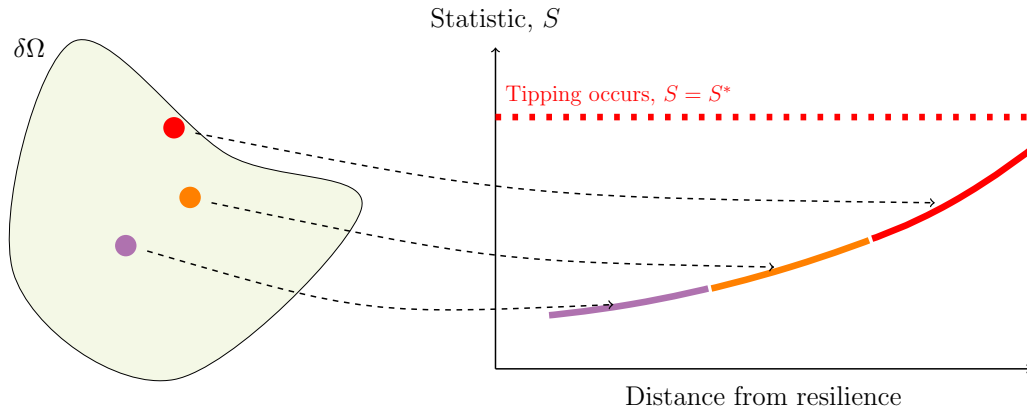


Figure 6. Schematic of one form of “space for time” substitution, based on *edge first tipping* in Fig.5. The boundary $\delta\Omega$ may represent, for example, the edge of a biome of interest that could tip. An EWS statistic, S , is considered to be a good predictor of a TP, at which $S = S^*$ and where climate has changed sufficiently that the biome collapses to an alternative vegetation type. Points nearer $\delta\Omega$ are likely closest to tipping, needing little further climate change to change state, so their current S values will be nearer S^* . Values towards the domain centre, where the biome may be more resilient, are currently far from S^* . The right panel shows observed S against distance from $\delta\Omega$. The space for time substitution hypothesis proposes that, as climate change increases at a single location, S will evolve along this curve towards S^* .

on the historical path of the temperature rise. This path independence would reduce the degrees of freedom of any suitable optimal EWS statistic, S , to $S = S(\Delta T)$ rather than $S = S(\Delta T, t)$ for time t . If, as in previous Sections, tipping occurs when $S = S^*$, then $S^* - S$ estimates the distance to tipping. Invariance to the warming trajectory implies that, in future projections, $S^* - S$ relates to a single value of additional warming before tipping, independent of how long it takes to occur. Fig 7 illustrates the simplification. The three curves represent scenarios in which global warming increases over time at different rates, while an Earth system process responds to this warming and approaches a TP. For each level of global warming, regardless of the preceding path, an EWS statistic, S , takes a unique value (horizontal dashed lines). This includes its value, S^* , at the fixed level of global warming, ΔT^* , at which tipping occurs.

An EWS that evolves with global temperature but is independent of the warming pathway is advantageous, as comparing the statistic, S , for the contemporary period with S^* gives a single measure of the remaining warming to tipping. We suggest that path-independence holds when forcing timescales are slow relative to the system dynamics. For strongly forced systems, where the forcing timescale is no longer slower than the system dynamics, path independence can break down. This applicability may also require relatively small inertia-like effects, such as low values of C in Eq. (1).

In detail, the indicators designed to detect CSD (such as increasing AR1 and variance) assume the system is in pseudo-equilibrium, where its state keeps pace with evolving, climate-change-related forcing. Under this assumption, variance-based EWS statistics are independent of the warming path, whereas this does not hold for strongly forced systems (Clarke et al., 2026). A rapidly changing forcing can also tip a system through rate-induced tipping (Ashwin et al., 2012). In these circumstances,

classical EWSs fail, whereas geometric EWS (Chapman et al., 2025) or machine learning (Huang et al., 2024) approaches offer promising warning alternatives. In such scenarios, the system leaves its original basin of attraction, signifying the onset of tipping.

Most ESMs have been run under several standard future emission scenarios, such as the Shared Socioeconomic Pathway (SSP) storylines (Meinshausen et al., 2020; Riahi et al., 2017). Whether an EWS statistic, S , maps one-to-one onto global warming, ΔT , can be tested by comparing, for each ESM, the equivalence of values of S across two or more prescribed scenarios as the simulated warming passes identical temperature levels. Where this hypothesis holds, the warming threshold for tipping, ΔT^* , should also be invariant across ESMs, occurring at a unique value of $S = S^*$. We note that a direct mapping of the statistic S to mean global temperature rise does not imply a one-to-one mapping to, e.g. equivalent CO₂e (ppm) levels. For example, if CO₂e levels were held fixed at present-day values, global mean temperature would continue to rise (Huntingford et al., 2020), giving a many-to-one mapping.

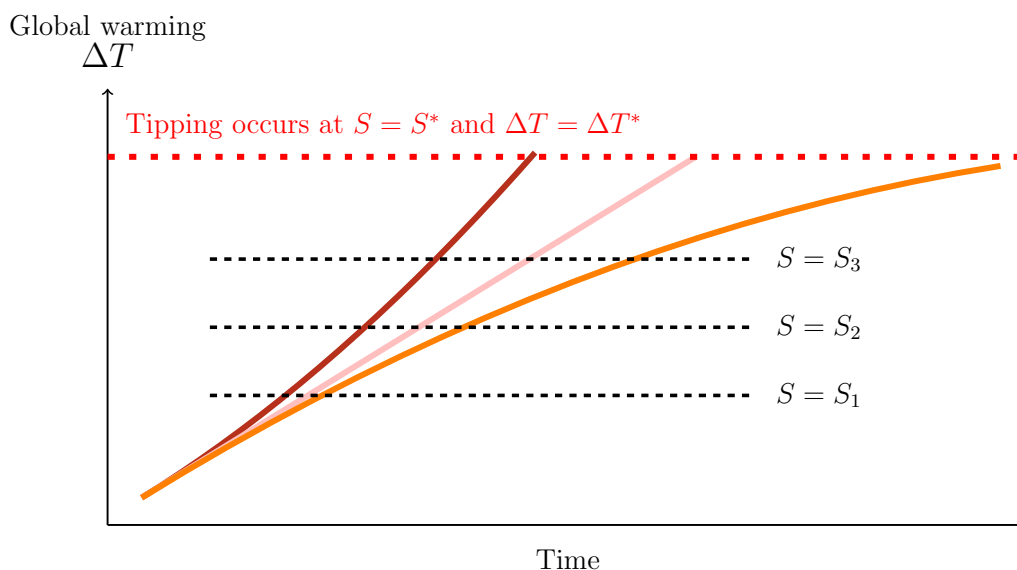


Figure 7. Three illustrative future warming pathways (coloured curves) with different rising global temperature trajectories. An Earth system component tips in all cases at $\Delta T = \Delta T^*$. We assume an EWS statistic, S , is available to describe the evolution toward the TP, which occurs at the threshold $S = S^*$. For this component, S has a unique value at each temperature level, so it is independent of the warming trajectory. We illustrate this with representative EWS values, S_1 , S_2 and S_3 , valid for the same temperatures for all three warming curves, and so horizontal lines.

3.5 Known EWSs for single quantities may reveal if additional tipping elements are connected

Any particular TP could interact with other parts of the Earth system that can also tip, giving “tipping cascades”. Klose et al. (2021) define three types. In a “joint cascade”, two tightly linked processes tip at the same time. The related “domino cascade”



is broadly where the tipping of one process immediately sets the driving conditions for a second to tip at the same time or shortly after. In a “two phase cascade”, the tipping of a first process may adjust the vulnerability of a second process to tipping. In this third case, Klose et al. (2021) suggest that an EWS for the second process tipping may only be fully informative in the intermediate period after the first process has tipped.

- 5 We suggest that the timing of a key TP may be altered by a second process, an effect that may be observable in the EWS of the first. This would occur where the two processes are tightly coupled, as in the “two phase cascade” of Klose et al. (2021). In our example, however, features of the second tipping process emerge and are observable in the behaviour of the first, before the first has tipped. Suppose a theory-led understanding of how a key process varies with a climate-change metric, such as global warming, generates an EWS, S , represented by the yellow curve in Fig. 8 (uncertainty shaded), with tipping at $S = S^*$.
- 10 A second key external process capable of tipping could begin to emerge before S reaches S^* (marked), either accelerating (orange) or delaying (mauve) the first tipping. Any observed deviation from a robust theory for the first process may warn that a second, coupled, nonlinear process may be starting to move towards tipping.

- A second tipping event that causes earlier activation of a TP of concern (e.g. at lower global warming levels) is a cascade risk (orange curve, Fig. 8), whereas a second TP that reduces the risk of, or delays, activation of the TP of interest is stabilisation (mauve curve, Fig. 8). Wunderling et al. (2024) present a mathematical framework for TP interactions covering both cascade risk and inter-TP stabilisation. One proposed example of increased resilience through TP interaction links potential AMOC changes to Amazon rainforest stability (Hoegner et al., 2025). (The possibility that new factors may later affect a key process, changing our understanding, is cited as a reason for caution in ranking climate projections. Rejecting an ESM for poorly estimating key contemporary climatic attributes may prove inappropriate if that model better represents an important process,
- 15
 - 20 activated at higher global temperatures, than other models.)

3.6 Matched asymptotic expansions may support EWS development

- In a final suggestion for advancing EWS development, we draw attention to the method of matched asymptotic expansions. This perturbation technique was first applied to fluid dynamics problems (Van Dyke, 1964), with a more general treatment in Lagerstrom (1988). Problems in fluid dynamics are often too complex to allow exact solutions to the governing equations that
- 25 are valid everywhere, especially when different processes dominate in different locations. For instance, depending on the spatial domain and boundary conditions, major gradients in fluid flow properties may occur near domain edges, known as boundary layers, or inner regions, with much smaller gradients in more central parts, known as outer regions. Instead, the main “zero-order” behaviour in each domain can often be found by scaling the equations and retaining only the dominant terms. This yields much simpler equations, often amenable to analytical solution but, by design, region-specific. However, outer solutions often
 - 30 contain unknown constants, even after fitting to any outer boundary conditions that are a long way from the inner boundary layer. These constants cannot be found by also fitting to the inner boundary conditions, because the outer equations, not being designed to represent inner boundary layers, are often incompatible with them. Similarly, the inner boundary-layer solution may contain unknown parameters that its adjacent inner boundary conditions alone cannot resolve.

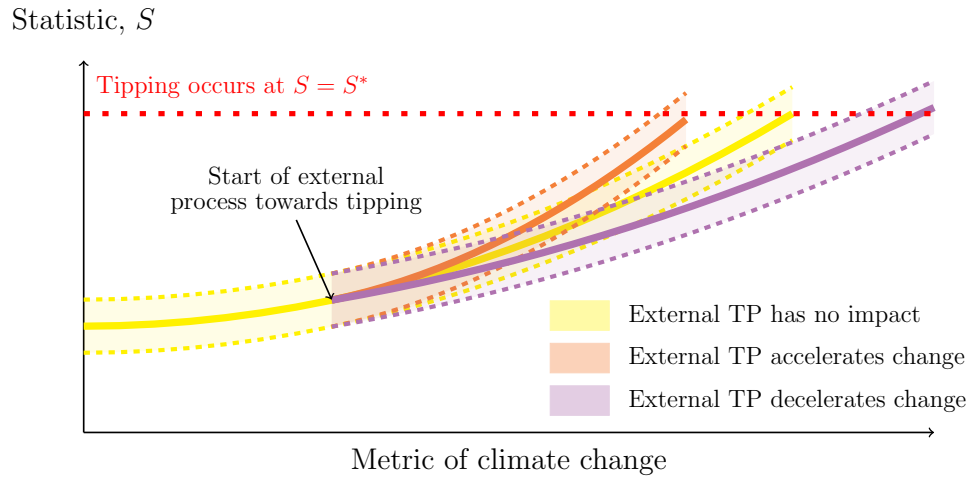


Figure 8. Schematic of an EWS statistic, S , which equals S^* when a system tips. The yellow curve, potentially derived from theory, maps uniquely to a climate change metric such as global warming, and so is similar to the EWS type described in Section 3.4. A second interacting Earth system component, which may also approach tipping as climate change increases, can either advance (red curve) or delay (mauve curve) the rate at which the first component approaches tipping.

To address parameter uncertainty, the method of matched asymptotic expansions extends solutions found in different spatial parts of the problem domain so that they match where the domains meet, i.e. in an intermediate region (Fig. 9). Importantly, matching also constrains the unknown constants. In the overlapping region, information is exchanged between regions, allowing the unknowns in the equations derived for each part of the domain to be calculated. Information from the boundary condition passes through the inner boundary layer to constrain unknown parameters in the outer domain. Similarly, information from the outer part and outer boundary condition can constrain parameters in the equations for the boundary layer.

We suggest that matched asymptotic expansions may help in developing EWSs for TPs, with the independent variable representing time rather than space. The inner region of rapid change (i.e. the boundary layer) would then correspond to the short period of major transition just before the TP, while the outer region would represent the longer period leading up to it, potentially including the present, for which observations exist. Hence, the “ x ” axis of Fig. 9 would denote increasing time from the present, and the rapid change in the inner solution would appear inverted horizontally and at the far right of the diagram, signifying the future activation of the TP. Of particular relevance is the potential two-way exchange of information via matching. Characteristics of present-day measurements in the outer period, placed in the context of asymptotic matching, may help to parameterise an EWS, S , around the future inner tipping period. Conversely, any expected structure of S around tipping could be sent back in parametric form to the outer period and compared with present-day measurements and their trends. Both exchanges may yield a better understanding of the timing and attributes of any approaching TP based on current measurements.

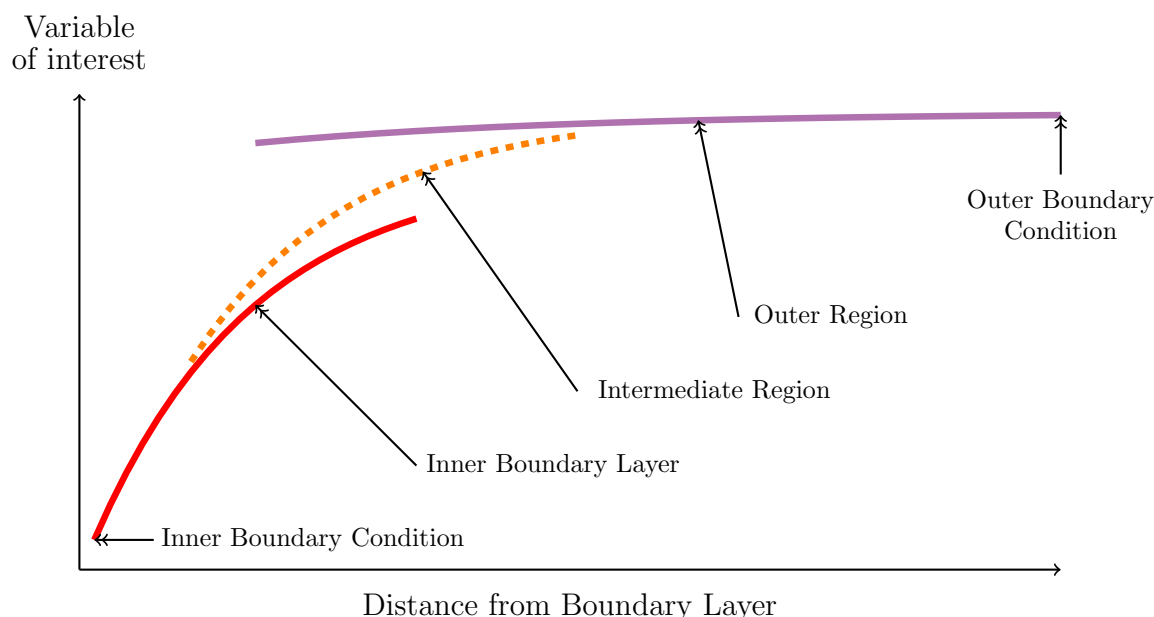


Figure 9. Schematic of the method of matched asymptotic expansions. The “ x ” axis represents space. The outer region solution covers most of the domain and satisfies any outer boundary conditions. On the left, an inner boundary layer spans a much smaller distance, responds to a left-hand boundary condition, and exhibits substantial variability in the variable, as shown. The method advances both the inner and outer solutions to generate an intermediate solution valid where the two domains overlap. Solving for this overlap region exchanges information between the domains and may constrain unknown constants in either solution. Hence this method may help predict the timing or features of future TPs by transmitting information from the current measured period to projections of TP occurrence. In such an application, the horizontal axis would represent time, with rapid change around the TP forming the inner region, mirrored horizontally on the right-hand side. The contemporary period would lie in the outer region, to the left.

4 Discussion and Conclusions

Concern persists that further climate change could push Earth system components past TPs into new states. Some TPs may be crossed with little global warming beyond 1.5 K above preindustrial (Ritchie et al., 2026). This concern has prompted calls to search historical and contemporary measurements for any evidence that TPs are being approached. Recent syntheses review

- 5 TP detection and early warning methods across climate, ecological and human systems (e.g. Dakos et al., 2024), describing indicators, implementation and pitfalls in inference from real-world data. We complement these studies in two ways. First, we consider EWSs for land surface response and the benefits of EO for refining them (Lenton et al., 2024). Many EO products have parallel forcing datasets (e.g. reanalyses of near-surface meteorology), allowing fluctuations caused by external “noise” to be separated from responses to drivers more representative of a changed future climate (e.g. high temperature events), so
- 10 emphasising the latter may greatly improve EWSs predicting TP timing. Second, we present hypotheses that could yield EWSs



with higher predictive accuracy, many suggesting introducing process knowledge into EWSs. Statistical EWSs are valuable, but in climate science they may be incomplete if they do not capture aspects of the substantial parallel investment in ESMs that also simulate future large-scale environmental change.

Rather than cataloguing and evaluating existing warning methods, we focus on mathematical and conceptual foundations for accurate EWSs. We propose a possible one-to-one mapping between governing equations and an optimal EWS. Often these equations may be dynamical systems that spatially integrate the fine-resolution processes discretised in ESMs. Recent critiques stress ambiguity and false positives of statistical EWSs in complex, strongly forced climate systems. Variance and autocorrelation can arise from mechanisms unrelated to TP proximity, so such EWSs should only be used alongside rigorous process understanding (Rietkerk et al., 2025). Work on rate-dependent and non-autonomous tipping also shows that CSD, which underpins many indicators, may not hold in rapidly forced systems (Ashwin et al., 2012). EWSs tied more closely to processes may be less prone to these problems.

Such links to process understanding might, for instance, add equation terms to existing statistics, S , to refine their mean projections of distance from tipping and narrow uncertainty bounds. This approach may counter the view that historical data alone cannot reveal approaching TPs (Ben-Yami et al., 2024). ESMs, developed over decades, represent process equations on numerical grids, so developing EWSs independently of this encoded understanding may seem odd unless viewed as a stopgap until ESMs become more accurate and inter-model differences shrink. Although total investment in ESMs is not quantified, calls have been made for around US\$200 million per year to improve climate models (Goddard et al., 2009). We suggest that next-generation EWSs be developed alongside ESMs, while EWS understanding merged with data could, in turn, advance ESM parameterisation.

Intermediate conceptual dynamical system models may best link ESM projections to EWS development. Dynamical systems capture averaged ESM behaviour yet remain simple enough to understand, even with high-frequency variability added. Understanding such variability superimposed on dynamical systems may relate fluctuations to processes and so inform EWSs. Extracting the main equation terms from ESMs will be difficult, however. Conventional scaling to retain dominant equation terms is unlikely to work, because forcings vary across the globe and produce a broad range of responses. Furthermore, ESMs resolve small-scale processes that require complex spatial aggregation into summary equations. Moreover, although built from detailed knowledge of their components, ESMs behave as highly complex models whose inner workings, especially inter-component couplings, are not fully understood (Huntingford, 2017). Nevertheless, derived dynamical systems would allow exploration of the hypotheses in Section 3 with the added advantage of extrapolation of computationally expensive ESM simulations to a broad range of future forcings (e.g. different GHG concentration scenarios).

AI methods may help extract dominant summary equations from data, or from ESMs diagnostics treated as data, for example through equation discovery (e.g. Klishin et al., 2025; Brunton et al., 2016), particularly sparse regression (e.g. Egan et al., 2024), and as already proposed for climate research (Huntingford et al., 2025). Other disciplines have also addressed extracting dynamical systems from complex systems. We identify six books on system identification (Pillonetto et al., 2022; Keesman, 2011; Billings, 2013; Ljung, 1999; Isermann and Münchhof, 2011; Nelles, 2020), some focussing on nonlinear underlying systems.



In summary, we offer perspectives and hypotheses to help EWSs more accurately project the thresholds at which climate change may induce tipping in key Earth system processes. Using EO data, y , alongside forcing data (e.g. meteorological measurements), Q , clarifies the causes of fluctuations in satellite measurements, with implications for EWS development. We argue that characterising individual process behaviours may map onto new EWSs that warn of TPs more accurately than generic forms, linking EWS development to ESM advances rather than treating it as independent. The risk that small additional climate change triggers major Earth system TPs remains a major threat to society, so research improving warnings of whether or when this may occur deserves continued support.

5 Code availability

This is a review proposing hypotheses to guide future research. As such, it does not present original analyses or computational results. Most diagrams are created in the Tikz drawing package, codes for which are available from C.H. (chg@ceh.ac.uk).

6 Data availability

No new data are used in this manuscript.

Author contributions. C.H. developed the original concept, structure, hypotheses and overall content of the manuscript. T.M.L., J.F.A., C.H., P.M.C., J.C., J.E.B., C.A.B., A.M.C., V.L., R.J.P., D.G. and S.P developed the original proposals supporting the analysis. P.A., A.M.C., C.R.V, R.J.P, H.M. and J.F.A. helped with reviewing and editing early versions of the manuscript. All authors contributed extensively to finalising the submitted paper.

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