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Integrating tipping point concepts across diverse systems

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The concept of a "tipping point" is widely used to describe abrupt, potentially irreversible changes in complex systems - from climate subsystems to ecosystems and social dynamics. However, concerns have been raised about definitional ambiguity and conceptual overuse that may obscure rather than highlight potential systemic risk. Here, we offer a cross-disciplinary synthesis of the tipping point literature that identifies three essential properties—self-reinforcing feedbacks, threshold behavior, and persistence—as the defining characteristics of tipping dynamics. While different interpretations reflect genuine system-specific differences and offer complementary insights, these three properties help identify underlying patterns and causal mechanisms across diverse systems. This synthesis promotes conceptual clarity in how tipping point terminology is applied across diverse contexts. In doing so, we identify research priorities: moving beyond single-threshold models, developing cross-system early warning indicators, understanding cascading dynamics between interconnected systems, and advancing integrated models capturing climate-ecological-social feedbacks.

The term "tipping point" has become a widely adopted concept across disciplines for describing abrupt, often irreversible shifts in complex systems. Originally rooted in bifurcation theory and nonlinear dynamics, the idea has expanded to encompass regime shifts—the transition between a systems "state" or "regime"—in ecosystems, regime shifts in social systems, rapid transitions in technological adoption, and thresholds in the Earth's climate system[1]. As environmental, social, and economic systems are increasingly pushed toward critical thresholds by human activities, the tipping point concept has become central to sustainability science, risk assessment, and global governance debates[2–7].

Yet despite increasing attention, the concept is used inconsistently across disciplines and sometimes dismissed due to perceived vagueness. The term is often used imprecisely, leading to conceptual overstretch and potentially misleading narratives. Recent discussions highlight both the value and challenges of tipping point concepts, including the potential for terminological ambiguity to impede scientific understanding and effective action, conceptual overextension to phenomena lacking genuine tipping characteristics, or difficulties translating tipping point science into policy frameworks given uncertainties in identifying thresholds[8–16]. These ongoing debates reflect a need for greater conceptual clarity about when and how tipping phenomena occur across different types of systems.

To analyze tipping points research, we conducted an exploratory bibliometric analysis. We examine publication trends and shifts in disciplinary engagement and research collaboration to offer a broader perspective on the evolution and use of the concept. This approach provided a foundation for synthesis by revealing shared properties and topics across disciplines, while clarifying how different fields define and apply the concept.

On the basis of this synthesis, we then address the challenges outlined above by contributing to clarifying tipping point dynamics. First, we identify three essential properties that characterize tipping dynamics: self-reinforcing feedbacks that amplify change, threshold behavior where small parameter changes trigger large responses, and persistence that makes transitions difficult to reverse. We use these three properties not only to define tipping points, but also to distinguish them from other forms of change. Where one or more of the properties are weak or absent, we treat such cases as important transitions, but not as tipping points in the strict sense. Second, we demonstrate how these properties manifest across

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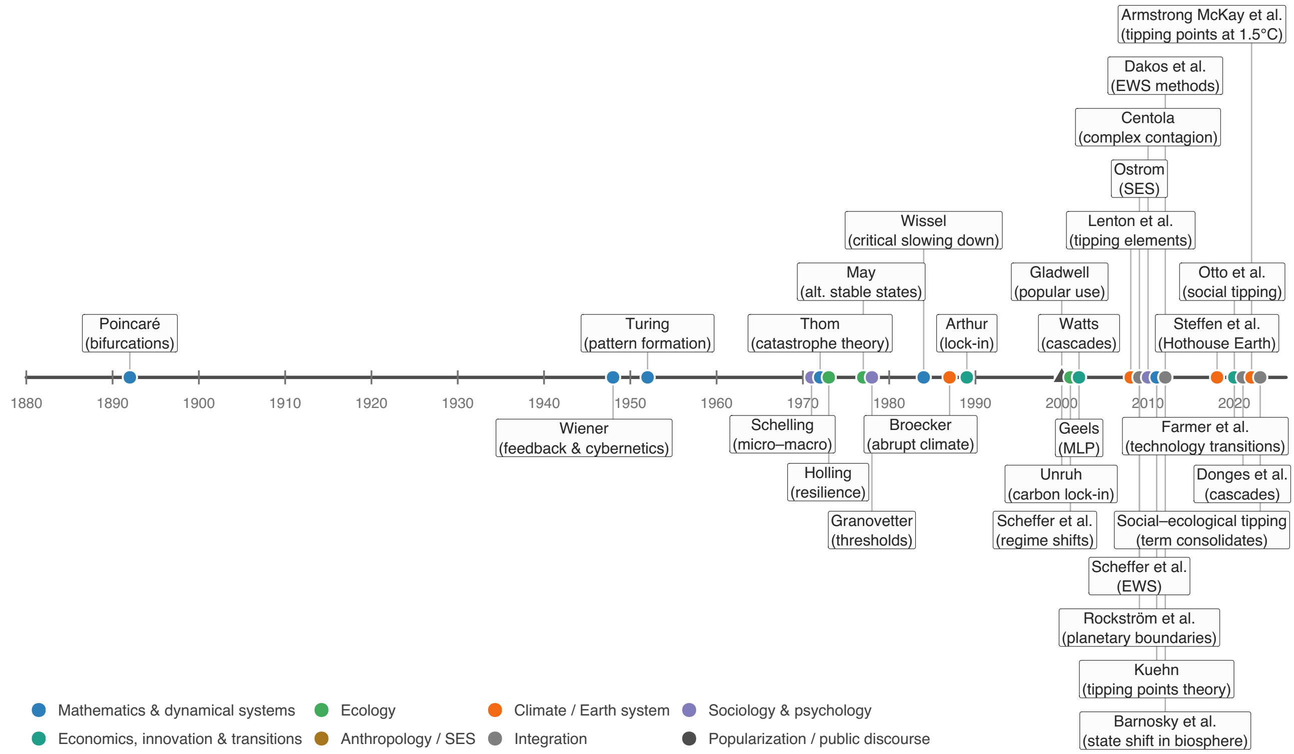

Fig. 1 | Historical development of tipping point concepts across disciplines. The timeline shows key theoretical advances and empirical discoveries from Poincaré's bifurcation theory (1880) through contemporary interdisciplinary applications. Dots indicate major milestones, with colors representing disciplines. The evolution demonstrates parallel development across multiple fields, with social science applications emerging alongside ecological work in the 1970s-80s, followed by increasing integration across disciplines in the 2000s-present.

different system types and disciplinary contexts. Third, we show that tipping thresholds exist in multi-dimensional parameter space rather than at single points, addressing a common source of confusion. Together, these provide a shared definitional basis for determining when the tipping point concept applies while avoiding conceptual overextension to phenomena that lack genuine tipping characteristics.

Mathematical foundations and historical development

The tipping point concept has evolved from its mathematical foundations finding applications across physical, life and social sciences (Fig. 1 and Table 1). The mathematical understanding of tipping points emerged from bifurcation theory in the late 19th century, pioneered by Henri Poincaré[17] and advanced by scholars including Andronov and Pontryagin[18]. A bifurcation occurs when small parameter changes cause sudden qualitative behavioral changes. During the mid-20th century, dynamical systems theory formalized how systems evolve over time and identified mathematical structures leading to tipping behavior. René Thom's catastrophe theory[19] advanced understanding of how continuous parameter changes can lead to qualitative system changes, providing valuable insights about system stability and sudden transitions.

Parallel developments on phase transitions in statistical physics provided complementary perspectives on tipping dynamics. It was found that first-order transitions exhibit hysteresis - a form of path dependency where the transition threshold depends on the direction of change and historical conditions. For example, water can be supercooled below 0 °C before freezing, but ice melts at exactly 0 °C, creating different thresholds depending on direction. In economics, unemployment rates may remain high after recessions end, even when economic conditions improve[20]. Second-order transitions, by contrast, occur at the same parameter value regardless of direction and show no hysteresis. In physics, "critical" refers to second-order phase transitions where phase distinctions disappear and systems exhibit unique properties like scale invariance.

The transition of the tipping point concept from pure mathematics to applied science accelerated with the recognition of multiple stable states (or regimes) in ecological systems during the 1970s[21–23]. Work on shallow lakes[5,24,25], coral reefs[26], and other ecosystems[27] demonstrated that natural systems could exist in alternative stable states and undergo rapid transitions between them. The dynamics of such change has been termed regime shifts[28], catastrophic shifts[5] or critical transitions[29]. Similarly, in climate science, the realization of the role of chaos in weather prediction[30] and the emergence of paleo evidence for abrupt climate shifts in ice and sediment records[14,31–34] initiated the search for potential alternative states in parts of the climate system such as the Atlantic Meridional Overturning Circulation (AMOC)[35,36]. This ecological and climate research helped bridge the gap between mathematical theory and real-world applications.

Recent years have seen a significant increase in publications on tipping points (Fig. 2). By tracing citation networks, we found that the tipping point concept has evolved from discrete mathematical origins to a truly interdisciplinary framework (Fig. 3). The analysis shows an increasing interconnectedness between mathematical, ecological, and social science domains, reflecting the concept's expanding conceptual complexity but also the potential for synthesis (Fig. 4). Details of the bibliometric analysis can be found in the Supplementary Information.

Definition and essential properties

Based on this historical assessment and mathematical foundations, we define a tipping point as the point where small additional changes in one or several of the system conditions shift feedback mechanisms, such that positive feedbacks become dominant over stabilizing negative feedbacks and drive self-propelling, substantial, widespread, and often difficult-to-reverse system changes. While we use the term "tipping point" for simplicity, most systems actually exhibit what mathematicians would call "tipping surfaces" or "critical manifolds" in a multi-dimensional parameter space. For instance, the Amazon rainforest's stability depends on at least four key

Table 1 | Evolution of tipping point concepts

Period	Key Conceptual Advances	Disciplines
1880s–1970s: Mathematical Foundations	Bifurcation theory, catastrophe theory, phase transitions	Mathematics, Physics
1970s–1990s: Empirical Applications	Alternative stable states, regime shifts, social threshold models	Ecology, Social Science
1980s–2000s: Climate System Integration	Abrupt climate change, AMOC, climate tipping elements	Climate Science
2000s–Present: Cross-Disciplinary Synthesis	Critical transitions framework, integrated social-ecological systems	Interdisciplinary

parameters: temperature, precipitation, dry season intensity and the extent of deforestation[37]. This means that the critical threshold is not a single point but rather a surface in a multi-dimensional parameter space. This complexity partly explains why identifying exact thresholds in empirical data is challenging—the "point" moves depending on other controlling variables. Nevertheless, we maintain the term 'tipping point' for consistency with the literature while acknowledging this important conceptual distinction. A "point" can also convey a moment in time, which can be an effective way to communicate how tipping points emerge in systems as a result of human impacts over time.

The tipping point phenomenon emerges from three essential properties that we identify as distinguishing tipping points from other types of transitions: self-reinforcing feedbacks, threshold behavior, and persistence (Fig. 5). Before examining these properties in detail, we note that from a mathematical perspective, there are many types of bifurcation that capture many kinds of qualitative changes in system behavior[38]. These bifurcations aren't limited to transitions between equilibrium states; they can involve shifts to oscillatory regimes, long transients, or even chaotic dynamics. However, what distinguishes tipping points as a specific class of transitions is the particular combination of the three properties we identify.

While these properties have been recognized in various forms across different disciplines, different research communities have emphasized different subsets of these three properties, creating both fragmented understanding and opportunities for cross-disciplinary learning. Climate scientists have focused primarily on threshold behavior and persistence (irreversibility)[2,3]. Ecologists have emphasized self-reinforcing feedbacks and alternative stable states, but have sometimes been less precise about threshold identification and the conditions for true irreversibility[5,28]. Social scientists have highlighted network effects, emergence and social contagion processes (feedbacks), but have given less systematic attention to threshold behavior and persistence given human agency and reflexivity[39,40].

Amplifying feedback mechanisms

The first essential property is amplifying (or self-reinforcing) feedback loops. If a system crosses a tipping point, internal dynamics drive continuous change even if the initial perturbation is later removed. This arises from reinforcing feedbacks becoming dominant over stabilizing negative feedbacks and strong enough to be self-propelling. Specifically, one unit of change propagated around the feedback system must give rise to at least one additional unit of change for that change to be self-propelling. In contrast, weaker positive feedbacks will converge on a finite change in the original state. The centrality of strongly amplifying feedbacks in tipping point behavior has been emphasized in seminal work across climate[2,3,41], ecology[5], and social systems[1,39]. A common example is audio feedback in sound systems, where once the gain of an input that is looped back into input exceeds a critical threshold, a self-reinforcing loop creates a high-pitched squeal that continues until someone intervenes (Fig. 5). Such self-reinforcing feedbacks operate through physical processes (ice-albedo effects) in climate systems, biological interactions (predator–prey dynamics) in ecosystems, and information networks (social contagion) in social systems—yet all follow the same underlying logic of amplification beyond critical thresholds.

Self-reinforcing feedbacks manifest differently across system types but share the common feature that change amplifies itself. In climate systems, ice-albedo feedback provides a quantitative example: when ice cover decreases, darker surfaces absorb more solar radiation, causing further warming and ice loss. Observational data suggest that a 1 °C warming in the Arctic removes approximately 2.5 million km^2 of sea ice, which in turn amplifies regional warming by 0.3–0.5 °C through reduced albedo[42]. This creates a feedback loop where initial warming triggers changes that cause additional warming.

In ecological systems, shallow lake eutrophication demonstrates multiple interacting feedbacks. When nutrient loading causes algal blooms, several reinforcing processes occur simultaneously: (1) turbidity reduces light penetration, killing benthic plants that would otherwise compete with algae and stabilize sediments; (2) organic matter from dead algae enriches sediments, creating an internal nutrient source; (3) low oxygen conditions favor phosphorus release from sediments; and (4) fish communities shift from piscivores to planktivores that preferentially graze zooplankton, releasing algae from top-down control[5]. Each process amplifies the others, creating a stable turbid state.

Social systems also exhibit self-reinforcing dynamics. In electric vehicle (EV) adoption, initial purchases by early adopters trigger multiple feedbacks: more EVs increase demand for charging infrastructure, making EVs more practical for subsequent buyers; larger EV markets incentivize manufacturer investment in better models and lower prices; visible EV adoption changes social norms, reducing perceived risks; and economies of scale in battery production reduce costs further[43–45]. These feedbacks can create rapid adoption cascades once a critical mass of early adopters is reached.

Mathematically, self-reinforcing feedbacks can be characterized by the loop gain g, which measures how much a small perturbation is amplified through a feedback loop. When $g > 1$, perturbations grow and the feedback is self-propelling; when $g < 1$, perturbations decay and the system returns to its original state. Tipping points occur in regions where feedback loops have sufficient strength ($g \geq 1$) to maintain alternative stable states[3]. This can be expressed mathematically as:

$$\Delta x(t+1) = g \times \Delta x(t)$$

Threshold behavior

The second defining property is threshold behavior (Fig. 5), where small additional changes in conditions can trigger large, qualitative shifts in system state. This nonlinearity emerges because the necessary shift in the balance of feedbacks described above only occurs under a specific range of conditions that define the threshold (or critical manifold in higher dimensions). In social systems such thresholds emerge as the result of cumulative forces and structural changes, such as growing inequality or political instability, that create the conditions for a small additional action to create large system changes[46]. For example, growing public dissatisfaction and political mobilization can create conditions where a small event—like a disputed election or peaceful protest—triggers large-scale transition from autocratic to democratic governance. Before reaching this threshold, a system may show only a small—or linear—response to changing conditions. However, once crossed, the same system can change abruptly due to positive feedback becoming self-propelling (as described above). Abrupt change is not necessarily 'rapid' on human scales: the millennial time scales on which ice sheets collapse are abrupt relative to ice cap formation, but slow compared to human lifetimes. Threshold behavior in tipping points can arise

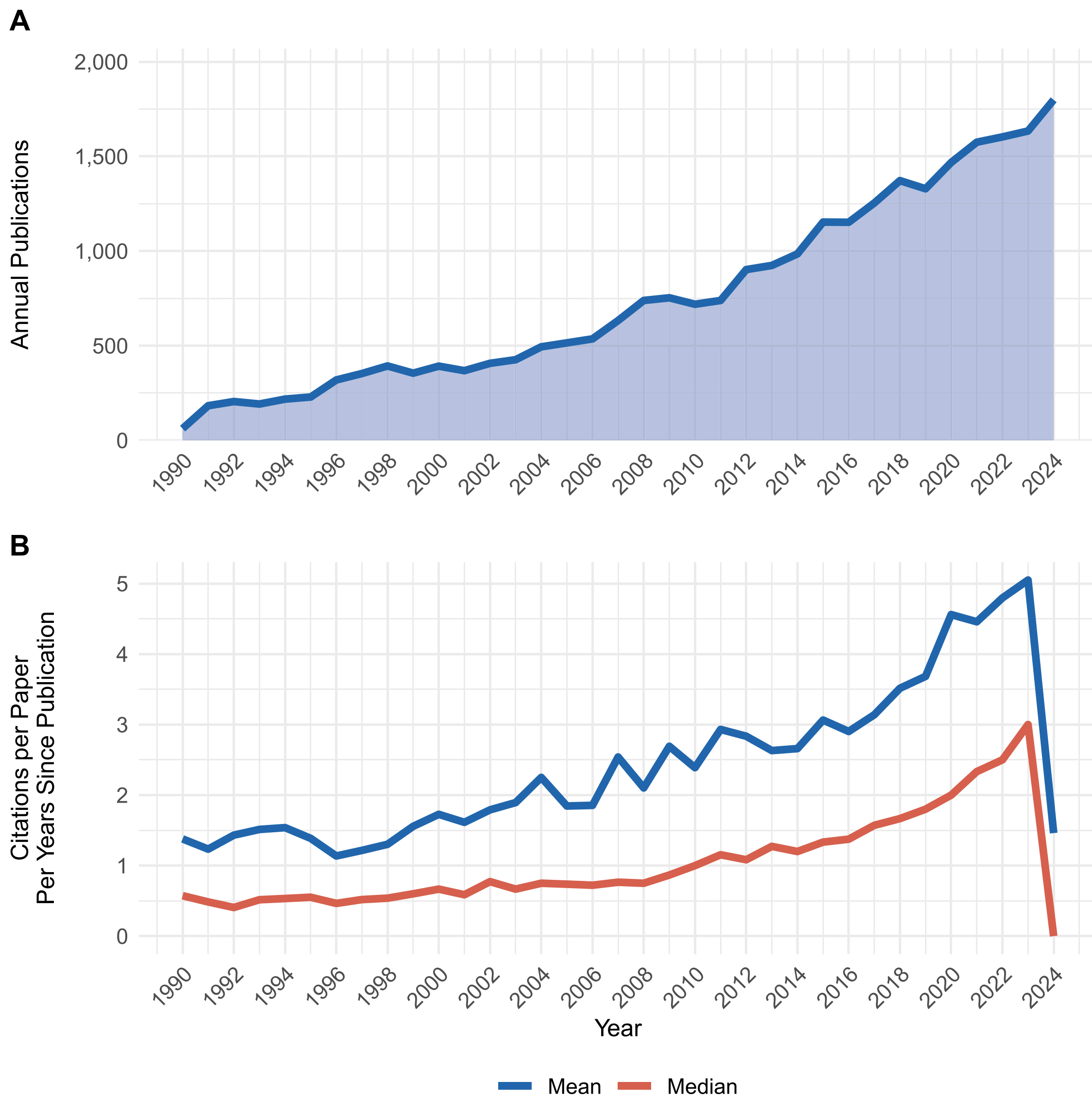

Fig. 2 | The temporal evolution of the tipping points scientific literature. A The number of publications published annually and **B** mean (blue) and median (red) number of citations per publication. To analyze the evolution of tipping points research, we conducted an exploratory bibliometric analysis using the Web of Science database. We performed a focused search for publications containing "tipping point" in the title, abstract, or keywords, covering the period from 1990 to 2024. This yielded a dataset of publications that we analyzed for temporal trends, disciplinary distribution, and interdisciplinary collaboration patterns. Highlighted papers were selected based on high citation counts and disciplinary representation. This single-term approach provides a preliminary analysis that captures core tipping points literature rather than an exhaustive survey of all related research.

through a range of distinct mechanisms[42], each with different implications for detection and reversibility.

Bifurcation-induced tipping occurs when gradual parameter changes cause a qualitative change in system dynamics, eliminating one stable state. This is the most commonly studied mechanism. For example, in the Stommel model of thermohaline circulation, increasing freshwater input gradually reduces the positive feedback between circulation strength and northward salt transport until a saddle-node bifurcation eliminates the "on" state of circulation[36]. The system then exhibits a sharp threshold: once freshwater forcing exceeds the bifurcation point, circulation collapses regardless of the rate of change.

Rate-induced tipping occurs when a forcing changes too rapidly for the system to track its changing equilibrium, even if that equilibrium never disappears. This mechanism can trigger transitions that may be either transient or permanent, depending on system characteristics. For instance, if atmospheric CO_2 rises rapidly, ecosystems may fail to adapt quickly enough and undergo dieback, even though they could theoretically remain stable if the change occurred more slowly[47,48]. The relevant timescale comparison is between forcing rate and ecosystem adaptation rate, not between forcing and internal dynamics alone. If the timescale of a system is slow compared to the timescale of the forcing, then it is possible to briefly overshoot a tipping point and not cause a shift in long-term behavior[43,44]. Rate-induced tipping is particularly concerning because it can occur even in systems where bifurcation-based thresholds would not be crossed under slower forcing. Recent work has identified rate-induced tipping in climate subsystems[49], and coral reef ecosystems under rapid warming[50]. The ubiquity of rapidly changing forcing in the Anthropocene—from accelerating climate change to rapid technological disruption[51–53] - makes rate-induced mechanisms increasingly relevant across systems.

Noise-induced tipping arises when stochastic fluctuations push a system across a threshold between alternative stable states. In systems with small basins of attraction or weak stability, random perturbations can trigger transitions even without systematic parameter changes. This mechanism is particularly relevant in ecological systems subject to environmental variability and may explain apparently "random" transitions in paleoecological records[54].

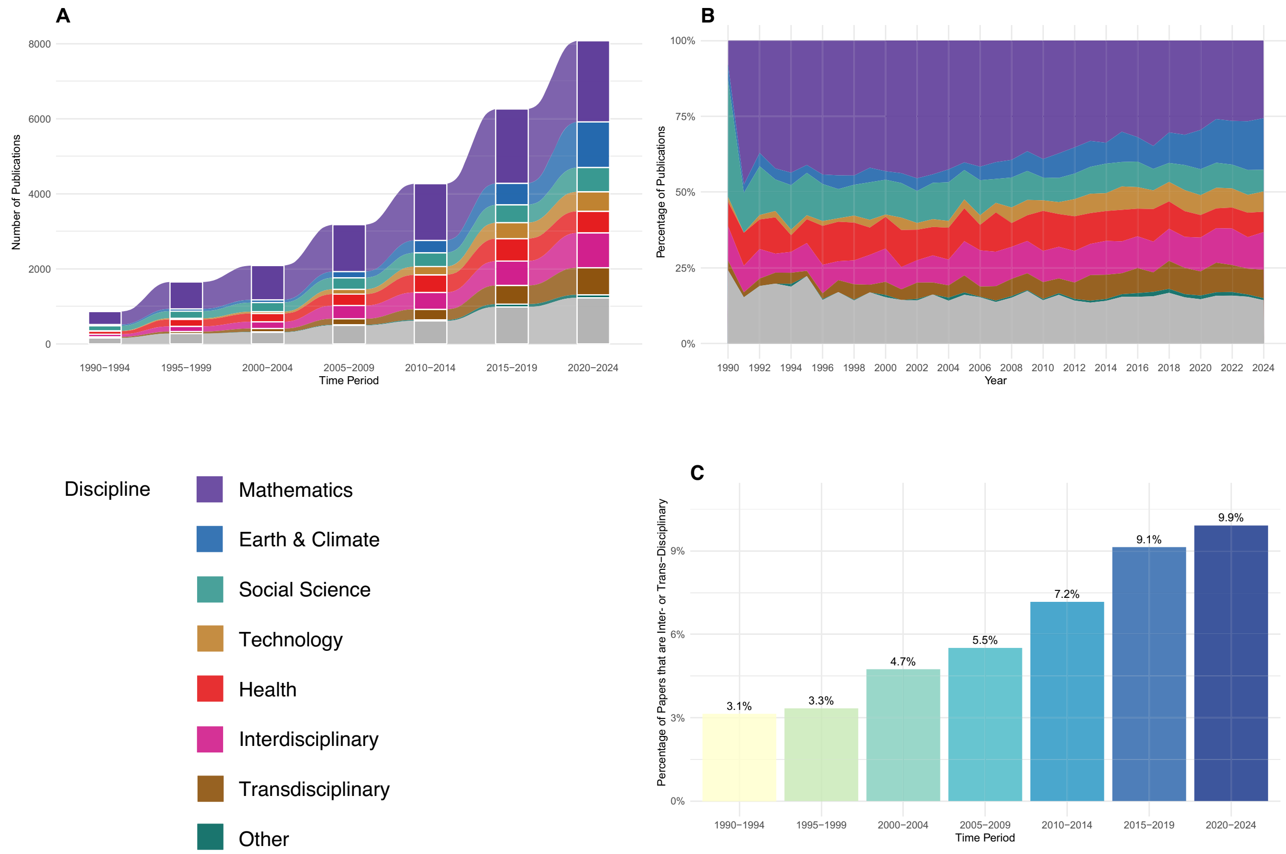

Fig. 3 | An analysis of how tipping points research has evolved from 1990 to 2024. Publications were classified into eight disciplinary categories: Mathematics, Earth & Climate, Social Science, Technology, Health, Interdisciplinary, and Transdisciplinary research. We tracked the evolution of these disciplines over seven time periods to identify shifts in research focus and the emergence of interdisciplinary approaches. **A** shows an alluvial diagram depicting the changing volume of publications across disciplines over seven time periods. **B** shows the changing proportional composition of disciplines, showing an increase in Earth and climate, social science and interdisciplinary studies, while the share of math, ecology and technology research has become smaller. **C** shows the growth of inter- and transdisciplinary research, which has more than tripled from 3% in 1990–1999 to 9% in 2020–2024, demonstrating the field's shift toward integrated approaches to studying tipping points.

Importantly, neither rate-induced nor noise-induced tipping produces the critical slowing down signals that characterize bifurcation-induced transitions[55], complicating early warning efforts and emphasizing the need for mechanism-specific detection approaches. These mechanisms are not mutually exclusive. Real systems often exhibit combinations: a bifurcation may reduce the basin of attraction, making noise-induced tipping more likely; or parameter drift toward a bifurcation point may combine with rapid forcing rates to produce rate-induced transitions. The coexistence of multiple mechanisms creates challenges for empirical detection, as different indicators may be relevant for different tipping types.

Persistence

The third defining property is the persistent nature of the changes following a tipping point. We use "persistence" rather than "irreversibility" to better capture the range of behaviors observed across systems—from effectively permanent transitions in physical systems to more flexible but still consequential changes in social systems—emphasizing that tipped states resist spontaneous return to their original conditions. While absolute irreversibility is not a requirement, some form of "lock-in" is expected, whereby the system does not return to its original state if the forcing factors are reduced to, or even below, the values at which tipping occurred.

Importantly, this persistence refers to the system's intrinsic dynamics and structure; while external actors may be able to reverse tipped states through deliberate intervention, the system will not spontaneously return on its own. For example, restoring a eutrophic lake to a clear-water state typically requires reducing nutrient inputs far below the levels that triggered turbidity[5], or active management interventions such as removing accumulated sediments. Similarly, a power grid collapse represents a tipping point that persists until external repair efforts restore functionality—the system will not spontaneously recover even if the original disturbance is removed. This asymmetry—known as hysteresis—creates path dependence whereby the current state of a system is contingent on its history. The hysteresis effect means that reversing a tipped system typically requires conditions far beyond those that originally triggered the transition.

Persistence manifests through different mechanisms depending on system type. In physical systems, persistence often reflects changes to system parameters themselves. In climate systems, persistence emerges from long time scales of physical processes—ice sheet collapse is persistent because ice loss exposes land or ocean at lower elevations where temperatures are warmer, even if climate forcing returns to pre-collapse conditions, the topographic change prevents ice regrowth[56]. In ecological systems, persistence often arises from biological legacy effects and altered species composition—a degraded coral reef cannot spontaneously restore its original species assemblage even if water quality improves, because coral recruitment requires existing reef structure for settlement[57]. In social systems then persistence can arise from lock-ins and path dependence[58] or system stabilization dynamics (ranging from psychological system justification[59] to measures of repression and co-option[60]) that kick in or can be deliberately initiated.

The degree of persistence varies across systems and scales. Persistence is not binary but exists along a spectrum with important practical implications. Effectively irreversible changes occur on timescales far exceeding

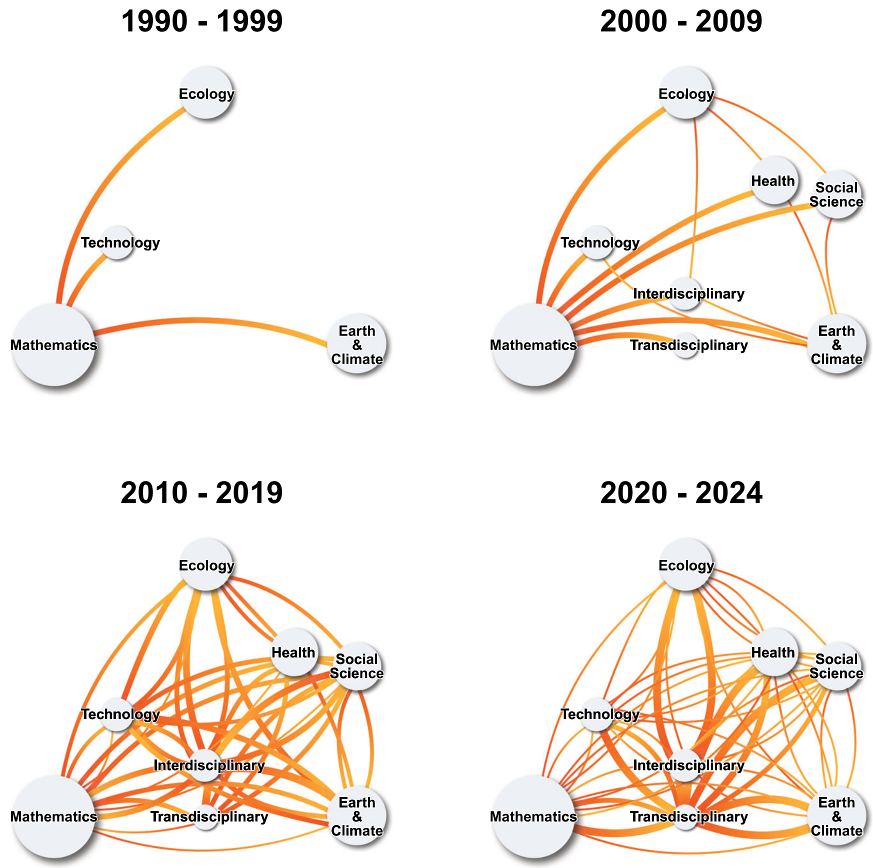

Fig. 4 | The evolution of citation patterns between disciplines in tipping points research across four time periods. Citation network analysis was performed to understand knowledge flows between disciplines across four distinct time periods (1990–1999, 2000–2009, 2010–2019, and 2020–2024). Network diagrams illustrate how citation relationships between disciplines have evolved from isolated mathematical and ecological origins to highly interconnected transdisciplinary exchanges. The network diagrams show knowledge flows between disciplines, with node size representing publication volume. In the 1990s, mathematical and ecological research were the central origin with limited connections to other fields. By 2000–2009, more bidirectional exchanges emerged, particularly with ecology. During 2010–2019, interdisciplinary research became a hub, facilitating knowledge exchange across disciplines. By 2020–2024, we see the emergence of transdisciplinarity with robust connections between all disciplines, while interdisciplinary approaches remain dominant.

human planning horizons or require conditions outside the range of plausible intervention. Ice sheet collapse represents the archetype: even aggressive climate mitigation would not restore ice sheets for millennia, and active ice sheet restoration is technologically infeasible. Similarly, species extinctions are effectively irreversible within timeframes relevant to ecosystem management. Practically difficult to reverse changes could theoretically be reversed but face major economic, technological, or social constraints. In socio-technological systems, this often manifests as lock-in effects, where early adoption choices limit future options even when alternatives become superior[61]. For instance, early adoption of fossil fuel infrastructure creates lock-in effects through sunk costs, supply chains, social practices[62] and institutional dependencies that persist even as renewable alternatives become superior[63]. Eutrophic lake restoration is possible but costly, requiring sustained nutrient input reduction often below pre-transition levels, plus potentially expensive interventions like sediment removal. Urban infrastructure lock-in can be overcome but typically only over decades as capital stock gradually turns over[64]. Reversible with intervention describes systems where persistence is moderate and deliberate action can restore original functions and main patterns of interaction relatively quickly. Some social tipping points fall in this category - for example, temporary adoption of a communication platform can reverse if users coordinate migration to alternatives, though network effects create friction.

These distinctions matter for risk management and policy design. Effectively irreversible tipping points demand preventive action and precautionary approaches given the impossibility of correction. Practically difficult transitions may justify early intervention to avoid costly future restoration. Reversible transitions still warrant attention but allow for adaptive management approaches that respond to observed changes. The spectrum of persistence also interacts with threshold behavior: systems with sharp thresholds and high persistence pose greatest risks, while gradual transitions with low persistence offer more opportunities for course correction. This property of persistence distinguishes tipping points from other non-linear phenomena, highlighting their importance for long-term system management. The locking-in of substantially different system states makes tipping points particularly consequential for human and natural systems alike.

Multi-dimensional parameter spaces and tipping surfaces/objects

A critical insight that addresses a fundamental criticism of tipping point concepts is that thresholds are contingent and multi-dimensional rather than fixed at single parameter values. Critics have correctly noted that transitions are often oversimplified - for instance, stating that "the Amazon will tip at X% deforestation" or "AMOC will collapse at X Sv freshwater forcing" implies fixed thresholds independent of context. In reality, system stability typically depends on multiple interacting factors. Rather than a single temperature threshold, the critical temperature at which a transition occurs depends on other changing conditions such as deforestation, precipitation patterns, or atmospheric composition. This creates tipping "surfaces" or "objects" in multi-dimensional parameter space - a concept that fundamentally changes how we understand and identify tipping points in real-world systems.

The Amazon rainforest provides a well-studied ecological example. Common discussion focuses on a "40% deforestation threshold" beyond which large-scale dieback becomes likely[65]. However, more recent work reveals that the threshold depends on at least four parameters operating simultaneously:

1. Regional temperature: Warming increases drought stress and fire susceptibility, lowering the deforestation threshold at which dieback occurs
2. Precipitation patterns: Changes in rainfall distribution affect forest resilience, with dry season length particularly critical

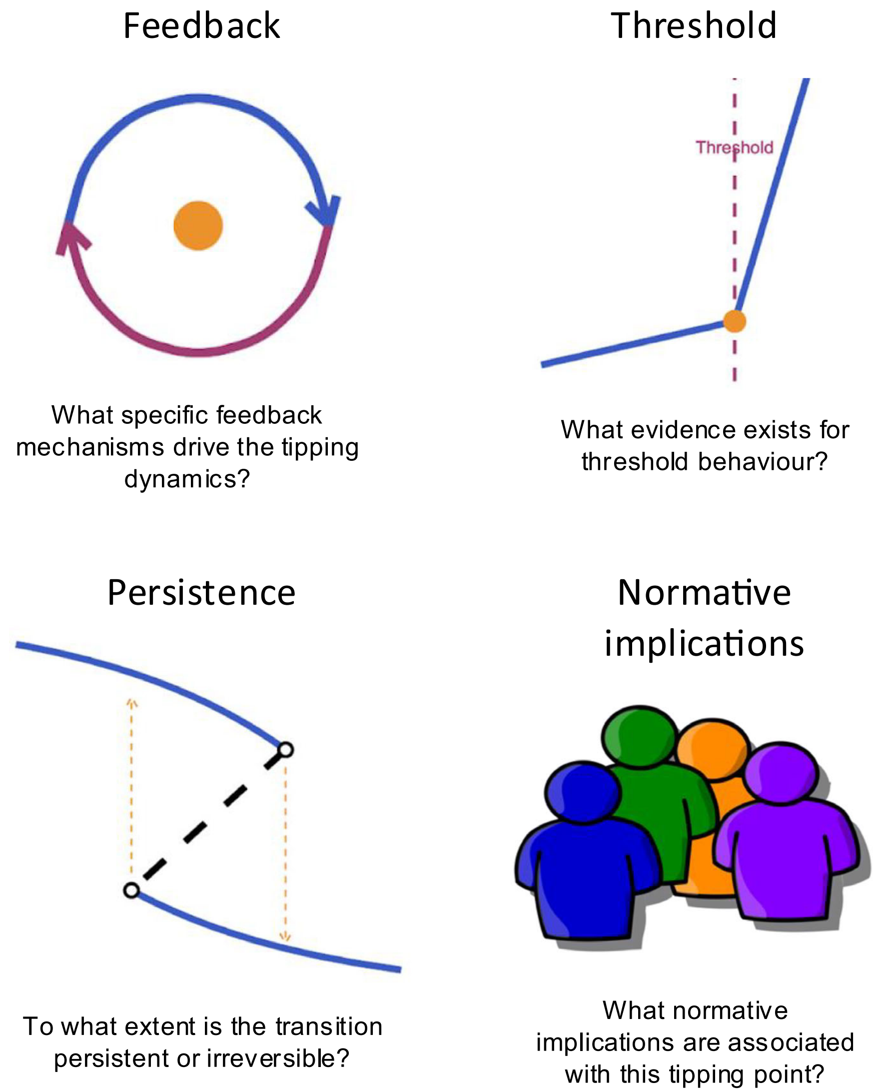

Fig. 5 | Core properties and assessment criteria for tipping point dynamics. The figure illustrates the three essential properties that distinguish genuine tipping points from other forms of nonlinear change: self-reinforcing feedbacks (circular arrows showing amplifying loops), threshold behavior (step function showing abrupt transitions at critical points), and persistence (hysteresis curve showing path dependence). The fourth panel addresses normative considerations, recognizing that the desirability of tipping points depends on values and perspectives of different stakeholders. Together with the associated assessment questions, this provides a systematic approach for evaluating whether a system exhibits genuine tipping point characteristics across climate, ecological, and social systems.

3. Atmospheric CO_2 concentration: Higher CO_2 may partially offset drought stress through improved water use efficiency, but also drives warming
4. Fire frequency: More frequent fires reduce forest regeneration capacity and favor savanna vegetation

These factors interact, creating a multi-dimensional "tipping object" in (deforestation, temperature, precipitation, CO_2, fire) space. In one region of this space, the forest may remain stable even with 50% deforestation; in another, it may collapse with only 20% deforestation. There is no single universal threshold—the critical deforestation level varies continuously depending on background climate and disturbance conditions[37].

Social tipping points also exist in multi-dimensional spaces, though parameters differ. For example, electric vehicle adoption depends on: (1) upfront cost differential vs gasoline vehicles, (2) charging infrastructure density, (3) battery range, (4) social network effects (peer visibility of EVs, norms and vested interests), (5) policy incentives, and (6) gasoline prices. The "tipping point" for rapid EV adoption is not a single cost threshold but a 5-D object in this 6-D space. With high gasoline prices and strong policy incentives (parameters 5-6 favorable), adoption may tip even with limited charging infrastructure (parameter 2 unfavorable). With dense charging networks, adoption may tip even without strong policy support.

If we have n relevant parameters then the tipping threshold will be an $n-1$ dimensional object. Figure 6 illustrates how this tipping threshold should be visualized based on the number of parameters that determine the tipping dynamics. The classical scenario is to consider a single parameter which gives rise to a single tipping point. However, with two parameters the tipping threshold is a curve in 2D space. For three parameters the threshold is a surface in 3D space, while for even more parameters the tipping threshold is harder to visualize. These visualization approaches are essential for conveying how thresholds shift with changing background conditions and for identifying safe operating spaces in multi-parameter systems. Though regardless of the tipping threshold dimension the concept remains the same. One side of the threshold the system may be bistable, but the other side of the threshold could correspond to the loss of one of these states. If the state that is lost corresponds to the current state of the system, then tipping would occur to the alternative state if the threshold is transgressed for sufficiently long.

The multi-dimensional nature of tipping surfaces has several implications:

1. Threshold mobility: As background conditions change (e.g., climate warming), tipping points shift. A parameter value that is currently "safe" may become dangerous as other parameters change.
2. Synergistic effects: Multiple stressors can interact non-linearly. The combined stress creates threshold locations that cannot be predicted from studying each stressor independently. As in our Amazon example, the combined effect of moderate warming and moderate deforestation may exceed the sum of their individual effects.

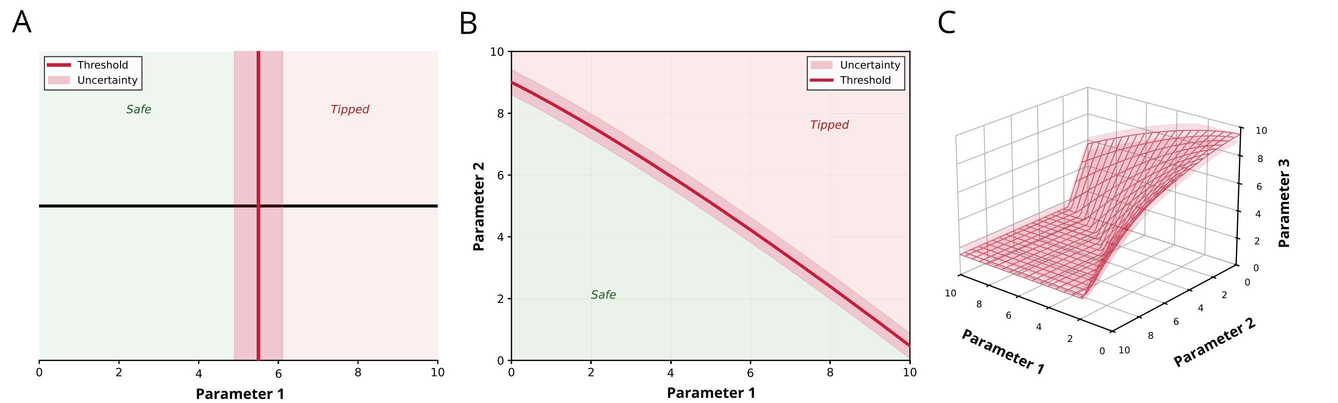

Fig. 6 | Tipping thresholds in parameter space. Tipping thresholds divide a parameter space into regions representing qualitatively different regimes. The thresholds can be represented independently of system states as geometric boundaries in parameter space. Dimensionality of tipping point thresholds scales with the number of controlling parameters. For one parameter governing the tipping dynamics, each tipping threshold is represented by a point (**A**) for two parameters it is represented by a curve (**B**) and for three parameters a surface (**C**). This geometric framework generalizes to p parameters producing a $(p-1)$-dimensional threshold manifold, highlighting the challenges of characterizing multi-parameter tipping points in Earth system components.

3. Safe operating spaces: Rather than single safe thresholds, we need to identify multi-dimensional safe operating spaces[66,67]. This requires understanding how multiple pressures interact.
4. Monitoring challenges: Early warning signals must account for multi-dimensional forcing. A system may approach a tipping point even if individual parameters show modest changes.
5. Precautionary management: Anticipating the exact occurrence of a tipping point may be challenging. Management should therefore take a precautionary approach, focusing on avoiding tipping risks, mapping alternative scenarios for different forcing factors and avoid fixating on precise prediction.
6. Intervention flexibility: Multi-dimensional spaces offer multiple intervention pathways. Even if addressing climate change globally remains inadequate, reducing deforestation through local legislation or increasing precipitation through land management could at least build some resilience in the system.

This multi-dimensional tipping framework directly addresses a major objection to tipping point concepts. Critics correctly note that single-threshold claims oversimplify complex transitions, creating the impression that tipping dynamics are either poorly understood or not useful for decision-making. By explicitly acknowledging that thresholds form objects in parameter space rather than exist at fixed points, we provide a more realistic and defensible representation of tipping behavior and a larger set of options for acting. This does not weaken the tipping point concept—rather, it provides a more realistic framework for understanding why threshold identification proves challenging while clarifying the nature of systemic risk. Imprecision exists in most decision-making contexts, yet we still act. Indeed, the existence of complex tipping objects strengthens rather than weakens the case for precautionary management—the complexity of threshold behavior means that surprising transitions may occur as systems approach poorly-mapped regions of parameter space, making early action prudent given the potentially severe and persistent consequences of crossing tipping points.

Identifying tipping dynamics

To distinguish genuine tipping phenomena from other forms of nonlinear change, four key assessment questions help operationalize these properties:
1. What specific feedback mechanisms drive the tipping dynamics?
2. What evidence exists for threshold behavior?
3. To what extent is the transition persistent or irreversible?
4. What normative implications are associated with this tipping point?

For example, applying these questions reveals that while smartphone adoption exhibited network feedbacks and lock-in effects, it lacked the sharp threshold behavior of genuine tipping phenomena. Similarly, gradual climate warming lacks self-reinforcing feedbacks and should not be characterized as a "tipping point," while Arctic sea ice loss exhibits albedo feedback but may lack the threshold behavior and persistence of genuine tipping dynamics.

Methodological advances continue to expand our ability to identify and detect tipping points across systems[68], though important limitations remain[69–71]. Emerging machine learning approaches show promise in identifying patterns preceding transitions[72–74], with techniques developed in one domain increasingly applied to others. For example, deep learning and ensemble machine-learning models have been empirically applied to real-world systems from paleoclimate transitions, rapid climate change, to ecological population collapse, by learning nonlinear precursors from high-dimensional time-series data[72–74]. By contrast, while early warning signals based on critical slowing down offer theoretical promise across diverse systems, empirical studies reveal practical constraints including limited applicability to real-world data[75,76], narrow detection windows[77], and challenges distinguishing genuine warnings from noise. These limitations are compounded by the multi-dimensional nature of tipping surfaces and mechanism-specificity of different signal types. Effective prediction therefore requires combining multiple approaches—generic statistical indicators, mechanism-specific process understanding, and computational methods—rather than relying on any single technique.

From system-specific manifestations towards conceptual integration

The three core properties of tipping points manifest differently across different types of systems due to differences in system structure, dynamics, and operational scales, which affect how tipping behavior emerges. They provide conceptual coherence across different manifestations of tipping behavior: climate systems exhibit hysteresis through physical phase changes, ecological systems through species interactions and spatial heterogeneity, social systems through institutional lock-in and network effects, and molecular and cellular systems through for example cancer metastasis. Understanding these differences is crucial for appropriate application— what constitutes "persistence" in a social institution differs fundamentally from persistence in ice sheet dynamics, yet both follow the same underlying principle of resistance to reversal (Table 2 and 3). This demonstrates that the three core properties—self-reinforcing feedbacks, threshold behavior, and persistence—characterize tipping dynamics across scales from individual cells to planetary systems, further validating the cross-system utility of clear definitional frameworks.

In climate systems, tipping points typically involve large-scale physical processes operating over seasons (monsoon onset) to millennia (ice sheet

Table 2 | Manifestation of tipping point properties across system types

System Domain	Feedback Mechanisms	Threshold Characteristics	Persistence Features	Timescales
Climate Systems	Physical/chemical (ice-albedo, carbon cycle, circulation patterns)	Well-defined, often identifiable from models and paleoclimate (Bifurcation-induced; sharp transitions)	Very strong - millennia for reversal in many cases	Decades to millennia
Ecological Systems	Biological interactions, species composition, nutrient cycles, Predator-prey, vegetation-climate, nutrient cycling	Moderate - spatial heterogeneity creates local variation (Bifurcation and noise-induced; context-dependent)	Moderate to strong - biological legacies and altered species pools	Years to decades
Social Systems	Network effects, social norms, Information diffusion, behavioral contagion, institutional structures	Weakest - human agency and reflexivity can shift thresholds (Rate-induced; often gradual)	Moderate - lock-in through infrastructure and norms, but potentially reversible through collective action	Months to decades
Socio-ecological Systems	Coupled human-natural feedbacks across multiple domains	Highly context-dependent - thresholds emerge from interaction of social and ecological processes	Variable - depends on relative strength of social vs. ecological lock-in	Multiple timescales interacting

melt), governed by thermodynamics and fluid dynamics. The mechanisms are predominantly physical and chemical, with relatively well-defined causal chains. Climate tipping points often feature strong hysteresis and effective irreversibility on human timescales. For example, the Atlantic Meridional Overturning Circulation (AMOC) exhibits threshold behavior where warming/freshwater input can disrupt circulation, leading to persistent changes lasting centuries[78].

Ecological systems, while also governed by physical laws, incorporate the complexity of biological adaptation and evolution. Ecological tipping points emerge from interactions between species, their environment, and human activities, often involving multiple positive feedback loops operating across different spatial and temporal scales. These can sometimes be better described as social-ecological tipping points, especially where tipping dynamics involve feedbacks operating through both ecological and societal processes[79]. Unlike purely physical systems, ecological systems can exhibit adaptive responses to environmental changes - for example, species migration and horizontal gene transfer or improved management of human shocks such as pollution. Although these capacities have limits and may not prevent tipping point behavior when environmental changes exceed adaptive capacity, they do offer a greater set of options to increase the resilience of social-ecological systems to drivers of tipping. Coral reef systems illustrate this complexity, where shifts from coral- to algae-dominated states involve feedbacks between coral health, herbivore populations, nutrient levels, and water quality[57] allowing for improved management strategies like reduced impact from fishing and reduced water pollution as interventions to build more resilient reefs even in the face of warming waters[75].

The inclusion of social systems adds yet another layer of complexity through human agency, norms, intentionality, learning, and institutional change[39,76]. Even though the boundaries, properties, and dynamics of social systems are always relationally defined and historically contingent, the three core properties identified here - self-reinforcing feedbacks, threshold behavior, and persistence—remain applicable to certain recurring entities, patterns, and functions within social systems. Social tipping points emerge from social contagion, cumulative processes, and collective behavior shifts affecting technology adoption or political regimes[40,77,80]. Unlike physical or purely ecological systems, social systems can, in theory, anticipate potential thresholds and deliberately work to trigger or avoid them (i.e., reflexivity or proactive management). While ecological systems exhibit adaptive responses such as species migration and information transfer through mechanisms like horizontal gene transfer, socio-technical systems possess uniquely sophisticated information processing capabilities through technological networks and human communication systems that can rapidly anticipate and respond to potential thresholds. Once established, new social practices and patterns of interaction can become locked-in through institutional structures and norms, though even some consolidated structural conditions or power distributions remain potentially reversible - various dynamics may undermine stability until a new critical threshold is reached and part of the system functions tips back to a previous configuration[39].

A key distinguishing characteristic of social tipping is the susceptibility of social systems to perturbations caused by rapid, intentional information diffusion[39]. The spread of a new transformative vision[81,82], set of values and ideas (e.g., human rights and the end of slavery[83]) or a false narrative (e.g., climate change denial[84] and vaccine misinformation[85] can act as a catalyst for the emergence of tipping points, leading to self-perpetuating shifts in beliefs[46,86]. Social tipping points also emerge from endogenous dynamics, including population growth and interactions with technologies, information systems and biophysical systems, creating new opportunities but also risks that may expand or restrict societal configurations. Whether a tipping point is perceived as negative[41] or positive[38] is ultimately a normative question requiring clarification of who defines desirability in given contexts[53,87].

Beyond single thresholds

Rather than treating tipping points as binary phenomena—where a system either possesses the core properties that will produce tipping or not—we suggest conceptualizing them along a spectrum of behavior defined by the strength and nature of the three properties. This approach recognizes variation in how tipping properties manifest across systems. Some systems, like certain climate subsystems, exhibit well-defined self-reinforcing feedbacks, identifiable thresholds, and long-term persistence. Others, like some ecological systems, show partial self-reinforcement moderated by adaptive responses, with thresholds that may shift depending on other system conditions. Social systems may display tipping dynamics that can be substantially modified through anticipatory action, learning dynamics and intervention, creating different types of persistence effects. Finally, some systemic changes, such as gradual transitions without self-reinforcing dynamics or abrupt changes without persistence, are not tipping points because they lack one or more of the three core properties of tipping points identified above.

This approach resolves practical problems that binary classifications create. Rather than debating whether Arctic sea ice "counts" as a tipping point, researchers can assess that it exhibits strong feedback mechanisms but weaker threshold behavior than, for example, AMOC collapse (Table 1). This shifts the discussion toward more productive questions about which core properties are present, how strongly they manifest, and consequently how the system may respond to increased forcing, and enables more nuanced risk assessment and targeted interventions based on which properties are strongest in each system.

Moving beyond a binary view of tipping points can enhance anticipatory governance by framing tipping dynamics as a spectrum shaped by interacting feedbacks, thresholds, and persistence. This approach provides policymakers with earlier, more actionable insights into system evolution and enables targeted interventions—such as weakening feedbacks or shifting thresholds—before critical transitions occur. In social and socio-ecological systems, where learning and intentional action can alter trajectories, it supports proactive strategies that reduce risks, prevent lock-ins, and

Table 3 | Cross-system comparison of tipping dynamics in example systems

System example	Self-reinforcing feedbacks	Threshold behavior	Persistence	Notes
AMOC	✓ Strong (salinity-density loop)	✓ ~4 °C warming threshold	✓ Centuries-scale hysteresis	Classic climate tipping element
Amazon rainforest	✓ Vegetation-precipitation coupling	✓ Multi-parameter surface	✓ Centuries to regrow	Social-ecological system
Coral reefs	✓ Algae-nutrient feedbacks	✓ 1-2 °C local warming	✓ Requires active restoration	Regional driver sensitivity
EV adoption	✓ Network and cost effects	✓ S-curve	✓ Market lock-in effects	Social tipping with positive potential
Democratic collapse	✓ Institutional breakdown cascades	✓ Rapid regime shifts	✓ Requires rebuilding institutions	Complex social reversibility

shift governance from reactive crisis response to adaptive, forward-looking management.

Conclusion

The concept of tipping points has proliferated across disciplines, offering a compelling framework for understanding abrupt, transformative shifts from climate systems to social movements, yet this broad appeal has created conceptual ambiguity that can impede scientific understanding and climate action. Varied interpretations across disciplines reflect meaningful differences in system dynamics rather than confusion - the core properties of self-reinforcing feedbacks, threshold behavior, and persistence manifest differently across climate, ecological, and social systems while providing a common foundation for understanding rapid, nonlinear transitions.

We emphasize that tipping thresholds exist in multi-dimensional parameter spaces rather than at single points. This addresses a fundamental criticism—that tipping point concepts oversimplify transitions by implying fixed, context-independent thresholds. Recognizing tipping surfaces rather than tipping points resolves apparent contradictions in the literature and highlights why "safe" thresholds shift as background conditions evolve. Moreover, systems exhibit these three properties at varying strengths, creating a spectrum of tipping behavior rather than binary classification. This nuanced view enables rigorous assessment while maintaining clear criteria for when "tipping point" terminology is appropriate.

These definitional clarifications create opportunities for productive cross-disciplinary integration. Different disciplines have emphasized different properties: climate scientists focus on threshold identification and persistence but give less attention to feedback diversity; ecologists extensively study feedbacks but are less focused on precise thresholds; social scientists highlight network effects and the combination of multiple enabling conditions over threshold behavior. Rather than viewing these as contradictions, we can leverage them as complementary strengths. Climate science's mathematical precision could enhance social tipping research, while social insights into networks and anticipatory behavior could improve climate early warning systems. Such cross-learning already extends to methods, with critical slowing down indicators now detecting market transitions and agent-based modeling providing tools for understanding behavioral-biophysical interactions.

These insights carry crucial implications for management and policy. The multi-dimensional nature of tipping surfaces means that threshold mobility is inevitable: parameter values considered "safe" under current conditions may become dangerous as background conditions evolve. Risks arise when multiple moderate stressors combine to exceed tipping surfaces even when no single stressor appears critical. Effective monitoring must therefore track trajectories in full parameter space rather than focusing on single variables, requiring integrated assessment approaches that account for multiple interacting drivers.

The cross-disciplinary nature of the tipping point concept represents one of its greatest strengths, providing the foundation for an emerging cross-disciplinary epistemic community that can address the complex, interconnected challenges of the Anthropocene. The definitions and essential properties we have outlined have implications for governance approaches and communication. The way we understand and apply tipping point concepts shapes how we study complex systems, and how we engage with and respond to tipping point dynamics in different contexts. By clarifying what makes a transition considered a tipping point, this synthesis provides the foundation for more rigorous science and more effective risk management in systems where crossing thresholds may trigger abrupt, persistent, and consequential change.

Data availability

The data and scripts for the bibliometric analysis and figures can be found at https://doi.org/10.5281/zenodo.18414918.

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Competing interests

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Additional information

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