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Science Needs for a Terrestrial Biosphere Tipping Point Early Warning System

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Abstract Tipping points in the Earth system have the potential to cause major detrimental impacts to the biosphere and societies. Their inherent nonlinearity implies that even relatively small additional increases in external forcing might result in disproportionately large adjustments to components of the Earth system. In some cases, tipping points may lead to alternative states that would be difficult to return from. Here, we discuss ways to maximize the usefulness of Earth Observation (EO) data to improve Early Warning Systems of tipping points in the terrestrial biosphere. We focus on the terrestrial biosphere because it provides critical ecosystem services, offers more tractable dynamics for early warning development, and is exceptionally amenable to remote sensing across multiple spatial scales. We synthesize two key elements: potential tipping elements and dynamics in the terrestrial biosphere, and corresponding mathematical theory and methods that can determine resilience levels. With such combined knowledge, we discuss the feasibility of generating warnings of approaching tipping points, filtered through consideration of what can be remotely sensed. EO data is generally of short length in time but has extensive spatial coverage at fine resolution, leading to emphasis on spatial-temporal resilience sensing and building early warning indicators that may incorporate parallel data on system forcing. We describe how "space-for-time" substitutions may capitalize on EO's strong areal coverage to understand whether ecosystems might be nearer to tipping depending on location, enabling more complete assessment of emerging signals on the approach to strong nonlinearities.

Plain Language Summary Climate change is pushing Earth's ecosystems toward critical thresholds called tipping points, where relatively small additional changes could trigger large, persistent shifts in how these systems function. Forests could become grasslands, wetlands could flip from storing carbon to releasing it, and frozen ground could thaw, releasing carbon and disrupting ecosystems that people depend on for food, water, and shelter. Scientists are developing early warning systems using satellite data to monitor changes in vegetation, temperature, and moisture across the planet. This review examines how we can best use Earth observation satellites to spot warning signs of approaching tipping points in terrestrial ecosystems. While satellites provide unprecedented spatial coverage of Earth's land surface, most records are too short to capture slow ecosystem changes that unfold over decades. The review identifies promising approaches, including using patterns across space to understand changes over time and combining multiple types of satellite data. Key challenges include distinguishing genuine warning signals from natural variability, monitoring critical underground processes that satellites cannot directly observe, and developing methods that work in complex real-world ecosystems. Successfully detecting approaching tipping points could provide crucial lead time for management actions to prevent catastrophic ecosystem losses.

Key Points:

- Satellite data enables global tipping point monitoring, but short records limit detection in slow-changing ecosystems like forests
- Space-for-time methods using spatial gradients can overcome temporal limitations by identifying systems at different vulnerability stages
- Spatial early warning signals remain underexploited despite advantages over temporal methods for Earth observation data

Supporting Information:

Supporting Information may be found in the online version of this article.

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1. Introduction

Tipping points in the Earth system represent critical thresholds beyond which relatively small changes in environmental conditions, particularly associated with climate change, may trigger disproportionately large, often abrupt and persistent transitions in system state (J. F. Abrams et al., 2026; Lenton et al., 2008). These regime shifts can fundamentally alter the functioning of ecosystems and biogeochemical cycles, with profound consequences for biodiversity, climate regulation, and human wellbeing (Barnosky et al., 2012; Folke, 2006; Scheffer & Carpenter, 2003; Scheffer et al., 2012). In the terrestrial biosphere, tipping points may emerge through nonlinear

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feedbacks, threshold-dependent disturbances, and interactions among climate, vegetation, and soil processes. Anticipating these transitions is increasingly important as climate change and other anthropogenic pressures intensify, and may provide critical insights into what constitutes "dangerous" levels of global warming beyond established policy thresholds (Solé & Levin, 2022).

There is a growing concern that anthropogenic climate forcing and land-use change are pushing key components of the terrestrial biosphere toward critical tipping thresholds (Mace et al., 2014; Steffen et al., 2018). Potential tipping elements span diverse biomes and mechanisms, including tropical forests vulnerable to changing precipitation regimes, boreal ecosystems sensitive to warming thresholds, permafrost regions characterized by strong biogeochemical feedbacks, and dryland systems susceptible to vegetation state transitions (Figure 1 and Table 2). Such transitions could substantially degrade ecosystem services including food production, water regulation, and carbon storage, while also generating feedbacks that influence the global climate system (Armstrong McKay et al., 2022; Lenton et al., 2019; Richardson et al., 2023) a carbon source (Cox et al., 2004; Flores et al., 2024; Gatti et al., 2021), while permafrost thaw could release substantial greenhouse gas emissions (Brovkin et al., 2025; Schuur et al., 2022).

The prospect of detecting impending transitions has stimulated intense interest in Early Warning Systems (EWS), which seek to identify measurable signals of declining resilience prior to tipping events (Dakos et al., 2024; Lucarini & Chekroun, 2023; Scheffer et al., 2009). Rooted in nonlinear dynamics and bifurcation theory, EWS approaches often focus on phenomena such as slowing recovery from perturbation, increasing variance, or changes in spatial organization that emerge as systems approach critical thresholds. While these methods have shown considerable promise in theoretical and experimental settings, their application to real ecosystems remains challenging. Tipping mechanisms are diverse, observational records are often short, and environmental systems exhibit substantial stochastic variability that can obscure warning signals (Bathiany et al., 2024; Boettiger & Hastings, 2012; Clements & Ozgul, 2018; Dakos, van Nes et al., 2012; Verbesselt et al., 2010; Wulder et al., 2022).

Despite these challenges, terrestrial ecosystems may represent some of the most tractable Earth system components for the development and application of EWS. Unlike atmospheric or oceanic tipping phenomena, which emerge from high-dimensional turbulent fluid dynamics, many terrestrial tipping mechanisms are governed by comparatively simpler ecological and biogeophysical feedbacks, including vegetation-moisture coupling, fire-vegetation interactions, and carbon-cycle feedbacks. Crucially, many of the state variables associated with these processes can be observed directly from space. Furthermore, terrestrial tipping dynamics frequently operate on timescales that are sufficiently rapid for contemporary satellite archives to capture a meaningful portion of the approach to transition, increasing the practical feasibility of resilience monitoring and early warning detection.

Earth Observation (EO) data provide an unprecedented opportunity to address many of the challenges that have constrained operational EWS development (Lenton et al., 2022, 2024). Satellite observations offer globally consistent, spatially extensive, and increasingly high-resolution measurements of vegetation condition, land-surface temperature, soil moisture, surface water dynamics, and other ecosystem properties. These observations can help overcome limitations associated with sparse in situ monitoring, while providing the spatial consistency required to distinguish resilience loss from local variability, Importantly, EO offers not only temporal records of ecosystem change but also detailed information on spatial structure and organization that is unavailable from most ground-based monitoring networks.

The greatest strength in EO may lie in its ability to characterize spatial patterns and gradients across landscapes. Satellite observations enable the detection of spatial early warning indicators, including changes in spatial correlation, patch-size distributions, and other emergent spatial properties that may signal declining resilience (Dakos et al., 2010; Kéfi et al., 2007). Spatial observations can also support space-for-time approaches that exploit environmental gradients to infer different stages of system vulnerability and transition dynamics (Hirota et al., 2011; Kéfi et al., 2014; Lovell et al., 2023). Such approaches are particularly valuable given the relatively short duration of most satellite records and may help overcome a fundamental limitation of purely temporal EWS methods. Nevertheless, despite their theoretical promise, spatial approaches remain substantially underutilized relative to temporal indicators (Dakos et al., 2011; Kéfi et al., 2014; Nijp et al., 2019).

Several recent syntheses have reviewed aspects of EO-based tipping point monitoring and resilience assessment. Lenton et al. (2024) considered EO monitoring across Earth system tipping elements, Bathiany et al. (2024)

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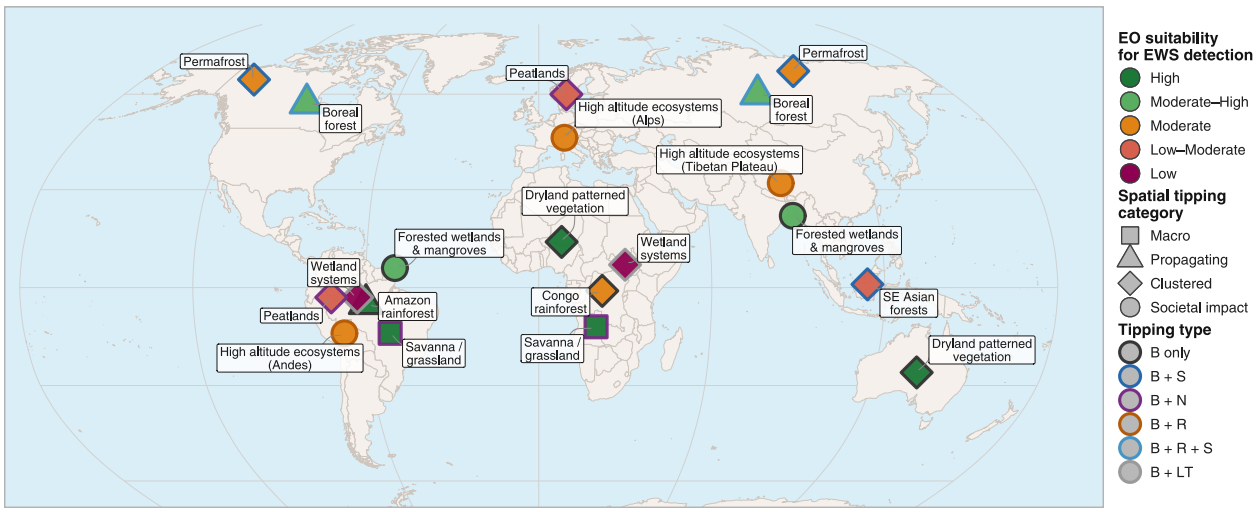


Figure 1. Terrestrial biosphere tipping elements occur across all major global biomes and exhibit distinct spatial tipping characteristics. Symbol shape indicates the spatial tipping category: squares = macro (cases where crucial reinforcing feedback mechanisms that can propel tipping operate across large spatial scales); triangles = propagating (transitions spread through a spatial coupling mechanism); diamonds = clustered (near-simultaneous transitions driven by coherent forcing across a region); diamonds = pattern-forming (transitions produce or alter spatial self-organization); circles = societal impact (local transitions in the provision of ecosystem services that have large impacts on society). Symbol fill color indicates current Earth Observation suitability for early warning signal detection, from High (dark green) to Low (dark purple), as assessed in Section 4 and summarized in Table 5. Symbol stroke color indicates the dominant tipping type: black = B-tipping only; blue = B + S-tipping; purple = B + N-tipping; orange = B + R-tipping; light blue = B + R + S-tipping; gray = B + LT-tipping (see Table 1 for tipping type definitions). Where a system occurs across multiple regions, the primary labeled occurrence is shown at full size; secondary occurrences are shown at reduced size and opacity. Spatial tipping categories follow Lenton et al. (2024).

evaluated the empirical performance of EO-derived resilience indicators, Loriani et al. (2025) reviewed operational monitoring frameworks, and Runge et al. (2025) assessed current evidence for resilience loss across terrestrial systems. Collectively, these studies have focused primarily on a single class of tipping behavior and the corresponding generic early warning indicators, and have largely evaluated the capabilities and limitations of existing applications. However, no current synthesis explicitly links the full diversity of critical behaviors and tipping mechanisms (which we distinguish in Section 2) to the spatial characteristics of transitions, the theoretically appropriate classes of early warning signals, and the EO observations required for their detection.

Here we examine how EO data can be used most effectively to improve the early warning of tipping points in the terrestrial biosphere. We synthesize advances in tipping point theory, early warning science, and EO technologies to develop a mechanistic framework linking tipping dynamics, spatial manifestations of resilience loss, and EO-based detectability. We first review the theoretical foundations of tipping behavior and their implications for detectability (Section 2), then assess the capabilities and limitations of EO systems for early warning applications (Section 3). We then evaluate major terrestrial tipping systems in terms of their observational tractability and early warning potential (Section 4), before concluding with priorities for the development of robust operational early warning systems for terrestrial biosphere tipping points (Section 5).

2. Theoretical Foundations

Understanding how to detect approaching tipping points using EO data requires a solid foundation in both the dynamical mechanisms that drive critical transitions and the theoretical basis for early warning signal detection. This section synthesizes recent advances in tipping point theory and early warning science, with particular emphasis on their implications for remote sensing applications in terrestrial ecosystems.

In this review, we adopt a criterion consistent with the broader tipping points literature: a process qualifies as tipping behavior when the transition involves positive feedbacks capable of generating bistability and hysteresis. This distinguishes genuine tipping from reversible threshold responses, in which a system tracks a shifting equilibrium continuously and would recover if forcing were reversed. Under this criterion, gradual processes such as treeline migration or woody encroachment may still constitute tipping behavior, provided they are underpinned

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by self-amplifying feedbacks that generate alternative stable states. We return to this distinction in the context of specific tipping systems in Section 4.

2.1. Tipping Types and Mechanisms

Over the last decade, a number of dynamical mechanisms leading to ecosystem tipping have been identified, see Table 1 (also Figure 2) for a brief overview of the different types of tipping and their general potential for EWS (e.g., high, low). They differ significantly in terms of the preconditions required for them to occur and hence also differ in terms of their applicability and generality. The most well-known one, usually referred to as Bifurcation induced tipping or B-tipping, is linked to the disappearance of an attractor/steady state (e.g., as a result of saddle-node bifurcation, cf. Ashwin et al., 2012; Scheffer et al., 2001). For the bifurcation to occur, a change in some parameter values is required to eliminate the corresponding minimum of the quasi-potential (Lucarini & Bódai, 2019, 2020; Margazoglou et al., 2021; Zhou et al., 2012); such a change is associated with a change in the environmental conditions, which in turn can be linked to the global climate change. Once the steady state disappears, the ecosystem would necessarily evolve into another state (or, more generally, another attractor/dynamical regime): a regime shift that is often associated with biodiversity loss and ecosystem degradation.

The classical B-tipping mechanism does not require any stochasticity; however, stochasticity (which we refer to here as noise) is ubiquitous in natural systems. Once noise is present, and under some weak conditions on its properties, a regime shift in a bistable or multistable system can occur (known as N-tipping) without any parameter change, as noise can occasionally "push" the system out of its stable basin to the basin of another steady state. Since the effect of noise does not destroy the original stable steady state, a reverse transition may also be possible. The time that an ecosystem spends in each steady state (more generally, in each of the stable dynamical regimes) is therefore finite and depends on the properties of the noise, for example, the variance, whether the noise is correlated, etc. On a longer timescale, the corresponding ecosystem dynamics becomes a succession of alternating steady states (or regimes): the phenomenon that is sometimes referred to as long transient dynamics (Hastings, 2004) or metastability. Quasi-potential theory allows a quantitative estimate of the probability of transition between competing states associated with stochastic forcing (Börner et al., 2024; Lucarini & Bódai, 2019, 2020).

We mention here that the existence of noise-induced critical transitions implies a certain amendment to the common understanding of a tipping point as a certain threshold (e.g., in external forcing or a parameter value) where "a small change can have large, long-term consequences for a system" (Lenton et al., 2008). While such small change near the threshold is indeed necessary in the case of a bifurcation-induced tipping, it is not required for N-tipping to occur. In more mathematical terms, the only essential prerequisite for N-tipping is that the given steady state of the corresponding dynamical system is stable locally but not globally (or, equivalently, its attraction basin is finite). Because of the probabilistic nature of noise, N-tipping occurs with a certain probability $P < 1$, which increases along with the approach to the tipping threshold, ultimately reaching the value $P = 1$ once the threshold is crossed. In contrast, B-tipping is an entirely deterministic phenomenon.

An interesting question arises here as to which tipping mechanism, that is, B-tipping or N-tipping, is more likely observed in real-world systems and under what conditions. We mention here that ecosystem dynamics are usually very noisy. Therefore, since B-tipping is a purely deterministic scenario, it can hardly be expected to occur as such. Before B-tipping can happen (as a result of a fold bifurcation), it is likely that noise will push the system out of its current basin of attraction to an alternative state. Therefore, tipping occurs before the deterministic tipping point (threshold) is actually crossed. How much earlier it can happen and/or what is the corresponding probability distribution for the critical transition to happen would depend both on the properties of the underlying deterministic skeleton and the properties of the noise.

We note here that studies on N-tipping usually focus on time-continuous noise, that is, where perturbations of various magnitude occur very frequently, following each other without any time lag. The main focus of research so far has been on the effect of Gaussian noise, for which large-magnitude events are extremely rare. These noise properties, however, are not in full agreement with climate data where extreme weather events became increasingly frequent over the last several decades. For these reasons, recently the focus has been shifting toward the effect of anomalous noise (e.g., Levy noise) where the large-magnitude events are not rare. Although the main effect of noise in a multistable system remains largely the same, that is, tipping is likely to occur before the deterministic tipping threshold is crossed, for the anomalous noise the probability distribution of the tipping is

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Table 1
A Brief Overview of Tipping Mechanisms in Ecologically/Environmentally Inspired Dynamical Systems

Type of tipping	Brief description	Conditions and limitations; persistence	Examples and references	Potential for EWS
B-tipping ("Bifurcation tipping")	Transition of a dynamical system to an alternative regime (e.g., a different steady state or oscillations with different frequency or magnitude)	Persistent; requires a change in parameter values (correspondingly, a persistent environmental change or trend)	Amazon forest (Cox et al., 2004; Parry et al., 2022), savanna vegetation (Scheffer et al., 2001)	Classical EWS theory applies (CSD, AR(1), variance), if the external forcing (e.g. climate change) changes slowly relative to the system timescale (Ritchie et al., 2021). Generalization of CSD is possible (Lucarini & Chekroun, 2023, 2024). In strongly forced systems, system specific indicators may be required (Boulton et al., 2013; Ritchie et al., 2022), and spatial EWS is much more effective (Clarke et al., 2026). Collision of reference state with edge state could be tracked (Börner et al., 2026)
N-tipping (Noise induced tipping)	Transition of a system to an alternative regime due to the impact of noise	Reversible; bistability or multistability is required; persistent change in mean parameter values is not required; increase in the noise intensity may increase the likelihood of tipping	Ubiquitous in all natural systems (Scheffer et al., 2012)	Limited potential—reversible transitions, noise-dependent, escape is a Poisson process Challenges to quantify the level of noise in real-world environmental systems. Precursors could be identified (Lucarini & Bódai, 2020). Rare event algorithms can help identify optimal paths of transitions (Cini et al., 2024)
S-tipping ("Shock-tipping": tipping due to a singular large perturbation of a state variable)	Transition to an alternative steady state or regime following a single large perturbation of state variables	Persistent; change in parameter values is not necessary	Extreme/rare weather events; bolide collision (Halekotte & Feudel, 2020; Lucarini et al., 2022; Romanou et al., 2025)	Low potential—single perturbations, no gradual approach
P-tipping ("Phase tipping")	For systems exhibiting a periodical or quasi-periodical dynamics, similar to N and SL tipping but showing a much higher probability of tipping at certain specific times (or "phases") due to the effect of noise	Persistent; change in mean parameter values is not required, an increase in the noise variance may increase the likelihood of tipping	Seasonal timing effects in prey-predator cycles; phytoplankton bloom timing (Alkhayuon et al., 2021; Rinaldi & Scheffer, 2000)	Phase-dependent potential—timing matters. High potential: classical EWS theory may apply
LT-tipping (Tipping at the end of long transients)	For systems exhibiting a "long transient" (LT)—transient dynamics that mimics a sustainable (asymptotic) regime but only lasts for a finite time—tipping occurs at the end of the LT	Persistent; change in parameter values is not required	Plankton blooms; savanna-forest transitions (Hastings et al., 2018, 2021; Morozov et al., 2020)	Unknown potential—sudden transitions without parameter change
R-tipping (Rate induced tipping)	Tipping occurs if the rate of change in a certain parameter(s) exceeds a critical value	Persistent; sufficiently fast (overcritical) change in parameter values is required	"Compost bomb"; *r*-tipping in bacterial communities; (Ashwin et al., 2012; Luke & Cox, 2011; Ritchie et al., 2023); Zombie fires (Clarke et al., 2021; O'Sullivan et al., 2023)	Emerging potential—deep learning approaches being developed

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Table 2
Examples of Terrestrial Biosphere Systems Affected by Climate Change, With Observed or Predicted Changes in the Properties Potentially Leading to Regime Shift

System type	Type of change in the pattern/dynamics	Empirical evidence	Theory/models
Forest as a whole (e.g., Amazon or taiga)	Area shrinking: A decrease (shrinking) of the total forest area/size, especially through a retreat of the forest edge	"Waves of degradation" (Ahrends et al., 2010); Amazon forest edge retreat (Lapola et al., 2023)	Generic models predict a retreat of the forest edge (considered as a traveling front) as a result of environment degradation, for example (Mikhailov, 1994; Volpert & Petrovskii, 2009); vegetation-climate feedbacks (Cox et al., 2000; Parry et al., 2022); forest-savanna bistability models (Staver et al., 2011)
	Forest fires: Increase in fires frequency can be expected in response to the climate change (increase in temperature, decrease in rainfall), potentially leading to tipping through emerging critical cluster ("megafire")	Inconclusive (no prediction of tipping) (Cui & Perera, 2008; Saravia et al., 2025; X. Wang et al., 2020); Amazon fire frequency increase (Aragão et al., 2018); Boreal megafires (Walker et al., 2019)	Threshold for the critical cluster (Zinck et al., 2011); fire-vegetation feedback models (Beckage et al., 2009); Lévy noise model of forest fires (Serdukova et al., 2017); spatiotemporal prediction of wildfire size extremes (Bernardino et al., 2021; Joseph et al., 2019; Shen et al., 2026)
Forest edge	Change in the structure (e.g., species composition) of the forest edge in response to climate change	Edge effects on carbon dynamics (Reinmann & Hutyra, 2017); species turnover at range edges (Padullés Cubino et al., 2024)	Edge dynamics models (Harper et al., 2005); microclimate feedback models (Ewers & Banks-Leite, 2013)
Semi-arid vegetation	Savanna-desert transition	Global dryland expansion (Eby et al., 2017); Sahel greening/browning cycles (Olsson et al., 2005; Pausata et al., 2020)	Vegetation-precipitation feedbacks (Eigentler & Sensi, 2026; Rietkerk et al., 2004; Sterl et al., 2026)
	Slowing down in the advance of the vegetation stripes, an increase in the wave-length of the spatial pattern	Tiger bush dynamics in Niger (Barbier et al., 2006); pattern changes (Deblauwe et al., 2008, 2012)	Observed in a reaction-diffusion model (Eigentler & Sensi, 2024); turing instability theory (Meron, 2015)
	Change in the statistical distribution of the vegetation patches size (e.g., from a power law to a truncated power law)	Desertification was ascribed to the grazing pressure (Kéfi et al., 2007); scale-dependent patch dynamics (Scanlon et al., 2007)	Observed in simulations using a cellular automata model (Kéfi et al., 2007); self-organized criticality theory (Pascual & Guichard, 2005)
	Woody shrub/bush encroachment	North American shrubland expansion (Van Auken, 2000); African savanna thickening (Buitenwerf et al., 2012); Woody encroachment (Luvuno et al., 2018)	CO_2 fertilization effects (Higgins & Scheiter, 2012)
Wetlands	Change in size, change in species composition	Tennessee forested wetland transitions (Evans et al., 2022); Arctic wetland expansion (Sim et al., 2019)	Hydrological feedback models (Rodriguez-Iturbe et al., 2001)
	Changes in radiative forcing of carbon fluxes	Hydroclimatic vulnerability of peat carbon (Garcin et al., 2022)	Wetland carbon dynamics (Mitsch et al., 2013)
Permafrost	Change in lake area; change in the lake size distribution function	Thermokarst lake dynamics (E. E. Webb & Liljedahl, 2023); Arctic lake drainage (L. C. Smith et al., 2005); Alaska coastal erosion (Ward Jones et al., 2025)	Talik formation models (Ling & Zhang, 2003)
	Changes in carbon flux radiative forcing	Flanner et al. (2011)	Permafrost-carbon feedback models (Randers & Goluke, 2020; Schuur et al., 2022)
High altitude systems	Alpine treeline advance	Treeline advancement/area expansion (Harsch et al., 2009; Zou et al., 2025)	Range shift models, for example (Eigentler et al., 2022)
	Glacier retreat impacts	Alpine shrubification (Myers-Smith et al., 2011)	None known
	Vegetation band shifts	Himalayan vegetation shifts (Telwala et al., 2013)	None known

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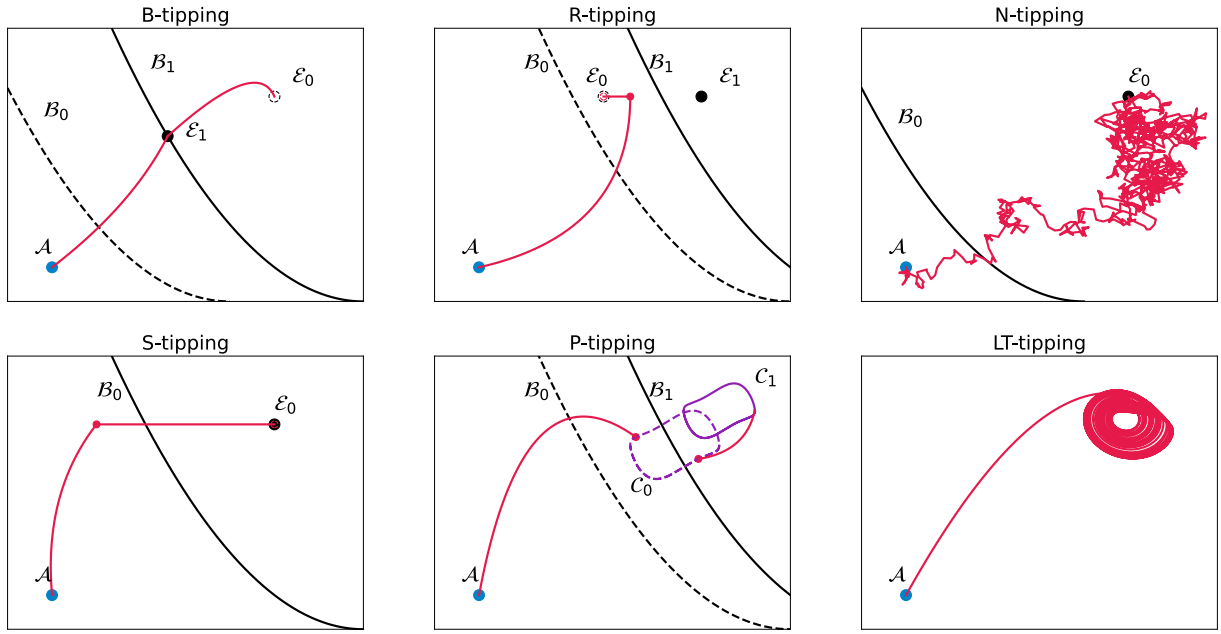


Figure 2. Six different types of phase space tipping mechanisms or behaviors have been identified, which has implications for the detectability of early warning signals. The system begins in an initial attractor, E0, which is separated from an alternative attractor, A, by a basin boundary, B0. The trajectory of the system is given in red. As parameters change, E0 becomes E1 and the basin boundary moves to B1. In the B-tipping case, E1 becomes unstable when it collides with B1 and therefore the system flows toward A. In the R-tipping case, the state of the system cannot reach E1 before it is crossed by B1, and flows to A. In the N- and S-tipping cases the system is pushed across B0 and then flows to A. In the P-tipping case the initial state is a limit cycle C0 which becomes C1 as parameters change. The system will flow to A or C1 depending on which side of B1 the system is on. In the LT-tipping case, the system begins far from A and persists far from A for a very long time compared to the characteristic timescales of the system before flowing to A.

significantly different compared to the Gaussian noise (Jiao & Gottwald, 2023; Lucarini et al., 2022; Serdukova et al., 2017).

Moreover, there is growing evidence that anomalous perturbations of very high magnitude are not necessarily a part of the same statistics, as they may be generated by processes of different origin (e.g., subsurface or extra-terrestrial). One example of such singular high-magnitude perturbations is given by large volcanic eruptions (Rymer et al., 2005). Those processes are not parts of the climatic system in the strict sense but may lead to a significant climate change and potentially to tipping. It therefore seems reasonable to consider such events separately. The dynamical system corresponding to the affected Earth (sub)system can be pushed out of the basin of its stable equilibrium by a single short-term perturbation, provided its magnitude is sufficiently large. In the literature, a critical transition caused by a single high-amplitude anomalous perturbation is referred to as "Shock" or S-tipping (cf. Halekotte & Feudel, 2020). Probably the most remarkable example of this tipping scenario occurred in the Earth's deep history when an asteroid collided with Earth about 65 Ma ago; that singular event led to a dramatic global climate change, in particular resulting in a mass extinction (Alvarez et al., 1980). In the present-day Earth and the contemporary climate change when the frequency and severity of extreme climate events clearly increase (Romanou et al., 2025), the concept of shock-tipping arguably becomes increasingly relevant. However, we mention here that the question as to whether the extreme events can be better understood as anomalous noise or shocks remains largely open; the answer is probably context dependent.

Many ecosystems and ecological communities exhibit cyclic dynamics (Alkhayuon et al., 2021; Rinaldi & Scheffer, 2000) where the cycles can be either self-organized (cf. prey-predator cycles) or externally forced (e.g., driven by seasonal changes). In such a case, the system's sensitivity to perturbations can depend on its position ("phase") on the cycle, and hence on the timing of the perturbation. For instance, a noise of the same intensity may lead to tipping when applied at one time during the cycle (e.g., if/when the system trajectory is close to the boundary of the attraction basin), but will not lead at another time. A similar statement is true also for a single perturbation of a given magnitude (Rinaldi & Scheffer, 2000). This type of tipping due to time-varying (phase dependent) system sensitivity is called Phase or P-tipping (Alkhayuon et al., 2021).

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A dynamical system can respond differently to perturbations of different rates. As a paradigmatic example, consider the case where the value of a system parameter—say, μ—is changing from $\mu 0$ to $\mu 1$ over the time interval Δt. It has been observed in several studies (Abbott et al., 2024; Ashwin et al., 2012; O'Sullivan et al., 2023; Ritchie et al., 2023; Vanselow et al., 2024; Wieczorek et al., 2011) that an ecosystem may be resilient to a slow change (i.e., for a large Δt), so that its dynamics and properties remain largely unchanged but would experience a regime shift potentially leading to catastrophic changes in case of a sufficiently fast change (for small Δt). Arguably, this mechanism, commonly referred to as Rate or R-tipping (Ashwin et al., 2012), is particularly relevant in the context of ongoing climate change, as it is known to be happening much faster than many climate change events in Earth history (Rothman, 2017).

Finally, there is one more tipping mechanism that acts somehow differently from those described above. Dynamical systems can be in an apparently self-sustained, stable regime over a long time before "suddenly" exhibiting a regime shift. The essential difference from other mechanisms is that such tipping is not preceded by any change in parameter values. Else, it can follow a parameter change that happened a very long time before the tipping. This tipping mechanism is called long transient dynamics (Hastings et al., 2018, 2021); here we refer to it as LT-tipping. As the existence of long transients is linked to some common dynamical system structures (ghost attractors, unstable manifolds, multiple timescales, etc., see Morozov et al., 2020), the presence of any noise or a single large perturbation are not required for LT-tipping to happen. Noise can make them shorter, longer, or can create new long transients in systems where they do not exist in a purely deterministic case (Hastings et al., 2021). Long transients and the corresponding LT-tipping have been observed in many real-world ecological and environmental systems (Morozov et al., 2024). LT-tipping plays a primary role in many areas of complex system science, including the transition to turbulence in many flow configurations (Eckhardt et al., 2007).

2.1.1. Spatial Typology

Understanding these mechanisms and corresponding spatial patterns is crucial for early warning because different types of tipping require different detection approaches and monitoring strategies. For instance, propagating tipping may be detectable at leading edges before spreading, while clustered tipping might be spatially coherent and may show coordinated signals across multiple locations simultaneously.

Tipping mechanisms and scenarios become more diverse and more complex in systems with explicit space. Tipping points manifest across multiple spatial scales and through different mechanisms, requiring a framework that accounts for spatial interactions. We adopt a phenomenology of four types of tipping from Lenton et al. (2024) that differ in their spatial manifestations and detection requirements (Figure 3 and Table 3).

Macro tipping refers to cases where crucial reinforcing feedback mechanisms that can propel tipping operate across large spatial scales—for example, vegetation-monsoon interactions—and may give rise to synchronous tipping at macro scale. Propagating tipping refers to cases where tipping may start locally but causal interactions—for example, moisture recycling to the atmosphere, the spread of fires, invasive species or disease vectors—support its spatial propagation. In rare cases, tipping of the most sensitive components of a larger system may ultimately destabilize the rest in a "domino cascade." Clustered tipping refers to case where spatial coupling is less strong but localized tipping may still occur near-synchronously in larger clusters, due to a spatially coherent climate or anthropogenic forcing reaching a common threshold, for example, thermokarst and lake formation in degrading permafrost. This mechanism is reminiscent of the so-called chimera states observed in systems of coupled oscillators (D. M. Abrams & Strogatz, 2004). Societal impact tipping refers to (special) cases of localized tipping points in the provision of ecosystem services that have unusually large impacts on societal systems because tipping intersects with high human population density, for example, the abrupt loss of headwater glaciers that provide dry-season runoff in key watersheds.

2.2. Early Warning Principles

Early warning systems for tipping points aim to detect approaching critical transitions before they occur, providing crucial lead time for management interventions and societal preparations. Early warning approaches fall into two broad categories that differ fundamentally in their theoretical foundations and practical implementation. The vast majority of currently used early warning approaches rely on statistical indicators that detect the phenomenon of critical slowing down (CSD) (Scheffer et al., 2009, 2012)—the tendency for systems to recover more slowly from perturbations as they approach tipping points. These statistical approaches look for

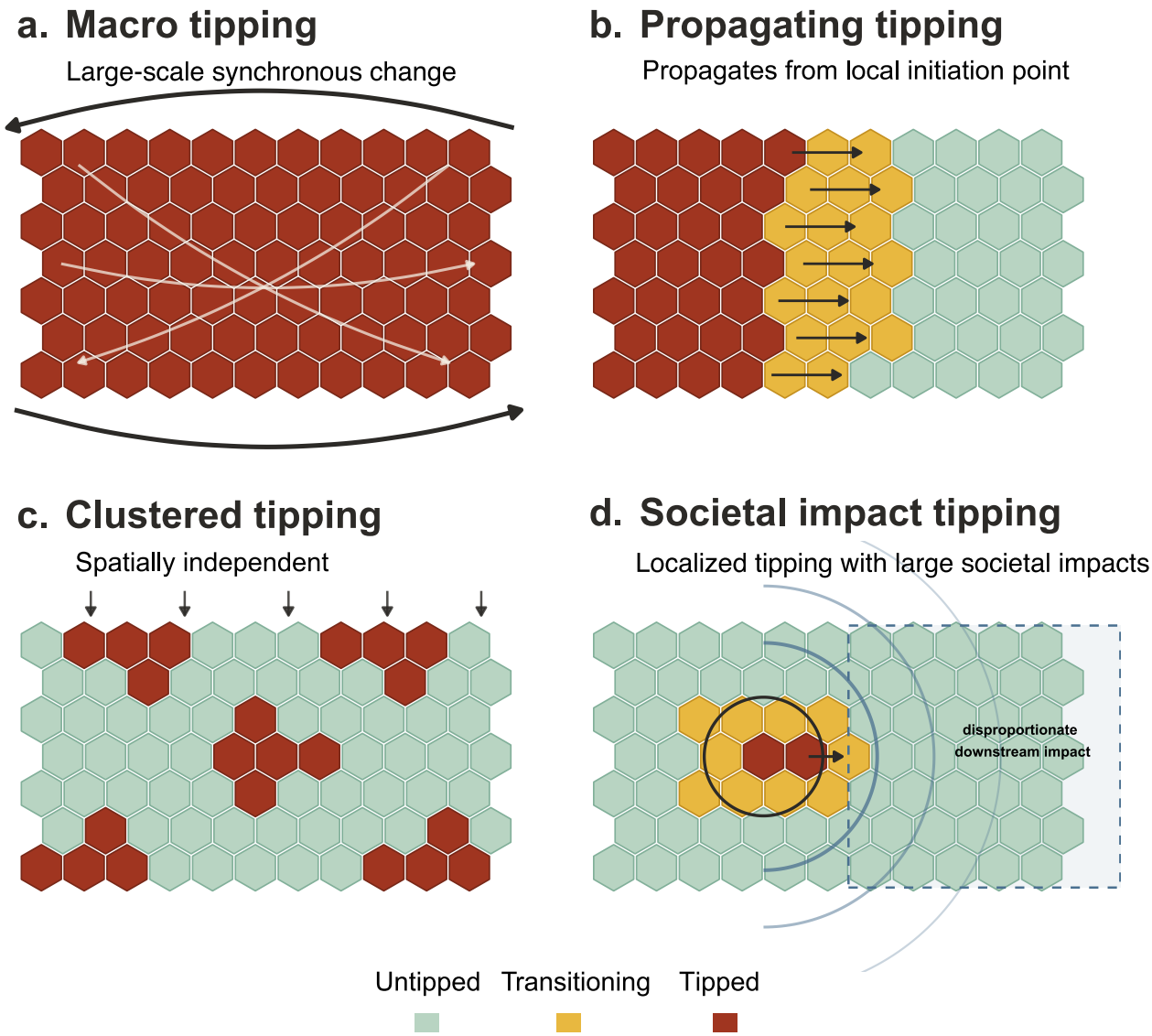


Figure 3. Spatial categories of terrestrial biosphere tipping points. Each panel shows a schematic landscape of hexagonal cells colored by ecosystem state: untipped (sage-green), transitioning (gold), and tipped (brick-red). (a) Macro tipping: the entire landscape tips synchronously because large-scale atmospheric feedbacks couple all cells at landscape scale. Curved arcs above and below the grid represent the vegetation–precipitation moisture-recycling loop; crossing arrows within the grid illustrate the non-local, landscape-wide coupling that drives this synchrony. (b) Propagating tipping: tipping initiates at a local point and spreads spatially via nearest-neighbor coupling (e.g., fire spread, moisture-recycling feedbacks); arrows indicate the direction of wavefront advance. (c) Clustered tipping: spatially independent patches tip near-synchronously because a common external forcing signal (downward arrows) drives separate locations past their individual thresholds without direct coupling between patches. (d) Societal impact tipping: a small localized tipping event (solid circle, ecological footprint) disrupts an ecosystem service on which a large dependent population relies; concentric arcs illustrate the disproportionate downstream impact expanding into the population exposure zone (dashed box). Illustrative examples of each category are: (a) Amazon basin vegetation–monsoon system, African savanna–grassland transition; (b) Amazon fire–moisture feedback, boreal forest dieback; (c) permafrost thermokarst, Congo basin forest–savanna margins; (d) Andean headwater glacier loss, mangrove collapse in populated coastlines.

generic signatures of approaching transitions in time series data, such as increasing variance, temporal autocorrelation, and skewness, without requiring detailed knowledge of the underlying system dynamics. Generic early warning signals (EWS) of a system approaching a bifurcation tipping point look for indications of CSD (Wissel, 1984). This happens because the balancing feedbacks that restore the system to its original attractor get weaker before a tipping point. This is also widely referred to as loss of resilience. It applies for different types of low-order bifurcation in dynamical systems (including saddle-node and transcritical bifurcations) broadly corresponding to the B-tipping mechanism.

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Table 3
Spatial Tipping Categories, Their Underlying Mechanisms, Key Spatial Early Warning Indicators, Space-for-Time Applicability, Earth Observation (EO) Suitability, and Minimum Resolution Requirements

Spatial tipping category	Mechanism	Key spatial EWS indicators	Space-for-time?	EO suitability for EWS	Min. Resolution	Example terrestrial systems
Macro	Large-scale reinforcing feedbacks (e.g., vegetation-moisture coupling, vegetation-albedo) synchronize transitions across the whole system simultaneously	Basin- or continental-scale temporal AC(1) and variance; loss of large-scale spatial heterogeneity as system homogenizes	Yes, along continental forcing gradient (e.g., rainfall, temperature)	High	250 m–1 km	Amazon rainforest (vegetation-moisture), West African savanna (vegetation-monsoon)
Propagating	Tipping initiates locally and spreads via spatial coupling mechanisms (moisture recycling, fire spread, invasive species, disease vectors); in extreme cases produces domino cascades	Spatial correlation ↑ ahead of advancing front; irregular wavefront detectability; temporal AC(1) and variance in EO time series near front	Yes, along propagation gradient; spatial gradient can substitute for temporal trajectory	High	30 m–1 km	Amazon rainforest (moisture recycling), boreal forest (fire spread)
Clustered	Spatial coupling is weaker but coherent climate or anthropogenic forcing reaches a common threshold across similar patches near-synchronously, producing clusters of co-tipped units	Patch-size distribution shift; spatial variance ↑ within cluster zones; bimodality in cover distributions; temporal EWS within individual patches	Partial, within cluster zone where forcing gradient exists	Moderate–high	30–250 m	Permafrost thermokarst, dryland patterned vegetation, peatlands, Congo rainforest, SE Asian forests
Societal impact	Localized tipping in the provision of ecosystem services intersects with high human population density or critical infrastructure, producing disproportionately large societal impacts relative to the ecological footprint	Service-flow indicators (runoff volume, coastal extent, fisheries yield); downstream hydrological and coastal monitoring; combination with exposure and vulnerability data	Limited, localized dynamics without broad forcing gradient	Variable: Moderate–high for surface expression; low for subsurface drivers	3–30 m for service-critical features	Headwater glaciers and alpine treeline (dry-season runoff), mangroves (coastal protection)

Note. EO suitability reflects current operational capability for detecting the listed spatial EWS indicators, assuming multi-temporal records of ≥10 years. The minimum resolution describes the coarsest pixel size at which the relevant spatial EWS signal can be resolved. Space-for-time refers to the use of spatial environmental gradients as proxies for temporal trajectories, enabling EWS inference without long time series. See Section 2 for theoretical basis. Spatial tipping categories: follow Lenton et al. (2024). See Figure 3 for schematic illustrations of each category.

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In contrast, process-based early warning approaches attempt to monitor the specific mechanisms and feedbacks that drive tipping in particular systems (Boettiger & Hastings, 2012; Boulton et al., 2013; Lade & Gross, 2012). Rather than relying on CSD, these methods focus on tracking the state of key system components, the strength of stabilizing feedbacks, or the proximity to known thresholds. Correspondingly, process-based early warning systems require detailed mechanistic understanding of complex system dynamics as well as the ability to observe critical processes. The latter are, however, often difficult or impossible to measure directly; for this reason, practical use of process-based EWS remains limited.

This fundamental divide between statistical and process-based approaches has important implications for EO applications, as it determines both what needs to be monitored and how the resulting signals should be interpreted.

2.2.1. Temporal Early Warning Indicators

Where there are known perturbations to a system that can eventually lead to B-tipping, CSD may be directly observable as a slowing recovery rate from perturbation. CSD also manifests in continuous statistics as increasing temporal autocorrelation (usually measured at lag-1, AR(1), where the duration of the lag in physical units [e.g., in years] should be chosen appropriately) and variance (Scheffer et al., 2009, 2012). In some cases, skewness and/or other statistics are expected to increase (Dakos, Carpenter et al., 2012; Guttal & Jayaprakash, 2008). Operationally, these statistical EWS can be measured after detrending time series data from a system and monitoring the residuals in a sliding window, creating a time series of the corresponding statistical indicators (Dakos et al., 2008). Trends in those indicators can then be estimated (e.g., using Kendall's tau coefficient) and compared to a suitable null model of what may happen by chance (such as by creating surrogate time series by resampling from the original time series; Dakos et al., 2008), to see if they are significant.

These generic temporal EWS have been found for a range of systems heading toward bifurcation-type tipping points (B-tipping), for example, see (Lenton et al., 2024). A general mathematical framework for understanding how these indicators arise has been developed using the notion of transfer operator (Chekroun et al., 2020; Lucarini & Chekroun, 2023; Tantet et al., 2018). Mathematically, they require a timescale separation: the characteristic time at which the system is forced must be sufficiently longer than its intrinsic timescale, so that it remains close to its statistical steady state. Also, it must be monitored more frequently than its intrinsic timescale, so that the response from the system to the forcing can be fully observed, and for a duration that is considerably longer than its intrinsic timescale, for CSD to be detectable. Statistical indicators can then be calculated (in a sliding window on the corresponding time series) to see if there is any statistically significant increase (Lenton et al., 2024). The window length when calculating EWS (as in Figure 4) must also be considered, such that it is long enough to capture the response to forcing over the intrinsic timescale, whilst at the same time allowing a long enough time series of the statistical indicator for significant trends to be found. The ratio of the sliding window length to full time series length can alter the distribution of the null model described in Section 3.1 below (Dakos et al., 2008); if the ratio is around 1:2, then a bimodal null model is found with peaks around −0.5 and 0.5 in Kendall tau, for example. Beyond these classical statistical approaches, machine learning and deep learning methods have increasingly been applied to temporal EWS detection, with recurrent neural networks and transformer-based models trained on simulated tipping-point trajectories showing ability to classify whether a system is approaching a critical transition and to distinguish between tipping types, outperforming classical indicators in some settings (Bury et al., 2021; Dylewsky et al., 2023; Y. Huang et al., 2024).

In cases where the effective dynamics of the system is high-dimensional, the observable might project more or less prominently on the slowest mode of decaying variability; in the latter case spurious effects might mask the efficiency of EWS (Lucarini & Chekroun, 2023; Morr et al., 2024). As shown in Figure 5, the presence of multiscale effects and multiple competing states, especially in the presence of strong noise, might lead to strong difficulties in using the idealized approach described in Figure 4. Additionally, if the observable can efficiently distinguish the reference attractor from the edge state that separates it from the competing attracting state, its ability to provide early warning is greatly enhanced (Lohmann et al., 2024, 2025).

In general, standard CSD indicators are much less reliable in systems that experience rapidly changing forcing, compared to the characteristic system timescale. A further limitation of EWS is that they sample locally in phase space, that is, they are able to assess whether the current state is experiencing loss of stability but, if the system features more than two competing states, in absence of information on its global (in phase space) properties, and

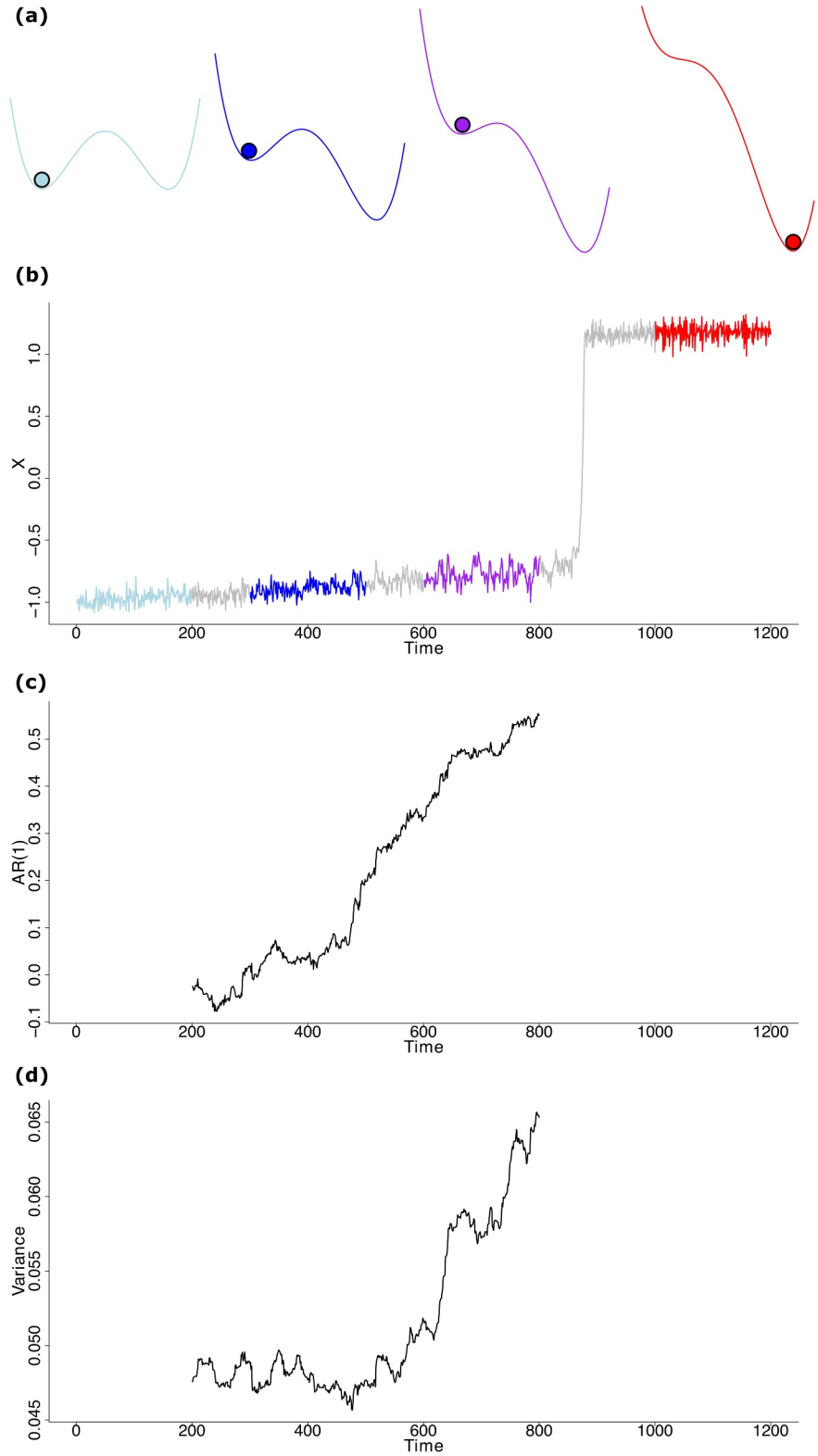


Figure 4. Critical slowing down generates characteristic statistical signals before a tipping point. As a generic system approaches a tipping point, represented as a "ball-in-well" diagram in (a) and a time series of the system state in (b), statistical indicators calculated across a sliding window show characteristic changes in (c) increasing temporal autocorrelation (AR1) and (d) increasing variance, indicating loss of resilience.

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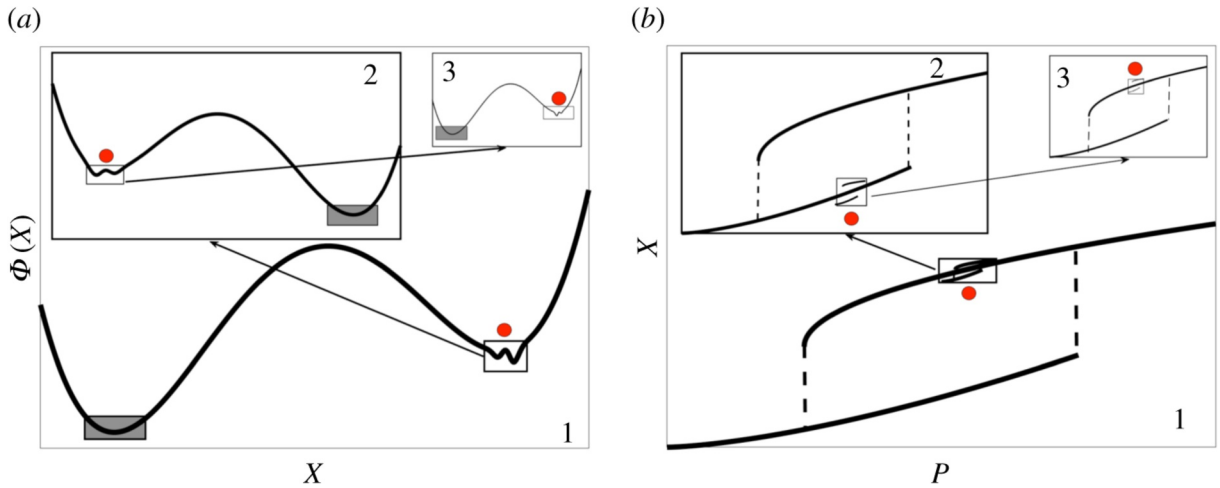


Figure 5. Multistability, noise, and hierarchical bifurcations can complicate early warning detection. The system of interest might feature a complex, hierarchical structure of bifurcations following changes in the parameter P, as highlighted by the state variable X (panel b). This is associated with a rugged, multiscale quasi-potential $\Phi(X)$ (panel a). In this case B-tipping might dramatically depend on the precision exerted when changing the parameter P, whilst strong noise leading to N-tipping might wash out the fine structure of the competing metastable states. From Margazoglou et al. (2021).

especially if noise is present, one cannot easily understand which is going to be the final state of the system after the tipping occurs (Lohmann & Lucarini, 2024; Lohmann et al., 2025).

2.2.2. Spatial Early Warning Indicators

As systems approach a bifurcation, small disturbances around the current system state take longer to decay due to CSD, and this phenomenon manifests spatially as well as temporally. It leads to an increase in the correlation length of the system, a measure which quantifies the increase in spatial coherence of the system. In particular, an increase in the correlation length preceding system's tipping has been observed in ecologically relevant reaction-diffusion type mathematical models (Petrovskii et al., 2003, 2004). This can also be understood theoretically using Linear Response theory, in which correlation and response functions are closely linked (Lucarini & Chekroun, 2023; Santos Gutiérrez & Lucarini, 2022). Linear response theory foresees the emergence of a critical spatial mode dominating the variability and the response near the tipping, thus providing the foundation for the degenerate fingerprinting originally proposed by Held and Kleinen (2004). However, their empirical validation remains limited (Buelo et al., 2022).

Many spatial early warning signals are designed to detect changes in spatial correlation as a system approaches a tipping point. For example, calculating changes in Moran's I (Kéfi et al., 2014), spatial variance (Guttal & Jayaprakash, 2009), spatial skewness (Dakos et al., 2011), power spectra (Carpenter & Brock, 2010), patch-size distribution (Kéfi et al., 2007), permutation entropy (Tirabassi & Masoller, 2023), and fractal dimension (Bian et al., 2024) can all indicate an approaching transition.

There is an apparent parallel between tipping points and phase transitions (Yan et al., 2023), which leads to different terminology sometimes used interchangeably in the literature. The language of phase transitions is more commonly used in studies on physical systems or where the approach to study a complex environmental-ecological system is directly inspired by ideas from physics (Liu et al., 2013; Noble et al., 2018; Siteur et al., 2023; Solé et al., 2011). For some spatially-coupled systems, including vegetation ecosystems, phase transitions can occur (Liu et al., 2013; Noble et al., 2018; Siteur et al., 2023). These may be first-order or continuous. In general, first order phase transitions (driven by an imposed external forcing) are discontinuous and exhibit bistability and hysteresis in common with saddle-node bifurcations—making it natural to describe them as "tipping points." Continuous phase transitions are continuous in the order parameter and thus reversible, in common with transcritical and pitchfork bifurcations, and they tend to show characteristic changes in spatial structure beforehand. Deep learning models can be trained to provide early warning of both types of phase transition and to successfully distinguish between them (Dylewsky et al., 2023). There have been suggestions that the emergence of a spatial structure (e.g., of vegetation) may indicate the proximity to a discontinuous tipping

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point (Rietkerk et al., 2004), although recent work has emphasized how spatial structure may help evade tipping dynamics (Rietkerk et al., 2021) by turning a discontinuous phase transition to a continuous one, hence making it reversible.

One example of a phase transition that has been applied to the biosphere is *percolation theory* (Stauffer & Aharony, 2018). Percolation theory is the study of systems that can be modeled as a lattice with sites that can be occupied or empty with a certain probability. The aim of percolation theory is to study how the sizes of clusters of occupied sites scales with this probability. This has been applied to the fragmentation of tropical forests, whose fragments were shown to exhibit the scaling predicted by percolation theory, indicating the forests were close to their critical point (Taubert et al., 2018). A similar approach was used to study forest fires (Clar et al., 1996; Wuyts & Sieber, 2023) where tipping over the percolation threshold can result in megafires.

These spatial approaches share a common logic with the mathematics of free boundary problems, which offers another route from observable pattern to system stability. Free boundary problems (e.g., Chen et al., 2015) concern a moving interface between two entities, where the boundary position is to be determined. The boundary itself is often found to be either smooth, or highly unstable, the latter sometimes exhibiting dendrite-like features. One classic example is the Stefan problem (Rubinšteĭn, 2000) in which the free boundary is between the ice and liquid phase of the same quantity, and whether the boundary is stable depends on whether the solid phase is melting (stable boundary) or the liquid phase is solidifying (unstable boundary). A second example is the Hele-Shaw cell where there are two fluids between parallel plates that do not mix and have different viscosities, with one displacing the other (Hele-Shaw, 1898). When the more viscous fluid replaces the less viscous fluid, the boundary is smooth, whereas finger-like patterns occur in the opposite case. If EO could be used to determine the shape of boundaries between, for instance, two biome types, this could potentially provide valuable information on the features of those biomes and the expected form of any displacement as climate drivers change.

2.2.3. Space-for-Time Substitutions

Extensive spatial data may provide opportunities to understand systems particularly in circumstances when long-term data is not available. For example, across a sufficiently large geographical area, different locations can experience different climate regimes and management, and therefore could be in different states. By identifying where the state change occurs, and relating it to local forcings, an assessment of the possible distance to tipping for other locations becomes possible. For example, (Hirota et al., 2011) found a relationship between mean annual precipitation (MAP) and tree cover, which suggested the existence of a critical rainfall rate. Additionally, under certain assumptions, the frequency of occurrence of a certain state in space is related to the potential of the system and thus gives a measure of the system's resilience (Hirota et al., 2011). However, more complex models incorporating additional remotely sensed covariates—such as potential evapotranspiration, soil moisture, topography, and soil properties—can lessen these assumptions and provide more nuanced assessments of system resilience by accounting for the multiple factors that mediate ecosystem responses to climate forcing (Anderegg et al., 2018; W. Li et al., 2021; X.-Y. Li et al., 2021). Environmental gradients can also be exploited to calculate the higher-order statistics used for early warning signals. For example, plotting the AR(1) or other resilience metrics at each grid cell against climate indices such as precipitation or temperature, which can provide information about how the resilience of the system varies with those environmental variables (see Figure 6 for an example).

However, space-for-time substitution approaches rely on an assumption of equivalence between differences in space and differences in time for a given system, hence essentially assuming the ergodicity of the system. These assumptions do not hold true in general (e.g., Drótos et al., 2016) and are hard to test as these substitutions are typically performed on systems with short observed time series. The space-for-time substitution approach can fail when there are strong correlations within the data. This is a problem for early warning signals as typically systems become increasingly correlated as the tipping point is approached.

Recent work has shown that increasing spatial variance as an EWS can be especially useful in strongly-forced systems for which the external forcing changes rapidly compared to the timescale of the system (Clarke et al., 2026). When the coupling between spatial points is relatively weak, and the spatial patterns of forcing are relatively smooth, the variability across the spatial points acts as a proxy for ensemble variability. Figure 7, right column, shows that temporal EWSs (e.g., increases in temporal variance and autocorrelation) fail when the

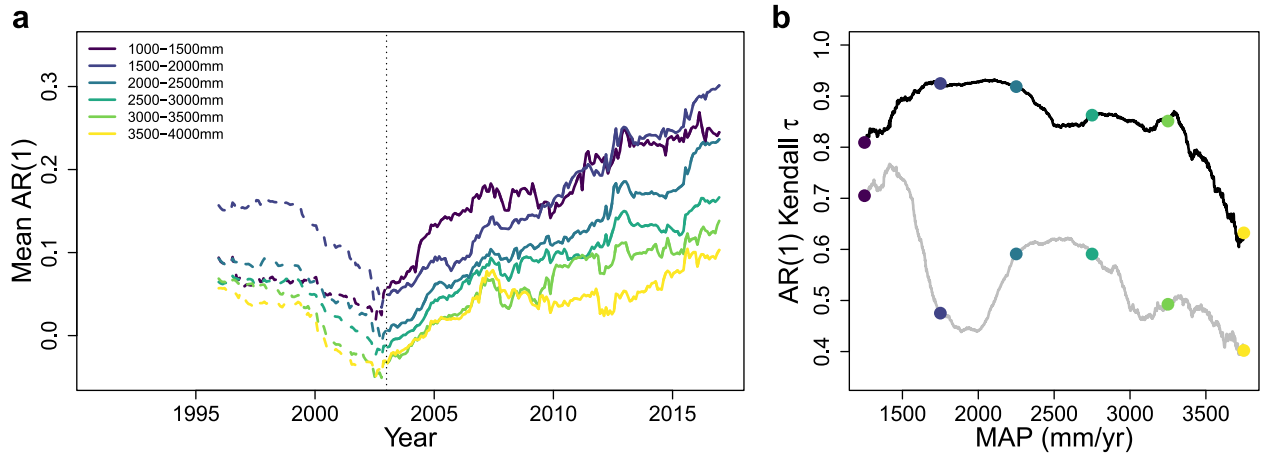


Figure 6. Space-for-time substitutions can reveal resilience gradients along environmental drivers. An example of this is shown for the Amazon rainforest using Vegetation Optical Depth, which acts as a proxy for above ground biomass. Here, AR(1) is calculated for each grid cell on a moving window of 5 years, and then each month's AR(1) values are averaged across bands of mean annual precipitation (MAP) values. (a) Shows examples of the mean AR(1) time series for different MAP ranges from the driest (dark—1,000–1,500 mm/yr) to wettest (light—3,500–4,000 mm/yr) regions. The driest regions show the strongest signals of resilience loss, particularly from 2003 onwards, indicated by a faster increase in AR(1). (b) Shows this relationship more clearly, by measuring the Kendall τ value for the AR(1) time series created by taking the average AR(1) values from a sliding MAP-band, and plotting this as a series. This shows a decreasing trend as MAP increases and therefore weaker signal of resilience loss in wetter regions. Kendall τ values are plotted at the MAP value that is the midpoint of the window used to create them, with colored circles matching those colors in panel (a) for both the full AR(1) time series (gray) and from 2003 onwards (black). Adapted from Boulton et al. (2022).

forcing (e.g., climate change) is changing rapidly compared to the characteristic system timescale. However, spatial EWSs (Figure 7, left column) remain reliable as long as the spatial coupling is relatively weak.

2.3. Mechanism-Specific Early Warning Potential

Different tipping mechanisms offer fundamentally different opportunities for early earning detection because these arise from different underlying dynamics (Figure 2, Table 1). Classical early warning theory is most developed for bifurcation-induced tipping ("B-tipping"), where resilience declines before a transition. In contrast, other mechanisms may require alternative approaches or may offer limited warning potential. For systems approaching rate-induced tipping (R-tipping) emerging deep learning methods show promise despite the absence of a corresponding mathematical theory (Bury et al., 2021; Dylewsky et al., 2023; B. Huang et al., 2024). For N-, P-, S-, and LT-tipping, early warning potential depends on the specific dynamics driving the transition.

Bifurcation tipping (B-tipping) represents the strongest theoretical foundation for early warning detection. As systems slowly approach saddle-node or transcritical bifurcations, CSD produces increasing temporal autocorrelation and variance in observables (Lenton et al., 2012). These signatures are theoretically well understood (Lucarini & Chekroun, 2023) and have been detected in numerous ecological systems (van Nes & Scheffer, 2007). For EO applications, vegetation indices may exhibit increasing memory and variance over multi-year timescales as systems approach tipping. Because the environmental drivers associated with B-tipping, such as declining precipitation or rising temperatures, often change over decades, there is typically sufficient time for detection given appropriate monitoring. Spatial indicators, including increasing spatial correlation and the emergence of characteristic spatial patterns (Kéfi et al., 2014), further strengthen the suitability of EO for monitoring B-tipping.

Noise-induced tipping (N-tipping) is difficult to predict because system stability does not necessarily change before the transition. Consequently, classical indicators based on declining resilience may provide little warning. However, susceptibility to N-tipping often increases near bifurcation boundaries, where conventional indicators remain informative (Lucarini & Bódai, 2019, 2020). In bistable systems, EO may instead monitor transition frequencies between alternative stable states spatially (Dakos et al., 2013). For example, increasing rates of switching between forest and grasslands states could indicate heightened vulnerability. Because N-tipping transitions are often reversible, monitoring efforts may be more effective at identifying vulnerable regions than predicting the timing of individual transitions (R. Wang et al., 2012).

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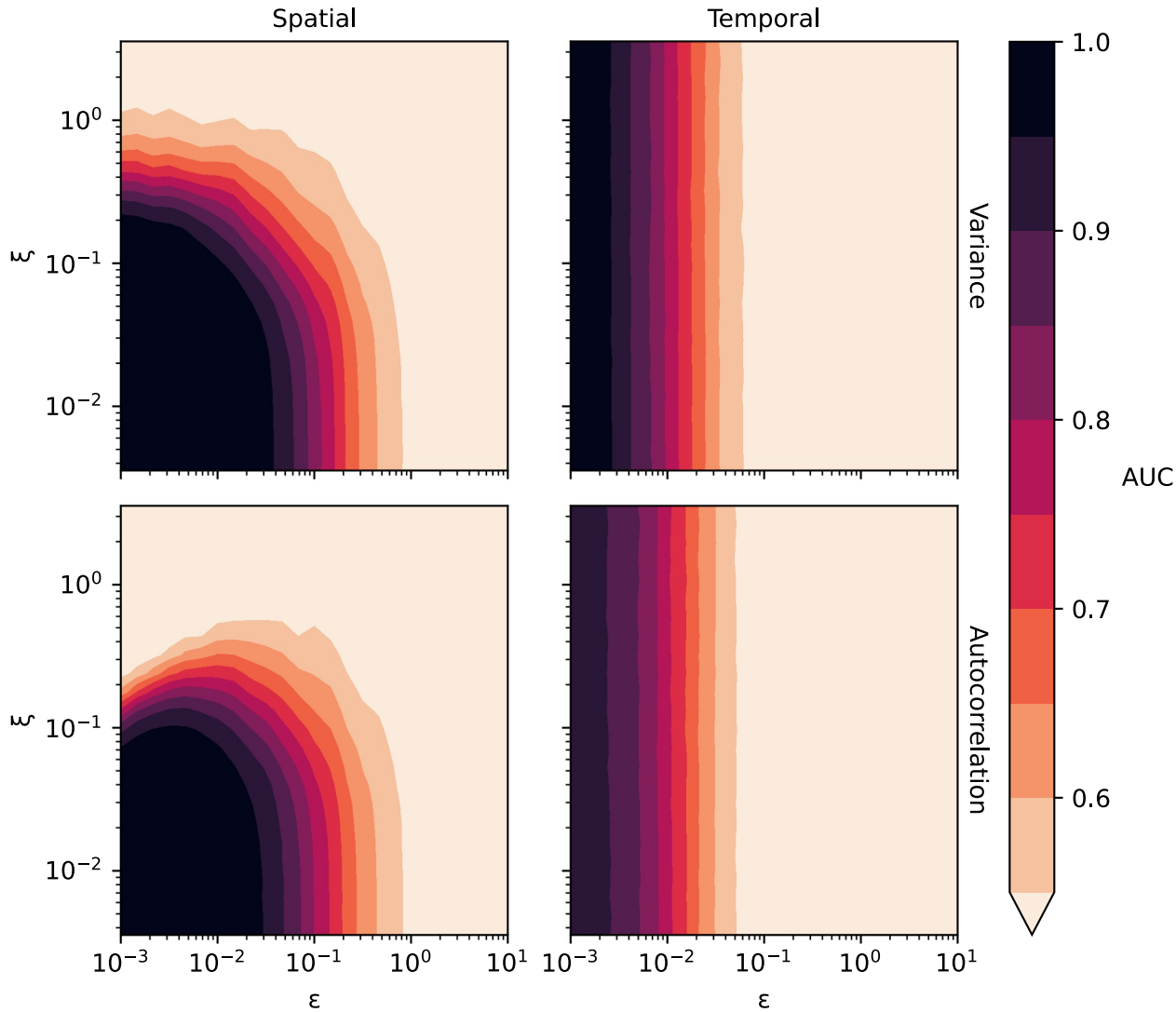


Figure 7. Spatial early warning signals can outperform temporal indicators when environmental forcing changes rapidly. This figure contrasts the skill of temporal and spatial early warning signals at anticipating tipping in a simple system with a fold bifurcation and spatial coupling. The spatial early warning signals are obtained from a space-for-time substitution. The skill is quantified using the area under a ROC curve (AUC) with 1 indicating perfect skill and 0.5 indicating no skill. This is plotted as a function of two system parameters. These are ε, the ratio of the forcing timescale to the system timescale and ξ, the correlation length normalized by the size of the domain. The spatial early warning signals show more skill than temporal early warning signals when the forcing occurs quickly (larger ε) as long as the spatial correlation length scale is short enough. Conversely, temporal early warning signals show some skill no matter the correlation length as long as the forcing occurs slowly enough. If the forcing occurs extremely rapidly (very large ε) neither approach shows any skill. Figure taken from Clarke et al., 2026.

Rate-induced tipping (R-tipping) can occur without classical warning signals because systems fail to keep pace with environmental change. In contrast to B-tipping, the underlying equilibria remain stable, but the system is unable to track them as forcing changes too rapidly. This limits the usefulness of conventional resilience indicators. Instead, lag relationships between environmental drivers and ecosystem response may provide useful information (Wu et al., 2015). For EO applications, changes in the phase relationship between climate anomalies and vegetation responses across seasonal cycles could indicate increasing vulnerability. Deep learning approaches are particularly promising because they can identify complex temporal dependencies without requiring a predefined dynamical models (Bury et al., 2021; B. Huang et al., 2024).

Phase-dependent tipping (P-tipping) requires indicators that account for where a system is within its cycle (Alkhayuon et al., 2021; Dyck & Tyson, 2024). Standard variance-based metrics may be misleading when vulnerability varies seasonally or across other recurring cycles. Phase-specific indicators, calculated conditional

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on system-state, are therefore likely to be more informative. For example, forest vulnerability to drought-induced tipping may be highest during the early growing season when water demands peak. EO data sets are well suited to this challenge because regular observations can be used to construct phase-resolved resilience metrics and track how vulnerability changes over time.

Shock-induced tipping (S-tipping), and N-tipping due to jump processes like those associated with Levy noise are better approached through vulnerability mapping that through traditional early warning detection. Since transitions are triggered by larger perturbations rather than gradual loss of resilience there may be little opportunity for classical early warning. Instead, the key quantity is the distance between the current state and the boundary separating competing attractors or states (Halekotte & Feudel, 2020; Lucarini et al., 2022). EO data can contribute by identifying regions that recover poorly from previous disturbances. For example, forests exhibiting prolonged recovery following fires or droughts may require smaller shocks to cross a basin boundary (Brodrick & Asner, 2017; Halekotte & Feudel, 2020; Verbesselt et al., 2016). Machine learning approaches that map recovery failure and disturbance vulnerability may therefore offer a promising route for assessing S-tipping risk, although this remains largely unexplored.

Long-transient tipping (LT-tipping) may be detectable through spatial patterns even when temporal indicators show little warning (Hastings et al., 2018; Meng et al., 2020). During extended transient phases, systems can appear stable despite ongoing internal reorganization (Börner et al., 2026). Spatial heterogeneity may therefore provide important clues, with some areas beginning to transition before others. High-resolution EO could detect these early changes through local variance metrics or the emergence of spreading zones of altered vegetation structure (Buxton et al., 2022; Verbesselt et al., 2016). In such cases, apparent stability at broad scales may conceal gradual reorganization that becomes visible through spatial analysis (Dakos et al., 2010).

Spatial organization may provide additional early warning information that is largely independent of the tipping mechanisms discussed above. Although these approaches have not generally been framed as early warning signals, they offer promising opportunities for EO-based EWS. Transitions can produce characteristic changes in cluster-size distributions before large scale system reorganization (Rietkerk et al., 2004, 2021; Saravia et al., 2018; Siteur et al., 2014). More recently, deep learning approaches have shown promise for recognizing critical spatial configurations directly from imagery (Dylewsky et al., 2023). These spatial signatures may provide valuable complements to conventional resilience indicators.

2.4. Implications for Earth Observation Applications

The diversity of tipping mechanisms and their varying early warning potential has profound implications for designing EO-based monitoring systems. Most critically, successful early warning requires initial system characterization to identify likely tipping mechanisms before selecting appropriate indicators. The implications for monitoring strategy vary dramatically across mechanisms: B-tipping and phase transitions favor long-term, consistent monitoring with a focus on statistical trend detection; R-tipping requires high-frequency observations to capture system-forcing relationships; P-tipping demands regular sampling to resolve cyclic vulnerabilities; while S-tipping and LT-tipping benefit more from spatial pattern analysis and anomaly detection than temporal statistics. This mechanism-aware approach contrasts with one-size-fits-all applications of generic indicators and may explain mixed success in previous early warning attempts (Boettiger & Hastings, 2012). While bifurcation tipping provides robust theoretical foundations and clear implementation pathways, the prevalence of alternative mechanisms in real terrestrial systems demands more sophisticated approaches. The spatial richness of EO data offers unique opportunities to detect spatial manifestations of approaching transitions and implement space-for-time substitutions, but requires careful attention to the specific spatial signatures associated with different tipping types.

Moving forward, the integration of mechanism-specific theory with EO capabilities requires methodological frameworks that can extract meaningful signals from complex, multi-dimensional satellite data while accounting for the inherent challenges of real-world ecosystems. The following sections examine how these theoretical foundations can be operationalized using current EO capabilities and applied to specific terrestrial biosphere systems.

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3. Earth Observation Capabilities and Limitations

The translation of early warning theory into operational systems for terrestrial ecosystems requires bridging the gap between theoretical indicators and the practical realities of EO data measuring relevant attributes. While EO provides distinctive capabilities that ground-based monitoring cannot match, implementing early warning concepts with EO presents both unique challenges and unprecedented opportunities that fundamentally shape how approaching tipping points can be detected.

3.1. Earth Observation Fundamentals

Earth Observation encompasses the systematic monitoring of Earth's physical, chemical, and biological systems through remote sensing technologies, primarily satellite-based sensors that observe electromagnetic radiation reflected or emitted from the Earth's surface. For tipping point detection, EO provides unparalleled capabilities for large-scale, repeatable ecosystem-scale monitoring that would be impossible through ground-based approaches alone. The synoptic perspective of satellites enables simultaneous observations across vast and relatively inaccessible biomes, capturing spatial gradients and emerging patterns that are fundamental to understanding how terrestrial systems approach critical thresholds.

Modern EO systems employ diverse sensor technologies across the electromagnetic spectrum, each providing unique insights into terrestrial system properties relevant to tipping point detection. These sensors can be mounted on different platforms, providing different sampling characteristics in terms of their coverage, spatial support, and temporal and spatial resolution. Optical sensors operating in visible and near-infrared wavelengths (0.4–2.5 μm) form the backbone of vegetation monitoring, measuring reflected solar radiation to derive indices of vegetation health, productivity, and phenology. Key products include the Normalized Difference Vegetation Index (NDVI, Tucker, 1979) and Enhanced Vegetation Index (EVI, Huete et al., 2002), which are associated with vegetation greenness, structure, and aboveground biomass. Thermal infrared sensors (8–14 μm) measure surface temperature and thermal anomalies that indicate water stress, active fire activity, and energy balance changes valuable for understanding some ecosystem state transitions.

Microwave sensors provide unique capabilities for monitoring subsurface properties and penetrating atmospheric interference. Passive microwave instruments measure naturally emitted radiation to monitor soil moisture, freeze-thaw cycles, and vegetation water content via indices such as Vegetation Optical Depth (VOD), while active microwave systems (radar) transmit signals and measure the intensity and phase of the reflected energy to assess surface roughness, vegetation structure, and some soil properties. Light Detection and Ranging systems provide precise three-dimensional measurements of vegetation structure, canopy height, and inferred aboveground biomass that provide insight into forest dynamics and structural changes that might precede tipping events (Dubayah et al., 2020).

3.1.1. Trade-Offs in EO Data Characteristics

EO data inherently entails fundamental trade-offs between spatial resolution, temporal frequency, historical record length, and differing sensitivity to the biophysical environment that significantly affects early warning applications (Lenton et al., 2024). Spatial resolution ranges from sub-meter (commercial high-resolution satellites, e.g., Pleiades, Denis et al., 2025) to several kilometers (meteorological sensors, e.g., AVHRR, Earth Resources Observation And Science (EROS) Center, 2017), with each scale suited to different types of tipping and scale of manifestation. Fine resolution (1–10 m) captures local processes and patch dynamics, medium resolution (10–500 m) suits landscape-scale transitions, while coarse resolution (>1 km) enables global monitoring of large-scale synchronous changes.

Temporal resolution varies from sub-hourly (geostationary meteorological satellites) to 10–16 days (Landsat, Crawford et al., 2023, Sentinel-2, Drusch et al., 2012), or ca. 24–35 days for older Sentinel-1 data (Rucci et al., 2012; Torres et al., 2012) operating in particular sensing modes, due to orbital mechanics and sensor capabilities. Commercial high-resolution satellites are often specifically tasked to perform an observation for a client and as such, the revisit time can be very infrequent. Finer spatial and spectral resolution sensors typically have narrower swath widths, resulting in lower temporal resolution, while sensors with wider swaths provide more frequent coverage but at coarser spatial and spectral resolution. For example, Landsat offers 30 m resolution with 16-day revisit, while MODIS (Justice et al., 2002) provides daily coverage at 250 m to 1 km resolution.

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3.2. EO Suitability for Early Warning Applications

Earth Observation data is particularly well-suited for spatial early warning signals and space-for-time substitution methods to circumvent the significant limitations undermining temporal approaches. Comprehensive spatial coverage enables identification of spatial patterns like vegetation patchiness, forest fragmentation, and ecosystem boundaries that may signal approaching transitions. Space-for-time substitutions capitalize on EO's spatial strength by recognizing that ecosystems may be nearer to tipping than others along environmental gradients (Clarke, 2023; Hirota et al., 2011), using spatial variation to infer temporal trajectories when long time series are unavailable.

For current early warning methods that rely on statistical indicators like temporal autocorrelation and variance, temporal frequency is more critical than spatial detail. However, different tipping mechanisms require different optimal balances: macro tipping may be detectable through coarse-resolution daily sampling, while clustered tipping events need high-resolution monthly sampling to detect local threshold crossing, and societal impact tipping points require very high-resolution monitoring of critical service areas.

The spatial richness of EO data offers unique advantages for detecting the spatial manifestations of approaching transitions that complement temporal approaches. Spatial autocorrelation analysis can detect increasing spatial coherence that often precedes transitions, while patch-based metrics can reveal changes in fragmentation patterns and connectivity. These spatial approaches become particularly valuable when temporal records are insufficient for robust trend detection.

3.3. Critical Limitations and Constraints

Despite the substantial potential of EO for tipping point detection, several critical limitations constrain the development and implementation of operational early warning systems (Table 4).

3.3.1. Temporal Coverage Constraints

The most fundamental limitation for early warning applications is that satellite records are typically shorter than the multi-decadal to centennial timescales over which many terrestrial systems evolve. While Landsat provides the longest continuous record spanning over 50 years, most operational data sets have much shorter temporal coverage—MODIS since 2000, Sentinel-2 since 2015—fundamentally limiting detection power for systems with slow dynamics (Drusch et al., 2012; Wulder et al., 2022). This temporal limitation is particularly acute for permafrost systems, peatlands, and forest ecosystems where critical dynamics may unfold over century timescales. The challenge is compounded by the fact that robust statistical detection of trends in higher-order moments (variance, autocorrelation) typically requires time series considerably longer than those needed for detecting changes in mean values alone (Verbesselt et al., 2010).

3.3.2. Data Quality and Consistency Challenges

Early warning systems impose more stringent data quality requirements than typical remote sensing applications due to the need to detect subtle statistical changes in time series. The Global Climate Observing System (GCOS) stability requirements for Essential Climate Variables (GCOS, 2022) provide crucial guidance, demanding data stability over time that meets threshold requirements as minimum standards. This encompasses not just measurement accuracy but long-term consistency in observation methodology and processing algorithms (Popp et al., 2020). Sensor degradation, orbital drift, and calibration changes can introduce artificial trends in higher-order statistics that may be misinterpreted as genuine early warning signals. Multi-sensor products present additional challenges where successive satellites with different characteristics must be harmonized while preserving statistical properties needed for EWS detection (Popp et al., 2020).

3.3.3. Scale Mismatches and Environmental Complexity

Additional constraints include optical observations interrupted by clouds, spatial resolution that may not align with the scale of critical ecological processes, and limitations in the EO data products commonly used for tipping point studies. The disconnect between satellite pixel sizes and relevant ecological processes, combined with edge effects and aggregation issues, means that many critical feedbacks operating at sub-pixel scales may remain undetectable. Conversely, processes operating at scales larger than typical satellite swaths may be incompletely

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Table 4
Requirements and Limitations for Early Warning Signal Detection From Earth Observation Data

Requirement	Specific requirements	Limitations	EO data considerations
Temporal resolution	Monitoring frequency must exceed system's intrinsic timescale for CSD detection; sufficient to resolve perturbations and recovery	Satellite revisit times may be insufficient for fast dynamics; cloud cover creates gaps in optical data and can change over time Changes to temporal resolution can modify AR(1) and variance	Dense time series from daily sensors (MODIS) allow shorter analysis windows than sparse observations (Landsat)
Temporal duration	Multi-decadal length for robust trend detection; considerably longer than system's intrinsic timescale	Most EO records <40 years; insufficient for centennial-scale processes	Climate-quality records need >30 years; most high-resolution EO much shorter
Spatial resolution	Sufficient to resolve key feedbacks and tipping mechanisms	Trade-off with temporal frequency; computational demands for fine-scale analysis	Pixel size must match ecological unit; coarse pixels average out fine-scale processes critical for tipping detection
	Observation scale must match process scale	Scale mismatches between satellite pixels and ecological processes	
Spatial coverage	Sufficient spatial extent to capture system boundaries	Polar regions have seasonal gaps; some sensors have inconsistent global coverage; edge effects	Spatial sampling strategies affect computational efficiency; consider nested approaches for multi-scale analysis
Data quality	High signal-to-noise ratio; consistent calibration over time; minimal artifacts	Sensor degradation; multi-sensor harmonization challenges; atmospheric effects	Multi-sensor products can artificially increase AR(1) over time due to improved accuracy; causes anti-correlation in variance
Data consistency	Stable measurement methodology; consistent processing algorithms; no artificial trends	Algorithm updates; orbital drift; changing sensor characteristics	Changes in retrieval algorithms can create step changes in time series; version control essential for EWS stability
Analysis readiness	Properly calibrated, validated, and corrected data; clear uncertainty estimates	Processing latency; incomplete metadata; varying quality flags across products	Gap-filling methods can dampen variance signals; minimal interpolation recommended to preserve EWS
System observability	Key state variables and drivers must be remotely sensible; feedbacks detectable	Subsurface features are largely hidden; some variables only indirectly observable	NDVI saturates in dense vegetation; VOD sensitive to surface water; radar less affected by atmospheric conditions
System understanding	Knowledge of relevant state variables and forcing factors; understanding of system boundaries	Limited mechanistic understanding of many terrestrial systems; unclear system boundaries	EO variables may not capture critical state variables; proxies may miss key processes
Baseline conditions	Clear definition of reference state and range of natural variability	Shifting baselines due to ongoing changes; natural variability is often poorly characterized	Historical EO data may already reflect altered states; need paleoecological context
Environmental context	Account for external drivers and confounding factors; separate anthropogenic from natural signals	Multiple interacting stressors; difficulty separating climate from land-use signals	EO detects combined effects; challenging to attribute signals to specific drivers

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captured. Real terrestrial ecosystems experience multiple interacting stressors, exhibit spatial heterogeneity, and contain numerous feedback mechanisms that can generate false signals or mask genuine early warning indicators.

3.3.4. Validation and Uncertainty Challenges

Validation presents unique challenges given the rarity of observed tipping events in the satellite record. Traditional validation approaches based on ground truth become problematic when the phenomena of interest—critical transitions—may occur only once per system over multi-decadal timescales. This creates fundamental difficulties in establishing confidence in early warning signals and distinguishing genuine approaching transitions from false alarms. Compounding these challenges, uncertainty propagation through complex processing chains remains poorly understood, particularly when combining multiple data sources or transitioning between sensors.

3.3.5. Computational and Operational Constraints

Computational demands of spatial EWS analysis at continental scales remain a significant barrier, particularly for high-resolution data sets where calculating spatial autocorrelation or patch metrics across millions of pixels requires substantial processing resources and specialized algorithms. The distinction between real-time operational monitoring and retrospective research analysis creates additional challenges, as operational systems must balance timeliness with data quality and processing complexity.

3.4. Challenges in Detection and Anticipation of Tipping Points

3.4.1. From Single Time Series to Forcing-Response Models

Much existing early warning research has focused on changes to the statistics of a single time series, which is essentially observing variable x only, satisfying $\frac{dx}{dt} = f(x, \mu)$. However, the use of EO data in tandem with climatological measurements brings a much more rigorous assessment. Some fluctuations that contribute to altered variance and autocorrelation can be related to instantaneous forcings, $F(t)$, described by climatological "weather" reanalysis products.

The model can then be written as $\frac{dx}{dt} = f(x, \mu, F)$, where knowledge of the more high-frequency non-climatological features of F helps determine the underlying process described by function f. This simultaneous use of EO measurements alongside known meteorological forcings enables a much deeper understanding of the underlying processes, potentially allowing generation of early warning signals beyond current generic assessments based solely on state variable statistics. Furthermore, this will help remove from any EWS system the "noise" caused by variations at interannual timescales or shorter, leaving the remaining EWS component changes to apply in response to climate change.

3.4.2. Temporal Early Warning Signal Performance

Temporal EWS approaches using EO data show variable performance across different terrestrial systems and environmental conditions. Water-limited ecosystems appear to demonstrate stronger early warning signals than other system types, with multiple studies documenting relationships between resilience indicators and water availability across diverse biomes (T. Smith & Boers, 2023a, 2023b; S. L. Smith et al., 2022; T. Smith et al., 2022; T. Smith et al., 2023). Forest systems show generally positive results for temporal autocorrelation measures where vegetation indices provide clear signals of ecosystem state changes (Boulton et al., 2022; Dakos, van Nes et al., 2012; van Nes & Scheffer, 2007). However, performance appears to degrade in systems with slow intrinsic dynamics or where relevant timescales exceed available satellite record lengths (Bathiany et al., 2024).

Detection reliability varies considerably depending on system type, data quality, and analytical approaches. Recent reviews highlight significant concerns about false positive rates and the difficulty of distinguishing genuine early warning signals from statistical noise in complex environmental systems (Boettiger & Hastings, 2012; Clements & Ozgul, 2018). The proliferation of different methodological approaches has led to contradictory resilience estimates across approximately 73% of Earth's land surface, highlighting fundamental challenges in establishing consistent detection approaches (Feng et al., 2021; Runge et al., 2025; S. L. Smith et al., 2022; T. Smith et al., 2022).

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3.4.3. Spatial Early Warning Signal Maturity

Spatial EWS approaches remain significantly less mature than temporal methods, with limited empirical validation and inconsistent performance across different systems (Nijp et al., 2019). Where spatial approaches have been successfully applied, they appear to perform better in systems with clear spatial organization, such as patterned vegetation in drylands or fragmented forest landscapes (Buxton et al., 2022; Kéfi et al., 2014). Spatial indicators show theoretical promise for complementing temporal approaches, particularly in systems where spatial coupling is weak enough to allow spatial variance to serve as an ensemble proxy (Clarke et al., 2026).

By combining data from multiple locations, it becomes possible to cultivate a more complete understanding of how a system approaches a tipping point. This analysis can reveal whether theory-based expected changes in early warning statistics are valid across the spatial gradient. If confidence is built in the underlying dynamical systems theory, this opens the possibility to integrate EO data with underlying models through data-model fusion, potentially revealing μ values at each location and estimating the critical value μ^*.

The computational and methodological complexity of spatial EWS has limited widespread adoption, with most studies focusing on relatively small spatial domains or coarse-resolution data sets (Génin et al., 2018). Scale-dependent effects create additional challenges, as spatial signals often vary depending on the analysis scale chosen, and optimal scales are rarely known a priori (Slade et al., 2023).

3.4.4. System-Dependent Performance Patterns

Performance appears to vary systematically across different terrestrial system types, though comprehensive comparative studies remain limited. Vegetation-dominated systems with strong EO signals generally show better detection potential than systems where critical processes are poorly observable from space (Loriani et al., 2025). Current Essential Climate Variables often lack the temporal scale and stability requirements necessary for robust EWS detection, with many variables showing poor performance for capturing the rapid changes that precede tipping points (Loriani et al., 2025).

Ecosystem heterogeneity significantly affects detection reliability, though systematic studies of this relationship remain limited. Theoretical considerations suggest that homogeneous systems or those with clear spatial organization should produce cleaner early warning signals than highly heterogeneous landscapes where multiple processes operate simultaneously (Dakos et al., 2010).

3.4.5. Methodological Reliability Concerns

Scale dependencies create systematic challenges for EO-based early warning detection (Assmann et al., 2020). The appropriate scale for monitoring often remains unclear, and detection results can vary dramatically depending on analytical choices, creating reproducibility concerns across different studies (Génin et al., 2018).

The choice of detrending methods, window lengths, and statistical indicators significantly influences detection performance, but standardized approaches for making these choices remain limited (Dakos, Carpenter, et al., 2012; Dakos et al., 2008, 2023). Recent research emphasize that uncertainty propagation through complex processing chains remains poorly understood, particularly when combining multiple data sources or transitioning between sensors (Bathiany et al., 2024).

3.4.6. Integration and Multi-Variable Approaches

Multi-variable approaches combining multiple EO data sets show theoretical promise for improving detection reliability but remain technically challenging to implement operationally (Bathiany et al., 2024). A significant gap exists in integrating multiple EWS approaches—temporal, spatial, and multivariate—with current studies typically focusing on single indicators or single data sources, missing opportunities for more robust detection through integrated approaches. Indeed, by performing a spatially-conscious multivariate analysis of the system it is in principle possible to extract the decay rate defining the resilience of the system as a whole and the associated spatial patterns (Lucarini & Chekroun, 2023, 2024).

Machine learning approaches demonstrate potential for identifying complex patterns across multiple variables (Bury et al., 2021; Dylewsky et al., 2023), but validation remains challenging due to the rarity of observed tipping

events in the satellite record. Current applications focus primarily on pattern recognition rather than genuine predictive capability, and mechanistic understanding of detected patterns often remains limited.

3.4.7. Current Operational Readiness

Most EO-based early warning approaches remain in the research phase rather than operational implementation. While numerous proof-of-concept studies demonstrate potential for detection, few approaches have been validated sufficiently for routine operational monitoring (Lenton et al., 2024). Research-to-operations transition faces significant challenges including computational requirements for large-scale monitoring, data continuity concerns across sensor transitions, and the need for robust uncertainty quantification methods (Bathiany et al., 2024; Loriani et al., 2025).

4. Application to Terrestrial Biosphere Tipping Elements

Terrestrial ecosystems present diverse potential tipping systems with distinct characteristics, mechanisms and early warning signals (Table 2). This section assesses candidate tipping systems across biomes, focusing on those where empirical evidence, theoretical understanding, and EO feasibility align to enable effective early warning. Figure 8 illustrates examples of these ecosystems and some of their properties as observed from space.

Each tipping system assessed in this section is evaluated using a consistent four-part structure. We begin with empirical evidence: what observations, monitoring studies, and remote sensing analyses show about state changes, instabilities, or resilience loss in the system, prioritizing documented alternative stable states, hysteresis, or abrupt transitions. We then describe the theoretical understanding of the underlying tipping mechanism: which feedbacks generate bistability or threshold behavior, how the system is expected to evolve under continued forcing, and what the dynamical systems typology implies for the nature of any transition (B-, N-, R-, or S-tipping). Third, we address spatial scale: at what level the tipping mechanism operates and what this implies for the spatial structure of any transition (local, clustered, propagating, or pattern-forming). Finally, we assess observational tractability: what EO currently can and cannot detect for this system, where key gaps lie, and what sensor capabilities or record lengths would most improve early warning potential. Where information is missing or genuinely uncertain for any category, we say so explicitly rather than inferring from adjacent systems. This structure is intended to enable systematic comparison across the full range of terrestrial tipping systems and to make clear the often asymmetric relationship between theoretical understanding and operational monitoring capability.

Our assessment reveals substantial variation across systems in their suitability for EO-based early warning, with some systems offering well-established monitoring capabilities while others present significant observational challenges that limit current detection potential. A list of key EO data sets that have been used or have the potential to be used to derive early warning signals for vegetation and permafrost tipping systems can be found in (Tables S1 and S2 in Supporting Information S1). Although theoretical frameworks suggest multiple terrestrial systems may exhibit tipping behavior, EO-based early warning applications remain heavily concentrated in a few well-studied systems. Amazon rainforest, boreal forests, and dryland systems dominate the empirical literature, while applications to wetlands, permafrost, and high-altitude systems remain largely theoretical or limited to basic monitoring rather than early warning signal detection. As an illustrative example, a summary of recent literature for vegetation and permafrost systems can be found in (Tables S3 and S4 in Supporting Information S1). This research bias likely reflects both the observational tractability of vegetation-dominated systems and the availability of longer time series for these regions.

4.1. Forest Systems

4.1.1. Tropical Forest Systems

While Amazon studies dominate the EO-based early warning literature for tropical forests, comparable applications to Congo and Southeast Asian systems remain limited. This partly reflects the different tipping dynamics and vulnerabilities of these systems compared to the Amazon. The Congo rainforest is assessed as having potential for localized tipping but uncertain potential for regional-scale tipping, with evidence suggesting transitions may be smoothed out over larger spatial scales through states of forest-savanna coexistence (Zwaan et al., 2024). Additionally, the Congo is expected to receive increased rainfall with climate change, making widespread tipping

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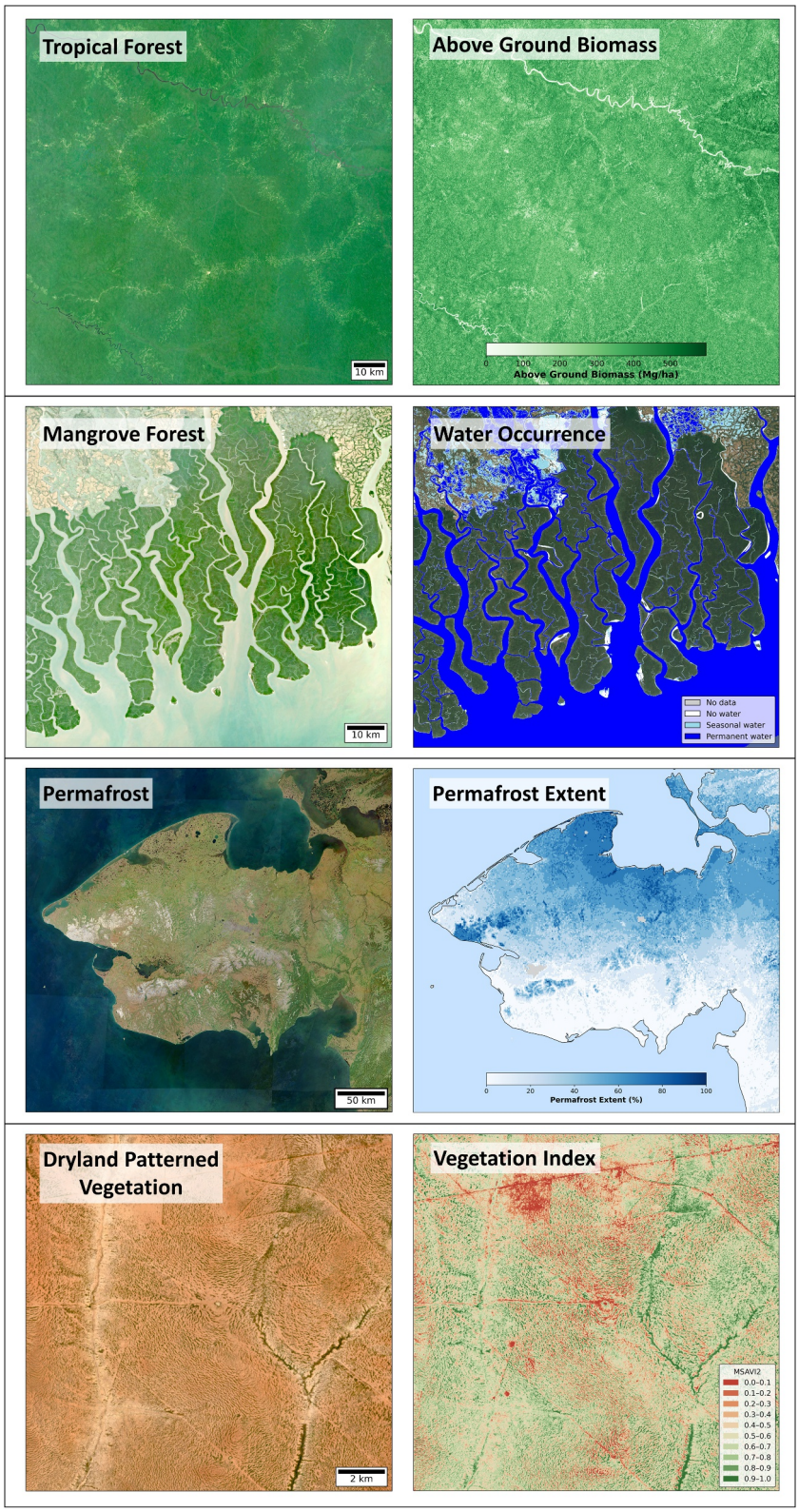


Figure 8.

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less of a concern than in the Amazon. Southeast Asian rainforests are assessed as unlikely to experience regional-scale tipping due to abundant ocean-derived rainfall, though local-scale tipping remains uncertain. The limited EO applications to these systems also reflects persistent cloud cover challenges in these regions.

4.1.1.1. Amazon

Parts of the southeastern Amazon may already be transitioning from carbon sink to source (Gatti et al., 2021), indicating the system may be approaching critical thresholds. Increasing fire frequency and edge retreat provide additional evidence of system stress. Analysis using VOD from multiple microwave sensors has demonstrated approaching tipping behavior through increasing temporal autocorrelation, particularly in southeastern regions experiencing the greatest climate stress (Boulton et al., 2022; Figure 9). These studies reveal spatial patterns of vulnerability across the basin, with strongest resilience loss signals in areas with lower MAP and closer proximity to human land use. Complementary studies using optical vegetation indices have tracked forest resilience changes in response to drought events (Hirota et al., 2011).

The Amazon represents the world's largest tropical rainforest and a paradigmatic example of potential climate-driven tipping, identified as such for over 25 years (Cox et al., 2000). The fundamental tipping mechanism involves disruption of moisture recycling feedbacks, where approximately 28% of precipitation derives from forest evapotranspiration (Flores et al., 2024; Staal et al., 2018, 2020; Zemp et al., 2014). As forest cover decreases through climate stress or deforestation, moisture recycling weakens, reducing downwind precipitation and creating conditions favoring fire-prone savanna vegetation over closed-canopy forest (Flores et al., 2024). Climate change is also increasing the risk of forest fires which can alter rainforest composition (Pueyo et al., 2010). The system exhibits propagating tipping behavior where localized forest loss spreads through atmospheric moisture transport disruption, potentially triggering basin-wide transitions.

The tipping mechanism operates at the basin scale through propagating moisture transport feedbacks, though initiation occurs at landscape scales (~10–100 km) in the southeastern transition zone. The system qualifies as propagating tipping: localized forest loss spreads downwind through reduced moisture recycling, meaning the effective tipping unit is the basin as a whole rather than any individual stand.

The Amazon has high utility for EO-based tipping detection, with good monitoring of vegetation state through optical and microwave sensors. Passive multispectral data sets (Sentinel-2, Landsat, MODIS) provide high-resolution monitoring with long temporal spans through vegetation indices such as NDVI or EVI, though saturation can occur in high-biomass environments. VOD and Sentinel-1 assess moisture content and canopy structure more directly (Frappart et al., 2020; Hethcoat et al., 2021; Moesinger et al., 2020). L-band radar provides indications of sub-canopy structural change, while GEDI data identifies forest age and recovery status (Doyle et al., 2025). Because the Amazon tipping mechanism is driven by moisture recycling feedbacks rather than direct forest state change alone, EO applications need to monitor not just vegetation condition but the feedback mechanisms and drivers (Wunderling et al., 2026), such as precipitation patterns, evapotranspiration, fire occurrence, that determine whether the system is approaching a threshold. Key observational gaps include insufficient monitoring of deep soil moisture determining drought resilience, limited coverage of atmospheric moisture transport patterns, and inadequate fire detection during peak burning seasons due to cloud cover and smoke (Loriani et al., 2025). Care must be taken with resilience signals from multi-sensor products, as changes in signal-to-noise ratios can alter apparent resilience trends (T. Smith et al., 2023). The rainfall gradient from the wet interior to the drier southeastern transition zone provides a natural space-for-time transect: locations currently experiencing lower MAP can be treated as analogs for the future trajectory of wetter areas under continued drying, enabling space-for-time inference about basin-wide resilience without requiring long temporal records at any single location (Hirota et al., 2011; Staal et al., 2020).

Figure 8. Earth observation captures both the structure and state of diverse terrestrial tipping ecosystems. True color composites from Sentinel-2 (left panel), and satellite-derived biophysical variables that could be useful to detect EWS (right panel). *Locations*: Tropical Forest (Democratic Republic of the Congo; −1.07°, 22.59°), Mangrove Forest (Bangladesh; 22.03°, 89.43°), Permafrost (Alaska; 65.58°, −164.02°), and Dryland Patterned Vegetation (Sudan; 11.12°, 28.37°). *Data*: European Space Agency (ESA) CCI Biomass v6.0 2022 (Santoro & Cartus, 2025); yearly JRC Global Surface Water v1.4 2021 (Pekel et al., 2016); ESA CCI Permafrost v5.0 2023 (Westermann et al., 2025); Sentinel-2 Level-2A Surface Reflectance (European Space Agency, 2025; true color composites used the RGB bands, and MSAVI2 was calculated using the red and NIR bands). *Tools*: Copernicus Data Space Ecosystem (CDSE; https://dataspace.copernicus.eu/); Google Colab and Google Earth Engine (Gorelick et al., 2017). This work used JASMIN, the UK's collaborative data analysis environment (https://www.jasmin.ac.uk; Lawrence et al., 2013).

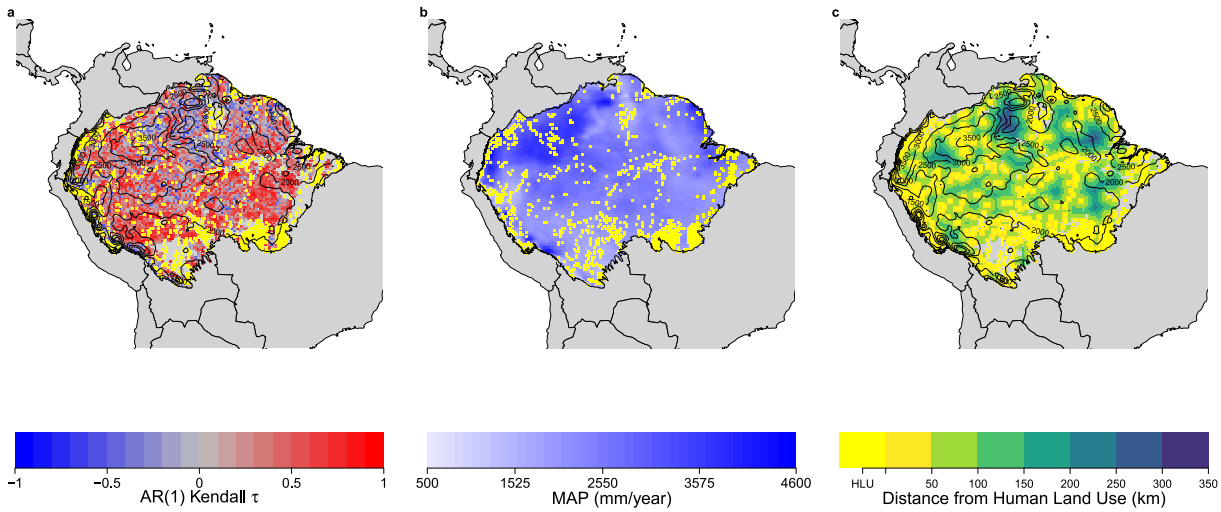


Figure 9. Amazon resilience loss is concentrated in drier regions and areas closer to human disturbance. (a), Vegetation Optical Depth lag-1 autocorrelation trends (Kendall τ values), where higher values indicate greater resilience loss since the early 2000s. (b), Mean annual precipitation (MAP) from CHIRPS data set (1991–2016). (c), Distance from human land use activities. In all panels, MAP contours and human land use grid cells (yellow) are overlaid to show the relationship between resilience loss, rainfall patterns, and anthropogenic pressure. Areas exhibiting the greatest resilience loss are associated with lower precipitation and closer proximity to human activities. Adapted from Boulton et al. (2022).

4.1.1.2. Congo

Empirical evidence for approaching tipping in the Congo is more limited than for the Amazon. The Congo remains severely under-observed, with particular gaps in ground-based validation data and high-resolution fire monitoring. Evidence of state-transition risk comes largely from analogy with the Amazon and from analysis of forest-savanna boundary dynamics in climatically marginal zones.

The Congo exhibits forest-savanna bistability through somewhat different mechanisms from the Amazon. While moisture recycling is important, with approximately half of precipitation within the basin being internally recycled (Tuinenburg et al., 2020), the system also depends substantially on moisture transport from the Indian Ocean (van der Ent & Savenije, 2011). The primary tipping mechanism involves fire-vegetation feedbacks at forest-savanna boundaries, where fire frequency maintains open canopy conditions preventing forest recovery. Unlike the Amazon's potential for basin-wide tipping, the Congo's dynamics appear more localized, capable of creating substantial regional impacts through clustered transitions along climatically marginal zones. The Congo is expected to receive increased rainfall with climate change, making widespread tipping less of an immediate concern than in the Amazon, and evidence suggests transitions may be smoothed out over larger spatial scales through states of forest-savanna coexistence (Zwaan et al., 2024).

Tipping is assessed as more localized than the Amazon, with clustered transitions along the southern and northern forest margins rather than basin-wide propagating tipping. The effective spatial unit for transitions is the forest-savanna ecotone rather than the forest interior.

Current early warning potential is limited despite reasonable theoretical understanding. The observational gaps in ground-based validation data, persistent cloud cover, and limited high-resolution fire monitoring constrain EO-based EWS applications. This is an area where investment in radar-based approaches would most improve detection capability.

4.1.1.3. Southeast Asian Forests

Evidence for bistability in Southeast Asian forests is less clear than for Amazon or Congo systems. Observable vulnerability manifests primarily through drought-fire interactions during strong El Niño events, when reduced precipitation combines with human ignition sources to create fire conditions that can shift forests toward more open, fire-prone states.

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Southeast Asian forests differ markedly from Amazon and Congo counterparts in showing less evidence of bistability, potentially due to more reliable monsoon-driven precipitation and complex topography creating diverse microclimates. Vulnerability remains through drought-fire interactions, particularly during El Niño events. Southeast Asian rainforests are assessed as unlikely to experience regional-scale tipping due to abundant ocean-derived rainfall, though local-scale tipping under compound drought-fire-land use pressure remains uncertain.

Tipping risk is primarily local rather than regional or basin-wide. Unlike the Amazon, there is no basin-scale moisture recycling feedback that could amplify local transitions into propagating events.

Current utility is moderate due to persistent observational challenges. Frequent cloud cover creates substantial gaps in optical monitoring, making radar-based approaches essential for continuous observation. This observational challenge partly explains the relative scarcity of EWS applications to Southeast Asian systems compared to the Amazon.

4.1.2. Boreal Forest Systems

EO applications have successfully detected approaching mortality events using temporal autocorrelation in productivity indices, providing early warning of large-scale dieback before visible symptoms appear (Rogers et al., 2018). Arctic-boreal vegetation resilience studies across northwestern North America have revealed clear signals of declining resilience in permafrost-affected regions, with strongest signals in areas experiencing rapid warming (Y. Zhang et al., 2024). Fire regime shifts provide observable evidence of transitions, with megafires documented in boreal regions at scales and severities inconsistent with historical fire cycles (Walker et al., 2019).

Boreal forests, covering approximately 33% of global forest area, exhibit multiple interacting tipping mechanisms (Foster et al., 2022; Gauthier et al., 2015). Fire regime shifts represent a primary mechanism where warming and altered precipitation change fire frequency and intensity beyond resilience thresholds of fire-adapted species. When combined with drought stress, fires can kill seed sources and alter soil conditions, preventing regeneration and triggering transitions to grassland or shrubland states in the form of clustered tipping where large regions experience near-synchronous transitions due to coherent climate forcing. Insect outbreak dynamics provide another critical mechanism: rising temperatures allow insects to expand ranges and increase reproductive rates while simultaneously weakening tree defenses through drought stress, rapidly transforming vast areas from carbon sinks to sources and creating positive feedbacks through increased fire susceptibility. Permafrost interactions in permafrost-underlain boreal forests create additional cascading tipping dynamics, where forest cover insulates permafrost but disturbances removing canopy cover can trigger permafrost thaw, altering soil hydrology and stability.

Tipping operates across multiple scales: local disturbances (insect outbreaks, individual fires) can trigger clustered tipping across large regions through coherent climate forcing, while permafrost interactions create cascading dynamics at landscape scale. The spatial manifestation is primarily clustered rather than propagating.

Boreal forests have high utility for vegetation state monitoring but poor monitoring of underlying processes (Bathiany et al., 2024; Loriani et al., 2025). Critical gaps include limited ability to detect soil thermal regime changes influencing regeneration, insufficient monitoring of insect outbreak dynamics triggering large-scale mortality, and challenges distinguishing natural fire cycles from regime shifts. Latitudinal temperature gradients across the boreal zone represent a suitable opportunity to apply a space-for-time analysis. The transition from closed-canopy boreal forest to open woodland to tundra along a north-south transect may serve as a spatial analog for the temporal evolution expected at any given location under continued warming (Harsch et al., 2009), though this inference assumes the gradient reflects tipping dynamics rather than reversible climate-envelope tracking.

4.2. Dryland and Semi-Arid Systems

4.2.1. Savanna and Grassland Systems

Savanna and grassland ecosystems are among the strongest candidate terrestrial tipping systems because they combine well-established ecological feedbacks with extensive EO observations across broad climatic gradients. Continental-scale analysis have identified multimodal tree-cover distributions consistent with closed forest (≥70% tree cover), woody savanna (40%–50% tree cover), and open savanna (<20% tree cover) states across

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gradients of water availability (Cheng et al., 2021). These patterns have frequently been interpreted as evidence for alternative stable states maintained by vegetation-fire feedbacks. However, the strength of this evidence remains debated, as some apparent discontinuities in remotely sensed tree-cover distributions may arise from methodological artifacts associated with products like MODIS Vegetation Continuous Fields product rather than underlying ecosystem dynamics (Gerard et al., 2017). Despite these uncertainties, multiple studies have detected resilience changes and approaching transitions between forest, savanna, and grassland states along rainfall gradients, broadly supporting theoretical expectations of nonlinear ecosystem responses (Staver et al., 2011). Similar approaches have been applied to detect woody encroachment in temperate grasslands using Landsat time series (Archer et al., 2017). Collectively, these observations suggest that many dryland systems may be vulnerable to rapid vegetation state changes, particularly under predicted climate and disturbance regimes (Higgins & Scheiter, 2012; Luvuno et al., 2018).

Evidence for multiple vegetation states is supported by well-established ecological feedbacks capable of generating bistability across broad environmental gradients. The savanna-forest boundary is widely regarded as one of the strongest candidate examples of bistability in terrestrial ecosystems (Hirota et al., 2011; Staver et al., 2011)., although the spatial extent of bistability and the interpretation of remotely sensed evidence remain subjects of ongoing debate (Gerard et al., 2017). In areas receiving 1,000–2,500 mm annual rainfall, both forest and savanna may persist under similar climatic conditions, with disturbance regimes influencing which state dominates (Hirota et al., 2011). Fire-vegetation feedbacks play a central role: open canopies promote grass growth that provides fuel for frequent fires, suppressing tree recruitment, whereas closed canopies reduce grass biomass and inhibit fire spread (Hoffmann et al., 2012). Temperate grasslands show related dynamics through woody encroachment, where fire suppression, altered grazing, and elevated atmospheric CO_2 facilitate shrub and tree establishment, generating self-amplifying feedback (Archer et al., 2017).

Multiple spatial tipping modes may operate across savanna landscapes. At local scales, fire spread and vegetation recovery generate pattern-forming dynamics that influence the spatial organization of woody and grassy vegetation. At larger scales, transitions may propagate through landscapes via fire transmission, seed dispersal, herbivore movements, or coordinated responses to coherent climatic forcing. Consequently, the effective tipping unit can range in scale from individual fire-managed landscapes to continental-scale forest-savanna transition zones. The resulting spatial complexity highlights the importance of considering both local ecological processes and large scale climatic controls when interpreting resilience indicators.

Drylands are attractive systems for spatial resilience assessment because environmental constraints are often expressed through strong climatic gradients. Spatial vegetation structure, patch organization, and ecosystem functioning vary systematically along aridity gradients, suggesting that resilience properties can be inferred from landscape structure as well as temporal dynamics (Berdugo et al., 2017). In addition to vegetation cover, spatial metrics such as vegetation connectedness, patch-size distributions, fragmentation, and pattern wavelength may provide complementary indicators of resilience loss because they directly capture changes in landscape organization associated with approaching transitions (Buxton et al., 2022; Rietkerk et al., 2004, 2021; Siteur et al., 2014).

Vegetation structure is well-monitored through a range of EO sensors, providing multiple opportunities for resilience assessment. Detecting genuine tipping dynamics is a key challenge in dryland systems where woody encroachment can represent either a directional but reversible vegetation response or a threshold-crossing shift between alternative stable states. Consistent long-term monitoring at appropriate spatial scales is required to distinguish between these possibilities (Bathiany et al., 2024). However, several key processes remain difficult to observe directly from space, including fire intensity, herbivore impacts, and demographic processes such as tree recruitment and mortality. Enhanced thermal infrared monitoring could improve monitoring of fire behavior (Eames et al., 2023), while better integration of high-resolution optical data could enable better tracking of tree demographic change.

Strong climatic gradients also make drylands promising candidates for space-for-time approaches. Continental aridity gradients spanning forest, woody, and open savanna, and grassland states provide natural laboratories in which resilience can be examined across a wide range of environmental conditions. Locations distributed along these gradients may approximate different positions relative to forest savanna transition thresholds, providing a theoretically motivated basis for spatial resilience assessment. However, local variation in soils, herbivory, disturbance regimes, and land-use history can modify these relationships, meaning that spatial gradients should be

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interpreted as informative analogs rather than direct temporal trajectories. When combined with long term Earth Observations, these spatial approaches provide one of the most tractable opportunities for large scale monitoring of resilience and tipping risk in terrestrial ecosystems.

4.2.2. Dryland Patterned Vegetation

Patterned dryland vegetation provides one of the clearest examples of spatial self-organization generating ecosystem-scale tipping behavior. In resource-poor environments, vegetation can form striking spatial patterns arising from competing feedbacks, including local facilitation, whereby plants retain water and other limiting resources, and longer-range competition, whereby resource uptake reduces availability for neighboring plants (HilleRisLambers et al., 2001; Klausmeier, 1999). These dynamics can generate regular spatial structures, including gaps, labyrinths, and spots, that belong to the class of Turing patterns (Turing, 1952), as well as more irregular vegetation mosaics. Because pattern formation emerges directly from ecosystem feedbacks, changes in spatial organization have long been viewed as potential indicators of ecosystem resilience and approaching tipping points.

Changes in vegetation pattern morphology have long been proposed as indicators of resilience loss, although their interpretation remains an active area of research. Early theoretical work suggested that transitions from gaps to labyrinths to spots indicate declining resilience as systems approach critical thresholds under increasing aridity (Meron et al., 2004), while pattern morphology has been linked more generally to ecosystem resilience (Buxton et al., 2022; Mayor et al., 2013). More recent work, however, suggests a more nuanced interpretation in which pattern formation itself allows vegetation to maintain resilience under increasing environmental stress. Under this framework, tipping may be better characterized as a Turing bifurcation rather than a fold bifurcation (Kéfi et al., 2024). In irregular patterned systems, changes in patch-size distributions have also been linked to resilience in theoretical models (Kéfi et al., 2014). Additional complexity arises from other drivers, including woody encroachment and herbivory, with herbivory potentially producing effects on vegetation patterns that oppose those of increasing aridity (Pichon et al., 2025).

Multi-decadal EO records demonstrate that dryland vegetation patterns are dynamic and responsive to both climatic and anthropogenic pressures. Tiger bush systems in Niger provide one of the best-documented examples, with changes in pattern wavelength and morphology tracked over multiple decades (Barbier et al., 2006; Deblauwe et al., 2008, 2012). Elsewhere, desertification processes have been linked to grazing pressure through observed changes in patch-size distributions (Kéfi et al., 2007). 10 m grain optical EO data sets, including Sentinel-2, have been shown to be capable of detecting changes in vegetation spatial organization and pattern morphology (Buxton et al., 2022). At larger scales, some climate model simulations suggest the possibility of nonlinear Sahel greening responses as a tipping point under future climate forcing (Pausata et al., 2020).

Monitoring patterned drylands requires EO systems capable of resolving vegetation organization at the scale at which tipping processes operate. Unlike biome-scale tipping systems such as the Amazon rainforest, tipping dynamics in patterned drylands occur primarily at patch-to-landscape scales, ranging from meters to kilometers (Rietkerk et al., 2004). Consequently, appropriate spatial resolution is a critical consideration for detecting resilience changes and tracking pattern evolution. Sentinel-2 imagery (10 m resolution) has been demonstrated to be suitable for monitoring broad changes in pattern morphology (Buxton et al., 2022), while Landsat products provide valuable longer-term observations. However, many of the ecological processes that govern resilience in these systems, including patch formation, vegetation connectedness, recruitment, mortality, and localized degradation, occur at sub-meter to meter scale (Cunliffe et al., 2016; Kéfi et al., 2007; W. K. Smith et al., 2019). Very-fine-resolution imagery, such as commercially available the WorldView constellation, therefore offers substantial advantages by resolving fine-scale landscape structure at the scale of individual plants. Such observations are often better aligned with the scales at which the underlying ecological feedbacks operate, potentially enabling more sensitive detection of resilience loss and pattern reorganization. The strong scale dependence of dryland reflectance patterns further emphasizes the value of very-fine-resolution observations for linking ecological processes with satellite-derived indicators and bridging the gap between field-scale measurements and satellite products (Slade et al., 2023). However, widespread application remains constrained by data access costs, limited temporal depth and spatial coverage, and the considerable computational demands associated with processing and analysing large volumes of sub-meter imagery. In addition to conventional vegetation indices, dryland monitoring benefits from metrics that quantify vegetation connectedness, fragmentation, patch-size

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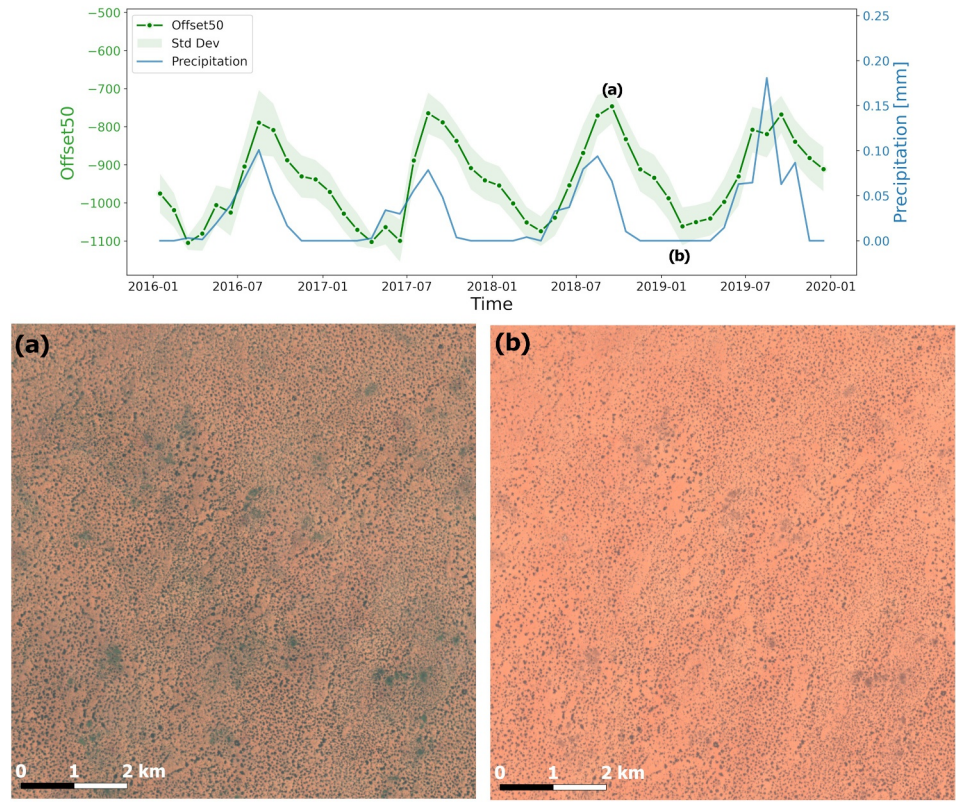


Figure 10. Vegetation connectedness captures seasonal changes in dryland spatial organization, as seen in this example of a patterned vegetation site in the Sahel. In the upper panel, the green time series, Offset50, is a measure of vegetation connectedness derived from a network of neighboring pixels, while the blue time series corresponds to precipitation levels. In the lower panels, (a, b) present Sentinel-2 imagery of the same patterned vegetation site with a seasonal maximum and minimum. Source: Buxton et al. (2022).

distributions, and pattern morphology (Figure 10), as well as indices that minimize soil-background effects, such as MSAVI2. Long observational records are desirable for resilience trend analysis, although space-for-time approaches may also be informative along strong resource gradients, such as the north-south precipitation gradient of the Sahel. While climatic drivers and rainfall variability can be partially monitored remotely (e.g., via CHIRPS or TAMSAT), direct drivers such as herbivory remain considerably more difficult to observe using EO data.

4.3. Wetland Systems

No studies have explicitly applied early warning signal theory to detect wetland tipping points using EO data. Recent work has linked wetland extent changes to methane emissions using TROPOMI (2018-present), GOSAT (2009-present), and SAR inundation mapping (Drinkwater et al., 2023; Lin et al., 2024; Lunt et al., 2021; Qu et al., 2024), but these focus on attributing observed trends rather than detecting approaching transitions.

Wetland ecosystems are substantial sources of atmospheric methane (France et al., 2022; Gloor et al., 2021; Saunois et al., 2025; Shaw et al., 2022), a powerful short-lived climate forcer, creating strong potential for climate feedbacks (Z. Zhang et al., 2023) and possibly a tipping point (Gedney, 2004; Nisbet, 2023). The tipping potential relates to positive feedbacks between warming, increased wetland methane emissions, and further warming. Theoretical evidence for a discrete tipping threshold in total wetland extent or methane flux is currently limited compared to other systems.

The tipping concern is primarily global through the methane-climate feedback rather than at the scale of individual wetland systems. Individual wetland systems undergo state changes (e.g., drainage, open water expansion)

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but these are mostly gradual or site-specific. The spatial scale at which a coherent wetland methane feedback tipping could operate is poorly constrained.

Wetland tipping point detection from EO has limited near-term potential for operational early warning. Satellite methane records are too short (<15 years) for robust temporal EWS detection, and high natural variability obscures resilience signals. Critical subsurface processes (water table dynamics, soil biogeochemistry) remain unobservable from space. Spatial approaches leveraging inundation-vegetation-methane coupling across environmental gradients may prove more tractable than temporal methods, but substantial advances in record length and subsurface sensing would be needed before wetlands become a high priority.

4.3.1. Peatlands

Current EO studies focus primarily on surface wetness monitoring using radar data and fire detection in peat areas (Lees, Artz, et al., 2021). InSAR applications detect subsidence associated with peat decomposition but monitor ongoing degradation rather than providing early warning of approaching thresholds. UK heather moorland studies using Sentinel-2 have assessed management frequency and vegetation recovery rates as potential resilience indicators (Lees, Buxton, et al., 2021). Tropical peat systems, particularly in Southeast Asia, have been extensively monitored for fire and deforestation (Brown et al., 2024; Cole et al., 2015; Crezee et al., 2022; Dargie et al., 2018; Franke et al., 2012; Page & Baird, 2016; Roucoux et al., 2017), though applications focused on early warning signals of tipping remain limited.

Peatland ecosystems maintain themselves through hydrological feedbacks where accumulated peat creates waterlogged, acidic, anaerobic conditions that slow decomposition (Page & Baird, 2016). These systems can exhibit bistability with forests, where both wetland ecosystems on thick peat soils and forest ecosystems on thin organic soils can coexist as alternative stable states (van der Velde et al., 2021). The tipping mechanism involves disruption through drainage, warming, or precipitation changes: once water tables drop below critical thresholds, aerobic decomposition accelerates, releasing stored carbon and causing subsidence that further lowers water tables, which is an amplifying feedback transforming peatlands from carbon sinks to major sources (Page & Baird, 2016). Fire risk increases dramatically as peatlands dry, potentially causing deep burns that release centuries of accumulated carbon and create further positive feedbacks.

Tipping operates locally to regionally. The bistability is between waterlogged peatland and drained terrestrial states; the threshold is fundamentally a water table depth at a given location, not a spatially propagating mechanism. However, large contiguous peatland complexes (especially tropical domes) can undergo coordinated degradation if drainage is regional. The spatial scale ranges from individual peat domes (km^2) to entire drainage basins.

Peatlands have particularly poor observational coverage for tipping detection. While surface vegetation and wetness can be monitored, critical variables including water table depth, peat temperature profiles, and subsurface carbon dynamics remain largely unobservable from space (Crichton et al., 2025). Detection requires integrating multiple data streams: thermal anomalies for smouldering detection, InSAR surface deformation for subsidence monitoring, and vegetation indices for health assessment (Lees, Artz, et al., 2021; Lees, Buxton, et al., 2021). While restoration of degraded peatlands can return them to net carbon sequestration, biodiversity, hydrological regime, and peat soil structure are not always fully restored even after decades of effort, potentially weakening resilience to future disturbances (Loisel & Gallego-Sala, 2022).

4.3.2. Forested Wetlands and Mangroves

Mangroves are vital coastal ecosystems that protect shorelines from erosion, absorb wave energy, and sequester vast amounts of carbon, and have long been associated with human settlements (Friess et al., 2021, 2022). Human activities, for example, aquaculture, coastal development, and deforestation, have historically caused massive mangrove losses, leaving coastal communities highly vulnerable to extreme weather, even if recently there have been changes thanks to new economic drivers and to the implementation of conservation policies (Hagger et al., 2022). Recent observational evidence highlights the vulnerability of mangroves to compound climate stressors. Large-scale dieback events have been documented, including the El Niño-linked 2015–2016 dieback in the Gulf of Carpentaria (Duke et al., 2017), drought-hurricane compound events (Amaral et al., 2023), and category 3+ cyclones (Duke et al., 2024). The combination of climate-intensified tropical cyclones and sea-level

rise is estimated to put around half of global mangrove area at high to severe risk of loss (Hülsen et al., 2025). The capacity of mangrove forests to re-establish has been compromised by rapidly rising sea levels coupled with increased severe weather and ENSO events (Chung et al., 2023; Duke et al., 2022).

Forested wetlands are maintained by specific hydrological regimes; climate-driven changes in precipitation can alter flood frequency and duration, disrupting regeneration of wetland-adapted tree species. Where canopy loss following recruitment failure is consolidated by vegetation-hydrology feedbacks, this may constitute a genuine tipping transition; however, evidence for bistability distinct from directional hydrological forcing is limited for most forested wetland systems. For mangroves, the primary mechanism involves imbalance between vertical accretion through sediment trapping and organic matter accumulation versus relative sea-level rise (Duke et al., 2022; Saintilan et al., 2020). Mangrove habitat is constrained within a narrow elevational range, and the time needed for seedling establishment is essentially fixed, meaning this capability can be overwhelmed by rapid sea-level rise (Duke et al., 2024; MacLeod et al., 2023). Mangroves can keep pace with relative sea-level rise up to approximately 4–7 mm/year through accretion; at 2°C of global warming nearly all mangroves would be exposed to 4 mm/year and one third to 7 mm/year (Saintilan et al., 2020, 2022, 2023).

Mangrove tipping operates at the local to regional scale: individual stands can cross the accretion threshold independently, but correlated sea-level rise and storm intensification means large contiguous coastlines may tip together. The effective tipping unit is the connected mangrove belt along a coastline segment, ranging from tens to thousands of kilometers.

Mangrove monitoring benefits from good optical and radar coverage for detecting area changes and mortality. EO applications to mangrove tipping focus primarily on area change detection rather than early warning signals of approaching transitions. Studies have used optical satellite data to track area loss in response to sea-level rise (Saintilan et al., 2020), but few applications have attempted to detect early warning signals of approaching submergence thresholds. The relatively rapid timescales of mangrove responses to inundation stress may mean that classical CSD-based gradual warning signals are limited in this system; monitoring of structural change and accretion rates may be more informative.

4.4. Permafrost Systems

Permafrost systems exhibit perhaps the most diverse and poorly defined array of tipping mechanisms among terrestrial biosphere components. Around 24% of the Northern Hemisphere land surface is covered or partially covered by permafrost, storing an estimated 1,460–1,600 Pg of organic carbon (Schuur et al., 2015). Permafrost persistence depends on mean annual ground temperatures remaining below 0°C perennially, but actual dynamics involve complex interactions between surface conditions, soil properties, and hydrology (Myers-Smith et al., 2019, 2020; Phoenix et al., 2025). Therefore, permafrost tipping elements are highly heterogeneous and often location-specific (Brovkin et al., 2025).

Empirical evidence for widespread permafrost degradation is strong, but evidence for self-amplifying tipping behavior remains limited to a subset of thaw processes and environmental settings. Mechanisms of permafrost degradation range from processes of gradual thaw, to abrupt thaw that may or may not be reversible (H. Webb et al., 2025), and threshold-crossing processes with self-amplifying feedbacks. However, many observed forms of abrupt permafrost change do not necessarily constitute tipping behavior, even where they are abrupt or effectively irreversible on human timescales. The critical distinction is whether thaw dynamics become self-sustaining through internal positive feedbacks after an initial threshold is crossed (J. F. Abrams et al., 2026). Early warning systems must therefore distinguish genuine tipping dynamics from broader classes of non-linear or threshold-driven degradation processes.

Observations across Arctic permafrost regions document increasing active-layer thickness (G. Li et al., 2022; S. L. Smith et al., 2022; T. Smith et al., 2022), thermokarst development (Kokelj & Jorgenson, 2013), retrogressive thaw slump expansion (Y. Li et al., 2024), talik formation (Farquharson et al., 2022), vegetation regime shifts (Berner et al., 2020; Frost et al., 2020; Myers-Smith et al., 2020; Phoenix et al., 2025), and widespread hydrological reorganization (Jin et al., 2022). However, whether any particular mechanism constitutes a tipping system depends strongly on local environmental conditions, including ground-ice content, drainage structure, topography, and thermal state.

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Theoretical understanding of permafrost tipping dynamics remains comparatively weak relative to other Earth system tipping elements. There is no single global threshold for permafrost collapse. Instead, permafrost is better viewed as a mosaic of locally distinct tipping elements whose behavior depends on ground ice content, soil properties, hydrology, vegetation cover, disturbance regimes, and landscape connectivity (Nitzbon et al., 2024). However, not all abrupt or difficult-to-reverse permafrost change qualifies as tipping behavior and distinguishing genuine self-amplifying transitions from threshold responses that require sustained external forcing to continue is essential for early warning system design.

Large-scale Arctic change reflects the cumulative aggregation of many asynchronous local transitions occurring under different environmental conditions and warming trajectories (Brovkin et al., 2025; Nitzbon et al., 2024). Processes such as ice-wedge thermokarst formation (Kokelj et al., 2023), talik formation (Farquharson et al., 2022), lake changes (Nitze et al., 2017) and thaw slump expansion (Nesterova et al., 2024) often occur over meter to kilometer scales before propagating into larger degradation landforms. This scale dependence complicates the application of conventional tipping-element theory, which often assumes coherent subsystem-scale transitions. For permafrost, early warning systems may therefore need to operate at the landsystem or geomorphic province scale rather than at the biome scale.

A process-level classification framework for permafrost is needed before permafrost tipping theory can be translated into observable early warning indicators. Such a framework would need to distinguish explicitly between reversible non-linear responses, irreversible threshold systems, and self-propagating tipping systems. It would also need to identify the state variables governing each of those classifications.

Once a classification framework is developed, observational tractability remains a major limitation for permafrost early warning systems. Permafrost observational coverage remains limited, with surface expressions often detectable remotely while subsurface thermal and hydrological dynamics remain difficult to observe directly (Loriani et al., 2025; Nitze et al., 2018). Despite this, EO applications to permafrost systems have used spatial patterns of vegetation change to infer subsurface thaw dynamics. Studies across Alaska and Siberia have utilized latitudinal temperature gradients to understand ecosystem response to warming, with spectral greening and browning patterns providing indirect indicators associated with changing permafrost stability (Myers-Smith & Hik, 2017; Myers-Smith et al., 2019, 2020). In addition, thermokarst lake monitoring using Landsat time series has tracked the formation and drainage cycles that indicate abrupt thaw processes (Jones et al., 2022; Ward Jones et al., 2022, 2025). High-resolution satellite monitoring of Arctic coasts is also technically feasible, although monitoring at sufficient temporal frequency and pan-Arctic consistency remains challenging (Cunliffe et al., 2019; Tanguy et al., 2024).

Surface temperature from MODIS LST, Sentinel-3 SLSTR and VIIRS provide additional indicators of permafrost state, although their spatial resolution cannot capture small-scale variations in thaw dynamics (Westermann et al., 2011). While it is possible to monitor growth of large permafrost thaw features such as retrogressive thaw slumps (Barth et al., 2025), early-stage formation and small-scale features indicating vulnerability to tipping remain challenging to monitor systematically (Bathiany et al., 2024). There remain critical EO gaps in monitoring of active layer thickness changes, detection of thermokarst initiation, and improved detection of greenhouse gas emissions from thawing permafrost.

4.5. High Altitude Ecosystems

Treeline advancement has been documented across multiple mountain ranges using Landsat time series (Harsch & Bader, 2011; Harsch et al., 2009; Zou et al., 2025). Alpine shrubification has been observed in high-latitude mountain environments (Myers-Smith et al., 2011). Himalayan vegetation band shifts have been recorded (Telwala et al., 2013). On the Tibetan Plateau, vegetation greening and browning trends have been detected via satellite (Myers-Smith et al., 2020), and glacial retreat is well-documented, though the downstream ecosystem consequences of retreat in terms of vegetation state change remain less quantified. Evidence for genuine bistability in these systems, as distinct from gradual range shift, is currently limited; few studies provide hysteresis evidence for alpine treeline systems.

Where these feedbacks are strong enough to generate genuine bistability, treeline advance would constitute a true tipping transition: once tree density exceeds critical thresholds, facilitative modifications become self-sustaining, preventing return to alpine vegetation even if climate conditions stabilize. Observed upward treeline migration

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under warming may reflect either directional climate-envelope tracking or approach to such a bistable threshold; distinguishing between these is a key empirical challenge. There is some theoretical and empirical support for alternative stable states between forest and alpine vegetation, maintained by feedbacks involving snow accumulation, growing season length, and establishment thresholds (Harsch & Bader, 2011; Myers-Smith & Hik, 2017), though direct hysteresis evidence remains limited. The Tibetan Plateau faces multiple interacting tipping mechanisms. Permafrost degradation alters soil moisture and stability, potentially triggering vegetation shifts from alpine meadows to steppe or bare ground, as well as pronounced vegetation expansion in the subnival Hindu Kush Himalaya (Anderson et al., 2020). Grassland degradation through overgrazing interacts with climate drying to create amplifying feedbacks where reduced vegetation cover increases albedo and decreases precipitation recycling (Bardgett et al., 2021; Y. Wang et al., 2023). Glacial retreat affects downstream water availability, potentially triggering vegetation transitions in areas dependent on glacial meltwater (Losapio et al., 2021; Milner et al., 2017; Xu, 2024). These mechanisms can interact synergistically, creating potential for cascading failures across multiple system components (Leng et al., 2023). In the high latitudes, albedo effects can lead to alternative stable states of vegetation cover between boreal forest and tundra or steppe grassland, and fire and disease (e.g., bark beetle) disturbance regimes are a function of vegetation state. There is evidence of bistability between different species compositions of boreal forest and between more closed and open forest states (B. Huang et al., 2024; Zeng & Yoon, 2009).

Treeline tipping is primarily local to landscape scale: individual microsites aggregate to ecotone advance, but the spatial unit of bistability is the stand rather than the entire mountain or range. Tibetan Plateau dynamics involve larger-scale interactions spanning thousands of kilometers in some scenarios (glacial-vegetation coupling). The spatial scale of observational need varies according to systems: 3–10 m for treeline microsites, coarser for plateau-scale vegetation. Elevational gradients in treeline position and vegetation cover provide a well-defined space-for-time opportunity, with communities at different elevations representing different stages of response to warming (Harsch & Bader, 2011). This is among the more tractable space-for-time applications in this review, given the clear forcing gradient, relatively short response timescales, and the availability of high-resolution optical data at the resolutions needed to resolve ecotone dynamics.

There are emerging EO monitoring capabilities of high altitude systems with moderate current utility. Challenges include complex topography affecting sensor observations, seasonal accessibility, and scale mismatches between satellite resolution and relevant processes. EO applications to high altitude tipping points have focused primarily on tracking ongoing changes rather than detecting early warning signals of approaching transitions. Studies using Landsat time series document upward treeline migration in alpine regions in response to warming (Harsch & Bader, 2011; Harsch et al., 2009), but few applications attempt to detect the gradual approach to establishment thresholds that would constitute early warning signals. Similarly, EO applications to Tibetan Plateau systems remain extremely limited despite the region's potential for multiple interacting tipping mechanisms. Most applications focus on general vegetation greening and browning trends (Myers-Smith et al., 2020) rather than early warning signal detection, while glacier monitoring applications track ongoing retreat but do not frame observations in terms of approaching tipping points in glacier-dependent ecosystems. Snow cover monitoring provides some indication of changing alpine conditions across both regions, but applications remain limited in their focus on tipping point dynamics rather than general environmental change tracking. The limited early warning applications likely reflect both the complex multi-causal dynamics of high-altitude systems and the challenges of distinguishing climate-driven changes from other anthropogenic pressures such as grazing.

4.6. Cross-System Synthesis

Several patterns emerge across terrestrial tipping systems that have important implications for EO-based early warning approaches. Moisture-mediated feedbacks appear central to many systems, whether through precipitation recycling in tropical forests (Flores et al., 2024; Zemp et al., 2014), soil moisture dynamics in peatlands (Page & Baird, 2016), or fire-vegetation interactions in savannas and boreal forests (Hoffmann et al., 2012; Rotbarth et al., 2025). Fire emerges as a critical mechanism across multiple biomes (Aragão et al., 2018; Walker et al., 2019), often serving as the proximate cause of transitions even when underlying drivers are climatic (W. Li et al., 2021; X.-Y. Li et al., 2021; O'Sullivan et al., 2023). Vegetation structure changes provide observable early indicators across systems (Boulton et al., 2022; Myers-Smith et al., 2019), making optical and structural sensing particularly valuable.

Table 5
Remote Sensing Capabilities for Terrestrial Biosphere Tipping Point Detection

Tipping properties						Remote sensing					
						Method(s) of sensing					
Tipping system	Type of tipping	Time-scale of event (yr)	Reversibility over 100 years?	Current utility in probing tipping processes	Properties sensed	Vis-Shortwave	Thermal infrared	LiDAR/ altimetry	Active microwave	Passive microwave	Gravimetry
Amazon forest	Propagating	~10	No?	High	Productivity indices	●					
Boreal forest	Clustered	~10	No?	High	Land cover types	●			●		
Forests (local)	Impact	~1–10	Yes?	Mid							
Savanna	Clustered	~10	Yes	High	Vegetation structure	●		●	●	●	
Patterned veg.	Impact	~10	Yes	Mid							
Tidal marshes	Impact	~10	Yes	Mid	Productivity indices	●					
Lake ecosystems	Impact	~1–10	Yes	Mid	Water indices	●					
Peatlands	Impact	~10–100	No	Mid	Water table depth	●					
					Burned area	●			●		
Permafrost soils	Clustered	~10–100	No	Low	Soil properties	●	●		●	●	
					GHG concentration	●	●				

Note. The table shows system characteristics (tipping type, transition timescale, reversibility over 100 years), current utility for probing tipping processes, key properties that can be remotely sensed, and applicable sensing methods across the electromagnetic spectrum. Filled circles (●) indicate primary sensing approaches for each system-property combination. Current utility ratings: High = well-established monitoring capabilities; Mid = emerging capabilities with limitations; Low = significant observational challenges remain. Adopted from Lenton et al. (2024).

Scale dependencies prove critical, with tipping mechanisms operating at scales from local patches to entire biomes (Lenton et al., 2024). This necessitates multi-scale monitoring approaches that can detect both local initiation of transitions and their potential for spatial propagation. Threshold behaviors are common but often involve multiple interacting variables rather than simple linear relationships (Hirota et al., 2011; Staver et al., 2011), suggesting the need for multivariate monitoring approaches.

Current EO capabilities show substantial variation across systems (Table 5). High detection potential exists for Amazon forests (Boulton et al., 2022; Loriani et al., 2025), boreal systems, savannas (Eby et al., 2017), and dryland patterns (Buxton et al., 2022) where key state variables are well-observed and theoretical understanding is strong. Moderate potential characterizes Congo forests (Bathiany et al., 2024), temperate grasslands, and some wetland systems where observational or theoretical gaps limit current capabilities. Low detection potential affects permafrost subsurface processes (Brovkin et al., 2025; Loriani et al., 2025), peatland water table dynamics (Crichton et al., 2025; Lees, Artz, et al., 2021), and some high-altitude systems where critical variables remain poorly observable from space.

4.7. Current State and Performance Assessment

Current applications reveal limitations in real-world performance. Performance assessments demonstrate variable success rates across different systems and indicators, with detection reliability depending on system type, indicator choice, forcing rate, spatial coupling strength, and data characteristics (Boettiger & Hastings, 2012; Clements & Ozgul, 2018; Dakos, Carpenter, et al., 2012). Comparative analyses using Receiver Operating Characteristic curves show that temporal autocorrelation-based early warnings can perform well across different spatial coupling strengths but may fail under rapid forcing changes, while spatial early warnings perform well at large rates of environmental change provided spatial coupling is not too strong (Figure 7). For EO-based applications, forest systems have shown stronger EWS performance than grasslands or croplands (Rogers et al., 2018), potentially reflecting differences in signal-to-noise ratios or transition dynamics.

Temporal EWS applications have been restricted largely to vegetation indices (S. L. Smith et al., 2022; T. Smith et al., 2022; T. Smith et al., 2023), potentially missing information from other ecosystem components (Bathiany et al., 2024). Success rates vary considerably across systems and regions, with some studies reporting high false positive and negative rates that undermine operational confidence (Boettiger & Hastings, 2012; Clements & Ozgul, 2018). Scale dependencies create inconsistent results where pixel-level signals can contradict ecosystem-

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level patterns (Assmann et al., 2020; Slade et al., 2023). Further, the relatively short duration of EO data records (typically 10–40 years) fundamentally limits detection power, particularly for systems with slow dynamics where relevant timescales may be decadal to centennial (Verbesselt et al., 2010; Wulder et al., 2022).

For spatial EWS, empirical validation remains far more limited than for temporal approaches, with few studies reporting quantitative performance metrics (Nijp et al., 2019; Slade et al., 2023). The choice of null model for significance testing substantially affects apparent performance, with phase randomization approaches providing more conservative but potentially more reliable assessments than simple permutation tests (Clements & Ozgul, 2018). A fundamental challenge lies in separating climate-driven spatial patterns from other sources of heterogeneity such as soil variations and land use legacies (Dakos et al., 2010; Génin et al., 2018). Spatial signals often prove ambiguous without long-term temporal context, as similar patterns can arise from fundamentally different mechanisms—self-organization indicating approaching transitions versus spatial heterogeneity in environmental drivers (Génin et al., 2018).

These performance challenges are compounded by underdeveloped quality assessment frameworks. Detection reliability across terrestrial ecosystem applications shows significant uncertainty, with contradictory resilience estimates across approximately 73% of Earth's land surface highlighting fundamental challenges in establishing consistent approaches (Feng et al., 2021; Runge et al., 2025; S. L. Smith et al., 2022; T. Smith et al., 2022). While ROC analysis and cross-validation provide standard performance metrics, few studies provide comprehensive uncertainty budgets tracking error propagation from raw observations through processing to final indicators (Bathiany et al., 2024). Bootstrap resampling and Bayesian frameworks can quantify statistical uncertainty and provide probabilistic transition estimates (Boettiger & Hastings, 2012; Dakos et al., 2008), yet these approaches are rarely applied systematically.

Critical gaps include the lack of standardized benchmarking data sets for method comparison across systems (Loriani et al., 2025), limited hindcasting validation using historical transitions with known outcomes (Verbesselt et al., 2010), and poorly defined operational thresholds—at what confidence level should warnings trigger management responses? Cross-validation using spatially or temporally independent data can assess generalizability (Bury et al., 2021; T. Smith et al., 2023), while process-based models enable systematic testing under controlled conditions. However, the rarity of observed tipping events fundamentally limits validation opportunities, necessitating development of community standards for uncertainty reporting and closer integration between EO scientists and decision-makers to establish decision-relevant confidence thresholds (Runge et al., 2025).

Despite significant theoretical advances and growing empirical applications, substantial challenges remain in applying early warning signals to terrestrial ecosystems. A fundamental issue is the significant gap between theoretical EWS frameworks and practical implementation in real terrestrial systems. While theoretical studies provide clear predictions for idealized systems, real ecosystems exhibit complex multi-causal dynamics, multi-scale dynamics, multiple interacting stressors, and heterogeneous responses that complicate signal detection (Génin et al., 2018; Kéfi et al., 2014). This complexity is compounded by the need to distinguish between changes in system resilience and changes in external forcing, a challenge that current theoretical frameworks inadequately address (Bathiany et al., 2024). Furthermore, many mediating variables influencing feedback processes in the causal pathways operating in real tipping systems are not captured by current Essential Climate Variables, creating blind spots in our observational and analytical capabilities (Loriani et al., 2025).

5. Conclusion and Outlook

The performance gaps, validation difficulties, and observational constraints documented in this review reflect the youth of EO-based EWS science rather than fundamental ceilings on what is achievable. Crucially, many of the limitations are tractable: record length grows with time, sensor continuity is improving, and the methodological gaps, in uncertainty quantification, multi-sensor integration, and spatial EWS theory, are active areas of research with clear paths forward. The diversity of terrestrial tipping systems assessed here, and the variable but often substantial EO suitability ratings across them, point to a field where targeted investment in both observational infrastructure and analytical frameworks could yield rapid progress. It is against this backdrop that the following conclusions and outlook are offered.

Earth Observation data offers unprecedented but under-exploited potential for creating early warning systems of future abrupt changes in the terrestrial biosphere. The exceptional spatial coverage and fine resolution of EO data,

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combined with sampling across large geographical domains, provides unique opportunities to detect spatial manifestations of approaching tipping points (Dakos et al., 2010, 2011; Kéfi et al., 2014). However, this potential remains largely unrealized due to current limitations in the understanding and development of early warning theory, and how to apply it to often noisy real-world systems.

EO data, having comprehensive spatial coverage but often for limited timeframes, suggests strong opportunities for theory enabling "space-for-time" substitutions to represent a key opportunity for early warning science. The spatial richness of EO data enables novel approaches where environmental gradients across landscapes can substitute for the long temporal records typically required for robust early warning detection (Boulton et al., 2022). By identifying locations closer to tipping thresholds within the same system, we can develop more complete assessments of system vulnerability and potentially overcome the critical limitation of short EO time series. The approach is most tractable where a clear, spatially extensive forcing gradient exists, such as the precipitation gradients driving savanna-forest bistability, or the temperature gradients governing treeline position, and less applicable where tipping dynamics are dominated by local feedbacks, disturbance legacy effects, or processes without a strong spatial analog.

Spatial early warning signals offer complementary information to temporal approaches but require different theoretical frameworks. While temporal EWS theory is well-established for bifurcation-type tipping (Scheffer et al., 2009), spatial manifestations of CSD, phase transitions, and percolation phenomena require distinct detection approaches (Dylewsky et al., 2023; Rietkerk et al., 2004). The integration of spatial structure analysis, spatial autocorrelation measures, and pattern-based indicators provides richer information about approaching transitions than temporal signals alone (Kéfi et al., 2014).

Different types of terrestrial tipping require tailored observational strategies. Macro tipping events may be detectable through coarse-resolution, high-frequency monitoring of large-scale synchronous changes, while propagating tipping requires medium-resolution tracking of spatial spread patterns. Clustered tipping events need high-resolution detection of local threshold crossing, and societal impact tipping points require very high-resolution monitoring of service areas (Lenton et al., 2024).

5.1. Key Limitations and Challenges

5.1.1. Temporal Coverage Constraints

Despite advances in EO technology, most satellite records remain too short (typically 10–40 years) to enable robust early warning signal detection in ecosystems with decadal or longer timescales, and when considering single locations in isolation. While the Landsat program provides the longest continuous EO record spanning over 50 years (Wulder et al., 2022), most operational data sets have much shorter temporal coverage. The key data set of MODIS has only been operational since 2000–2002, and Sentinel-2 only since 2015 (Drusch et al., 2012). This limitation is particularly acute for permafrost systems, peatlands, and forest ecosystems where critical dynamics may unfold over century timescales. The challenge is compounded by the fact that robust statistical detection of trends in higher-order moments (variance, autocorrelation) typically requires time series considerably longer than those needed for detecting changes in mean values alone (Verbesselt et al., 2010). These short timescales of data underpin our suggestion of the need for "space-for-time" substitution to calibrate EWS, although ideally data at individual locations is as long as possible to provide verification of the capability of such statistics.

5.1.2. Scale Mismatches and Environmental Complexity

The disconnect between satellite pixel sizes and relevant ecological processes often operating at very fine resolution, combined with edge effects and aggregation issues, means that many feedbacks operating at sub-pixel scales may remain undetectable. Conversely, processes operating at scales larger than typical satellite swaths may be incompletely captured, or may require process-informed spatial averaging of data. Real terrestrial ecosystems experience multiple interacting stressors, exhibit spatial heterogeneity, and contain numerous feedback mechanisms that can generate false signals or mask genuine early warning indicators (Dakos et al., 2010). Current theory, largely developed for idealized systems, may provide insufficient guidance for parsing these complex signals, ready for comparison against EO data.

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5.1.3. Theory-to-Practice Gaps and Methodological Challenges

While theoretical frameworks, such as Dynamic Global Vegetation Models (DGVMs), provide clear predictions for idealized systems, empirical validation in complex terrestrial ecosystems reveals substantial limitations (Clements & Ozgul, 2018). The performance gap between theory and practice suggests that current approaches may be inadequately accounting for the inherent complexity of terrestrial biosphere dynamics, including multiple interacting stressors, multi-scale dynamics, spatial heterogeneity, and scale-dependent processes. DGVMs may also have missing, or elementary representations of processes, such as the many geochemical cycles believed to affect vegetation productivity, and that may change in a changing climate.

5.1.4. Integration and Standardization Challenges

This emerging field currently lacks robust uncertainty quantification methods for the early warning signals themselves, which may consist of multiple sources of errors, making it difficult to assess detection reliability across different ecosystem types and data qualities (Bathiany et al., 2024; Loriani et al., 2025). In particular, a significant gap exists in knowledge as to the optimal way to integrate multiple EWS approaches—temporal, spatial, and multivariate—and multiple data streams from different sensors and platforms. At present, the majority of studies typically focus on single indicators or single data sources, missing opportunities for more robust detection through integrated approaches (Bathiany et al., 2024). The proliferation of methods for evaluating ecosystem resilience using EO data has introduced significant uncertainty, leading to contradictory resilience estimates across approximately 73% of the Earth's land surface (Feng et al., 2021; Runge et al., 2025; S. L. Smith et al., 2022; T. Smith et al., 2022).

5.2. Science Needs and Future Directions

5.2.1. Theoretical Developments

Ecosystem models, such as DGVMs, still require fundamental advances in theoretical frameworks that can accommodate the complexity of real terrestrial systems. Model enhancement can explain better EO observations, and may offer a better creation of EWS that include, implicitly, process features of the land surface. One potential technique is to employ newer machine learning approaches that can discover underlying system process equations and identify invariant features under changing climate forcings (Huntingford et al., 2025; Lucarini & Chekroun, 2023). Current Essential Climate Variables often lack the temporal scale and stability requirements necessary for robust EWS detection (Loriani et al., 2025).

5.2.2. Methodological Priorities

Development should prioritize space-for-time substitution approaches that lead to EWS statistics that maximize the value of EO data's spatial richness while overcoming temporal limitations. Rather than viewing multi-sensor integration as a purely technical challenge that may be too difficult to overcome, the opportunity instead lies in leveraging complementary observations to build a more complete picture of approaching tipping points.

5.2.3. Operational, Technological and Data Implementation Needs

The review article here argues that EO has huge potential to create reliable decision-relevant early warning information of TPs in ecosystems. However, to ensure robust uncertainty quantification methods, standardized integration approaches are needed. These factors will require not just technical advances to develop EWS systems, but also closer collaboration between the EO community and tipping point researchers to ensure that future missions and data products are optimized for early warning applications. Such interactions will help address the specific observational requirements identified for different tipping systems, including enhanced monitoring of subsurface processes, improved integration of multiple sensor types, and development of analysis-ready data sets with appropriate quality flags and uncertainty estimates.

The terrestrial biosphere provides critical ecosystem services that directly support human societies and plays a key role in global climate regulation. Developing effective early warning systems for terrestrial tipping points is therefore not just a scientific challenge but a societal need. Earth Observation data provides the foundation for meeting this challenge, but realizing its potential will require moving beyond current approaches toward more

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sophisticated, integrated, and uncertainty-aware methods that can reliably detect approaching transitions in complex, real-world systems.

Earth Observation offers transformative potential for detecting and anticipating tipping points in the terrestrial biosphere, yet this potential remains only partly realized. As satellite data expand by orders of magnitude each generation—capturing new biophysical variables at increasingly fine spatial and temporal resolutions—the central challenge is to convert this growing information stream into actionable early warning knowledge. Space-for-time substitution provides a particularly promising but underexplored pathway: by exploiting EO's unparalleled spatial coverage, we can infer temporal dynamics and identify systems at different stages of vulnerability, effectively turning space into a proxy for time. Realizing this capability requires coupling statistical indicators with process-based understanding, building early warning frameworks that draw on advances in land surface modeling and machine learning while remaining robust to noise, drift, and data discontinuities. Above all, the continuity and reliability of EO data streams remain essential foundations. With sustained investment and creative methodological development, EO could evolve from a predominantly observational enterprise into an operational backbone of global tipping point surveillance—transforming how we detect, interpret, and ultimately prevent critical transitions in Earth's systems.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

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Availability Statement

No new data was used or created for this article. The data and scripts used to generate Figures 1–4 are available on Zenodo (J. F. Abrams, 2025). All other figures were either created using publicly available data (CCI Biomass v6.0 2022, Santoro & Cartus, 2025; yearly JRC Global Surface Water v1.4 2021, Pekel et al., 2016; ESA CCI Permafrost v5.0 2023, Westermann et al., 2025; Sentinel-2 Level-2A Surface Reflectance, European Space Agency, 2025; true color composites used the RGB bands, and MSAVI2 was calculated using the red and NIR bands) and tools (Tools: Copernicus Data Space Ecosystem (CDSE; https://dataspace.copernicus.eu/); Google Colab and Google Earth Engine, Gorelick et al., 2017) or were reproduced from previously published sources (Boulton et al., 2022; Buxton et al., 2022; Clarke et al., 2026; Margazoglou et al., 2021). This work used JASMIN, the UK's collaborative data analysis environment (https://www.jasmin.ac.uk; Lawrence et al., 2013).

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