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Environmental Tipping Points in Human-Dominated Landscapes: A Cross-Ecosystem Review of Early Warning Signals

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ABSTRACT

Human-dominated landscapes, encompassing terrestrial, freshwater, and urban ecosystems, are increasingly vulnerable to abrupt and potentially irreversible changes known as tipping points, driven by anthropogenic pressures such as climate change, habitat fragmentation, and pollution. These tipping points represent critical thresholds where gradual stressors precipitate nonlinear shifts in ecosystem states, often leading to degraded functionality and loss of biodiversity. Early warning signals (EWS) offer a promising approach to anticipate such transitions, enabling proactive management. This narrative review synthesizes recent advancements in EWS detection across diverse ecosystems, emphasizing the unification of indicators that transcend traditional boundaries. Drawing from peer-reviewed literature published between 2019 and 2025, we examine generic EWS based on critical slowing down, such as increased autocorrelation and variance, alongside system-specific metrics like spatial patterns and trait variability. In terrestrial systems, remote sensing reveals resilience losses in forests and drylands through vegetation indices. Freshwater ecosystems, particularly lakes, demonstrate mixed EWS reliability due to data limitations and non-bifurcation shifts. Urban environments, as highly modified human-dominated spaces, exhibit social-ecological tipping dynamics, with EWS incorporating socio-economic factors like polarization and displacement. By integrating these cross-ecosystem insights, we highlight commonalities in EWS performance, such as the benefits of multivariate and machine learning approaches, while addressing challenges like noise, seasonality, and cascading effects. This unification fosters a holistic framework for monitoring and mitigating tipping risks in interconnected landscapes, underscoring the need for enhanced data integration and adaptive governance to enhance ecosystem resilience in the Anthropocene.

Keywords: *Tipping points, Early warning signals, Human-dominated landscapes, Terrestrial ecosystems, Freshwater ecosystems, Urban systems*

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INTRODUCTION

The Anthropocene epoch is increasingly recognized as a period in which human activities have become the dominant force shaping Earth's systems. Current estimates indicate that over 75% of the planet's ice-free land surface has been modified by humans through agriculture, urbanization, infrastructure development, and other land-use changes (Lenton *et al*., 2024). These human-dominated landscapes—ranging from intensive agricultural fields and managed forests to sprawling urban centers and engineered waterways—are not only altered physically but are also subject to cascading ecological and biogeochemical impacts. Such landscapes face mounting pressures from climate change, resource extraction, and intensifying land-use practices, which collectively threaten the stability and resilience of natural systems.

Under these compounded pressures, ecosystems can be pushed toward critical thresholds, commonly referred to as tipping points. Tipping points represent nonlinear transitions in system states, where incremental changes in environmental or anthropogenic drivers trigger abrupt, potentially irreversible shifts (Wang *et al*., 2025). These regime shifts often lead to substantial declines in ecosystem services, loss of biodiversity, and increased susceptibility to further disturbances (Lenton *et al*., 2019). For example, the collapse of coral reef systems under ocean warming and acidification or the transformation of grasslands into desertified landscapes illustrates how relatively small changes in stressors can precipitate large ecological consequences.

From a theoretical standpoint, tipping points are grounded in dynamical systems theory, where they correspond to bifurcations—qualitative changes in system behavior that alter stability landscapes (Krishnamurthy *et al*., 2020). Different types of bifurcations, including fold, Hopf, and transcritical, describe how ecosystems can lose resilience and move toward alternative stable states. In human-dominated systems, these processes are further amplified by feedback loops linking ecological and anthropogenic drivers. For instance, deforestation in tropical forests can exacerbate regional droughts, while urban expansion increases impervious surfaces, elevating flood risks in watersheds (Armstrong McKay *et al*., 2022). The consequences of such shifts are often global in scope: Amazon rainforest dieback could release enormous carbon stores, accelerating climate change (Rocha, 2022), while eutrophication in freshwater lakes can shift clear-water systems to turbid, algal-dominated states, degrading water quality and fisheries (O'Brien *et al*., 2023).

Given the potentially irreversible consequences of tipping points, there is an urgent need to anticipate these shifts before they occur. Early warning signals (EWS) offer a promising approach by detecting changes in system dynamics that precede critical transitions. EWS are grounded in the phenomenon of critical slowing down (CSD), whereby systems near thresholds exhibit slower recovery from perturbations, detectable as increases in temporal autocorrelation, variance, or spatial correlations (Nijp *et al*., 2019). While these indicators were initially developed in simplified mathematical models, their application has increasingly extended to complex, real-world datasets, including ecological time series, remote sensing products, and network analyses (Dakos *et al*., 2019). Despite these advances, most EWS research has remained ecosystem-specific, limiting cross-comparison and integration across terrestrial, freshwater, and urban systems, even though these systems often share common human pressures (Karavellas *et al*., 2020).

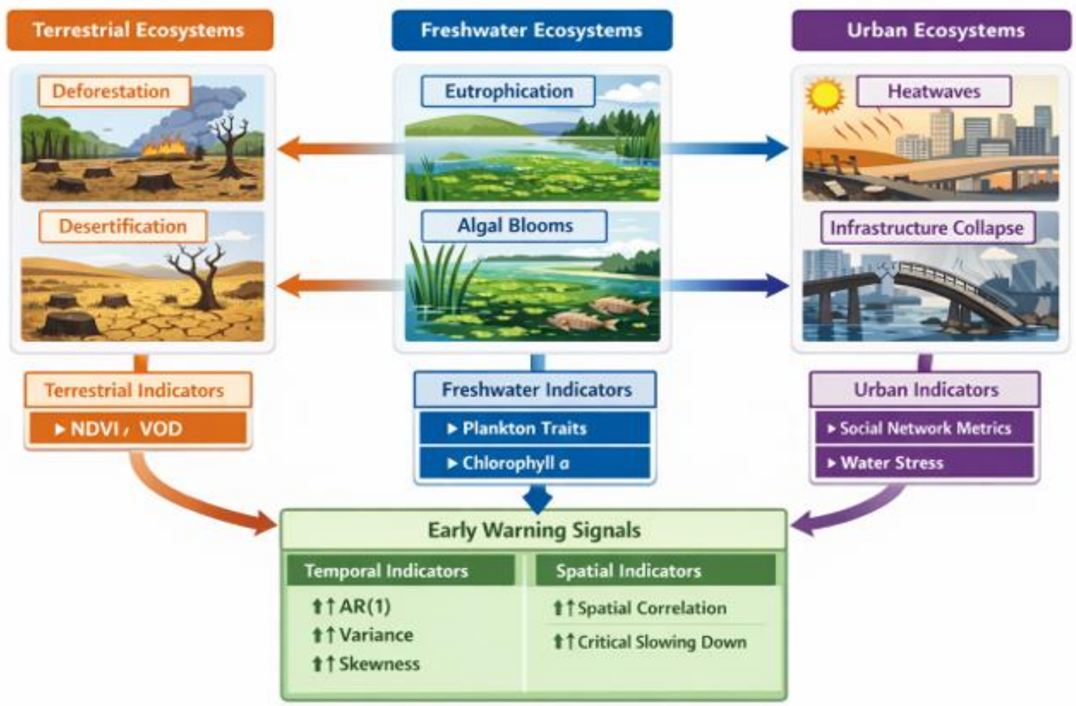

Figure 1. Conceptual Framework of Tipping Points Across Ecosystems

This review aims to bridge this gap by synthesizing EWS applications across diverse human-dominated ecosystems, highlighting indicators that capture generic dynamical signatures of approaching tipping points. Specifically, our objectives are threefold: (1) to outline the conceptual framework of tipping points and generic EWS applicable to human-modified landscapes; (2) to examine ecosystem-specific applications, identifying both methodological strengths and limitations; and (3) to propose a cross-ecosystem unification of indicators to support integrated monitoring and management strategies. By focusing on studies published between 2019 and 2025, we emphasize recent methodological innovations, including machine learning and network-based approaches, that enhance the detection and prediction of critical transitions. Such integrative strategies are crucial for informing adaptive policy and conservation efforts in an era of rapid environmental change.

The concept of environmental tipping points in human-dominated landscapes

Environmental tipping points are critical thresholds in dynamical systems where incremental changes in drivers trigger abrupt, qualitative shifts in system state. These shifts often arise when positive feedbacks outweigh stabilizing negative feedbacks, leading to sudden transitions that may be difficult or impossible to reverse (Wang *et al*., 2025). In human-dominated landscapes, anthropogenic pressures act as primary drivers that erode ecological resilience—the capacity of a system to absorb disturbances while maintaining essential functions and processes (Ibarra *et al*., 2022). For instance, land conversion for agriculture, infrastructure expansion, and urban development fragments habitats, diminishes ecological connectivity, and amplifies vulnerability to climate stressors such as droughts, heatwaves, or extreme precipitation events (Lenton *et al*., 2024).

From a dynamical systems perspective, tipping points emerge from specific types of bifurcations. Fold bifurcations produce hysteresis, meaning that returning to a previous state requires reversing drivers beyond the original threshold (e.g., desertification of drylands following prolonged land degradation). Hopf bifurcations induce oscillatory dynamics, as seen in predator-prey systems destabilized by overharvesting or habitat alterations. Transcritical bifurcations enable exchanges between system states without hysteresis, reflecting gradual yet structurally significant transitions (Krishnamurthy *et al*., 2020). In addition to these classic bifurcations, human-dominated systems introduce complexities such as rate-induced tipping, where the pace of change exceeds a system's capacity to adapt, or noise-induced tipping, where stochastic perturbations—like extreme weather or disease outbreaks—push systems past thresholds (Xu *et al*., 2020). Cascading effects further amplify risks: tipping in one subsystem, such as permafrost thaw releasing methane, can trigger downstream or teleconnected systems, leading to broader ecological or socio-economic consequences (Bury *et al*., 2021).

Across ecosystems, tipping points manifest in diverse ways. In terrestrial landscapes, regime shifts include transitions from forests to savannas or from grasslands to deserts, often driven by deforestation, land degradation, and warming (Rocha, 2022). Freshwater systems face eutrophication, salinization, and altered trophic structures, which compromise water quality and fisheries (O'Brien *et al*., 2023). Urban ecosystems, as hybrid social-ecological systems, are particularly susceptible to tipping in socio-economic dimensions—for example, flood risks can precipitate housing market collapses, and social polarization can impede collective action toward green transitions (Dabrowska *et al*., 2024). Despite variability in responses, human activities often homogenize drivers across these systems, such as nutrient loading, pollution, and the spread of invasive species; yet the outcomes are mediated by system-specific properties like spatial heterogeneity, connectivity, and network topology (Lenton *et al*., 2019).

Crucially, tipping points operate across multiple scales: local disturbances can propagate regionally or even globally, exemplified by food system disruptions resulting from regional droughts or market shocks (O'Brien *et al*., 2023). This interconnectedness highlights the importance of developing unified early warning signals (EWS) that integrate both biophysical and socio-economic dimensions, enabling proactive management of human-dominated landscapes before critical thresholds are crossed (Dipalma *et al*., 2022; İlhan *et al*., 2022; Sugimori *et al*., 2022; Uzun & Karataş, 2022; Vogel *et al*., 2023; Weerasinghe *et al*., 2023).

Generic early warning signals for tipping points

Generic early warning signals (EWS) exploit universal dynamical signatures that emerge as systems approach tipping points. Central among these is critical slowing down (CSD), where the system's dominant eigenvalues approach zero, causing slower recovery from perturbations and heightened sensitivity to disturbances (Nijp *et al*., 2019). Key temporal indicators of CSD include increasing lag-1 autocorrelation (AR(1)), variance, and skewness, all detectable in time-series data (Krishnamurthy *et al*., 2020). Spatial EWS complement these measures, capturing changes in heterogeneous landscapes through metrics like Moran's I (spatial autocorrelation) and the coefficient of variation (Pavithran *et al*., 2025).

Recent methodological advancements emphasize multivariate approaches, which combine multiple metrics to improve reliability in complex systems (Dakos *et al*., 2019). Machine learning techniques, particularly deep learning architectures like CNN-LSTM, have shown promise in detecting EWS across different bifurcation types. By learning subtle, high-dimensional patterns in time-series data, these models can outperform traditional indicators, successfully predicting tipping in empirical paleo-climate and ecological datasets (Li & Convertino, 2025).

Despite these advances, several challenges remain. EWS typically assume gradual forcing and low stochasticity, conditions often violated in human-dominated systems subjected to rapid anthropogenic changes or extreme events (Xu *et al*., 2020). False positives can arise from non-tipping fluctuations, while false negatives occur in rate-induced tipping, where changes outpace the system's ability to manifest CSD (Boulton *et al*., 2022). To address these issues, composite indices aggregate multiple signals, enhancing detection reliability in noisy, multi-stressor environments (Boers & Rypdal, 2021).

In cross-ecosystem applications, generic EWS provide a foundation for unification. CSD manifests similarly across diverse domains—for instance, increasing variance is observed in vegetation indices (terrestrial), plankton abundance (freshwater), and urban heat metrics (Ditlevsen & Ditlevsen, 2023). Nevertheless, system-specific adaptations remain essential, including adjustments for seasonality, network structure, and socio-ecological interactions, to improve interpretability and predictive power (Flores *et al*., 2024).

Early warning signals in terrestrial ecosystems

Terrestrial ecosystems in human-dominated landscapes—such as forests, drylands, and agricultural regions—are highly susceptible to tipping points like deforestation-induced dieback or desertification (Rocha, 2022). Here, EWS leverage remote sensing technologies to monitor resilience at large scales. Metrics such as vegetation optical depth (VOD) and the normalized difference vegetation index (NDVI) provide insights into vegetation health and stability (Rocha, 2022).

In tropical forests, notably the Amazon, increases in AR(1) and variance of VOD signal declining resilience, often linked to droughts and fire feedbacks (Rocha, 2022). Satellite-based studies since the 2000s reveal heterogeneous declines in resilience, with the strongest signals in areas heavily impacted by human activity. Spatial EWS, including measures of connectedness and patchiness, are particularly informative in drylands, where vegetation patterns reflect ecosystem vulnerability (Rocha, 2022; van Westen *et al*., 2024). Boreal forests exhibit mixed results, limited by spatial resolution and temporal coverage of VOD datasets (Rocha, 2022).

Table 1. Summary of Early Warning Signals by Ecosystem

Ecosystem	Key Tipping Points	Generic EWS Metrics	System-Specific Indicators	Data Sources / Methods	Limitations / Caveats
Terrestrial	Deforestation, desertification, forest dieback	AR(1), variance, skewness, critical slowing down (CSD)	NDVI, Vegetation Optical Depth (VOD), spatial patchiness	Remote sensing (satellite), ecological time series, network analysis	Cloud cover, short time series, seasonality, multiple stressors (fire, pests)
Freshwater	Eutrophication,	AR(1), variance,	Plankton trait variability,	Lake and river	Data gaps in rivers/wetlands,

	algal blooms, salinization, trophic collapse	skewness, composite indices	spatial heterogeneity, water chemistry	monitoring, mesocosm experiments, paleoecological data	stepwise shifts vs. bifurcations, high noise, short-duration datasets
Urban	Heatwaves, infrastructure failure, social instability	AR(1), variance, network autocorrelation	Social metrics (trust, cooperation, polarization), urban heat metrics	Socio-economic datasets, coupled socio-ecological models, sensor networks	Heterogeneous noise, rapid discontinuous changes, socio-economic complexity, cascading effects

Machine learning enhances terrestrial EWS detection. CNN-LSTM models trained on simulated phase transitions generalize to real-world vegetation-water systems, successfully identifying critical slowing down in desertification scenarios (Krishnamurthy *et al*., 2020). Network-based approaches assess spatial EWS in complex topologies, with metrics like coefficient of variation and skewness outperforming simpler measures in heterogeneous landscapes (Pavithran *et al*., 2025). Key challenges include data gaps due to cloud cover, short time-series, and confounding influences of seasonality or multiple stressors such as pests and fires, which necessitate detrending and multivariate analyses (Stelzer *et al*., 2021). Overall, terrestrial EWS emphasize spatially explicit metrics as essential tools for early intervention in human-altered landscapes (Constantin *et al*., 2022; Mojsak *et al*., 2022; Essah *et al*., 2024; Frost *et al*., 2024; Kajanova & Badrov, 2024; Lee & Ferreira, 2024; Rosellini *et al*., 2024; Umarova *et al*., 2024).

Early warning signals in freshwater ecosystems

Freshwater ecosystems, heavily modified by dams, pollution, nutrient loading, and water extraction, are prone to tipping points such as regime shifts from macrophyte- to algae-dominated lakes or river salinization (O'Brien *et al*., 2023). An evidence synthesis of 219 studies highlights both knowledge gaps and the dominance of research focused on lakes and chemical drivers (O'Brien *et al*., 2023).

EWS performance in freshwater systems is mixed. In empirical lake datasets, univariate indicators like variance succeed in detecting approaching transitions in less than 50% of cases, limited by non-critical shifts (e.g., abrupt stepwise changes) and data preprocessing sensitivities (Karavellas *et al*., 2020). Multivariate EWS generally perform better, but machine learning approaches such as EWSNet are still challenged by high false positive rates (Karavellas *et al*., 2020). Controlled experiments and mesocosm studies help bridge theory and application, validating indicators like AR(1) under gradual forcing, though real-world complexity reduces reliability (Ibarra *et al*., 2022). Notably, rate-induced tipping, where rapid environmental changes outpace bifurcation responses, can still produce detectable signals, with autocorrelation remaining one of the most robust indicators (Boulton *et al*., 2022).

Lotic (flowing water) systems are less studied compared to lentic (standing water) environments, though paleoecological evidence reveals long-term thresholds. Short-duration modern studies often limit the application of EWS (O'Brien *et al*., 2023). Trait variability (e.g., plankton size distributions) and spatial pattern metrics emerge as unifying indicators that can improve detection amid multiple interacting stressors (Brett & Rohani, 2020). The rarity of true critical transitions and the influence of compounded anthropogenic pressures underscore the importance of composite EWS, which integrate mechanistic understanding with multiple signals to improve forecasts for management and policy (Karavellas *et al*., 2020; O'Brien *et al*., 2023).

Early warning signals in urban ecosystems

Urban ecosystems, as densely populated and highly engineered human-dominated spaces, integrate both biophysical and socio-economic tipping points. Examples include heatwave-induced health crises, infrastructure failures from extreme flooding, and cascading disruptions in energy or transport systems (Dabrowska *et al*., 2024). In this context, EWS extend beyond ecological indicators to incorporate social and economic dynamics, such as political polarization, displacement, or financial instability, often triggered or amplified by climate-related stressors (O'Brien *et al*., 2023).

Negative social tipping processes—such as societal anomie following extreme events or radicalization arising from policy backlash—exhibit early warning behaviors analogous to ecological systems. For instance, increasing autocorrelation in social metrics (e.g., trust or cooperation indices) or contagion patterns across networks can signal approaching instability (O'Brien *et al*., 2023). These social dynamics often feedback into ecological and planetary systems, creating cascading effects, such as food insecurity leading to local conflicts, which in turn exacerbate environmental pressures (O'Brien *et al*., 2023).

Positive tipping points in urban contexts provide potential avenues for transformative change. For example, the adoption of low-carbon technologies, such as electric vehicles, can exhibit CSD in market shares, detectable as early warning signals preceding rapid societal shifts toward sustainability (Lenton *et al*., 2022). Deep learning approaches applied to coupled socio-technical models can generalize across urban networks, identifying emergent tipping points and projecting their likelihood under multiple scenarios (Li & Convertino, 2025).

Challenges in urban EWS include high heterogeneous noise, rapid and discontinuous changes, and complex interactions across social, economic, and ecological subsystems. To address these, node-selection methods optimize sentinel monitoring in networks, improving the detection of emerging instabilities (Boers *et al*., 2022). Integrating urban EWS with ecological indicators—for example, using sentinel species to track urban pollution—enables holistic assessments of system resilience and cross-domain risk (Ditlevsen & Ditlevsen, 2023).

Unifying indicators across ecosystems: challenges and opportunities

Efforts to unify EWS across terrestrial, freshwater, and urban systems reveal shared dynamical signatures, primarily critical slowing down (CSD), which manifests in generic metrics such as AR(1) autocorrelation and variance (Wang *et al*., 2025). Cross-scale monitoring is increasingly feasible through remote sensing, where analogous indicators track resilience across domains—for instance, VOD in terrestrial vegetation, plankton abundance in lakes, and urban heat metrics in cities (Karavellas *et al*., 2020; Rocha, 2022).

Machine learning provides a powerful unifying framework (Alhussain *et al*., 2022; Balaji *et al*., 2022; Tsiganock *et al*., 2023; Delcea *et al*., 2024; Ribeiro *et al*., 2024; Sanlier & Yasan, 2024; Uneno *et al*., 2024). Deep learning models trained on a diversity of bifurcation types can generalize across ecosystems, detecting approaching tipping points and distinguishing tipping types with greater lead time than traditional metrics (Li & Convertino, 2025). Similarly, network-based EWS, which quantify spatial patterns and interactions in complex topologies, bridge ecological and urban systems by capturing heterogeneity common to human-dominated landscapes (Lenton *et al*., 2019; Pavithran *et al*., 2025).

However, challenges persist. Ecosystem- and domain-specific noise—such as seasonal cycles in terrestrial and freshwater systems or social variability in urban systems—can obscure signals, while cascading interactions may render isolated EWS insufficient to capture systemic risk (Bury *et al*., 2021; O'Brien *et al*., 2023). Opportunities lie in composite and multivariate approaches, which integrate multiple indicators, and data fusion, combining satellite, paleoecological, and socio-economic datasets to provide holistic early warnings (Bury *et al*., 2019; Dakos *et al*., 2019).

Table 2. Machine Learning and Multivariate Approaches for EWS Across Ecosystems

Ecosystem	Method	Performance / Predictive Accuracy	Advantages	Limitations / Challenges
Terrestrial	CNN-LSTM, network-based models	High accuracy in simulated desertification and vegetation-water systems	Captures complex spatial-temporal patterns, generalizes across regions	Requires long time series, sensitive to seasonality, computationally intensive
Freshwater	EWSNet, multivariate indices	Moderate accuracy; improved over univariate but still false positives	Handles multiple interacting stressors, detects subtle multivariate signals	Short datasets, non-critical shifts, noisy data, high false negative rate
Urban	Deep learning on socio-ecological networks, composite EWS	Moderate to high in simulated networks; early detection of socio-economic tipping	Integrates social and ecological indicators, detects network contagion and cascading failures	Rapid, discontinuous changes; high heterogeneity; limited real-world validation

This cross-ecosystem perspective supports a proactive management framework, emphasizing adaptive strategies to anticipate and avert tipping points in interconnected human-dominated landscapes (Adeleke, 2022; Razhaeva *et al*., 2022; Rojas *et al*., 2022; Sri *et al*., 2022; Al Abadie *et al*., 2023; Guzek *et al*., 2023; Lee *et al*., 2023; Ncube *et al*., 2023; Oran & Azer, 2023; Simonyan *et al*., 2023; Ceylan *et al*., 2024; Maralov *et al*., 2024). By integrating generic indicators with system-specific adaptations, such a framework enhances resilience planning, policy design, and conservation interventions in the Anthropocene (van Nes *et al*., 2019).

RESULTS AND DISCUSSION

The unification of tipping-point indicators across terrestrial, freshwater, and urban ecosystems represents a significant advance in environmental science, as it bridges traditionally isolated domains under the common lens of human domination (Lenton *et al*., 2019; Armstrong McKay *et al*., 2022). By synthesizing recent literature, this review demonstrates that generic EWS, such as those based on CSD, can be applied cross-ecosystematically, but their effectiveness is modulated by system-specific attributes and anthropogenic influences (Bury *et al*., 2021; Wang *et al*., 2025). In terrestrial systems, where habitat fragmentation and climate stressors dominate, EWS like rising variance in VOD have proven reliable for detecting resilience losses, particularly in vulnerable biomes like the Amazon and boreal forests (Boulton *et al*., 2022; Lenton *et al*., 2024). However, the review highlights limitations in data resolution and the confounding effects of multiple drivers, which can obscure signals and lead to delayed warnings (Krishnamurthy *et al*., 2020; Rocha, 2022). For instance, in drylands, spatial EWS such as increased patchiness offer complementary insights, but require integration with temporal metrics to avoid false positives from seasonal variability (Nijp *et al*., 2019; Pavithran *et al*., 2025).

In contrast, freshwater ecosystems present a more challenging arena for EWS application, with empirical evidence indicating inconsistent performance due to non-linear responses and data constraints (Karavellas *et al*., 2020; O'Brien *et al*., 2023). Lakes, the most studied freshwater type, often exhibit regime shifts without clear CSD, as trophic cascades and nutrient pulses induce stepwise changes rather than bifurcations (Xu *et al*., 2020; Ibarra *et al*., 2022). This review's analysis of 219 studies underscores knowledge gaps in rivers and wetlands, where hydrological alterations from dams and pollution amplify tipping risks but elude standard EWS (Stelzer *et al*., 2021; O'Brien *et al*., 2023). Machine learning approaches, such as EWSNet, show promise in handling these complexities by identifying multivariate patterns, yet they struggle with false negatives in noisy, short-term datasets (Bury *et al*., 2021; O'Brien *et al*., 2023). Urban ecosystems, as the epitome of human-dominated landscapes, extend EWS beyond biophysical realms to include social tipping dynamics, such as polarization or economic instability (Lenton *et al*., 2022; Dabrowska *et al*., 2024). Here, the unification is particularly novel, as EWS incorporate metrics like network contagion, revealing how climate stressors interact with socio-economic feedbacks to precipitate shifts, e.g., in heat vulnerability or resource access (Bury *et al*., 2019; Dabrowska *et al*., 2024). However, urban heterogeneity—driven by rapid human interventions—poses unique challenges, often rendering generic EWS insufficient without hybrid socio-ecological models (Brett & Rohani, 2020; O'Brien *et al*., 2023).

Cross-ecosystem commonalities emerge in the form of shared dynamical behaviors, such as CSD manifesting in vegetation indices (terrestrial), plankton variability (freshwater), and social metrics (urban) (O'Brien *et al*., 2023; Dabrowska *et al*., 2024; Lenton *et al*., 2024). This supports the novelty of unification, where machine learning leverages universal bifurcation patterns to generalize EWS across domains (Bury *et al*., 2021; van Westen *et al*., 2024; Li & Convertino, 2025). For example, deep learning models trained on synthetic data have successfully predicted tipping in empirical series from diverse systems, providing earlier and more accurate warnings than univariate indicators (Bury *et al*., 2021; Ditlevsen & Ditlevsen, 2023). Composite EWS, combining autocorrelation, variance, and skewness, further enhance robustness by mitigating noise and seasonality common in human-altered environments (Dakos *et al*., 2019; Brett & Rohani, 2020). Nevertheless, challenges like rate-induced tipping—where fast anthropogenic changes outpace CSD detection—underscore the need for rate-sensitive modifications (Bury *et al*., 2019; Pavithran *et al*., 2025). Cascading effects, where tipping in one ecosystem triggers another (e.g., terrestrial drought affecting freshwater quality and urban water security), are understudied but critical, as they amplify risks in interconnected landscapes (Bury *et al*., 2021; Armstrong McKay *et al*., 2022; Boers *et al*., 2022).

The implications of this unification are multifaceted. Scientifically, it fosters a holistic understanding of resilience in the Anthropocene, where human activities homogenize drivers across ecosystems (Lenton *et al*., 2019; Armstrong McKay *et al*., 2022). Practically, it informs management by enabling integrated monitoring systems, such as satellite-based platforms that track cross-ecosystem signals for timely interventions (Krishnamurthy *et al*., 2020; Lenton *et al*., 2024). In terrestrial contexts, this could guide reforestation and fire management to avert desertification (Boulton *et al*., 2022; Wang *et al*., 2025). For freshwater, EWS-integrated nutrient controls might prevent algal blooms, preserving biodiversity and services (Xu *et al*., 2020; O'Brien *et al*., 2023). Urban applications could promote positive tipping, like accelerating low-carbon transitions through policy thresholds identified by EWS (Lenton *et al*., 2022; O'Brien *et al*., 2023). However, ethical and equity issues arise, particularly in urban and developing regions, where EWS deployment must avoid exacerbating vulnerabilities (Bury *et al*., 2019; Dabrowska *et al*., 2024). Limitations of the reviewed literature include a bias toward Northern Hemisphere systems and retrospective analyses, with few studies addressing adaptive capacities or reversal strategies post-tipping (Stelzer *et al*., 2021; Rocha, 2022). Future EWS unification should incorporate evolutionary perspectives, as species adaptation may alter tipping dynamics (Dakos *et al*., 2019; Lenton *et al*., 2022).

By addressing these gaps, unified EWS can transform environmental governance, shifting from reactive to anticipatory paradigms (Lenton *et al*., 2019; Brett & Rohani, 2020). This review's novelty lies in demonstrating that, despite ecosystem differences, shared indicators offer a scalable toolkit for mitigating tipping risks in human-dominated landscapes.

CONCLUSION

In conclusion, this cross-ecosystem review establishes that unifying tipping-point indicators enhances the detection of EWS in human-dominated landscapes, providing a novel framework for anticipating abrupt changes. Key insights include the broad applicability of CSD-based metrics, bolstered by machine learning, across terrestrial, freshwater, and urban systems, albeit with ecosystem-specific caveats. This unification not only highlights common resilience losses but also underscores the role of anthropogenic drivers in accelerating tipping, emphasizing the urgency for integrated management.

Looking ahead, future directions should focus on real-time EWS validation through global observatories and experiments to bridge theory and practice. Expanding data coverage to underrepresented ecosystems, like tropical rivers and megacities, via advanced remote sensing and citizen science, is crucial. Developing adaptive, rate-sensitive models that account for cascades and socio-economic factors will improve predictive accuracy. Policy-wise, embedding unified EWS in frameworks like the UN Sustainable Development Goals could facilitate proactive resilience-building. Ultimately, interdisciplinary efforts integrating ecology, data science, and social sciences will be pivotal to averting tipping points and sustaining ecosystems in an increasingly human-altered world.

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