Concepts, Reviews and Syntheses

Representational limits in detecting ecological change

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Abstract

Detecting ecological change remains a persistent challenge, even in systems with extensive monitoring data and increasingly sophisticated analytical tools. Uncertainty is usually attributed to stochasticity, limited observations, or imperfect models. Here, I argue that an additional and largely overlooked constraint arises from representational limits: systematic ways in which graphs, indicators, ordinations, and other common analytical outputs shape what ecological dynamics become perceptible and interpretable. Ecological information is rarely assessed directly, but through representations that selectively emphasize some system properties while downplaying others. In particular, subtle changes in variability, temporal structure, and multivariate coupling, features often associated with declining resilience or approaching transitions, may remain difficult to detect in dominant visual–statistical formats. As a result, signals of ecological change can be present in data yet weakly expressed in the forms used for inference. Drawing on examples from regime-shift research, long-term monitoring, forecasting, and broader ecological analysis, I show how alternative representations can alter what is detected and how system dynamics are interpreted. Representational limits therefore help explain why ecological change may remain difficult to identify even when data are abundant. Recognizing representation as a component of ecological inference expands current understanding of uncertainty and suggests practical opportunities to improve monitoring, early detection, and ecological decision-making through plural and better-matched representational approaches.

Key words: ecological inference; representational limits; regime shifts; early warning signals; resilience

Why is ecological change hard to detect?

Detecting ecological change remains a persistent challenge, despite rapid growth in monitoring capacity, long-term datasets, and increasingly sophisticated analytical tools. Across biology and environmental science, important shifts in system behavior are often recognized only after they have become pronounced or difficult to reverse. In ecology, this problem is especially evident where theory predicts that critical transitions, tipping points, or loss of resilience should leave detectable traces in variance, autocorrelation, or skewness, yet these signals frequently appear weak, noisy, or ambiguous (Carpenter et al. 2011; Dakos et al. 2015). Different analytical approaches can also yield conflicting interpretations of the same dataset, highlighting limits to early warning detection (Boettiger and Hastings 2012). These difficulties are usually framed as epistemic: too few data, excessive stochasticity, or models that fail to capture cross-scale dynamics. Yet persistent uncertainty even in intensively monitored systems suggests that additional constraints are at play. I argue that a substantial part of the difficulty in detecting ecological change arises not from the absence of signal, but from how ecological information is encoded into forms that shape what can be inferred from the same underlying data.

Part of this difficulty lies in a fundamental but underexamined dimension of ecological practice: representation. Ecological inference depends not directly on observations, but on how observations are transformed into representations (graphs, indicators, ordinations, model outputs) that render system dynamics perceptible. These representations are not neutral. They selectively emphasize some features of system behavior while suppressing others (Fig. 1), effectively acting as filters that shape what can be seen and inferred. Some failures to detect ecological change may therefore arise not only from ecological complexity itself, but from the representational conventions through which that complexity is interpreted.

Representation has long been recognized as central to scientific understanding. Models and diagrams function as mediating structures between data and theory (Oreskes et al. 1994; Frigg and Nguyen 2020), and visualization research shows that graphical encoding strongly shapes perception and interpretation (Cleveland 1993; Tufte 2001; Franconeri et al. 2021). Yet ecology, despite its heavy reliance on visualization, has rarely treated representation itself as a potential constraint on inference. This omission is notable because ecological systems are nonlinear, multivariate, and strongly temporal (Levin 1998; Folke et al. 2004). Such systems often exhibit changes in variability or correlation structure well before shifts in mean state (Scheffer et al. 2009; Carpenter et al. 2011; Dakos et al. 2015), precisely the features that standard visual displays may render least perceptible.

Here I introduce the concept of representational limits to describe systematic constraints on ecological inference that arise from how valid information is encoded into graphs, indicators, models, and related forms. I argue that many failures to detect ecological change reflect not an absence of signal, but a mismatch between the dynamics of ecological systems and the conventions used to render them observable. Because ecological inference relies overwhelmingly on visual–statistical representations, subtle temporal structure, irregular variability, and multivariate coupling may remain effectively invisible even when present in the data. Treating representational limits as a distinct source of inferential uncertainty reframes persistent difficulties in early warning detection and regime-shift analysis, and highlights representation, not only measurement or modeling, as a consequential factor in understanding, forecasting, and governing ecological change.

What are representational limits?

Scientific representations encode information about the world in forms that make it accessible to human perception and analysis. In ecology, the most common representational forms include time-series plots, statistical summaries, ordinations, maps, and model-based outputs. These tools are indispensable for interpreting complex systems, yet they also introduce representational limits (Box 1): constraints on inference that arise from how information is encoded, rather than from data scarcity or model structure alone.

Representational limits are related to, but distinct from, other familiar sources of uncertainty. Epistemic limits arise from stochasticity, short time series, or incomplete observations (Clark et al. 2001). Methodological limits arise from simplifying assumptions in models and analytical techniques (Levins 1966; Oreskes et al. 1994). Perceptual limits arise from the cognitive and sensory biases of observers (Franconeri et al. 2021). Representational limits can be understood as one component of epistemic uncertainty, but they are analytically distinct because they arise not from lack of knowledge or flawed models, but from how valid information is translated into forms that selectively foreground some features while rendering others difficult to detect. They operate at the interface between methodological choices and perceptual processes, shaping the conditions under which inference is made.

For example, summarizing a multivariate ecological system as a single time-series indicator is a methodological decision, but the resulting loss of visibility of changing correlations among variables is a representational limit. The information may still exist in the underlying data, yet become suppressed in the form chosen for interpretation. Similar issues arise when continuous spatial gradients are reduced to categorical maps, or when highly variable trajectories are summarized only by mean trends.

Three properties of ecological systems make these limits particularly important. First, ecological systems are often high-dimensional, yet representations typically compress them into a small number of variables. Ordinations reduce multivariate communities to a few axes, time-series plots collapse dynamics into a single trajectory, and early warning indicators reduce complex variance structure to scalar metrics. Such reduction is necessary but selective: it can obscure multivariate coupling, cross-scale interactions, or gradual increases in variability that precede regime shifts (Scheffer et al. 2001; Dakos et al. 2015).

Second, ecological dynamics are strongly temporal, but temporal structure is commonly encoded spatially. Time is represented along an axis, while subtle fluctuations or irregular dynamics must be visually inferred from static displays. As a result, early signals of instability may remain ambiguous in standard time-series plots, whereas alternative representations can reveal clearer changes in system organization (Spanbauer et al. 2014).

Third, representational conventions shape expectations. Ecologists are trained to interpret particular graphical forms (e.g., line plots, rolling-window indicators, response curves), which influence what patterns are sought and what counts as evidence. These conventions can bias interpretation toward directional trends or shifts in means while blurring irregular or pre-transition dynamics.

Representational limits are therefore not failures of measurement or perception, but consequences of how ecological information is structured for interpretation. Recognizing these limits broadens the explanation for why ecological change may remain difficult to detect even in systems with dense, high-quality data.

Modality, perception, and the dominance of visual representation

Ecology is overwhelmingly a visual science. Most ecological information, including field observations, remote-sensing products, model outputs, and early warning indicators, is communicated through plots, charts, maps, and other graphical displays. This reliance has clear advantages: human vision is highly efficient at detecting spatial structure, relative magnitude, and pattern contrast (Cleveland 1993). Visual representations are therefore well suited to many core ecological tasks, particularly comparison across space, gradients, or categories.

However, vision is not equally sensitive to all features of complex dynamics. Temporal irregularity, subtle instability, cross-variable coupling, and fine-scale fluctuations are often more difficult to detect visually, especially when embedded in noisy or high-dimensional data (Ware 2019; Franconeri et al. 2021). Static displays may further reduce sensitivity when dynamic processes must be inferred from snapshots, smoothed trajectories, or compressed summaries.

This limitation is consequential because ecological systems are strongly temporal. Nonlinear dynamics often manifest as changes in variability, persistence, or multivariate structure well before directional trends emerge (Dakos et al. 2015). If dominant representational forms emphasize trends in mean state while downplaying irregular temporal structure, the earliest signs of system reorganization may be underemphasized.

Alternative modalities illustrate this asymmetry. Sonification, the systematic translation of data into sound (Kramer et al. 2010; Hermann et al. 2011), provides one example. Auditory perception is highly sensitive to rhythm, temporal structure, and irregularity, allowing some patterns to be perceived that are less evident in visual displays (Martin et al. 2024; Angeler et al. 2026). More generally, perception is modality-dependent: different sensory systems are tuned to different properties of complex signals (Neuhoff 2011;

Spence 2011). Whereas vision often excels at spatial comparison, auditory perception can be more sensitive to temporal patterning, and other modalities (e.g., haptic or immersive interfaces) may, in principle, render fluctuation, intensity, or multi-stream dynamics perceptible in ways that visual displays alone do not (Rey et al. 2025).

These differences do not imply that any modality is inherently more accurate or universally preferable. Rather, they show that modality influences which features of the same data become salient. As a result, reliance on a single dominant modality can systematically shape what is detected and how it is interpreted. Representational limits therefore arise partly because ecological inference is grounded predominantly in visual representations of systems that are inherently multidimensional and time-varying.

How representation shapes the perception of ecological change

The influence of representation becomes most evident when different encodings of the same data support different interpretations. In early warning research, indicators such as rising variance or autocorrelation may be statistically detectable yet visually ambiguous in standard time-series plots (Carpenter et al. 2011). Representational limits help explain this discrepancy: subtle changes in statistical structure can remain perceptually difficult to distinguish from background variability when expressed in familiar graphical formats.

This effect is evident in empirical studies. In a long-term lake dataset, univariate early warning indicators did not clearly signal an impending regime shift, whereas alternative representations based on Fisher Information, multivariate ordination and discontinuity analysis revealed pronounced changes in system organization (Spanbauer et al. 2014, 2016). Complementary analyses of the same system further showed that temporal beta diversity captured abrupt compositional change operating at a different temporal scale from Fisher Information and discontinuity-based assessments, thereby refining inference about the transition itself (Angeler and Allen 2025). More recently, sonified representations of the same paleoecological sequence highlighted additional aspects of system dynamics, with simpler and more complex auditory encodings differentially emphasizing clarity, temporal structure, and system complexity (Angeler et al. 2026). In such cases, the signal is not absent, but differentially expressed depending on how the data are represented.

Comparable issues arise in other areas of ecology. For example, species distribution data can be represented as binary presence–absence maps, polygon range boundaries, or continuous habitat-suitability surfaces. Each representation may imply different conclusions about fragmentation, connectivity, or extinction risk, even when derived from the same underlying observations. The representational form therefore helps determine which ecological patterns become salient for analysis or management.

Alternative representations can shift what becomes perceptible. Phase plots reveal attractor structure not visible in time-series graphs, while multivariate visualizations expose correlation patterns collapsed in univariate summaries. Dynamic and interactive displays can further highlight changes in rate, direction, and cross-scale interactions that static graphs suppress. Each representation foregrounds particular system properties, enabling different ecological questions to be asked and answered (Table 1).

Modal variation amplifies these differences. Auditory or hybrid representations can make temporal irregularity, acceleration, or clustering more salient than visual displays (Hermann 2008; Martin et al. 2024; Angeler et al. 2026), while multisensory approaches can integrate multiple data streams in ways that enhance pattern detection in high-frequency monitoring contexts (Enge et al. 2024). Importantly, these approaches do not reveal new information; they reorganize how existing information is perceived.

Representational limits therefore arise not because representations distort ecological reality, but because they structure the perceptual encounter between observer and system. When ecological change is subtle, high-dimensional, and nonlinear, the choice of representational form can meaningfully influence what is detected, how it is interpreted, and whether it is recognized at all.

Implications for ecology and environmental governance

Recognizing representational limits has direct implications for ecological research, monitoring, and management. In resilience and early-warning studies, they help explain why signals predicted by theory often appear weak in practice. Variance and autocorrelation may increase statistically yet remain visually ambiguous, and different indicators may diverge not because they are inconsistent, but because they emphasize different representational facets of the same system (Dakos et al. 2015). Interpreting disagreement among indicators therefore requires attention not only to statistical performance, but also to how each indicator renders system change observable.

In long-term monitoring, these limits may become more pronounced as data volume and dimensionality increase. High-frequency sensor networks, remote sensing, automated imaging, and eDNA now generate data streams that are difficult to interpret through conventional static plots alone (Hampton et al. 2013; LaDeau et al. 2017). Under such conditions, interactive, dynamic, or multimodal representations can reveal patterns that standard displays suppress, including abrupt anomalies, changing covariance structures, or asynchronous responses among variables.

In ecological forecasting, representational choices also shape how uncertainty is interpreted. Ensemble spread, divergence among trajectories, and disagreement among models are not only properties of forecasts themselves, but also of how outputs are encoded and communicated (Dietze et al. 2018). Fan plots, probability surfaces, threshold maps, and summary statistics may each lead users to different perceptions of confidence or risk. Representational limits therefore influence both scientific inference and downstream decisions. This does not imply that a single optimal representation exists, but rather that representations should be matched to the ecological signal and decision context of interest.

These issues extend directly to environmental governance. Decisions about thresholds, accelerating change, restoration priorities, or system stability often depend on detecting weak signals under uncertainty. Representational choices can therefore influence how risk is perceived and how interventions are justified, for example by making warning signals appear either ambiguous or compelling depending on how they are displayed. This may alter the timing, scale, or likelihood of management action. Because ecological information is increasingly communicated beyond specialist audiences, representational choices may also shape public understanding of ecological risk and environmental change.

For practitioners, several practical implications follow. First, when signal detection is the inferential goal, the same data should be examined using multiple complementary representations. Second, monitoring programs should consider representational design alongside sampling design, particularly where high-dimensional data streams are involved. Third, reviewers and decision-makers should be cautious about treating a single graphical or analytical form as definitive when alternative encodings may yield different insights.

More broadly, these implications suggest that uncertainty in ecological inference is produced not only by system complexity or incomplete knowledge, but also by the forms through which ecological information is interpreted (Fig. 2). Some uncertainty is intrinsic to ecological dynamics, whereas some may be introduced or amplified by representational choices. Recognizing this distinction creates practical opportunities: improving ecological inference may depend not only on collecting better data or refining models, but also on developing representations better matched to the dynamics under study.

Concluding observations

Detecting ecological change depends not only on data and models, but also on how ecological information is represented. I have argued that dominant visual–statistical conventions can systematically obscure important features of nonlinear dynamics, particularly subtle changes in variability, temporal structure, and multivariate interactions. As a result, signals of ecological change may remain difficult to recognize even when they are present in the underlying data.

This perspective generates clear and testable predictions. If representational limits are consequential, then re-encoding the same data in alternative forms should alter the detectability of ecological signals. Controlled comparisons among representational formats, experimental studies of perception, and applications to real monitoring and forecasting systems provide direct ways to evaluate these effects.

Expanding the representational repertoire of ecology, from static summaries to interactive, dynamic, and cross-modal approaches, may therefore improve both scientific understanding and environmental decision-making. More broadly, the argument developed here suggests that uncertainty in ecology arises not only from complex systems and imperfect knowledge, but also from how ecological dynamics are rendered observable. Key directions for advancing this perspective are outlined in Table 2.

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Box 1. Key concepts in representational ecology

Representational limits

Systematic constraints on ecological inference that arise from how valid information is encoded into graphs, indicators, models, and other representational forms. Representational limits occur when certain aspects of system dynamics are foregrounded while others remain difficult to perceive, even when present in the data.

Inferential uncertainty

Uncertainty arising during the interpretation of ecological data. It encompasses epistemic uncertainty but also includes constraints introduced by representational choices that shape which patterns can be detected and how they are interpreted.

Epistemic uncertainty

Uncertainty arising from incomplete knowledge, including limited data, stochastic variability, and imperfect models. It is typically treated as the primary source of uncertainty in ecological inference.

Ontic uncertainty

Uncertainty arising from the intrinsic properties of ecological systems, including nonlinear dynamics, stochasticity, and indeterminacy. Ontic uncertainty reflects limits to predictability that persist even with complete knowledge and perfect representation.

Early warning signals (EWS)

Statistical indicators, such as increasing variance or autocorrelation, that are expected to precede critical transitions in ecological systems. Their detectability depends not only on data quality and model assumptions, but also on how signals are represented.

Multivariate coupling

Interdependencies among multiple ecological variables that jointly shape system dynamics. Such coupling is often reduced or obscured when complex systems are represented through univariate indicators or low-dimensional summaries.

Sonification

The systematic translation of data into sound to support analysis or communication. In ecological contexts, sonification can render temporal structure, irregularity, and dynamic change more perceptible than conventional visual displays.

Table 1. Examples (not an exhaustive taxonomy) of representational limits shaping the detectability of ecological change.

Ecological signal	Often obscured by	More easily detected with	Why detection improves
Slow increases in variance or skewness	Conventional time-series plots interpreted as noise	Alternative modalities (e.g., auditory or multimodal representations)	Auditory and cross-modal perception are highly sensitive to temporal irregularity and changes in signal structure
Multivariate coupling and correlation	Univariate indicators or scalar metrics	Multivariate visualizations (e.g., heatmaps, interactive displays)	Preserves relationships among variables that are collapsed in scalar summaries
Attractor instability and regime transitions	Linear trend lines and response curves	State-space or phase-space representations	Reveals system trajectories in state space rather than change in a single observed variable
Cross-scale interactions	Static low-dimensional ordinations	Multimodal or interactive representations	Enables simultaneous perception of processes operating across scales
High-frequency anomalies	Long-term averages or static summaries	Dynamic or real-time representations (including auditory alerts)	Enhances detection of rapid fluctuations that are visually subtle in aggregated displays

Table 2. Future directions for evaluating representational limits in ecology.

Research priority	Testable question or prediction	Possible approaches	Relevance for ecology
Quantifying representational limits	Do different representations of the same dataset lead to different rates of signal detection, confidence, or interpretation?	Controlled perception experiments; comparative re-analysis of existing datasets using multiple formats	Establishes whether representational limits measurably affect ecological inference
Sensitivity of ecological signals to representation	Are some ecological signals (e.g., rising variance, multivariate coupling, cross-scale interactions) more sensitive to representational form than others?	Simulation studies; benchmark datasets with known transitions; signal-specific comparisons	Identifies which forms of ecological change are most likely to be overlooked
Representational choice and inferential accuracy	Do interactive, dynamic, or cross-modal representations improve detection accuracy relative to standard static graphics?	Human-subject experiments; forecasting exercises; decision-support trials	Helps optimize representations for monitoring and early warning
Trade-offs between clarity and complexity	How much simplification can occur before ecologically important structure is lost?	Information-reduction analyses; comparisons of scalar indicators vs multivariate displays	Guides the balance between interpretability and ecological realism
Integration into ecological workflows	Can representational strategies be incorporated systematically into monitoring, forecasting, and assessment protocols?	Workflow comparisons across agencies or projects; protocol development and testing	Moves representation from ad hoc choice to part of standard ecological practice
Implications for governance and communication	Do representational forms influence how scientists, managers, or the public perceive ecological risk, thresholds, or urgency?	Stakeholder experiments; policy communication trials; participatory decision studies	Links ecological inference to management timing, public understanding, and governance outcomes

Figure 1. Representational filters in ecological inference. This figure illustrates how different representational filters suppress or amplify features of the same underlying data, thereby creating representational limits independent of data quality.

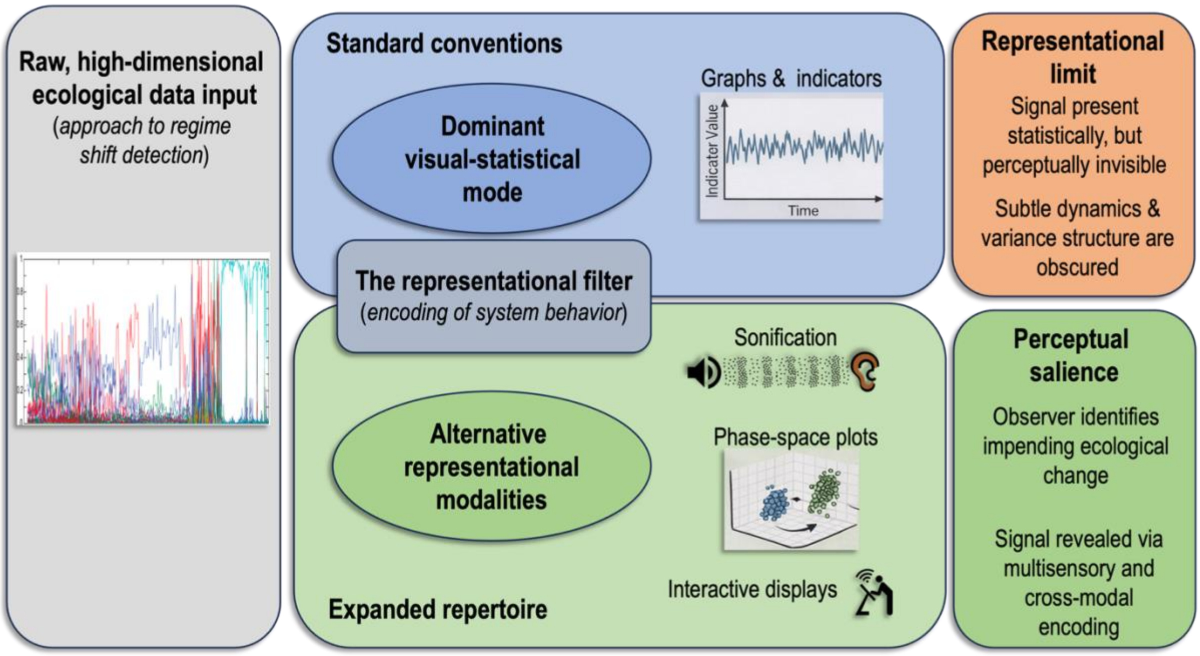

Figure 2. Schematic of multiple sources of uncertainty in ecological inference. Uncertainty arises from interacting system dynamics, epistemic limits of data and models, and representational frameworks. Alternative representations can make patterns perceptible that are obscured under dominant visual–statistical conventions.