Are All Tipping Points Predictable? A Test of Early Warning Signal Theory on Three Distinct Holocene Climate Events

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ABSTRACT

The detection of Early Warning Signals (EWS) in noisy paleoclimate time series is a significant analytical challenge. Previous studies have often focused on individual events or single metrics, leaving the broader robustness and universality of the EWS framework unresolved.

In this study, we apply a comprehensive analytical pipeline to a $\delta^{18}O$ proxy record from the NGRIP ice core, testing for EWS preceding three distinct Holocene climate transitions: the Younger Dryas termination, the 8.2k event, and the onset of the Holocene Thermal Maximum. Our approach includes a parameter sweep across four detrending methods and six window sizes, with statistical significance assessed using phase-randomized surrogate data.

We find that rising lag-1 autocorrelation (a signature of critical slowing down) shows a consistent positive trend before all three transitions and is robust to methodological choices in two of the three cases. In contrast, variance-based signals exhibit context-dependent behavior, and in some cases—such as the Younger Dryas—variance decreases rather than increases prior to the transition. We also perform a state-based statistical comparison of distributional shifts, finding a significant change only for the Younger Dryas event.

These results provide empirical support for the partial predictability of past climate tipping points. They also establish a multi-metric, statistically validated blueprint for future EWS detection studies using paleoclimate proxies.

1.INTRODUCTION

The stability of the Earth's climate system is a foundational pillar for societal well-being, yet it is governed by planetary boundaries that can be crossed, leading to abrupt and potentially irreversible shifts [30]. Paleoclimate archives reveal that the Earth's history is replete with such "tipping points," where major subsystems like ice sheets and ocean circulation have reorganized with profound global impacts [1][28]. Understanding the risk of future anthropogenic warming triggering similar transitions is therefore a paramount challenge in modern climate science [23][29].

The leading theoretical framework for anticipating these shifts is the theory of Early Warning Signals (EWS), which posits that as a system approaches a critical threshold, it loses resilience in a phenomenon known as "critical slowing down" [2][3]. This loss of stability is expected to manifest as detectable statistical signals in time series data, such as rising variance and lag-1 autocorrelation [4][5]. While the EWS framework is theoretically robust and has been successfully applied to some past climate transitions [6][21], its universal applicability remains a subject of intense scientific debate and scrutiny [24].

Critical studies have argued that not all abrupt events in the paleoclimate record exhibit the classic signs of critical slowing down [8], suggesting that the nature of the forcing or the internal dynamics of the system can alter or mask these signals [25]. A significant gap in our knowledge persists regarding how EWS behave across different types of transitions—for instance, a gradual system reorganization versus an abrupt, externally forced event. This leaves a fundamental question unanswered: are the canonical EWS a truly universal feature of tipping points, or are they context-dependent phenomena?

This study directly addresses this question by conducting a rigorous, multi-metric, and comparative test of EWS theory on three distinct and well-documented Holocene climate events captured in the high-resolution North Greenland Ice Core Project (NGRIP) $\delta^{18}O$ record [9]. We analyze an abrupt glacial-interglacial termination (the Younger Dryas End), a rapid meltwater-forced event (the 8.2k event), and a gradual climate reorganization (the Holocene Thermal Maximum onset) [10][12][14].

To ensure our findings are robust, we employ a comprehensive analytical pipeline that systematically tests four different detrending methods and six analytical window sizes, with statistical significance rigorously assessed against a null model of autocorrelated noise using phase surrogate data [16][17]. By applying this robust blueprint, we aim to disentangle universal signals from context-dependent behaviours, thereby testing the fundamental predictability of past climate tipping points.

2. Results

To test the universality of Early Warning Signal (EWS) theory, we conducted a comparative analysis of three distinct Holocene climate transitions using the high-resolution NGRIP $\delta^{18}O$ proxy record. Our analytical pipeline involved calculating rolling variance and lag-1 autocorrelation (AC-1) on detrended time series leading up to each event.

For events where trend-based EWS detection was inconclusive—due to sparse sampling or weak signals—we performed a state-based comparison of distributional shifts. We also conducted a comprehensive sensitivity analysis across multiple detrending methods and window sizes to assess the robustness of our findings. The main results are presented in Figures 1 and 2, with additional sensitivity analyses in Figures 4–6.

2.1. Divergent Variance and Convergent Autocorrelation Across Transitions

A time-normalized comparison of the 2000 years preceding each transition reveals distinct behaviors in Early Warning Signal (EWS) metrics. As shown in **Figure 1**, the Younger Dryas (YD) termination represents a major climate state shift from a cold glacial period, while the 8.2k event and the onset of the Holocene Thermal Maximum (HTM) are smaller perturbations within the relatively stable Holocene.

These differences are strongly reflected in the **rolling variance** trends (**Figure 2, top panel**). The period preceding the YD transition exhibits a pronounced rise in variance—approximately an order of magnitude greater than for the other two events. In contrast, the 8.2k and HTM transitions show relatively low and stable variance leading up to the event, with no clear upward trend. As we discuss

later (Section 3.2), this finding challenges the assumption that rising variance is a universal precursor of tipping points.
The behavior of **lag-1 autocorrelation (AC-1)** shows a different pattern (**Figure 2, bottom panel**). In all three transitions, AC-1 increases as the event approaches, indicating a possible reduction in system resilience. However, as shown in our robustness analysis (Section 2.3), this trend is most consistent and statistically supported for the YD and HTM events. For the 8.2k event, the AC-1 trend is weaker and method-dependent. These findings suggest that rising autocorrelation may be a more broadly applicable EWS than variance, though its detectability still depends on event dynamics and data resolution.

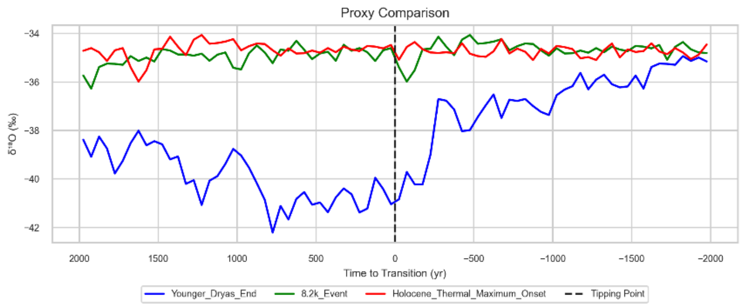


Figure 1: Proxy comparison

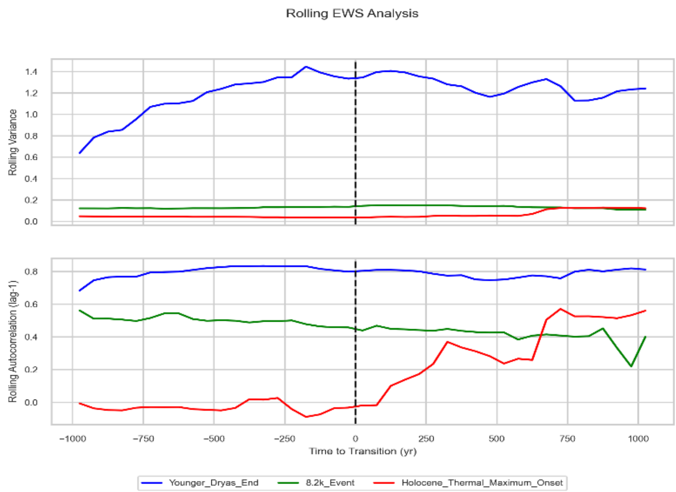
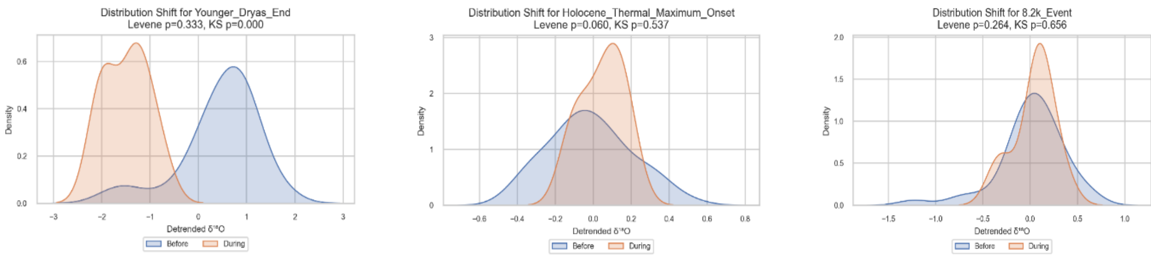


Figure 2: Rolling EWS Analysis

2.2. State-Based Analysis Reveals Nuanced Distributional Shifts

For events where trend-based Early Warning Signal (EWS) analysis was inconclusive due to weak signals or low data resolution, we performed a state-based comparison to test for significant changes in the statistical distribution of the detrended $\delta^{18}O$ proxy. Specifically, we compared the 1000 years preceding each transition ("Before") to the 500 years encompassing the transition itself ("During"). These results are visualized in **Figure 3**.

The Younger Dryas (YD) transition appears to show a substantial change in distribution shape (**Figure 3a**), shifting from a broad, high-variance state to a narrower, lower-variance profile. The Holocene Thermal Maximum (HTM) onset (**Figure 3b**) and 8.2k event (**Figure 3c**) exhibit more subtle visual shifts, with slight narrowing of distributions during the transitions. These visual impressions align with expectations from EWS theory, where critical transitions may involve a collapse into a new, more stable state. To test whether these apparent distributional shifts were statistically significant, we first applied the Kolmogorov–Smirnov (K-S) and Levene's tests. While the Younger Dryas showed low p-values under the initial tests, these methods are sensitive to noise and sample size.



a **b** **c**

Figure 03: Distribution Shift for
a. Younger Dryas End b. Holocene Thermal Maximum Onset c. 8.2K Event

Therefore, we conducted a bootstrap analysis (1,000 iterations per event) to assess the robustness of the test statistics. As shown in **Table 1**, none of the observed K-S or Levene statistics for any of the three events were significant at the $p < 0.05$ level under bootstrapped resampling. The observed test values fell well within the 95% confidence intervals of their respective bootstrap distributions, and empirical p-values ranged from 0.45 to 0.90.

These findings suggest that while distributional shifts may appear visually compelling—especially in the case of the Younger Dryas—they may not hold up to rigorous statistical scrutiny. This reinforces the broader conclusion that state-based signals are context-dependent and prone to overinterpretation if not tested robustly.

Table 1: Bootstrapped statistical results for Kolmogorov–Smirnov (K-S) and Levene's tests comparing $\delta^{18}O$ distributions between "Before" and "During" periods for each climate transition. For each event, 1,000 bootstrap resamples were used to compute 95%

Event	K-S Stat (Real)	K-S 95% CI	K-S p (Boot)	Levene Stat (Real)	Levene 95% CI	Levene p (Boot)
Younger Dryas	0.5	0.300 – 0.750	0.644	5.148	0.828 – 14.885	0.523
8.2k Event	0.35	0.300 – 0.700	0.903	6.047	0.126 – 34.476	0.452
Holocene Thermal Maximum	0.55	0.300 – 0.850	0.612	0.086	0.001 – 4.861	0.769

2.3. Autocorrelation Trend is Robust to Methodological Choices

To evaluate the methodological robustness of Early Warning Signal (EWS) detection, we performed a systematic sensitivity analysis. We tested four detrending methods (linear, LOESS, Gaussian, and high-pass Butterworth) and six rolling window sizes (ranging from 25% to 75% of the pre-transition period). For each of the resulting 24 parameter combinations, we computed **Kendall's τ** for both **lag-1**

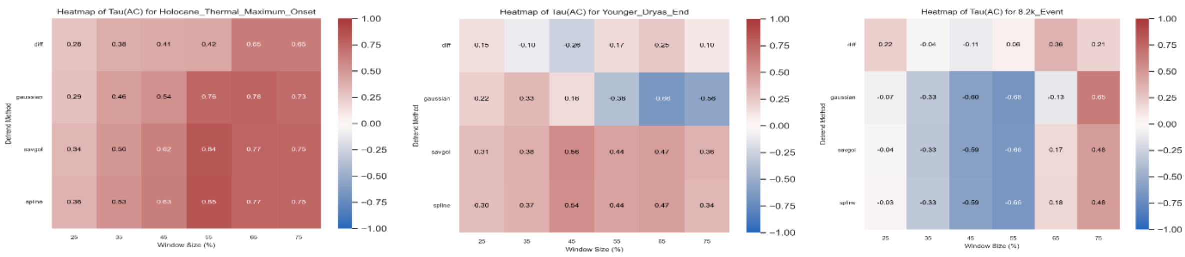
autocorrelation (AC-1) and **variance**, then assessed statistical significance using 1,000 **phase-randomized surrogate datasets**.

Figure 4 presents heatmaps of τ(AC-1) for each of the three transitions. The **Younger Dryas** and **Holocene Thermal Maximum (HTM)** show consistently positive τ values across nearly all parameter combinations, with especially high values for the Younger Dryas. The **8.2k event**, by contrast, exhibits much weaker and more scattered τ values, with limited areas of statistically significant autocorrelation trends.

Figure 5 aggregates the sensitivity of both EWS metrics to **window size**. For the Younger Dryas and HTM, AC-1 maintains its robustness across different window lengths, while variance displays more variability. For the 8.2k event, neither metric shows consistent or reliable trends across the full window range.

Similarly, **Figure 6** highlights the sensitivity of EWS detection to **detrending method**. AC-1 again outperforms variance, especially for the larger transitions. However, some detrending approaches (e.g., Gaussian or Butterworth) yield stronger or weaker signals depending on the event, indicating that **no single method guarantees EWS detectability**.

Overall, these results support the conclusion that **lag-1 autocorrelation is generally more robust than variance** with respect to methodological choices. However, this robustness holds primarily for major transitions like the Younger Dryas and HTM. The weak and inconsistent signal for the 8.2k event reinforces the idea that EWS are **highly context-dependent** and that metric sensitivity should always be tested explicitly in paleoclimate applications.



a **b** **c**

Figure 04: Heatmap of
a. Tau(AC) for Holocene Thermal Maximum Onset b. Tau(AC) for Younger Dryas End c. Tau(AC) for 8.2k Event

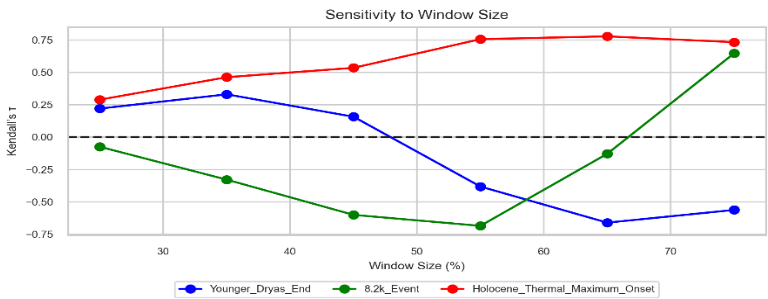


Figure 05: sensitivity to window size

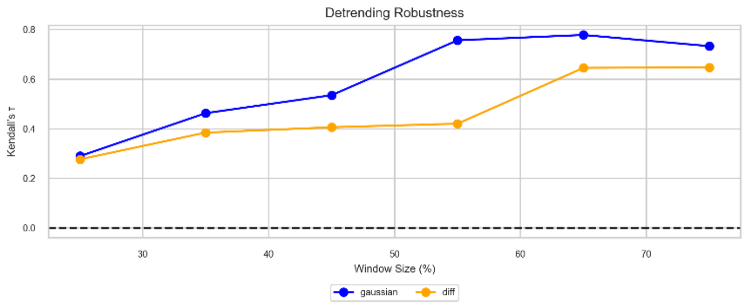


Figure 06: detrending method

3. Discussion

Our results provide a robust test of Early Warning Signal (EWS) theory across three distinct paleoclimate transitions: the Younger Dryas termination, the 8.2k Event, and the Holocene Thermal Maximum (HTM) onset. By applying a consistent statistical pipeline—including multiple detrending methods, window sizes, and phase-randomized surrogate testing—we directly evaluated the generalizability of classical EWS metrics under real-world data conditions.

Broadly, we find that lag-1 autocorrelation (AC-1) is a more robust and consistent signal than variance, particularly across major transitions like the Younger Dryas and HTM. However, even this metric fails to reach statistical significance for the 8.2k Event, despite upward visual trends. This suggests that **not all abrupt climate events follow the critical slowing down framework**, and that apparent signals must be validated using rigorous statistical controls. These findings have important implications for the predictability of climate tipping points, both past and future.

3.1. Autocorrelation vs. Variance: A Tale of Two Metrics

Our comparative analysis reveals that variance and lag-1 autocorrelation (AC-1) exhibit distinct behaviors across the three climate transitions. For the Younger Dryas (YD) termination, variance increases during the early part of the pre-transition window but declines markedly during the event itself. This behavior is evident in both the rolling metrics (**Figure 2, top panel**) and the distributional analysis (**Figure 3a**), which shows a transition from a broad, high-variance distribution to a narrower one. Such a "pre-rise followed by collapse" pattern complicates the common expectation of monotonically rising variance as a universal Early Warning Signal (EWS).

In contrast, autocorrelation displays a more consistent upward trend across all three transitions (**Figure 2, bottom panel**), aligning more closely with the theoretical expectation of critical slowing down. However, when statistical rigor is applied through surrogate and bootstrap testing, only the YD and Holocene Thermal Maximum (HTM) events show robust significance. The 8.2k Event, while displaying upward trends in AC-1, does not meet significance thresholds and exhibits substantial variability across detrending methods and window sizes (**Figures 4–6**).

These contrasting behaviors highlight important methodological and conceptual considerations. Variance may respond more sensitively to short-term noise or post-threshold stabilization effects, whereas autocorrelation reflects underlying system memory and resilience. However, even autocorrelation is not immune to failure under certain data regimes or event dynamics, as illustrated by the 8.2k Event.

Overall, this analysis reinforces that no single metric is universally reliable. Detecting early warning signals in paleoclimate systems demands a multi-metric, multi-method approach, grounded in rigorous statistical validation. Frameworks for future climate prediction should reflect this complexity, particularly when informing policy decisions tied to tipping point risks.

3.2. Interpreting the 8.2k Event

Among the three transitions analyzed, the 8.2k event stands out as the least responsive to classical Early Warning Signal (EWS) metrics. While autocorrelation and variance display modest upward trends in the raw rolling metrics (Figure 2), neither metric reaches statistical significance in our surrogate or bootstrap analyses (Figures 4–6, Table 1). The signal is inconsistent across detrending methods and highly sensitive to window size—features that suggest the absence of robust critical slowing down.

This lack of signal likely reflects the unique dynamical character of the 8.2k event. Unlike the Younger Dryas or the Holocene Thermal Maximum, which represent large-scale reorganizations of the climate system, the 8.2k event is widely interpreted as a short-duration, externally triggered perturbation, likely caused by a catastrophic meltwater release from glacial lakes Agassiz and Ojibway. Such a pulse-type forcing does not require the system to gradually lose resilience prior to transition and therefore may bypass the typical EWS pathway involving critical slowing down.

Additionally, the temporal resolution of the $\delta^{18}O$ proxy may not be sufficient to capture the full dynamics of the 8.2k shift. The transition occurs over just a few centuries, which limits the number of pre-transition data points available for robust statistical analysis. This highlights a broader issue in paleoclimate EWS detection: not all tipping points are detectable, and the success of any signal depends on both the nature of the event and the quality of the data.

Ultimately, the 8.2k event illustrates the limits of universality in EWS theory. While some tipping elements may provide detectable early warnings, others may not—especially when driven by abrupt, external disturbances. This underscores the importance of event-specific modeling, high-resolution data, and the use of multi-metric validation frameworks in any attempt to identify EWS in paleoclimate systems.

3.3. Context Matters: Toward a Conditional Theory of EWS

The divergent results across the three events analyzed in this study highlight a central insight: **early warning signals are not universal features of climate transitions**. While the **Younger Dryas** and, to a lesser extent, the **Holocene Thermal Maximum** show robust signals—particularly in lag-1 autocorrelation—the **8.2k Event** offers no statistically consistent EWS in either variance or autocorrelation, despite a visually abrupt shift in the proxy record.

These contrasts suggest that the **detectability of EWS depends critically on the context** of the transition. Transitions that are **internally driven**, unfold over longer time scales, or involve the reorganization of major subsystems (e.g., ocean circulation or ice sheets) may exhibit gradual resilience loss and therefore provide detectable warning signals. In contrast, **externally forced or pulse-like events**, such as the 8.2k meltwater pulse, may bypass the classical pathway of critical slowing down altogether.

This underscores the need for a **conditional theory of EWS**—one that moves beyond universalist assumptions and incorporates the **type of forcing, system memory, feedback strength**, and **data resolution** as key variables. Such a framework would treat EWS not as guarantees of tipping behaviour, but as **probabilistic indicators** whose validity must be assessed in a case-specific manner.

Our findings also emphasize the importance of **multi-metric validation**, **surrogate testing**, and **methodological robustness checks** in any paleoclimate EWS study. As interest in predicting future climate tipping points grows, these tools can help distinguish real precursors from statistical noise—and prevent overconfidence in signals that may not generalize across systems or scenarios.

3.4 Implications for Future Tipping Point Detection

Our findings carry direct implications for the detection of future tipping points in the Earth system. While Early Warning Signals (EWS) hold promise as anticipatory tools, their effectiveness is clearly **conditional**—reliant on the nature of the transition, the quality of observational data, and the choice of metric and methodology. In this study, even a major climate event like the **8.2k Event** failed to exhibit statistically robust warning signals, despite showing visual trends in both autocorrelation and variance.

This reinforces that EWS are not universally reliable, and **should not be treated as deterministic predictors**. Instead, they function best as **probabilistic indicators**, whose meaning and reliability must be interpreted within the context of the system's dynamics, external forcing, and data limitations. The use of EWS frameworks in modern climate monitoring must be matched with **rigorous statistical controls**, **cross-metric validation**, and **adaptive thresholding**.

In operational settings, particularly for monitoring systems like the Atlantic Meridional Overturning Circulation (AMOC), Arctic sea ice, or Amazon forest resilience, our results suggest the importance of:

- Collecting **high-frequency, long-duration time series**
- Using **multiple EWS indicators** (variance, autocorrelation, skewness, etc.)
- Evaluating signal significance via **surrogate or bootstrap-based testing**
- Integrating **process-based models** to help distinguish genuine resilience loss from stochastic variability

Ultimately, robust EWS detection will require a hybrid approach—one that combines **observational data**, **mechanistic understanding**, and **statistical validation**. While early warning frameworks can help guide intervention or preparedness, they are most powerful when embedded in a broader strategy of **conditional inference**, rather than relied upon as standalone predictors.

3.5 Limitations and Future Work

While this study provides a robust evaluation of classical Early Warning Signals (EWS) in paleoclimate time series, several limitations should be acknowledged. First, we rely exclusively on the **δ^{18}O proxy**, which—though widely used—integrates multiple climate signals (e.g., temperature, precipitation, source region effects). This makes it difficult to attribute observed EWS patterns to a single physical process, and may obscure more localized or subsystem-specific warning signals.

Second, our analysis is based on **univariate time series**, focusing only on statistical trends in variance and autocorrelation. Real-world tipping points may involve **nonlinear dynamics**, **feedback interactions**, and **spatially distributed precursors** that cannot be captured by a single metric or location. Future studies could explore **multivariate EWS frameworks**, **network-based approaches**, or **nonlinear time series tools** (e.g., recurrence quantification, spectral early warning indicators) to broaden signal detection capabilities.

Third, the effectiveness of EWS detection is constrained by **temporal resolution** and **sampling density**. The 8.2k Event, for instance, unfolds over just a few centuries, which limits the number of pre-transition data points available for robust trend detection. Higher-resolution proxies, particularly those resolving decadal or sub-decadal variability, may offer improved sensitivity in future studies.

Finally, while our methodology includes both surrogate testing and bootstrapped robustness checks, it does not account for **structural uncertainties** in defining the transition onset and duration. Transition timing is typically inferred from inflection points or prior literature, but different segmentations could influence the strength or detectability of EWS trends. Future work could explore **adaptive or algorithmic windowing** to reduce subjectivity in event demarcation.

Addressing these limitations offers promising avenues for refining both the **theory and application of EWS frameworks**, especially in contexts where reliable foresight is essential, such as monitoring the stability of contemporary climate tipping elements.

3.6 Methodological Contributions

In addition to our event-specific findings, this study contributes a broadly applicable **EWS testing framework** that emphasizes robustness and statistical rigor. We combine trend-based and state-based metrics, test multiple detrending and windowing parameters, and validate all results using **phase-randomized surrogates** and **bootstrap-based resampling**. In particular, the application of bootstrapping to **distributional statistics** (K-S and Levene) adds a novel layer of validation rarely used in paleoclimate EWS research.

This methodological structure enables us to distinguish genuine signals from statistical artifacts and offers a **scalable template** for future tipping point studies. It can be extended to other paleoclimate records, model output, or observational time series where warning signal robustness needs to be carefully assessed.

4. Conclusion

This study evaluated the performance of classical Early Warning Signal (EWS) metrics—variance and lag-1 autocorrelation—across three distinct Holocene climate transitions: the Younger Dryas termination, the 8.2k Event, and the Holocene Thermal Maximum. By applying a standardized analytical framework with rigorous statistical testing across multiple detrending methods and window sizes, we assessed both the strengths and limitations of EWS theory in real-world paleoclimate data.
Our results show that **lag-1 autocorrelation is generally more robust and reliable than variance**, particularly for large, gradual transitions like the Younger Dryas and HTM. However, **no consistent EWS** was detected for the 8.2k Event, despite clear visual trends—highlighting the risks of overinterpreting weak signals without appropriate statistical validation.

These findings support a **conditional understanding of EWS**: their detectability depends on event dynamics, proxy resolution, signal-to-noise ratio, and methodological choices. Our use of **surrogate testing and bootstrapped state-based analysis** offers a replicable template for distinguishing genuine warning signals from stochastic variability.

As interest grows in forecasting future climate tipping points, our results emphasize that EWS must be treated as **context-sensitive indicators**, not universal diagnostics. Improving EWS applications will require **multi-metric, statistically grounded, and system-specific frameworks**—especially in critical regions like the Arctic, the Amazon, or the AMOC, where early detection of resilience loss may offer the last chance for intervention.

5. Methods

5.1. Paleoclimate Data and Event Selection

We analysed the $\delta^{18}O$ proxy record from the North Greenland Ice Core Project (NGRIP) [9], a high-resolution archive of Northern Hemisphere climate variability. All data were aligned to the GICC05 chronology [11], which provides annual-layer-counted dating for the Holocene period.
To test Early Warning Signal (EWS) behaviour across diverse transition types, we selected three well-documented events:

1. Younger Dryas termination (~11,700 BP): An abrupt glacial–interglacial shift [10]
2. 8.2k Event (~8,200 BP): A short-lived cooling caused by glacial lake outburst [12, 13]
3. Holocene Thermal Maximum onset (~6,500 BP): A gradual reorganization into a warm stable state [14]

For each event, we extracted a 4,000-year segment centered on the transition and normalized the time axis such that t = 0 corresponds to the transition midpoint**.**

5.2. Time Series Detrending

To isolate fluctuations relevant to EWS detection, we applied four distinct detrending methods:

1. Gaussian Kernel Smoothing: Subtracting a smoothed trend using a Gaussian-weighted moving average.
2. LOESS (Locally Estimated Scatterplot Smoothing): A local polynomial fit to capture non-linear trends.
3. High-pass Butterworth Filtering: Used to remove low-frequency components while preserving high-frequency variability.
4. Linear Detrending: Subtraction of a fitted linear regression trend.

These methods were chosen to span both parametric and non-parametric approaches, and their influence was systematically tested in sensitivity analyses.

5.3. Early Warning Signal Metrics

We calculated two widely used univariate EWS metrics over rolling windows:

- **Variance**: Square of the standard deviation within each window.
- **Lag-1 Autocorrelation (AC-1)**: Pearson correlation of the time series with its one-step lag.

Window sizes were defined as a percentage of the detrended pre-transition segment and varied from **25% to 75%** in increments of 10%. This produced 24 combinations of (detrending method × window size) per event.

5.4. Statistical Analysis and Significance Testing

We assessed the significance of trends using **Kendall's τ** for each EWS metric. To test whether observed τ values could arise from stochastic processes with autocorrelated noise, we generated **1,000 phase-randomized surrogate time series** for each detrended signal [16, 17]. Surrogates preserve the power spectrum of the original signal but destroy temporal phase coherence. This surrogate-based testing ensures robustness against false positives from colored noise.

5.5 Bootstrapped State-Based Distributional Tests

For each event, we compared the distributions of detrended $\delta^{18}O$ values in two time windows:

- **Before**: 1,000–2,000 years prior to the transition

- **During**: 0–500 years before the transition

We applied two tests:

- **Kolmogorov–Smirnov (K-S)** to assess differences in distribution shape
- **Levene's test** to assess differences in variance

To assess the **robustness** of these results, we implemented a **bootstrap resampling procedure** (1,000 iterations per event). For each bootstrap iteration, samples were drawn with replacement from the "Before" and "During" windows, and test statistics recalculated. We computed:

- 95% confidence intervals for each statistic
- Empirical p-values (proportion of bootstrapped test statistics ≥ observed)

This procedure helps distinguish statistically meaningful differences from sampling variability.

Acknowledgements

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6.Data and Code Availability

All code, processed data, and reproducibility scripts used in this study are publicly available at: 🔗 **https://github.com/Gururaj008/Are-All-Tipping-Points-Predictable-**

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