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To cite this article before publication: Joaquina Noriega Giménez *et al* 2026 *Environ. Res. Lett.* in press <https://doi.org/10.1088/1748-9326/aeb55b>

Manuscript version: Accepted Manuscript

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Environmental Research Letters

PERSPECTIVE

From Noise to Signal: A Data-Driven Framework for Identifying Hot Moments in Water Quality Timeseries

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Keywords: water quality, timeseries analysis, hot moments, environmental monitoring

1 Introduction

Water quality degradation is a persistent and sometimes invisible threat [1]. Many of the processes driving degradation occur during short, intense episodes that are poorly captured by conventional monitoring strategies [2]. In this Perspective, we propose a framework for systematically identifying such *hot moments* [3] from high-frequency water-quality timeseries data.

Hot moment concepts have been highly influential in understanding the causes and consequences of spatial and temporal heterogeneity in aquatic systems. Bernhardt et al. [4] generalized hot moments as biogeochemical *control points* - locations or times where disproportionate biogeochemical activity is sustained by specific mechanisms such as the convergence of limiting reactants or hydrological export. Similarly, the concept has been refined through the lens of *ecohydrological interfaces* - temporally-limited, dynamic transition zones that often develop within ecotones or boundaries between ecosystems [5]. Despite their contributions, these frameworks have largely remained qualitative descriptors rather than quantitative tools for analysis of water quality and biogeochemistry [4].

Increasing availability of long-term and high-frequency water data has greatly expanded our capacity to measure hot moments. However, high system variability and non-stationarity remain major challenges. Environmental timeseries are inherently noisy due to natural temporal variability often leading to substantial increases in variance as the time period of observation increases [6], making it challenging to distinguish hot moments from patterns in measured variable values alone. Capturing temporal departures in system dynamics requires metrics that describe how measured variables change over time, rather than relying on their absolute values alone. Response and recovery metrics quantify these temporal changes by describing the magnitude and duration of the changes. When computed across all observations of a timeseries, their distributions provide a data-driven representation of system behavior, providing a basis for distinguishing common

dynamics from unusual ones. To fully leverage the growing data landscape, we highlight the need to identify hot moments as deviations from response-recovery distributions.

2 Toward Clearer Concepts of Hot Moments

We argue that many approaches for determining hot moments rely on preconceived assumptions about what constitutes a meaningful event rather than a data-driven strategy to identify deviations in response-recovery dynamics. Water quality events are commonly defined using fixed concentration thresholds, visual inspection, or high-flow periods associated with elevated export. Such *a priori* definitions of hot moments introduce bias, which propagates into subsequent analyses that characterize event dynamics, limiting comparability across systems and potentially obscuring important system behavior. This limitation is particularly consequential in nonstationary systems, where abrupt regime shifts and changes in variable behavior complicate parameter selection.

Common statistical and computational approaches for detecting events or anomalies in water-quality timeseries include threshold exceedance metrics [7], distributional measures such as skewness and kurtosis [8], spectral and wavelet analyses [9], machine learning techniques [10], and quantitative concentration–discharge metrics such as hysteresis indices [11]. While each of these methods provides valuable insight into system behavior, they have limitations in consistently and objectively identifying hot moments in water quality timeseries. Dynamic threshold approaches improve flexibility by accounting for temporal variability through sliding windows or exponentially weighted moving averages [12, 13], but remain sensitive to user-defined parameters, limiting transferability across sites [14].

Many approaches delineate hot moments by comparing individual variable values against predefined thresholds or ranges, without considering whether those deviations represent significant changes in system response and recovery. Methods such as rolling averages and locally estimated scatterplot smoothing (LOESS) are often used to characterize underlying conditions, but all smoothing methods inherently filter the timeseries and remove short-term variability. Similarly, signal decomposition approaches (e.g., seasonal–trend decomposition or wavelet analysis) formalize the separation of variability across timescales and are valuable for characterizing dominant modes of behavior, but they require long data records [15] and inherently redistribute variance in ways that can obscure individual events.

3 Proposed Conceptual Framework

To address these limitations, we propose to redefine hot moments as *substantive, quantifiable, and brief deviations in water quality relative to the system’s dynamics*. *Substantive* reflects the accepted notion that hot moments represent distinct departures from regular system dynamics rather than routine temporal variability. To enable broad and comparable assessments across ecosystems, hot moments must be *quantifiable* using explicit, reproducible criteria derived from timeseries data, rather than subjective interpretation or previously held assumptions. *Brief* indicates that hot moments are temporally-bounded, representing a rapid transition relative to the system’s characteristic dynamics. *Brief* is not a fixed duration, but depends on the resolution of available observations and temporal scale(s) of system variation (e.g., diurnal cycles and seasonal patterns). The system may subsequently recover or shift to a new state; however, the defining feature of a hot moment is the departure from the observed distribution of response–recovery dynamics, rather than the longer-term variable trajectory that follows. In this sense, a hot moment encompasses the transient dynamics associated with a process or perturbation and concludes when the response–recovery dynamics no longer represent an unusual departure from their observed distribution, regardless of whether the measured variable returns to its pre-disturbance value or stabilizes at a new value. As defined here, hot moments characterize departures in system dynamics rather than their ecological consequences or implications for ecosystem health. Assessing the ecological significance and consequences of identified hot moments is an important next step beyond their detection and quantification.

In this context, we propose a framework for identifying hot moments from timeseries:

- (i) defining the temporal scale of analysis, (ii) quantifying response and recovery dynamics, (iii) classifying observations based on response–recovery metrics, and (iv) aggregating classified observations into unified events (Figure 1).

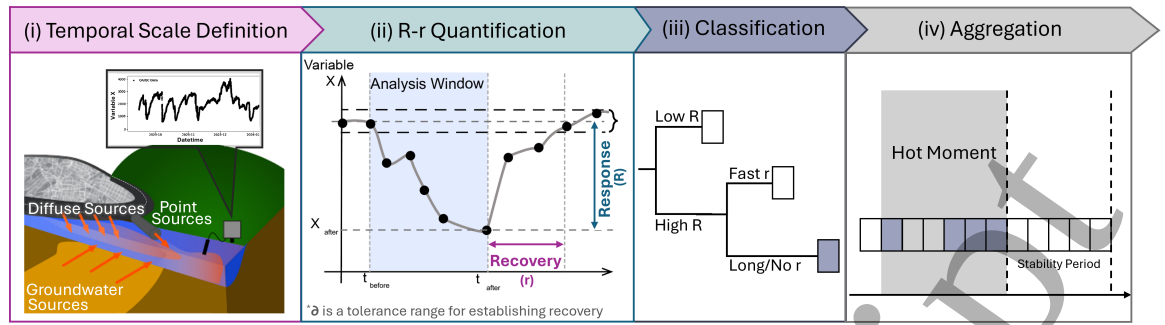


Figure 1. Schematic of the proposed hot moment identification framework. (i) Definition of the temporal scale of analysis, specifying the timescale over which change is evaluated. (ii) Point-wise quantification of response (R , magnitude of deviation within the analysis window) and recovery (r , time for the system to return to pre-existing conditions). (iii) Classification of each observation based on R and r . Observations exhibiting both high response and long recovery are identified as belonging to hot moments (shaded box). (iv) Aggregation of observations identified in (iii) into discrete hot moment events characterized by temporal properties such as onset, persistence, and recovery trajectory.

i. Temporal Scale Definition - Because hot moments can be applied to many different research questions, it is necessary to specify the relevant temporal scale of analysis. For example, in freshwater salinization from road deicing, an increasing issue in urban regions [16], changes occurring over hours to days reflect drivers such as storm-driven salinity pulses [17] and inform stormwater management strategies, whereas changes over years arise from cumulative salt application [18] and inform regional policy and regulation. The analysis window should therefore be selected based on the timescale of the processes and management questions of interest. Episodic processes require finer time windows to resolve event dynamics, whereas persistent or cumulative processes may require longer windows to capture their effects. Once the temporal scale is defined, the framework objectively identifies when and for how long hot moments occur within that temporal context.

ii. R-r Quantification - Once the timeframe is established, quantify response and recovery metrics for each individual observation in the timeseries. Response (R) is quantified as the magnitude of change in the measured variable over the defined analysis window relative to the value at the start of that window. Recovery (r) is defined as the time required for observations to approach the envelope of observations at the start of the analysis window. When data required to calculate R or r are unavailable for a given observation, the corresponding metric is treated as missing and excluded from the observed distribution. Unlike approaches that apply response-recovery metrics after events have been predefined, this framework calculates response-recovery dynamics for each observation across the full time series, generating a distribution of response-recovery behavior from which departures are identified. By evaluating deviations in response-recovery dynamics rather than variable magnitude alone, the framework captures hot moments associated with both increases and decreases in measured variable values. This dual-criterion response-recovery approach is grounded in ecological concepts of resistance and resilience [19], providing a systematic framework for characterizing transient disturbances directly from water quality timeseries.

iii. Classification - Classify individual observations that exhibit relatively high responses and prolonged recoveries as belonging to hot moments. Objective criteria for high response and long recovery can be based on prior knowledge of system dynamics or derived directly from the response-recovery timeseries generated in step ii using statistical criteria of their observed distributions. This keeps the framework data-driven and adaptable to systems without predefined parameter ranges, as classification criteria are derived from the observed distribution of response-recovery dynamics rather than fixed thresholds applied directly to measured variables. For variables with strong periodic dynamics, recurring responses are incorporated into the empirical response-recovery distributions. Consequently, classification based on statistical properties of these distributions identifies responses that are unusual relative to the observed variability, rather than treating all recurring responses as hot moments.

iv. Aggregation - Aggregate observations identified by the classification criteria (iii) into discrete hot moments. A hot moment begins with the first identified observation and continues until a period without identified observations occurs. Consolidating individual observations into discrete hot moments preserves the temporal structure of each identified event, including the onset, peak, and trajectory. Summary event statistics such as hot moment frequency, duration,

148 magnitude, fluxes and loads can be calculated to support ecological interpretation and
149 management. In doing so, the framework provides a quantitative basis for evaluating the
150 disproportionate influence that has traditionally defined hot moments conceptually.

151 4 Framework 152 Implications

153 The
154 proposed framework
155 segments continuous
156 timeseries into
157 comparable hot moment
158 events with quantifiable
159 event metrics (e.g.,
160 onset, duration, and
161 trajectory). Ecological
162 and management
163 significance of the
164 identified hot moments
165 can then be assessed
166 by incorporating
167 additional information,
168 recognizing that events
169 of similar magnitude
170 can cause different
171 ecological consequences
172 across systems.

173 The
174 identification framework
175 can be applied directly
176 to any timeseries
177 without requiring
178 labeled training data
179 and reduces reliance
180 on externally defined,
181 non-data-derived
182 parameter choices. Its
183 transparent sequence of
184 steps, each with a clear
185 and straightforward
186 objective, provides
187 a common basis
188 for application across
189 diverse hydrological
190 systems and enables
191 analyses such as source
192 attribution or process
193 inference. While the
194 framework establishes
195 these core steps,
196 the analytical tools
197 used to achieve them
198 remain flexible, allowing
199 different statistical and
200 analytical approaches
201 to be implemented
202 and new approaches to
203 be incorporated as they
204 emerge. Evaluating the
205 performance, sensitivity,
206 and suitability of these

Quantitative Illustration of the Hot Moment Response-Recovery Identification Framework

Response (R) quantifies the mag-
nitude of deviation within the
analysis window, and Recovery
(r) quantifies the time required
for return following the end of the
analysis window. Both metrics can
be quantified objectively from data
using multiple approaches.

For example, R can be calcu-
lated using absolute differences
from prior conditions, normalized
differences, or signal-to-noise ra-
tios, while r can be determined
as total time for return to a given
range of variability or a relaxation
time for return toward certain con-
ditions.

Similarly, multiple analytical
approaches can be used for classi-
fying observations and aggregating
them into hot moments.

We illustrate one simple implemen-
tation of the proposed framework
using a 5-minute specific conduc-
tivity timeseries from September
2025 to January 2026 in the Little
Calumet River, South Holland, Illi-
nois [20]. Here, we implement the
four steps as follows;

(i) A 24-hour analysis window cap-
tures rapid storm-driven devia-
tions. (ii) Within each window,
response is defined as the normal-
ized change between start and end
observations, and recovery is the
time to return within 15% of the
analysis window's initial value.
(iii) Observations are classified
as high R or long r based on the
joint distribution of R and r , us-
ing upper quantiles of the observed
distributions.

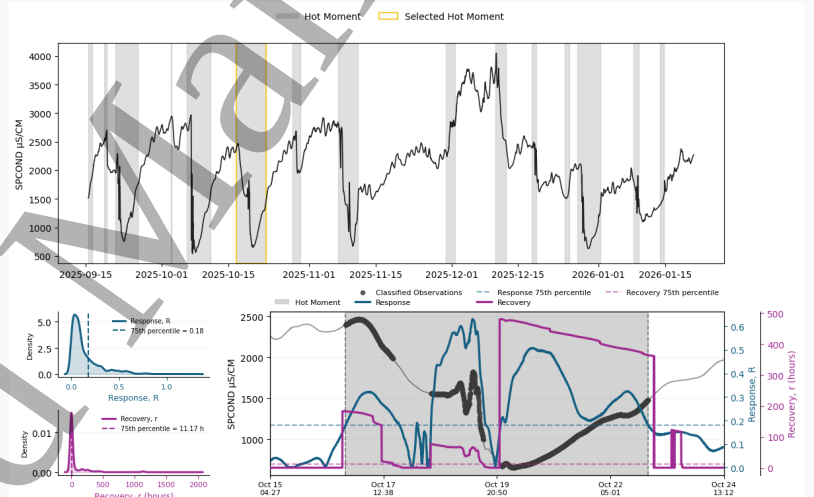


Figure 2. Illustration of the proposed hot moment framework applied to a timeseries of specific conductivity ($\mu\text{S}/\text{cm}$) measured at 5-minute intervals. Top: Full timeseries with identified hot moments (grey) and the example hot moment (yellow outline). Bottom left: R & r distributions. Bottom right: Example hot moment showing computed response (blue) and recovery (magenta) timeseries. Observations within the upper quantile (dashed lines) for both response and recovery are highlighted as wider points overlaid on the variable's timeseries.

(iv) Data are aggregated into
hot moments, with the stability
period defined as one full analysis
window where observations exhibit
low response and rapid recovery.

Using this implementation, 15
hot moments were identified, with
durations ranging from 1.83 hours
to 6.2 days.

Although high-frequency obser-
vations provide greater resolution
for capturing transient dynamics,
the framework can also be applied

to lower-frequency datasets, pro-
vided that the temporal resolution
is appropriate for the processes of
interest.

Evaluation of alternative imple-
mentations of the proposed
framework across diverse systems
is needed to assess sensitivity, com-
pare with existing approaches, and
evaluate missing-data strategies.
These efforts will help establish
standardized guidance for apply-
ing the proposed framework more
broadly and enabling comparisons.

alternative implementations across systems represents an important next step toward consistent application and, ultimately, cross-site comparison of hot moments.

As presented in the case study figure 2, the framework is applied to individual water quality variables but can extend to multivariate analysis. Many ecologically significant hot moments involve coupled or lagged responses, such as dissolved oxygen depletion, chemical pulses, and conductivity spikes during sewer overflow events, and coordinated changes in pH and conductivity associated with freshwater salinization syndrome [17]. Beyond single-variable detection, the framework can identify *ensemble hot moments*, where multiple variables show coincident high-response, prolonged-recovery behavior. This can be implemented through intersection-based methods or multivariate metrics. Capturing coincident and temporally offset responses improves ecological relevance and better represents how ecosystems respond to combined, interacting stressors.

5 Conclusions

This Perspective makes two related contributions. First, it redefines hot moments, providing a clearer conceptual basis for identifying brief and distinct deviations from regular system dynamics. Second, it introduces a quantitative response–recovery framework to operationalize this definition to delineate hot moments directly from time-series data. The framework offers several key advantages. It is simple, both conceptually and computationally, promoting transparency and reproducibility. It is holistic, capturing deviations in observed system behavior rather than relying on guideline exceedance or deviation from patterns in absolute variable values. The framework is also flexible, allowing application to individual timeseries across variables, sites, system types, and monitoring frequencies. Finally, it is robust, as the explicit aggregation step consolidates deviations into discrete, unified hot moments, preserving event structure and enabling direct comparison of event characteristics across sites and time periods.

By identifying discrete hot moments, the framework provides a consistent basis for quantitative event characterization, enabling subsequent investigation of the processes governing freshwater responses to stressors. The identified events can then be evaluated in the context of additional impact measures to determine their ecological significance, causes, and predictability. This supports applications ranging from ecosystem restoration and stormwater interventions to detecting regime shifts under changing climate and land use.

The approach presented is broadly applicable to other complex systems experiencing transient disturbances, offering a generalizable tool for understanding system stress and resilience. Ultimately, by identifying discrete, interpretable disturbance events within high-frequency or long-term data, the response–recovery framework helps bridge the gap between data collection and decision-making, supporting more effective monitoring, modeling, and management under changing conditions.

Funding

This material is based upon work supported by National Science Foundation’s Directorate for Geosciences (NSF/GEO) and the National Environment Research Council (NERC) of the United Kingdom (UK) via the NSF/GEO-NERC Lead Agency Agreement; Grant No. 2331932 (SMARTWATER, Project Reference NE/X018628/1) and the National Science Foundation Graduate Research Fellowship Program (DGE-2234667). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. JPRS and DJL publish with the permission of the Executive Director of the British Geological Survey (UKRI).

Author contributions

Joaquina Noriega Giménez: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing, Project Administration.

Thomas S. L. Rowan: Conceptualization, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review & editing, Project Administration.

Aaron I. Packman: Supervision, Conceptualization, Funding acquisition, Writing - review & editing.

Broader SMARTWATER Team: Conceptualization, Funding acquisition, Writing - review & editing.

Data availability

All source data and workflows are available at: <https://doi.org/10.5281/zenodo.23250177>

Conflict of Interest The authors declare no competing interests.

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