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ARTICLE

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Applying early warning indicators to predict critical transitions in a lake undergoing multiple changes

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Abstract

Lakes are dynamic ecosystems that can transition among stable states. Since ecosystem-scale transitions can be detrimental and difficult to reverse, being able to predict impending critical transitions in state variables has become a major area of research. However, not all transitions are detrimental, and there is considerable interest in better evaluating the success of management interventions to support adaptive management strategies. Here, we retrospectively evaluated the agreement between time series statistics (i.e., standard deviation, autocorrelation, skewness, and kurtosis—also known as early warning indicators) and breakpoints in state variables in a lake (Lake Simcoe, Ontario, Canada) that has improved from a state of eutrophication. Long-term (1980 to 2019) monitoring data collected fortnightly throughout the ice-free season were used to evaluate historical changes in 15 state variables (e.g., dissolved organic carbon, phosphorus, chlorophyll *a*) and multivariate-derived time series at three monitoring stations (shallow, middepth, deep) in Lake Simcoe. Time series results from the two deep-water stations indicate that over this period Lake Simcoe transitioned from an algal-dominated state toward a state with increased water clarity (i.e., Secchi disk depth) and silica and lower nutrient and chlorophyll *a* concentrations, which coincided with both substantial management intervention and the establishment of invasive species (e.g., *Dreissenid* mussels). Consistent with improvement, Secchi depth at the deep-water stations demonstrated expected trends in statistical indicators prior to identified breakpoints, whereas total phosphorus and chlorophyll *a* revealed more nuanced patterns. Overall, state variables were largely found to yield inconsistent trends in statistical indicators, so many breakpoints were likely not reflective of traditional bifurcation critical transitions. Nevertheless, statistical indicators of state variable time series may be a valuable tool for the adaptive management and long-term monitoring of lake ecosystems, but we call for more research within the domain of early warning indicators to establish a better understanding of state variable behavior prior to lake changes.

KEYWORDS
critical transitions, early warning indicators, invasive species, management actions, resilience indicators

INTRODUCTION

Ecosystems can persist for long periods of time in stable states characterized by specific sets of state variables (i.e., biotic and abiotic conditions) (Beisner et al., 2003; Scheffer et al., 2001). However, environmental perturbations may push state variables into the domain of an alternative stable state and incite ecosystem-scale changes (Holling, 1973). Critical transitions or abrupt shifts between stable states occur when environmental perturbations cause a change in the mean of certain state variables, resulting in a breakpoint in their respective time series (Gsell et al., 2016). Since critical transitions often result in the diminishment of ecosystem services and have historically been difficult and expensive to reverse, researchers have become interested in their underlying dynamics and forecasting their occurrence.

Lakes are particularly susceptible to environmental perturbations from anthropogenic activities, invasive species, and climate change (Janssen et al., 2019). Although ecosystem conditions in lakes are often stable across time, incremental fluctuations in external stressors can shift state variables and cause critical transitions within aquatic ecosystems (Holling, 1973). For example, with increased nutrient loading, lakes have been observed to abruptly shift from a clear-water state to that of an algal bloom state and persist under these eutrophic conditions even after substantial investment in management actions (Carpenter, 2005). Temporal patterns in state variables, such as algal biomass and Secchi depth, often track patterns in the delivery of nutrients and may be useful in forecasting the occurrence of these critical transitions in lakes (Melendez-Pastor et al., 2019; Wilkinson et al., 2018) in addition to other new and unknown global changes (e.g., brownification; Kritzberg et al., 2020).

Other stressors, such as invasive species (e.g., North et al., 2013), are also linked to ecosystem degradation and thus are of importance to the effective management of lake ecosystems. Invasive species threaten biodiversity and can cause significant social, economic, and environmental disruptions (Mainka & Howard, 2010). Moreover, the introduction and establishment of invasive species can incite cascading changes to both biotic and abiotic state variables. For example, decreasing trends in phosphorus and chlorophyll *a* (Chl *a*) and increasing trends in water transparency have often been observed within the first few years of zebra mussel (*Dreissena polymorpha*) colonization (e.g., Fahnenstiel et al., 1995; Leach, 1993). Abnormal trends in state variables from continuous monitoring data may therefore be leveraged to help detect the presence of a potential invasion and be used as a call for immediate management action and intervention.

Identifying transitions between different stable states within aquatic ecosystems is inherently difficult (e.g., D'Amario et al., 2019), but researchers have developed statistical indicators that empirically occur in the time series of state variables as ecosystems approach a critical transition (Scheffer et al., 2009). These various statistical indicators of data variability (Dakos, Van Nes, et al., 2012; Kéfi et al., 2013) signal a decline in an ecosystem's rate of recovery to equilibrium after perturbation (i.e., ecosystem resilience), whereby environmental perturbations are more likely to permanently shift an ecosystem with low resilience into an alternative stable state (Dakos, Van Nes, et al., 2012; Wilkinson et al., 2018). For example, as a state variable approaches a critical transition (i.e., a bifurcation or regime shift), temporal patterns become much noisier, and the state variable strays further from its equilibrium (lower return time), thereby increasing its standard deviation (SD) and increasing autocorrelation at lag 1 (AR1) (Dakos, Van Nes, et al., 2012). In addition, when a state variable approaches this transition, there is an increase in the presence of extreme observations and temporal patterns in the symmetry of the state variable distribution, which will change in skewness (SK) (increase or decrease according to transition) and decrease in kurtosis (K) (Gsell et al., 2016). Although more complex critical transitions and signals thereof may exist (e.g., Burthe et al., 2016; Dakos, Van Nes, et al., 2012; Titus & Watson, 2020), concurrent changes in the expected temporal patterns of time series statistical indicators are thought to indicate that an ecosystem has deviated from its previous norm and will likely transition into an alternative state (Scheffer et al., 2009). By signaling potential changes in resilience, these parameters can be combined with traditional ecological monitoring and used as early warning indicators (EWIs) of impending ecosystem-scale critical transitions.

Some previous studies found that trends in AR1, SD, SK, and K of certain state variables can offer managers an "early warning" that an ecosystem is approaching a transition toward a less-desired state (Buelo et al., 2018; Stelzer et al., 2021; Wilkinson et al., 2018). However, several studies have also reported mixed results and reported low detectability of EWIs prior to identified breakpoints in state variable time series (e.g., Bestelmeyer et al., 2011; Gsell et al., 2016; Hastings & Wysham, 2010), likely due to the stochastic or conservative behavior (i.e., nonbifurcation) of selected state variables or the occurrence of nonlinear critical transitions (Burthe et al., 2016). To generate further empirical evidence on the performance of EWIs, we investigated the substantial environmental changes that have occurred over a 40-year period (1980–2019) in a large temperate lake (Lake Simcoe) in southeastern Ontario (Canada). Notably, this time series reflects a period of improvement from decades of ecological impairment in Lake Simcoe (e.g., historical collapse of fisheries, eutrophication, poor water quality) and the establishment of invasive keystone organisms (e.g., *Dreissenid* mussels; North et al., 2013; Rawson, 1928; Young & Jarjanazi, 2015). Our goal was to determine whether the application of early-warning indicators could be used to detect improvements in an ecosystem that had transitioned from a more eutrophic to a clear water state. Here, we evaluated the performance of EWIs for individual state variables, in addition to the temporal progression of EWIs from time series generated through the multivariate analysis of all state variables. We hypothesized that temporal patterns in SD, AR1, SK, and K would correspond to transitions in Lake Simcoe state variables measured from 1980 onward and be more pronounced at the ecosystem or multivariate scale. To address this hypothesis, the two primary objectives of our study were to (1) identify historical breakpoints in Lake Simcoe state variable and multivariate time series and (2) determine whether these breakpoints coincide with the expected temporal patterns in early warning statistical indicators (i.e., EWIs). If EWIs can predict ecosystem-scale transitions, then expected deviations in the trends of SD, AR1, SK, or K will occur prior to identified breakpoints, with agreement among multiple EWIs increasing the odds that a critical transition was likely to occur. If temporal patterns in EWIs are measurable, timely, and reliable, managers may consider the adoption or investment in these methods within continuous long-term monitoring programs to better safeguard lake ecosystems from global change and track the success of management interventions.

METHODS

Study area

Lake Simcoe (latitude 44°25′ longitude 79°20′) is the largest lake in southern Ontario (Winter et al., 2011) outside of the Laurentian Great Lakes. This dimictic lake borders the cities of Barrie and Orillia and has a surface area of 722 km^2. The Lake Simcoe watershed spans 3634 km^2 and is composed predominately of agricultural land uses (Young & Jarjanazi, 2015). Lake Simcoe can be broken down into three major basins: the main-lake basin, the deep-water Kempenfelt Bay, and the shallow Cook's Bay.

Starting around the 1920s, human activities (e.g., urban development, agricultural practices) began and impaired the ecological health of Lake Simcoe, resulting in poor water quality, eutrophication, and the collapse of fisheries (Winter et al., 2011; Young & Jarjanazi, 2015). In response to widespread impairment, remediation efforts along with the establishment of a long-term monitoring program began in the 1980s and Lake Simcoe started to transition away from an impaired state (Young & Jarjanazi, 2015). Of concern in recent years has been the establishment of invasive species. The spiny water flea (*Bythotrephes cederstroemi*) was established in 1994, followed by the zebra mussel (*D. polymorpha*) in 1996, the quagga mussel (*Dreissena rostriformis bugensis*) in 2009, and later the round goby (*Neogobius melanostomus*) and starry stonewort (*Nitellopsis obtusa*) in 2010 (Ginn et al., 2021; Young & Jarjanazi, 2015). The establishment of these invasive species has potentially had ecologically significant effects on water quality and the lake food web. Long-term monitoring data reveal major shifts in Lake Simcoe water quality throughout the 1990s and 2000s (e.g., increased water clarity, increased silica, decreased total phosphorus), and these changes appear to coincide with the establishment of invasive species (Young & Jarjanazi, 2015). Meanwhile, efforts have been made to improve the water quality and ecological health of Lake Simcoe by decreasing phosphorus inputs, addressing climate change and invasive species, and protecting natural areas (e.g., Lake Simcoe Environmental Monitoring Strategy in 1990, Lake Simcoe Clean-Up Fund in 2007, Lake Simcoe Protection Plan in 2009). It is evident that substantial changes in Lake Simcoe have occurred over the past four decades, but it is unclear whether these past ecosystem-scale changes could have been reliably forecasted or tracked with the use of EWIs.

State variable monitoring

As part of its long-term monitoring program, the Ontario Ministry of the Environment, Conservation and Parks (MECP), in collaboration with the Lake Simcoe Region Conservation Authority, has measured state variables in Lake Simcoe at up to 12 stations since 1980. Of these stations, we focused our analysis on three to evaluate the utility of select state variables as EWIs (Figure 1). The deeper monitoring stations in Lake Simcoe exhibit a high degree of synchrony in state variables (Young & Jarjanazi, 2015). Thus, we selected two deeper monitoring stations with consistent data sets and the shallowest station. Station K42 has an average depth of 42 m (deep; station LS-D hereafter) and is located in Kempenfelt Bay. Station C9 has an average depth of 19 m (mid; station LS-M hereafter) and is located at the mouth of Cook's Bay. Lastly, Station C1 is near shore at the bottom of

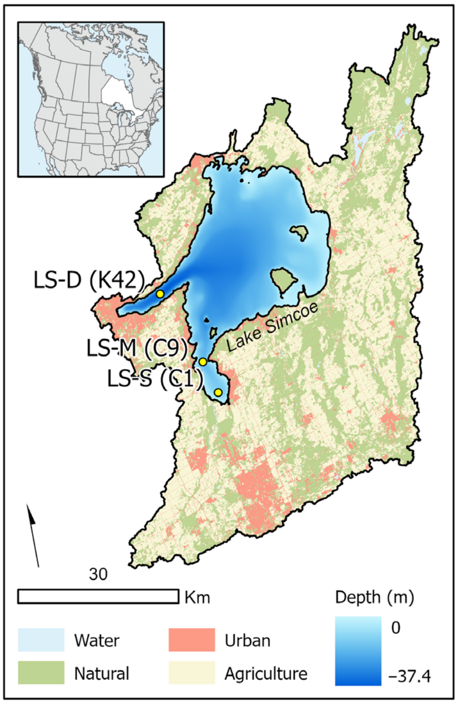

FIGURE 1 Map displaying Lake Simcoe stations studied (C1 [LS-S], C9 [LS-M], K42 [LS-D]) and watershed land cover.

Cook's Bay and is asynchronous in comparison to the other sampling stations on account of its shallow depth (average depth <3 m) (shallow; station LS-S hereafter) and proximity to the Holland River, which receives high nutrient inputs from both agricultural (Holland Marsh) and urban (Newmarket and Aurora) sources.

Samples from all three stations were collected fortnightly from the euphotic zone (i.e., surface to 15 m) throughout the ice-free season and analyzed for chemical, physical, and biological characteristics, including alkalinity, ammonia, and ammonium (NHx), Chl *a*, conductivity, dissolved inorganic carbon (DIC), dissolved organic carbon (DOC), total Kjeldahl nitrogen (TKN), nitrate and nitrite (NOx), reactive silica (Si), and total phosphorus (TP) (analytical methods described in Ralston et al., 1975; Young & Jarjanazi, 2015). This study will assess all the aforementioned variables, in addition to water clarity (i.e., Secchi disk depth), dissolved oxygen (DO), and temperature, which have been measured concurrently with water quality sampling in Lake Simcoe. Secchi disk depth was measured as the water depth in meters at which a black and white Secchi disk is no longer visible at the surface (Young & Jarjanazi, 2015). DO and temperature were measured as vertical profiles, probing at 1-m increments to the lake bottom (Young & Jarjanazi, 2015). In this study, top (1 m) and bottom (−1 m; LS-M and LS-D only) water temperature and DO was extracted and used to evaluate these variables. The state variables selected for analysis in this study (Table 1) are primarily derived from the EWI literature (e.g., Karki, 2019; Ortiz, 2019; Wang et al., 2012) but also include novel variables that have been monitored as part of the Lake Simcoe initiative.

Data analysis

Long-term monitoring data were summarized at a fortnightly resolution to ensure sample regularity in each time series. Time series were developed for each state variable from 1980 to 2019 at the three Lake Simcoe monitoring stations, and, as required for time series analysis, any missing data (primarily winter months) were interpolated using a Kalman interpolation method. With these interpolated time series data, first a principal component analysis (PCA) was conducted to visualize the multivariate progression of limnological variables in Lake Simcoe across time. Separate PCAs were performed on data from each station, and variables were mean centred and scaled prior to analysis. PCA axis scores were then extracted and subsequently used in further time series analyses. Interpolation and PCA were performed in R with the vegan and imputeTS packages (Moritz et al., 2021; Oksanen et al., 2020; Rstudio Team, 2020).

Time series analysis

To detect whether Lake Simcoe may have undergone any critical transitions, we began by assessing state variable and PC score time series using breakpoint analyses. The optimal number of breakpoints within each interpolated time series was determined by assessing deviations from stability in linear regression relationships using the strucchange package in R (Zeileis et al., 2002, 2003). The significance and strength of these breakpoints were then evaluated by comparing means of measured (i.e., not interpolated) state variable values before and after the breakpoint time using a Welch's *t*-test ($p < 0.01$). If multiple breakpoints were identified, the time series was correspondingly split into multiple segments, which were compared sequentially. Identified breakpoints that had nonsignificant differences in mean were removed in a stepwise manner until no breakpoints remained or all sequential differences in mean were significant. Cohen's *d* was also extracted from these comparisons as a measure of effect size using the emmeans package in R (Lenth et al., 2022).

EWIs

The earlywarnings R package was used to assess each time series for a loss of resilience prior to identified breakpoints (Dakos, Carpenter, et al., 2012). Using the

TABLE 1 Description and ecological significance of state variables measured by Lake Simcoe long-term monitoring program and evaluated in this study.

State variable	Description	Ecological significance
Alkalinity (mg L^{-1})	Measure of ability of water body to neutralize acids and bases	Positively associated with buffering (i.e., acid-neutralizing) capacity of water
Ammonia-ammonium (NHx; μg L^{-1})	Form of dissolved inorganic nitrogen	Nutrient that supports microbial and primary production; more readily taken up than other inorganic nitrogen forms (i.e., nitrate-nitrite)
Conductivity (μS cm^{-1})	Measure of total dissolved ions in water	General measure of water quality; a significant increase in conductivity can indicate a source of pollution
Dissolved inorganic carbon (DIC; mg L^{-1})	Measure of total aqueous inorganic carbon species (i.e., CO_2, H_2CO_3, HCO_3^-, and CO_3^{2-}) in water	Changes in DIC can reflect biological processes associated with CO_2 fixation (i.e., photosynthesis) and production (i.e., respiration and decomposition)
Dissolved organic carbon (DOC; mg L^{-1})	Measure of total aqueous organic carbon in water	Nutrient that supports growth and metabolism of microorganisms (i.e., heterotrophic bacteria)
Dissolved oxygen (DO; mg L^{-1})	Measure of amount of oxygen present in water	Sufficient DO is required for metabolism of aerobic organisms; changes in DO can reflect biological processes associated with O_2 production (i.e., photosynthesis) and consumption (i.e., respiration and decomposition)
Total Kjeldahl nitrogen (TKN; μg L^{-1})	Measure of total organic nitrogen plus ammonia and ammonium in water	Nutrient that supports microbial and primary production
Nitrate-nitrite (Nox; μg L^{-1})	Form of dissolved inorganic nitrogen	Nutrient that supports microbial and primary production
Reactive silica (mg L^{-1})	Micronutrient derived from physical and chemical weathering of rocks	Used by diatoms to build frustules and can limit algal production in low quantities
Secchi depth (m)	Measure of water transparency	Higher values indicate greater transparency; negatively correlated with primary production and turbidity
Temperature (°C)	Measure of heat present in water	Positively associated with metabolic rate of aquatic organisms
Total phosphorus (μg L^{-1})	Measure of total inorganic and organic phosphorus in water	Nutrient that supports and, in low quantities, often limits microbes and primary producers
Chlorophyll *a* (μg L^{-1})	Measurement of amount of photosynthetic pigment in water	Used as surrogate for algal biomass

generic_ews function, the statistical moments of AR1, SD, K, and SK were estimated within rolling windows for each decomposed state variable and PC score time series. In accordance with the existing literature, a rolling window size of 20% of the time series length (about 8 years) was used, as a compromise between estimating metrics accurately and generating enough windows to derive a trend (Dakos, Carpenter, et al., 2012; Dutta et al., 2018). Further, time series were decomposed prior to analysis to address the strong correlation structure associated with nonstationarity by removing overall trends and seasonal periodicities (Dakos, Carpenter, et al., 2012). Trends were removed through loess decomposition with the *generic_ews* function and seasonal periodicities were evaluated for strength (Wang et al., 2006) and, if significant (Appendix S1: Table S2), removed, using the tsfeatures package for both (Hyndman et al., 2020). Subsequently, from 1988 onward, time series were then developed for AR1, SD, K, and SK outputs and used to statistically evaluate EWI trends prior to each possible critical transition identified at state variable and PC score breakpoints. Because the strength and direction of EWI trends may differ given the length of the pre-breakpoint time series, similarly to Gsell et al. (2016), we evaluated monotonic trends in AR1, SD, K, and SK over multiple time windows that increased in length by 1-year intervals (26 observations) from 1 to 10 years prior to the possible critical transition or, if multiple possible critical transitions were identified, within a 10-year period, from

1 year to the previous critical transition. EWI trends within each time window were evaluated using a nonparametric Mann–Kendall trend test with the Kendall package in R (McLeod, 2011). Monotonic trends in EWIs were considered significant if the median Kendall τ rank correlation coefficient from the multiple time windows was >0.3 (large effect size) and its 95% confidence interval calculated with the DescTools package did not overlap zero (Signorell, 2021). Likewise, critical transitions (i.e., bifurcation) should be signaled by a lower rate of recovery to prior ecosystem conditions, so prebreakpoint EWI trends were considered to signal a critical transition if SD and AR1 were positive and there was a decrease in the symmetry (more extreme observations) of the state variable data distributions, as indicated by a change in SK (increase or decrease according to transition) and decrease in K. Critical transitions were considered increasingly likely to occur if there was agreement between multiple EWIs prior to the identified breakpoints.

RESULTS

Lake Simcoe time series

PCA showed a clear temporal multivariate progression in the limnology of Lake Simcoe from 1980 to 2020 (Figure 2);

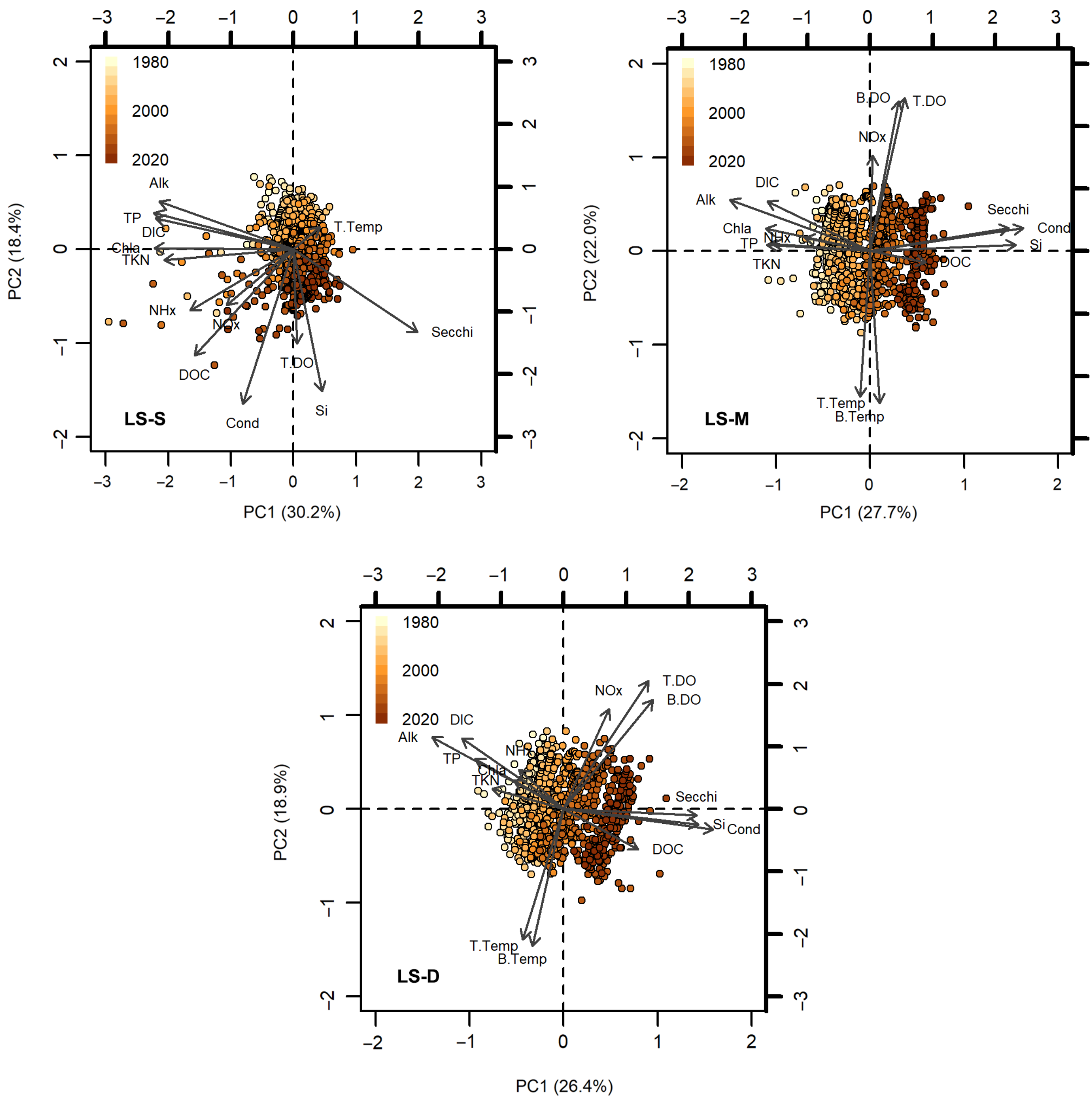

FIGURE 2 Principal component (PC) analysis of state variables in Lake Simcoe, where points represent the PC scores of biweekly time steps, and arrows show PC loadings of state variables.

however, this temporal partitioning of Lake Simcoe by state variables was less noticeable at the shallow, nearshore station LS-S. The separation of long-term monitoring data at the LS-S station revealed considerable overlap across time, but, though less pronounced, LS-S was somewhat synchronous with the other two stations in the overall loading of state variables in relation to time. State variable loadings at each station portrayed the progression of Lake Simcoe from a more eutrophic, high-nutrient system (i.e., Chl *a*, NHx, TP, TKN, and DIC) toward a system with lower nutrients and increased water clarity (i.e., Secchi disk depth). Moreover, contemporary Lake Simcoe appears to be associated with greater concentrations of Si and DOC and increased conductivity. Overall, monotonic trends in PC1 were strongest at LS-M (PC1: Kendall $\tau = 0.735$; PC2: Kendall $\tau < 0.000$) and LS-D (PC1: Kendall $\tau = 0.698$; PC2: Kendall $\tau = -0.170$), whereas monotonic trends in PC2 were strongest at LS-S (PC1: Kendall $\tau = 0.307$; PC2: Kendall $\tau = -0.702$) (Appendix S1: Figures S1 and S2).

Breakpoint analysis

Multiple breakpoints were detected at the three Lake Simcoe monitoring stations (Figure 3; Appendix S1: Table S1). At the multivariate scale, breakpoint analysis of PC scores revealed three general time periods corresponding to possible critical transitions in the limnology of Lake Simcoe: the mid-1980s, the late 1990s to early 2000s, and ~2010s (Figure 3). Around these time periods, breakpoints in individual state variables were also observed, and the direction of change was consistent at all three monitoring stations. The mid-1980s corresponded to decreased nutrient and silica concentrations and increased DO; the late 1990s to early 2000s corresponded to increased silica, Secchi depth, DOC, and conductivity but decreased alkalinity and DIC, whereas the 2010s corresponded to decreased nutrient and Chl *a* concentrations and further increases in silica. However, major differences were observed among monitoring stations where the shallow nearshore station (LS-S) had state variables with the most extreme mean values and were consistently more variable compared to the two deep-water stations (LS-M and LS-D).

EWIs

Early warning indicators were calculated as statistical moments and autocorrelation from moving windows of data across state variable and PC score time series, which could only be evaluated from about 1988 onward. Thus, monotonic trends in EWIs could not be assessed prior to select breakpoints that were identified in several state variables and PC scores (Appendix S1: Table S1). Altogether, we evaluated trends in EWIs prior to 86 breakpoints that occurred in state variables and PC scores across the three Lake Simcoe monitoring stations (Figure 3). In 47 cases (55%), three or more of AR1, SD, SK, or K displayed a consistent increasing or decreasing trend (indicated by "+" or "−" in Appendix S1: Table S1; Appendix S1: Figures S1–S17) leading up to the breakpoint. In 22 cases (26%), two metrics showed EWI trends, and in 17 cases (20%), one or no metrics demonstrated an increasing or decreasing trend leading up to the breakpoint. Of the four EWI metrics studied, SD most reliably demonstrated change prior to breakpoints (72% of cases), followed by K (66% of cases), AR1 (60% of cases), and SK (58% of cases). However, only 44%, 34%, 28%, and 26% of breakpoints had SD, K, SK, and AR1 trends in the direction expected with EWI theory; therefore, the level of agreement was reduced to 14% for three or more EWIs, 27% for two EWIs, leaving 59% of the breakpoints having agreement in only one or no EWIs. Corresponding to the three identified time periods associated with possible ecosystem-scale critical transitions in Lake Simcoe, we only found sufficient agreement (i.e., three or more) among the measured EWIs for the late 1990s breakpoint in Secchi depth at LS-M and LS-D. For almost all other state variables, there was poor agreement in the EWIs, or they were the opposite of what was expected, including for TP and Chl *a*, which we assume would have been linked to some of the known larger changes that have occurred in the lake (e.g., nutrient reductions and *Dreissenid* establishment). Moreover, there were no discernible patterns in EWI performance among monitoring stations, even though the effect sizes (Cohen's *d*) for changes in mean surrounding these breakpoints were largely greater at LS-M and LS-D compared to LS-S.

DISCUSSION

Lake Simcoe has a long history of environmental change that has been routinely monitored since the 1980s and thus is ideal for studying the utility of EWIs. As shown by other studies (e.g., North et al., 2013), we observed that Lake Simcoe continues to be fundamentally different now than it was in the 1980s, with many changes in water quality occurring in the 2000s. Specifically, the lake has slowly transitioned from a high-nutrient, chlorophyll-dominated state toward a clear-water, high-DOC state. Our study assessed the utility of four common statistical indicators (i.e., AR1, SD, SK, K) as EWIs of these observed changes in Lake Simcoe. To our knowledge, this is the first study to show the progression of these statistical indicators as an ecosystem improves from an impaired state (i.e., eutrophic to clear water state) and the first time data from the Lake

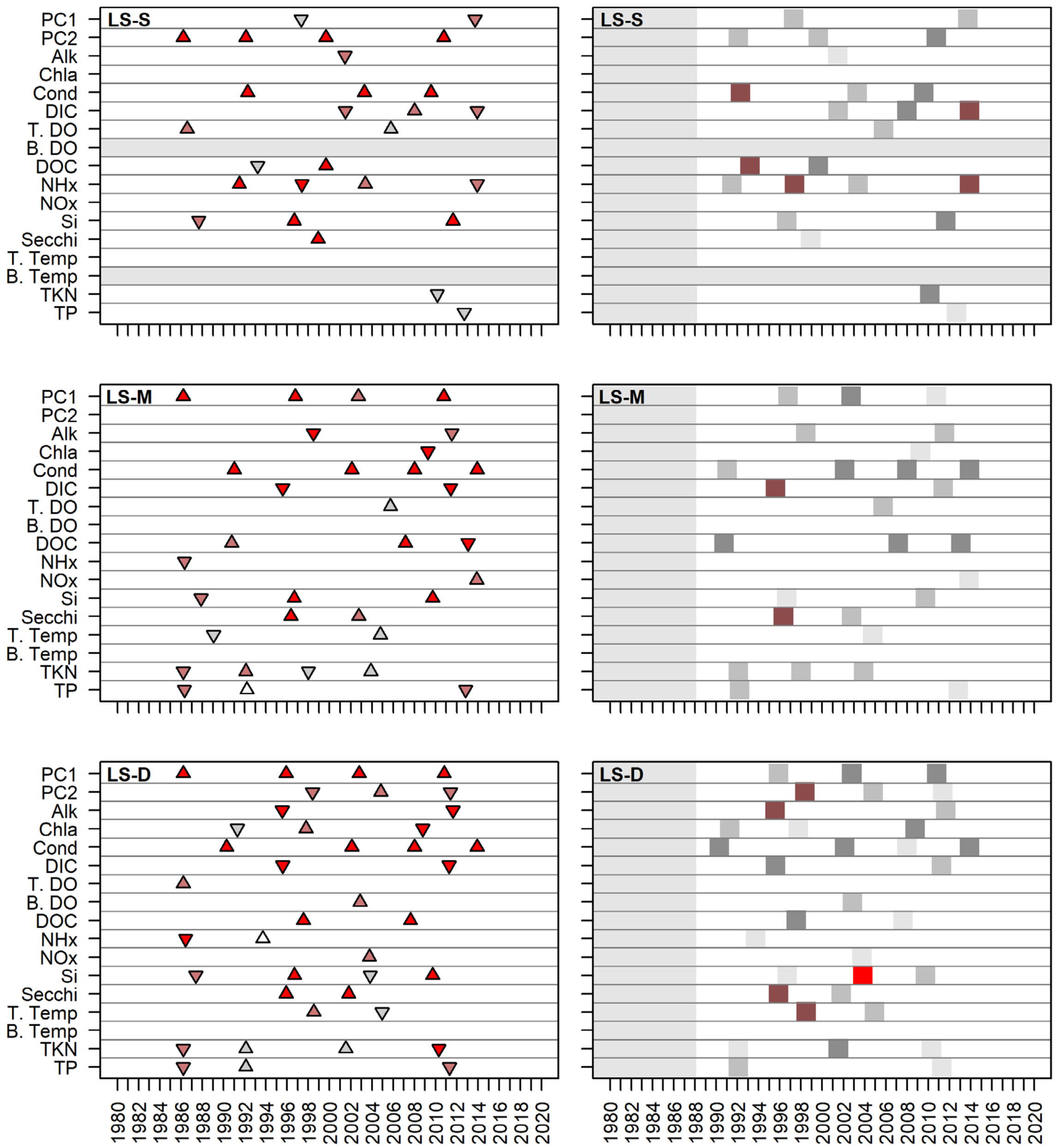

FIGURE 3 (Left) Breakpoint timing, direction of change (▲ = increase; ▼ = decrease), and effect size (white: Cohen's $d < 0.3$; gray: $0.3 <$ Cohen's $d < 0.5$; light red: $0.5 <$ Cohen's $d < 0.8$; red: $0.8 <$ Cohen's d) for principal component (PC) score and state variable time series across three Lake Simcoe monitoring stations (shallow: LS-S; middepth: LS-M; deep: LS-D). (Right) Number of EWIs with expected trends prior to corresponding critical transitions identified through breakpoint analysis (light gray = 0; medium gray = 1; dark gray = 2; dark red = 3; red = 4). EWI trends prior to 1988 (shaded time period) could not be evaluated due to lack of data availability.

Simcoe long-term monitoring program have been used to investigate EWIs. By studying long-term trends in Lake Simcoe, we show that, although breakpoints in some state variables and multivariate-derived whole ecosystem time series were preceded by characteristic EWI behavior, many state variables did not display clear EWI trends, or EWIs failed to change concurrently. Therefore, nuanced information on the success of management interventions or broader ecosystem-scale changes (e.g., invasive species) derived from the application of EWIs would likely need to be firmly contextualized by in-depth ecological knowledge of the study ecosystem for it to support decision-making.

Historical trends in Lake Simcoe

Over the last four decades, Lake Simcoe has gradually been improving from eutrophication, and state variables associated with this transition (i.e., TP, Chl a, and Secchi depth) have been observed to have significant breakpoints within their time series. Various management actions have been implemented in the lake since the 1980s. In 2007, the Government of Canada established the Lake Simcoe Clean-Up Fund to implement projects that would reduce phosphorus loading and restore aquatic habitat in Lake Simcoe, and in 2009 the Ontario Government adopted the Lake Simcoe Protection Plan to further enact immediate action to address threats associated with nutrient loading, invasive species, habitat degradation, and climate change (Palmer et al., 2011). Identified breakpoints in state variables associated with eutrophication appear to coincide with management interventions aimed at improving water quality in the lake. In particular, detected breakpoints indicate that after about 2010, Lake Simcoe transitioned toward significantly lower TP concentrations and, in turn, lower Chl *a* concentrations at LS-M and LS-D but not LS-S. Likewise, though not significant, more contemporary trends toward increasing Secchi depth were observed at all stations. This transition has also been accompanied by previously reported increases in deep-water DO, likely from lower rates of organic matter decomposition (Young & Jarjanazi, 2015).

In addition to management interventions, this major shift in lake water quality may be partially explained by the widespread colonization of invasive *Dreissenid* mussels in 1996 (*D. polymorpha*) and later in 2009 (*D. rostriformis bugensis*) (Evans et al., 2011). Through their feeding behavior, dreissenids filter small organisms and particles from the water column and can have far-reaching effects on water quality, particularly as mussels reach high densities (Kelly et al., 2017; North et al., 2013; Winter et al., 2011). Previous research showed that *Dreissenid* colonization could lead to reduced TP, phytoplankton, and Chl *a* in a lake's water column and increase water clarity (e.g., Higgins & Zanden, 2010; North et al., 2013). Though it is difficult to associate a specific stressor to ecosystem-scale changes in multistressor environments, we too observed a significant breakpoint in Secchi depth that coincided with the establishment of *D. polymorpha* in the mid-1990s. However, while there were overall decreasing trends in TP and Chl *a* prior to the mid-1990s, significant breakpoints did not occur until ~2010 following the shift in benthic dominance from *D. polymorpha* to *D. rostriformis bugensis* (Ginn et al., 2018). Thus, it is likely that high-volume filtration and grazing (i.e., nearshore P shunt; Hecky et al., 2004), coupled with the implementation of various management interventions, has contributed to declining TP concentrations and algal biomass (Winter et al., 2011) and increasing water clarity over this time series (Ginn, 2011; Jones & Montz, 2020; Nicholls et al., 1997).

Ecosystem-scale changes in Lake Simcoe were observed at the LS-D and LS-M monitoring stations but were less evident for LS-S. Breakpoints in state variables associated with eutrophication (e.g., Chl *a*, TP, and Secchi depth) at LS-S were consistently found to have lower effect sizes, with high variability around breakpoint means, or were nonexistent. Densities of dreissenid mussels were comparable among these three basins, and because the dominant species differ with depth, following the establishment of *D. rostriformis bugensis* (~2010), filtering capacities were similar between LS-S and LS-D and greatest at LS-M (Ginn et al., 2018). However, the nearshore proximity of LS-S to the mouth of the Holland River could also be driving the spatial heterogeneity due to higher nutrient inputs from the agriculturally intensive Holland Marsh and nearby urban areas (Newmarket and Aurora) (Palmer et al., 2011).

The establishment of dreissenid mussels and the reduction of algal biomass can have cascading impacts on other state variables (Figure 4). Lower algal biomass results in less silica being taken up from the water column, which could explain the increasing trend in silica concentrations in Lake Simcoe (Fahnenstiel et al., 2010; Nicholls et al., 1997; Winter et al., 2011). In contrast, decreased alkalinity coincided with the establishment of dressenids and may have been caused by the removal of ions to produce shells (Jones & Montz, 2020). We also observed an increase in DOC with no corresponding change in Secchi depth. Increased water transparency from the combination of reduced nutrient loading and dreissenid mussel establishment may have facilitated the growth of submergent macrophytes and subsequent DOC exudation (Reitsema et al., 2018). Evidently, state variables are largely interactive with one another and can be influenced by co-occurring environmental stressors, as indicated by commonalities observed in breakpoint timing.

Evaluating the temporal progression of state variables from a holistic multivariate perspective, we were able to identify three time periods with breakpoints that point to possible ecosystem-scale critical transitions in Lake Simcoe. Indeed, these periods aligned with the clusters of breakpoints in individual state variables but were often more pronounced and exhibited larger effect sizes than their individual counterparts. This multivariate approach may buffer against some of the common pitfalls (e.g., stochastic changes and false alarms) in changepoint detection and early warning thereof and be more representative of ecosystem dynamics. Capturing the influence of multiple stressors and internal ecosystem dynamics in the evaluation of critical transitions from continuous monitoring data may therefore help to better understand any signal cascading ecosystem change.

Utility and reliability of EWIs

Contrary to our expectations, we did not find overwhelming support for the idea that EWIs calculated from

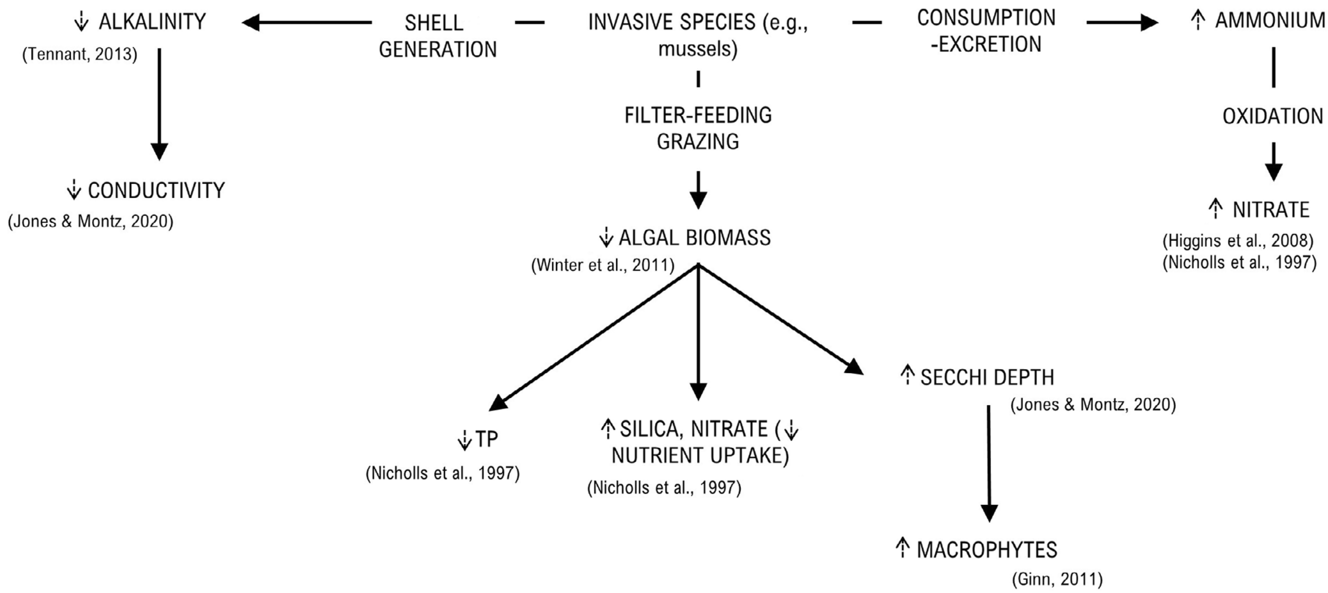

FIGURE 4 Flow diagram illustrating connections between introduction of invasive species and selected lake water quality variables. Similar patterns may be predicted with reduced phosphorus inputs.

multivariate-derived time series would be able to forecast possible critical transitions better than those from individual state variables. In fact, many univariate state variables (e.g., conductivity, DIC, NHx, TKN, NOx) also failed to demonstrate reliability and utility as EWIs in Lake Simcoe. Although EWI behavior was detectable prior to many breakpoints, the possible utility of EWIs was often compromised by a lack of agreement among statistical indicators prior to these changes in mean. These inconsistencies did not appear to be linked to the degree of change (i.e., effect size) in the mean of state variables since clear patterns in EWI performance did not emerge among state variables that had breakpoints with larger effect sizes. While we found potential early warning signals regarding the initial breakpoint in Secchi depth, our larger findings are consistent with those of Gsell et al. (2016) and others (Burthe et al., 2016; Spears et al., 2017), who concluded that EWIs failed to provide reliable and consistent signals of impending breakpoints in state variables of freshwater ecosystems. Thus, it is possible that ecosystem complexity in Lake Simcoe associated with highly variable limnological conditions, multiple breakpoints, and the occurrence of nonlinear/nonbifurcation changes in state variables may have disrupted the characteristic progression of EWIs that precedes critical transitions linked to more gradual changes in system dynamics (Dakos et al., 2015; Livina et al., 2012).

Interestingly, as previously observed in phytoplankton models (Batt et al., 2013), the reverse of expected EWI trends was observed for critical transitions associated with the alleviation of eutrophication in Lake Simcoe. For example, in ecosystems that are transitioning from clear water to eutrophic states, trends in Chl *a* and TP often had increased SDs in the years preceding breakpoints (Ortiz et al., 2020). In Lake Simcoe, particularly at LS-M and LS-D, we observed SD to decrease and SK and K to increase following identified breakpoints in TP and Chl *a*, indicating a transition to a more stable time series with less extreme values. Like the transition toward poorer water quality (i.e., eutrophication), characteristic statistical changes are expected to accompany the transition toward healthier water quality as the ecosystem gains stability. However, given the complexity in state variable behavior prior to critical transitions, trends in EWIs may differ from those expected in association with bifurcation (Burthe et al., 2016). Despite the utility of EWIs being perceived as contrary to their intended purpose due to the improvement observed in Lake Simcoe, we allude to the possibility that statistical moments of change provide an opportunity for managers to track the success of management interventions, but this will likely require specialized knowledge of time series statistics and ecosystem ecology, potentially limiting its ease of use in adaptive management strategies.

Future directions and conclusions

Most studies on EWIs investigated individual state variables as they underwent a critical transition toward poor ecological conditions (e.g., higher chlorophyll and TP; Pace et al., 2017; Wilkinson et al., 2018) and reported ambiguous results about their utility (e.g., Burthe et al., 2016; Gsell et al., 2016). Here, we show the progression of

EWIs derived from both individual and multivariate state variables over a period where management interventions and ecosystem engineering by invasive species resulted in a perceived improvement in lake status from more eutrophic conditions to those of a clearer water state (i.e., decreased chlorophyll and phosphorus). Although we also report ambiguous results, possibly due to complex critical transitions, state variables that were associated with this perceived improvement showed novel trends in the temporal patterns of SD, SK, and K surrounding breakpoints. This improvement in lake status is the opposite of that found in previous EWI research but highlights an opportunity to use these methods for the adaptive management of lake ecosystems. However, investment in routine (i.e., weekly to monthly) long-term monitoring is needed to better identify these indicators of change and to further advance the statistical tools available for resource managers to safeguard freshwater ecosystems more effectively. Long-term monitoring data with fortnightly observations, such as the Lake Simcoe monitoring program, are uncommon in most freshwater ecosystems, but even with such an expansive data set, our study was of low resolution and occurred only during the ice-free season, and, though other biological data are collected on this lake, our analyses were largely made up of data from state variables associated with water quality. High-frequency (i.e., hourly to daily) sensors and the use of this information to infer biological processes have considerable potential in the development of EWIs of critical transitions and may have applications in forecasting detrimental events (e.g., algal blooms) in real time. Moreover, as observed in our study, spatial heterogeneity in the temporal patterns of state variables within lakes is common, and future analyses could use all of the monitoring stations on this lake. To match the rapid pace of global environmental change, investment in effective ecological monitoring at appropriate spatial and temporal scales is needed to provide comprehensive data to make responsive yet informed policy and management decisions.

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CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY STATEMENT

Data (Rohde et al., 2022) are available in figshare at https://doi.org/10.6084/m9.figshare.19131815.v1.

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