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Lake Erie tributary nutrient trend evaluation: Normalizing concentrations and loads to reduce flow variability

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ABSTRACT

Establishing tributary load (i.e., the mass exported over a period of time) targets to reduce anthropogenic nutrient inputs to receiving waters — and thus eutrophication — is a common mitigation strategy in freshwater and coastal ecosystems. However, detecting and quantifying trends can be difficult because annual precipitation strongly influences tributary flow (e.g., average daily stream discharge). This may obscure trends as wet years tend to produce high tributary loads despite management activities to reduce nutrient export, and dry years typically generate low loads, even without management of nutrients. Furthermore, flow and nutrient concentrations are often correlated. Earlier efforts to reduce the effect of flow variability on tributary nutrient assessment were limited by computational and methodological constraints, until the weighted regressions on time, discharge, and season (WRTDS) method was introduced in 2010. Here we use WRTDS to assess nutrient concentration and load changes from 1982 to 2018 in three tributaries to the western basin of Lake Erie, of the Laurentian Great Lakes. Generally, trends revealed by flow-normalization do not contradict those of non-normalized metrics; however flow-normalization made the patterns more perceptible than in non-normalized metrics and reduced the influence of a particularly wet or dry period at the end of records on long-term trend analysis. We demonstrate that using WRTDS for flow-normalization removed the noise arising from annual precipitation variability and makes tributary nutrient trend evaluation more straightforward.

1. Introduction

Excessive nutrient (phosphorus and nitrogen) inputs are the principal cause of eutrophication in freshwater and coastal-marine ecosystems. Establishing targets to reduce tributary nutrient loads is a common eutrophication mitigation strategy (Jeppesen et al., 2005; Lathrop et al., 1998; Schindler et al., 2016). Phosphorus load (mass/time) targets for Lake Erie were originally established in the 1970s, and were considered highly effective into the 1990s (Makarewicz and Bertram, 1991). However eutrophication symptoms began to reoccur in the early 2000s (Bertani et al., 2016; Michalak et al., 2013); consequently updated, lower phosphorus load targets were recommended to control the resurgent eutrophication problem (Annex 4 Objectives and Targets Task Team, 2015). Thus, evaluating Lake Erie tributary phosphorus trends is necessary to assess progress toward meeting the new targets. While there is general agreement that reducing phosphorus is most important for eutrophication control, developing evidence for seasonal nitrogen limitation in some locations (Chaffin et al., 2018; Chaffin and Bridgeman, 2014; Newell et al., 2019) also invites an assessment of tributary nitrogen trends.

However, assessing trends can be difficult because annual precipitation variability strongly influences tributary flow (i.e., discharge). Wet years usually produce high tributary loads, even if management activities to reduce watershed nutrient losses from point (e.g., wastewater) and non-point (e.g., crop field runoff) are underway, and dry years typically generate low loads, even if no management occurs. Precipitation-induced flow (i.e., discharge) variability may also obscure tributary concentration trends because tributary flow and nutrient

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concentrations are typically correlated. For example, if nutrients are primarily from point sources this relationship is often negative, but if nutrients originate primarily from non-point source runoff the relationship is often positive. If both types of sources play a significant role then the relationship may be non-monotonic (Johnson, 1979).

In addition to loads, flow-weighted mean concentrations were recommended as a metric to assess phosphorus reduction progress in Lake Erie tributaries. The Annex 4 Objectives and Targets Task Team Final Report to the Nutrients Annex Subcommittee for Lake Erie states: "Flow Weighted Mean Concentrations (FWMC) provide a useful means to address inter-annual variability by normalizing the phosphorus delivery from a tributary with respect to flow, so that year-to-year performance is not confounded by inter-annual variability in hydrology" (2015, p. 16). While we believe that the motivation for this recommendation is correct, we demonstrate that FWMCs are also correlated with flow. Thus, as is the case with loads and concentrations, yearly flow variability can also obscure FWMC trends. Because flow variability can mask progress toward attaining tributary nutrient input goals, methods that reduce flow-induced noise would be valuable, complementary trend indicators.

The generality of earlier efforts to reduce the effect of flow variability on tributary nutrient input assessment was limited by computational and methodological constraints (Stow et al., 2001; Stow and Borsuk, 2003). More recently, Hirsch et al. (2010) introduced the weighted regressions on time, discharge, and season (WRTDS) method to minimize the influence of yearly streamflow variation while estimating load and concentration in Chesapeake Bay tributaries. Since then, WRTDS has been used, tested, evaluated, and extended by many (see http://usgs-r.github.io/EGRET/articles/References_WRTDS.html). Choquette et al. (2019) demonstrated the flexibility of using WRTDS to estimate long-term changes in nutrient flux and the concentration/flow relationship in ten tributaries to Lake Erie over 1995 to 2015. Choquette et al. (2019) extended the WRTDS method so it would be appropriate to watersheds where multi-decadal streamflow trends are common and of substantial magnitude. This extension of WRTDS, known as generalized flow-normalization, removes the influence of year-to-year variation in streamflow, but not the influence of longer-term trends in streamflow.

Using data spanning 1982–2018 from three Lake Erie tributaries (Fig. 1) with a wide range of watershed characteristics, we build on Choquette et al.'s (2019) analysis to demonstrate an aspect of WRTDS that is particularly useful — using flow-normalization to remove the noise arising from annual precipitation variability makes tributary nutrient trend evaluation more straightforward. We observe time-series of annual water quality metrics calculated five ways for five different nutrient species, and then compute the correlation coefficients between these annual metrics and annual mean discharge. We suggest that it is preferable to use a metric that has a relatively low correlation with discharge. Such a metric should provide a high signal to noise ratio, facilitating high trend detection power, and avoid the possibility that a perceived trend is simply an artifact of the last year or two of the period of record being either relatively wet or dry.

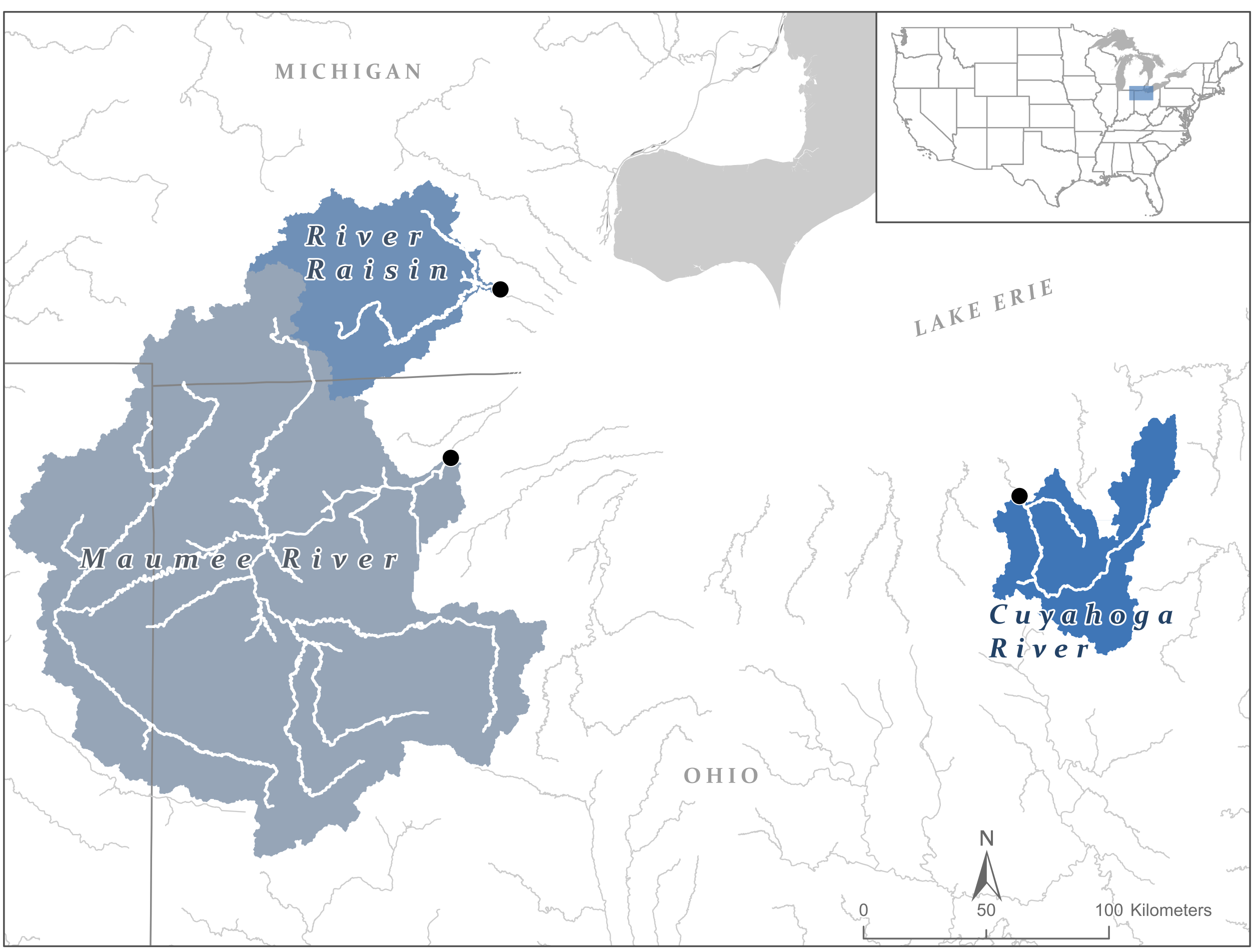

Fig. 1. The three stream gauging stations in this study (represented by red circles) are tributaries to Lake Erie (see Supplementary Table S1 for more details). The green area shows their respective watersheds. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2. Material and methods

2.1. Site description

We focused on three Lake Erie tributaries (Table S1; Fig. 1) that had daily flow data collected by the United States Geological Survey (USGS) and nutrient concentrations collected by Heidelberg University's National Center for Water Quality Research (NCWQR) since at least 1983. These three streams differ in their drainage area and land cover. The Maumee River watershed is the largest and is dominated by row-crop (73%) and developed land (11%). The River Raisin watershed is roughly 1/6 the size and is about half row-crop (49%) and then a mix of pasture land (18%), developed/forest/and other uses (11% each); whereas the Cuyahoga River watershed is the smallest, and is mostly developed (40%) or forested (33%) with comparatively small areas of row crop (8.9%) (Choquette et al., 2019). Nutrient inputs from the Raisin and Cuyahoga are small relative to those from the Maumee but their differing land-use patterns provide an informative comparison.

2.2. Sampling

We retrieved flow data for each stream from the USGS National Water Information Service (US Geological Survey, 2016). Stream flow is quantified as "daily discharge," which is a daily mean discharge value determined from high frequency (typically 15-minute interval) water level measurements along with the use of USGS protocols for revising and using stage-discharge relationships that depend on much less frequent direct discharge measurements (Nielsen and Norris, 2007; Olson and Norris, 2007; Turnipseed and Sauer, 2010). Unless otherwise noted, any reference to year is the US Geological Survey water year, defined as 1 October through 30 September (e.g., water year 2018 runs from 1 Oct 2017 to 30 Sept 2018). Water quality sampling and processing was conducted by the National Center for Water Quality Research using procedures and analytical methods described in Baker et al. (2014) and Stow et al. (2015). We examined long-term trends in total phosphorus (TP), soluble reactive phosphorus (SRP), nitrate and nitrite ($NO_{2/3}$), total Kjeldahl nitrogen (TKN), and total nitrogen (TN). TN was calculated as the sum of $NO_{2/3}$ and TKN. These records, for any given site and analyte, consist of more than 16,000 individual samples (typically 400–500 samples per year) collected over a period of 37 years.

2.3. Evaluating trends over time

We used WRTDS in the EGRET package in R to estimate the changing relationship of concentrations to discharge and season and then to remove the effect of flow on flux and concentration (Hirsch et al., 2015, 2010; Hirsch and De Cicco, 2015). Briefly, WRTDS estimates daily concentrations over the period of interest as a function of the long-term trends, seasonal variation, and discharge (Eq. (1)).

$$\ln(c) = \beta_0 + \beta_1 t + \beta_2 \ln(Q) + \beta_3 \sin(2\pi t) + \beta_4 \cos(2\pi t) + \varepsilon \quad (1)$$

where c is concentration, Q is discharge, t is time in years, β_3 and β_4 capture seasonal periodicity, and ε is unexplained variation. Eq. (1) uses locally weighted regression estimates for each day, in which the weights on all available observations are based on their distance in time, discharge, and season. For example, to estimate concentration for a day in May 2011, during a particularly high flow period, observations distant in time, season, and during low flow conditions, say October 2018, would receive low weights, whereas nearby observations in time, season, and discharge space, say April 2011 would receive high weights. Flow-normalization is then accomplished by integrating each estimated concentration value over the observed probability distribution of daily flow for that calendar day. Details for the weighted regression, flow-normalization, and generalization to consider hydrologic non-stationarity resulting in systematic flow changes over time (Milly et al., 2008) are available in Choquette et al. (2019). Complete guidelines about requirements for implementing WRTDS are elsewhere (Hirsch and De Cicco, 2015); briefly the method requires concentration data for parameters of interest and a complete record of daily mean flow/discharge over the duration of the water quality record. WRTDS was designed for large (i.e., greater than 200 concentration samples) datasets spanning long time periods but can produce reliable estimates of concentrations and/or fluxes with as few as 60 samples spanning a decade. Importantly, it is not appropriate for flashy watersheds and the flow data must cover the entire period of water-quality data used. This approach is currently used in the Chesapeake Bay restoration program (https://cbrim.er.usgs.gov/), Lake Champlain (Medalie et al., 2012), the Mississippi River Basin (Kreiling and Houser, 2016; Sprague et al., 2011), and for all coastal-draining watersheds in the United States (Oelsner and Stets, 2019). The temporal density of the records used here is much higher than what the WRTDS method requires, but experimentation has shown that the results we describe here would be very similar if these data sets were filtered to a much lower density.

We compared the annual estimates of generalized flow-normalized concentration (FNC; mg L^{-1}) and generalized flow-normalized flux (hereafter load, abbreviated to FN load; metric tons) to the traditional method of annual flow-weighted mean concentrations (FWMC; mg L^{-1}). In addition to annual estimates of FNC, FN load, and FWMC we also considered two other common annual water-quality metrics: time-weighted mean concentration (TWMC; mg L^{-1}), and total load (load; metric tons yr^{-1}). These last three estimates are calculations published by the NCWQR. Time-weighted and flow-weighted mean concentrations are adjustments for stratified sampling programs where each sample might not carry the same weight (e.g., some samples may represent one or more days while others represent only a few hours). TWMC adjusts the sample by the period of time it represents and might reflect the average concentration in river water as it flows past a station. FWMC, on the other hand, weights concentrations by both time and the flow (discharge). This metric may better reflect the concentrations a lake receiving water from a stream may experience. Lastly, load is simply the total estimated mass of a nutrient exported to Lake Erie over a specified period.

Finally, we present an example of how each estimate would have performed if applied to determine the decadal trend for Maumee River SRP as computed at the end of water year 1999 (see Supplementary Material for methods). In 1999, concentrations and loads were in transition from relatively low values in the early 1990′s to substantially higher values of 2005–present. We assess how well each method did at signaling the incipient upwards trend if the only available data were through water year 1999. Confidence intervals for trend slopes of FNC and FN load were computed using the block bootstrap method in the 'EGRETci' R package (Hirsch et al., 2015). Block bootstrapping accounted for the serial correlation in the data. Confidence intervals for the TWMC, FWMC, and total load were based on the Thiel-Sen (Sen, 1968; Theil, 1992) slope estimates of these values as a function of time. See Supplementary Material for more details.

3. Results

The yearly flow variability in each tributary imparts noise that obscures load and concentration trends (Fig. 2). From 1982 to 2018 Maumee annual average daily flows ranged from 83–254 $m^3 s^{-1}$, the Raisin ranged from 14–35 $m^3 s^{-1}$, and the Cuyahoga from 18–44 $m^3 s^{-1}$. The proportional flow variability across years was comparable in all three tributaries with respective interannual coefficients of variation of 25%, 21%, and 21%. Ordinary least squares regression lines suggest slightly increased annual flow in both the Maumee and Cuyahoga, while the Raisin appears relatively unchanged.

TP concentrations in all three tributaries showed an overall decline from 1982 to 2018 (Fig. 3a,b,c). The decrease in the Maumee (Fig. 3a) has been steady and gradual, particularly in comparison to the Raisin

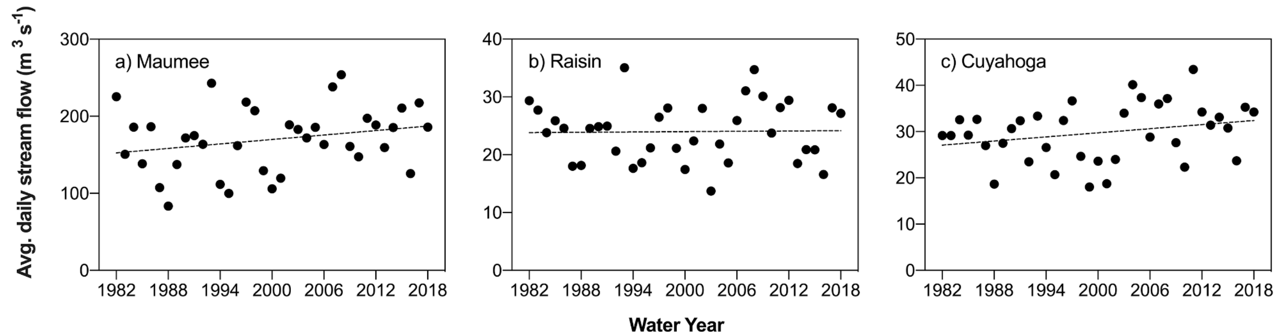

Fig. 2. Average daily stream flow (discharge) for each tributary. Dashed ordinary least squares regression lines through the data are provided to guide the eye. Note the y-axes have different scales.

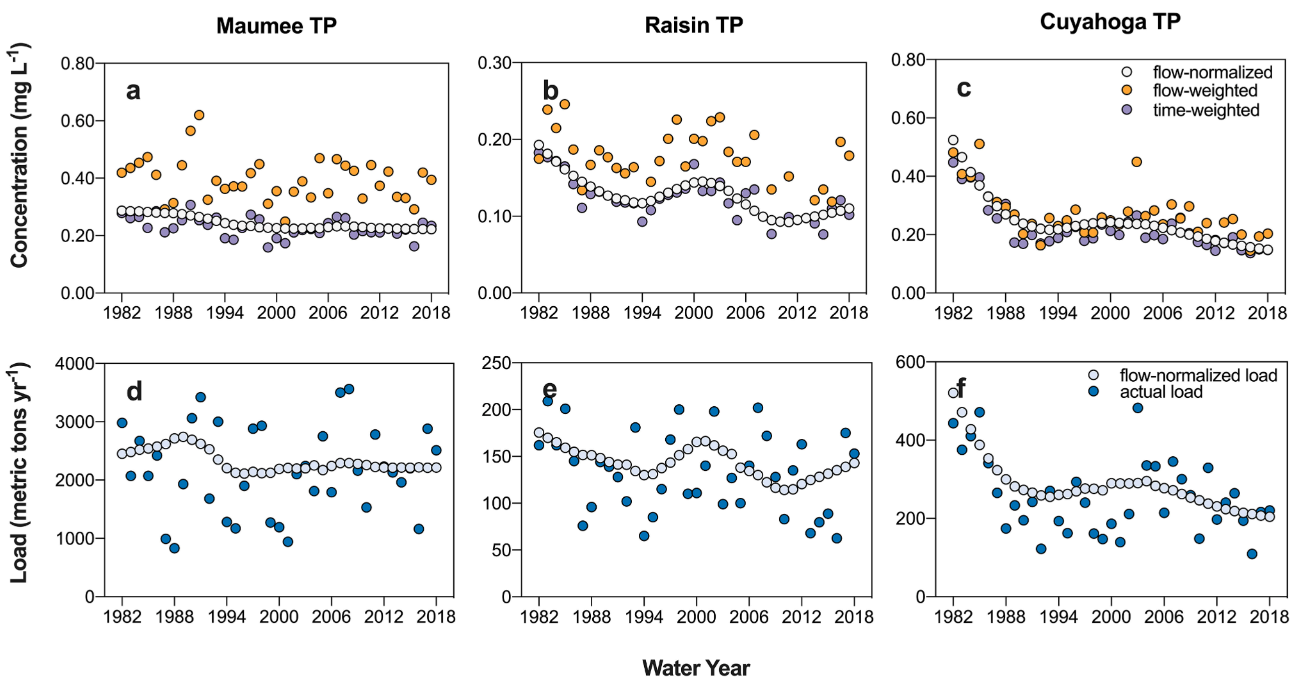

Fig. 3. TP concentration (a–c) comparison between flow-normalized concentration from WRTDS, flow-weighted mean concentrations, and time-weighted mean concentrations over time. Flux (d–f) is calculated the traditional way (dark blue) or using WRTDS to flow-normalize (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Fig. 3b) which exhibited a steep decline until about 1990, stabilized in the early 90s, and has declined gently since the early 2000s. While there was a net decrease from 1982 to 2018, concentrations in the Raisin exhibited a slight increase in the late 1990s, followed by a slight decline until approximately 2012, with a slight increase since then. FWMCs are more variable than either time-weighted or flow-normalized concentrations, making trends more difficult to discern, whereas patterns in flow-normalized concentrations are clear (Fig. 3a,b,c).

Trends in actual TP loads (Fig. 3d,e,f) are more difficult to see than the corresponding concentration patterns because yearly flow variability dominates the load variance. While an early load decline is apparent in the Cuyahoga (Fig. 3f), matching the corresponding concentration drop (Fig. 3c), patterns in the Maumee and Raisin are more difficult to discern (Fig. 3d,e). However, removing the variance using flow-normalization makes trends distinct. Both the Maumee and Raisin show an overall, net decline; while the Maumee has been stable since 1994 (Fig. 3d), the Raisin has undulated, with a steady increase since 2012, mirroring the corresponding concentration increase (Fig. 3e).

Maumee and Raisin SRP trends (Fig. 4) differed from the corresponding TP trends (Fig. 3) while Cuyahoga SRP and TP trends were similar (Figs. 3 and 4, respectively). SRP concentrations in all three tributaries exhibited an initial dip into the early 1990s, followed by increases into the early 2000s. The Maumee then stabilized, while the Raisin declined and then increased through 2018; in contrast the Cuyahoga declined through 2018. The loads in each tributary closely paralleled the corresponding concentration patterns, which is particularly apparent in the flow-normalized metrics.

Total nitrogen patterns were less pronounced in all three tributaries than the corresponding phosphorus patterns; Maumee and Cuyahoga concentrations suggested slight net decreases whereas the Raisin undulated with minimal net change (Fig. 5). Load and concentration patterns were similar in each tributary. Maumee flow-normalized loads highlight a slight increase into the early 1990s, followed by a slight, net decrease since. River Raisin TN peaked in the early 2000s, similar to the corresponding TP load peak (Fig. 4), declined until 2010 and then increased through 2018, also paralleling the corresponding TP load pattern (Fig. 4).

Unsurprisingly, nitrate patterns in each tributary are similar to TN patterns (Figs. 6 and 5, respectively), as nitrate is the dominant TN component.

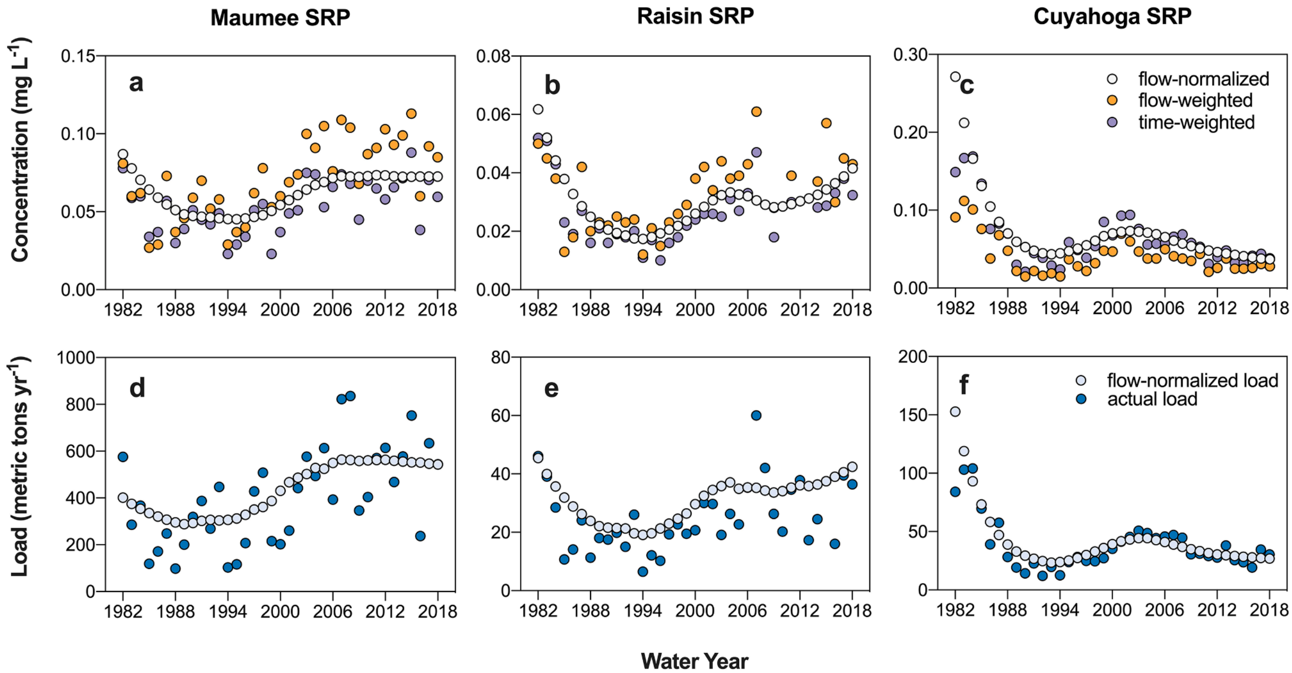

Fig. 4. SRP concentration (a–c) comparison between flow-normalized concentration from WRTDS, flow-weighted mean concentrations, and time-weighted mean concentrations over time. Flux (d–f) is calculated the traditional way (dark blue) or using WRTDS to flow-normalize (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

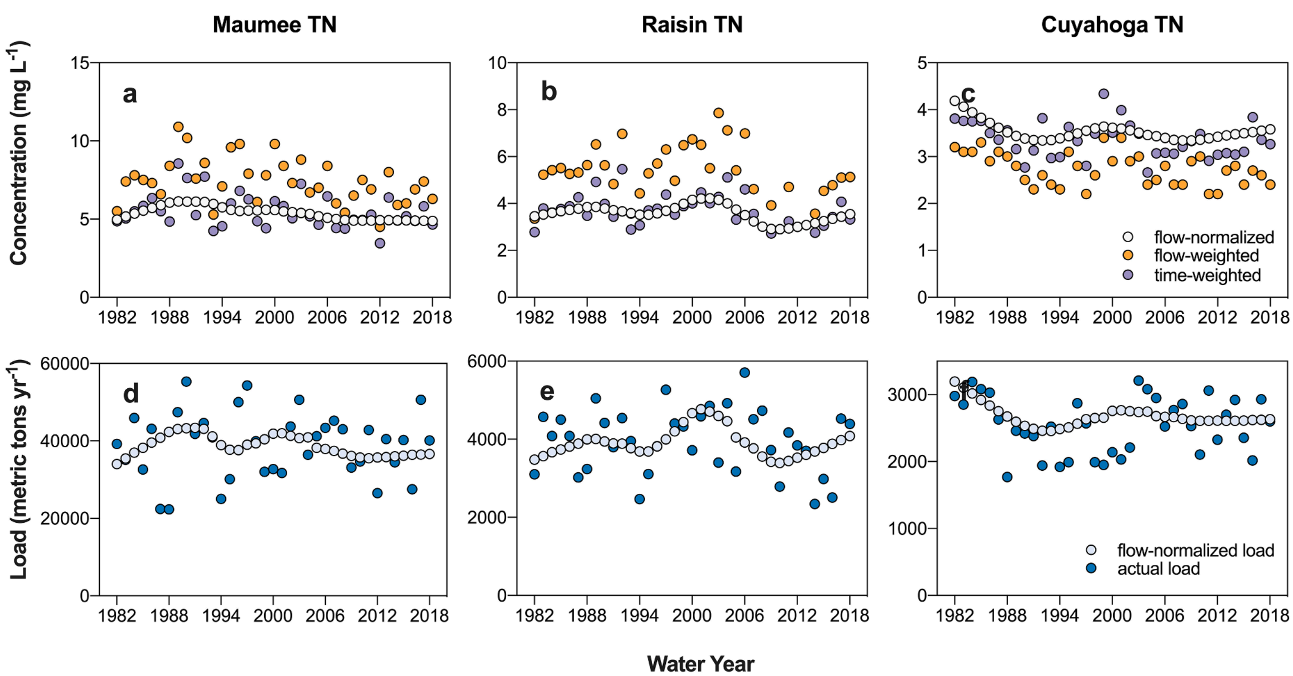

Fig. 5. TN concentration (a–c) comparison between flow-normalized concentration from WRTDS, flow-weighted mean concentrations, and time-weighted mean concentrations over time. Flux (d–f) is calculated the traditional way (dark blue) or using WRTDS to flow-normalize (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

TKN (Fig. 7) differed somewhat, and all three tributaries displayed slight, net declines. The Cuyahoga exhibited a steady decline from 1982 to 1994 and has been fairly stable since.

At the three sites and for all five analytes, the correlation coefficient between the five water quality metrics — FNC, FWMC, TWMC, load, and FN load — and annual flow shows that (see Supporting Information Figs. S1–S5) the two flow-normalized metrics are much less correlated with annual flow than any of the other metrics. FWMC had the highest correlation with flow, while FNC had the lowest (Fig. 8). Similarly, flow-normalizing greatly reduces the correlation between load and flow (Fig. 8).

As far as detecting slope trends, confidence intervals were narrower using the WRTDS flow-normalization method (Fig. 9). FNC did not show strong evidence of a trend (Fig. 9a) because most of data came from a period of moderate to high discharge (Fig. 1). The only metric that shows at least moderately strong evidence of a trend is the FN Load

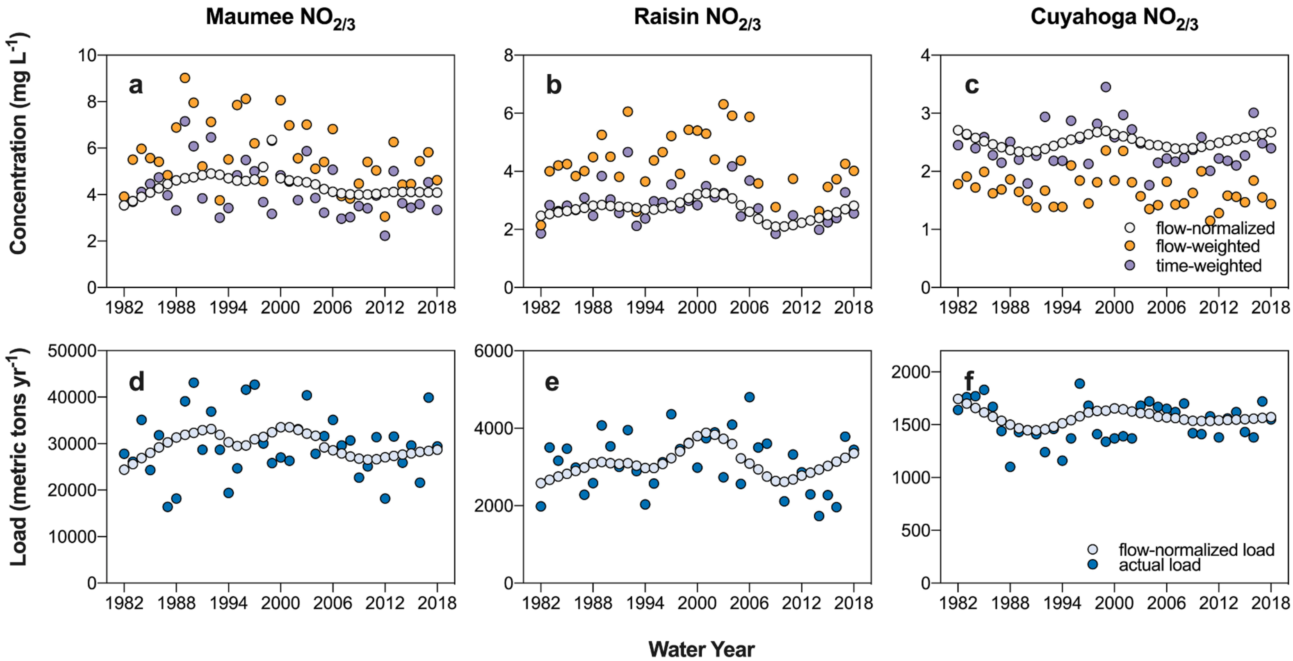

Fig. 6. Nitrate/nitrate concentration (a–c) comparison between flow-normalized concentration from WRTDS, flow-weighted mean concentrations, and time-weighted mean concentrations over time. Flux (d–f) is calculated the traditional way (dark blue) or using WRTDS to flow-normalize (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

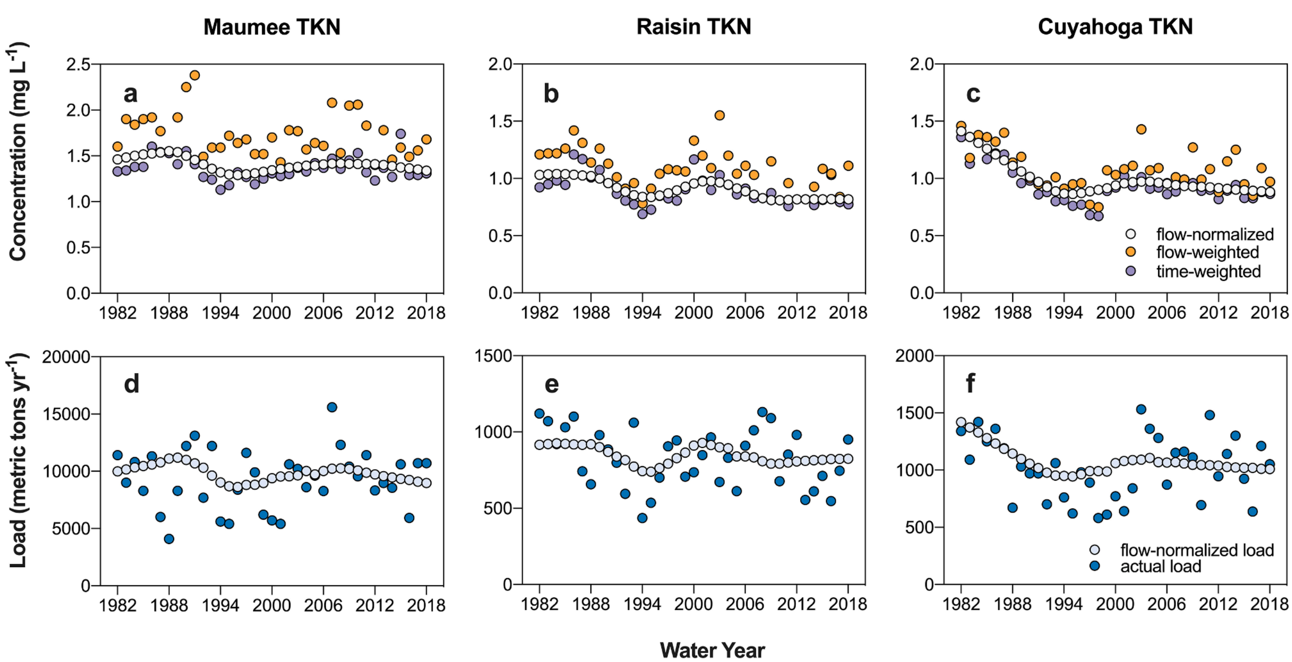

Fig. 7. TKN concentration (a–c) comparison between flow-normalized concentration from WRTDS, flow-weighted mean concentrations, and time-weighted mean concentrations over time. Flux (d–f) is calculated the traditional way (dark blue) or using WRTDS to flow-normalize (light blue). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

(Fig. 9b). The same analysis a few years later after the upwards trends are well established (results not shown) showed a reasonable level of agreement among all of the measures of trend, but the uncertainty about the slopes were much narrower for the flow-normalized measures.

4. Discussion

Method development for water quality trend assessment has a long history (Hirsch et al., 1991, 1982; Lettenmaier, 1976; Montgomery and Reckhow, 1984). Early papers emphasized approaches to ensure that the assumptions supporting classical statistical testing methods were essentially met (Gilliom et al., 1984; Helsel and Hirsch, 1988; Hirsch and Slack, 1984) or that sample sizes would be adequate to differentiate signal from noise using classical statistical tests (Reckhow and Stow, 1990). Recent statements by the American Statistical Association disavowing the use of p-values and statistical significance (Wasserstein et al., 2019; Wasserstein and Lazar, 2016) make methods that can reveal signals by reducing noise — such as we showed here using flow-

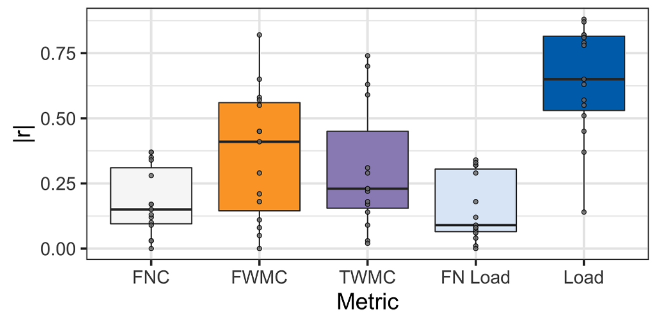

Fig. 8. Absolute value of the correlation coefficient between flow and analyte response across all sites, analytes, and metrics (each box n = 15 values; shown in detail in Supporting Information Figs. S1–S5). FNC = flow-normalized concentration, FWMC = flow-weighted mean concentration, TWMC = time-weighted mean concentration, FN Load = flow-normalized load, Load = actual load.

normalization — especially useful.

Because updated load targets have been adopted for both TP and SRP, these trends are of primary interest. Since the early 2000s, approximately the time that algal blooms began reoccurring in Lake Erie's western basin, flow-normalized TP concentrations and loads exhibited only slight changes. The Maumee, which is considered to be the main driver of harmful algal blooms in Lake Erie's western basin (Annex 4 Objectives and Targets Task Team, 2015), has exhibited steadily, but slowly decreasing flow-normalized TP concentrations while flow-normalized TP loads were almost unchanging (Fig. 3a,d). In contrast flow-normalization reveals Maumee SRP concentrations and loads were increasing in the early 2000s, and stabilized in approximately 2006 (Fig. 4a,d). Following a decline from approximately 2000–2009, flow-normalized TP and SRP concentrations and loads increased in the Raisin beginning in 2010 (Figs. 3 and 4, respectively), while all flow-normalized phosphorus measures have gradually declined in the Cuyahoga over that time. While nitrogen is of currently of secondary interest, it is interesting to note that overall, flow-normalized concentrations and loads of TN, nitrate, and TKN (Figs. 5–7) exhibit trends similar to flow-normalized TP concentrations and loads, in each respective tributary (Fig. 3), suggesting similar causal factors.

Our point in this analysis was not to interpret every bump and wiggle in the time-series of each metric presented, but rather to highlight the utility of flow-normalization in revealing those underlying patterns. Generally, trends revealed by flow-normalization do not contradict those of non-normalized metrics, however flow-normalization makes the patterns more perceptible. In addition, flow-normalization reduces the problem of mis-identifying trends that arise from having one or two wet or dry flow years near the end of the record. While FWMC better represents the average concentration delivered to the lake than either TWMC or FNC, making it an informative indicator to track, the high correlation with flow imposed by flow-weighting increases the variability of this metric making trends more difficult to discern. Whether the nutrient goal should be related to concentration or load targets — and depending on the nature of the control strategies these can describe rather different trend patterns — is not part of the present discussion. We simply suggest flow-normalized concentrations and flow-normalized loads should be used to evaluate progress toward meeting targets.

The flow-normalized concentrations, loads, and trends offer advantages: their much higher signal to noise ratio compared to time- or flow-weighted metrics means they are likely to identify a significant change sooner, the estimates of trend magnitude will be more accurate, and they are less likely to create "false alarms" when a particular pattern of high or low flows creates the appearance of trend that then disappears when flow conditions change. Although our results do not indicate any reductions through 2018 in response to actions taken to meet the new phosphorus targets, lags in the watershed are likely (Jarvie et al., 2013; Muenich et al., 2016) thus, hopes for a rapid response are probably optimistic. However, flow-normalization is our best approach for detecting and quantifying progress when it ultimately occurs.

CRediT authorship contribution statement

Craig A. Stow: Conceptualization, Writing, Reviewing and editing. **Robert M. Hirsch:** Conceptualization, Formal analysis, Reviewing and editing. **Laura T. Johnson:** Data curation, Reviewing and editing. **Freya E. Rowland:** Formal analysis, Visualization, Writing, Reviewing and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence

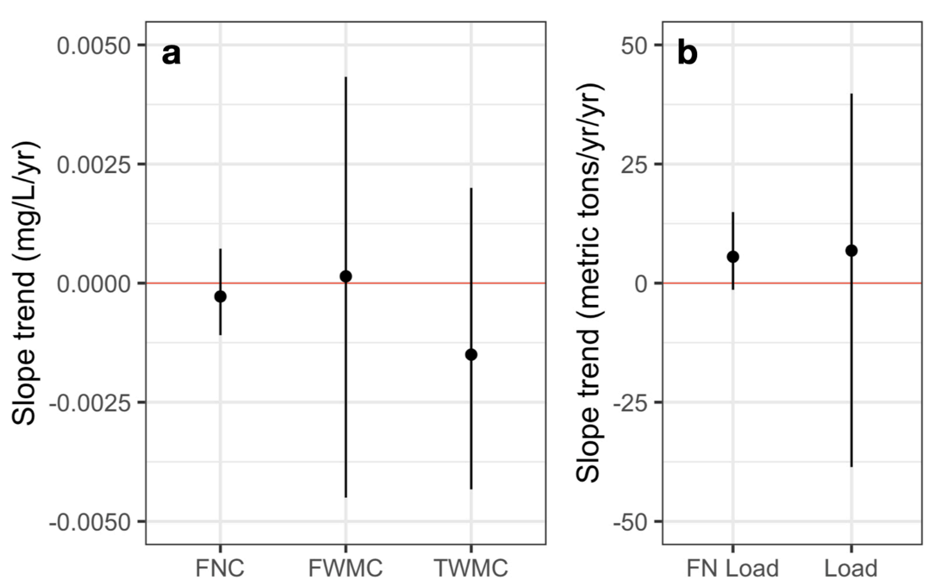

Fig. 9. Slope trends estimates and 90% confidence interval for (a) concentration trends and (b) load trends for SRP in the Maumee River for the decade ending with water year 1999. FNC = flow-normalized concentration, FWMC = flow-weighted mean concentration, TWMC = time-weighted mean concentration, FN Load = flow-normalized load, Load = actual load.

the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2021.107601.

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