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ARTICLE

Detecting Unusual Temporal Patterns in Fisheries Time Series Data

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Abstract

Long-term sampling of fisheries data is an important source of information for making inferences about the temporal dynamics of populations that support ecologically and economically important fisheries. For example, time series of catch-per-effort data are often examined for the presence of long-term trends. However, it is also of interest to know whether certain sampled locations are exhibiting temporal patterns that deviate from the overall pattern exhibited across all sampled locations. Patterns at these "unusual" sites may be the result of site-specific abiotic (e.g., habitat) or biotic (e.g., the presence of an invasive species) factors that cause these sites to respond differently to natural or anthropogenic drivers of population dynamics or to management actions. We present a Bayesian model selection approach that allows for detection of unique sites—locations that display temporal patterns with documentable inconsistencies relative to the overall global average temporal pattern. We applied this modeling approach to long-term gill-net data collected from a fixed-site, standardized sampling program for Yellow Perch *Perca flavescens* in Oneida Lake, New York, but the approach is also relevant to shorter time series data. We used this approach to identify six sites with distinct temporal patterns that differed from the lakewide trend, and we describe the magnitude of the difference between these patterns and the lakewide average trend. Detection of unique sites may be informative for management decisions related to prioritizing rehabilitation or restoration efforts, stocking, or determining fishable areas and for further understanding changes in ecosystem dynamics.

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Fisheries management typically relies on long-term data, such as those generated by fishery-independent surveys, to produce information about status and trends in fish stocks. For example, data from monitoring programs are frequently used to evaluate hypotheses about fish abundance and distribution, gear selectivity, and relationships with predictor variables of interest (Hamley and Regier 1973; Anderson 1998). Because many management decisions (Detar et al. 2014) as well as biotic (e.g., introduced species; Pine et al. 2005) and abiotic (e.g., climate change; Wenger et al. 2011) drivers of fish populations are often expected to produce changes in fish abundance over time, fishery-independent surveys are commonly used to detect temporal trends (Wagner et al. 2013). It is also common for management actions and research to span across many sites, with "sites" being defined as sampling locations within a single aquatic system (e.g., sites within a lake) or as individual lakes or stream systems within a larger geographic region. Regional management actions may include setting statewide or regionwide minimum length limits or bag limits. For example, the state of Wisconsin manages Walleyes *Sander vitreus* and the province of Ontario manages Lake Trout *Salvelinus namaycush* across a large number of inland lakes (Shuter et al. 1998; Beard et al. 2003).

In the context of trend detection, individual sampling sites may exhibit "unusual" or unique trends—those that quantitatively differ from the overall trend across the population of sites being monitored. Identification of sites that exhibit unusual trends is important in order to (1) potentially prioritize management efforts to unusual sites, if the unusual nature of the trend is of concern or interest to management (e.g., declining abundance of an endangered species or important fishery); (2) elucidate why management actions might not be having the intended effects on certain systems (e.g., is there something unique about the habitat at sites that are exhibiting unusual trends?); and (3) understand ecological drivers of temporal dynamics that could be used for projecting abundance at specific sites under future environmental scenarios.

TABLE 1. Middepth (m) of gill-net sets and total catch of Yellow Perch at 15 fixed-location gill-net sites in Oneida Lake, New York, 1957–2010. Sites are listed in ascending order based on the time of year in which they were sampled. Site number is listed for referencing in Figures 1–3.

Site name	Site number	Depth (m)	Yellow Perch catch
Phillips Point	1	18	4,287
Dakin Shoal	2	14	4,081
Shackelton Point	3	26	6,003
Buoy 125	4	9	6,473
Damon Point	5	28	6,374
Dutchman Island	6	17	7,773
Buoy 129	7	31	3,200
Buoy 113	8	18	5,083
Cleveland	9	19	4,801
Jewell	10	26	4,024
Buoy 133	11	14	2,923
Lewis Point	12	19	1,846
Dunham Island	13	21	1,215
Willard Island	14	20	839
Bushnell Point	15	22	998

Most aquatic systems exhibit spatial heterogeneity, and conservation and natural resource management has traditionally attempted to understand distinct spatial characteristics that might aid in resource management (e.g., source–sink dynamics). Unique spatial units have served as a basis for determining locations of marine reserves (e.g., Hooker et al. 1999; Airamé et al. 2003) or otherwise protecting spawning aggregations (Murawski et al. 2000) and also for mitigating the negative impacts of climate change on species distributions through landscape design and manipulation (Pearson and Dawson 2005). In each of these examples of spatially explicit management approaches, it was imperative to identify unique habitats that were most suitable in space and time as the targets of a management action. Because ecosystem dynamics are constantly changing, often in nonlinear ways, identifying unique patterns at varying spatial scales can be used as one tool in the decision making framework for effective, feasible, and timely management.

Although a temporal trend is often defined as a linear (monotonic) change over time (Wagner et al. 2013), this definition of temporal change may not always be sufficient to capture the nonlinear dynamics of fish population responses to management or environmental drivers (Shelton and Mangel 2011). Therefore, this study focuses on detecting temporal "patterns," which summarize year-to-year changes in dynamics that are often critically important to understanding systems but that may not be adequately quantified when estimating long-term linear trends. For instance, a site may exhibit important patterns over time (e.g., some years with very high or very low catches) but without showing a significant long-term temporal trend. In the present study, a Bayesian model choice approach modified from Li et al. (2012) was applied to gill-net data describing the catch of Yellow Perch *Perca flavescens* in Oneida Lake, New York (Rudstam and Jackson 2015). Our objective was to identify sample sites that exhibited unusual trends in comparison with the temporal pattern described by all available data. We also attempted to understand why sites that were identified as having unusual trends showed temporal patterns that deviated from the overall trend observed in the lake. Although we applied the approach to a long-term data set, it is also possible to use Bayesian model choice on much shorter time series (Li et al. 2012). Identification of unusual temporal patterns at varying spatial scales could help focus efforts to elucidate the mechanisms or underlying causes that influence the departure from a common temporal pattern.

METHODS

Study Site and Data Description

Oneida Lake, with a surface area of 20,700 ha and a mean depth of 6.8 m, is the largest lake that is located entirely within the borders of New York State. The lake has a long history of fisheries research and sampling and is the site of a fishery-independent gill-net sampling program that dates back to the 1950s. Currently, multifilament gill nets are set at 15 fixed locations, which are sampled in a standardized sequence from June to September (Table 1; Figure 1). The survey gear comprises two multimesh gangs, which are set on bottom and fished overnight for approximately 12 h, including dawn and dusk. For each gang, mesh size ranges from 38 to 102 mm (stretch mesh) in 13-mm intervals across six panels. Yellow Perch typically comprise the majority of the catch in annual gill-net sampling (Irwin et al. 2016). We focused on Yellow Perch for this study because they are a target species for a long-term monitoring program and because research and management interest in their spatiotemporal population dynamics continues to the present. Gill-net catch data were combined across mesh sizes, resulting in 15 observations for each survey year. We used 53 years of gill-net catch data from 1957 to 2010 (data were not available for 1974), resulting in 795 observations.

Model Description

*Trend modeling.—*We employed a Bayesian hierarchical modeling framework and a Bayesian model choice procedure to determine the probability that the temporal pattern for a given site deviated from a common trend, which was estimated from data across all sites. We followed a model structure similar to that of Li et al. (2012), who used the approach for detecting unusual temporal patterns in human mortality, by fitting two alternative models: one that assumed a common trend across all sites (model 1); and one that estimated trends independently for each site (model 2). We assumed a lognormal probability distribution for our response variable: $y_{i,t} = \log_e(\text{catch}_{i,t} + 1)$. A constant of 1.0 was added to the raw catch data prior to log transformation to accommodate four observations with zero catch. The two alternate models were

$$y_{i,t} = \begin{cases} \text{Norm}\left(\alpha_0 + \eta_i + \gamma_t, \sigma_1^2\right) \text{ model 1} \\ \text{Norm}\left(\phi_i + \nu_{i,t}, \sigma_2^2\right) \text{ model 2} \end{cases}.$$

Model 1 assumes that the temporal trend (γ_t) is the same for all i sites, where α_0 is the overall intercept (a diffuse normal prior, Norm[0, 1,000], was used for α_0); η_i is a random site effect (i.e., an adjustment to the overall intercept, allowing each site to differ in average $\log_e$[catch]; $\eta_i \sim \text{Norm}\left[0, \sigma_\eta^2\right]$; a diffuse uniform prior, Unif[0, 10], was used for σ_η); and γ_t is a random year effect. A Gaussian random walk prior of order 1 (RW[1]) was used for the temporal random effect. As outlined by Li et al. (2012), we used a one-dimensional conditional autoregressive

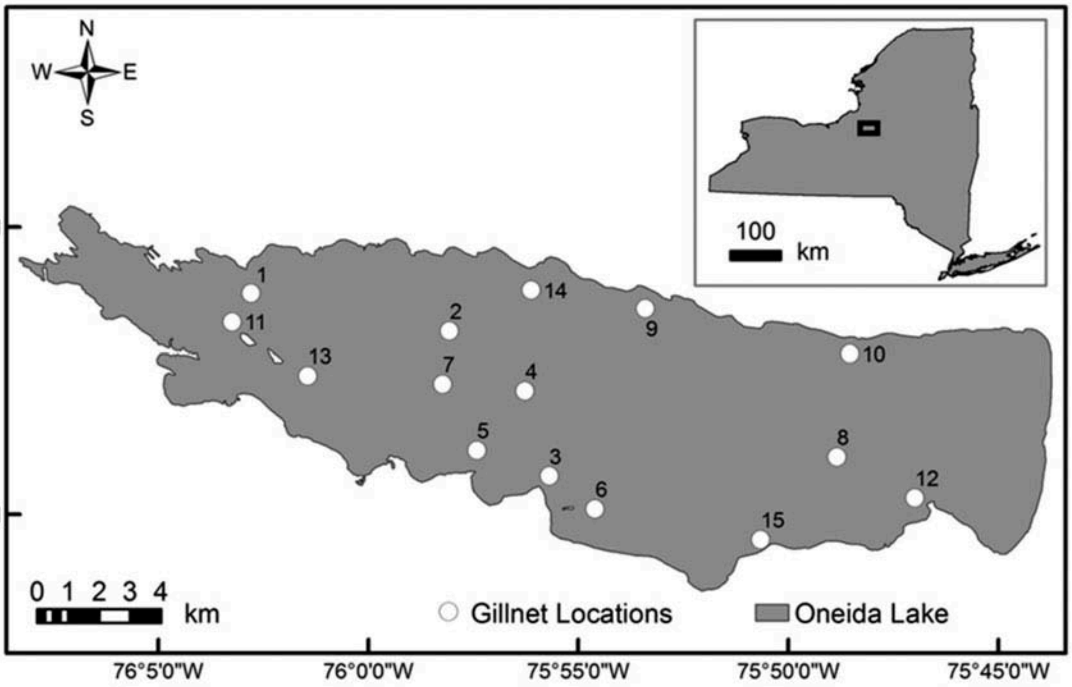

FIGURE 1. Fifteen fixed-location gill-net sites sampled in Oneida Lake, New York, from 1957 to 2010 (data were not available for 1974). Site numbers correspond to the locations listed in Table 1.

(CAR) model for the temporal RW(1), where $\gamma_{1:T} \sim CAR(Q, \sigma_{\gamma}^{2})$ and Q is a matrix that defines the temporal neighborhood structure. A diffuse uniform prior, Unif(0, 10), was used for σ_{γ}. Model 2 estimates the temporal trends for each site independently, where ϕ_i is the site-specific intercept (in this case, a diffuse normal prior, $\phi_i \sim$ Norm[0, 1,000], was used for each ϕ_i in contrast to the partial pooling allowed in model 1 for η_i); and $\nu_{i,t}$ is the site-specific trend. An RW(1) structure similar to that used in model 1 was assumed for $\nu_{i,t}$, where $\nu_{i,1:T} \sim CAR\left(Q, \sigma_{i,\nu}^{2}\right)$ and $\log(\sigma_{i,\nu}^{2}) \sim \mathrm{Norm}(\mu_{\sigma_{\nu}^{2}}, \omega_{\nu}^{2})$. A diffuse normal prior, Norm(0, 1,000), was used for $\mu_{\sigma_{\nu}^{2}}$ (the mean log site-specific variance); and a diffuse uniform prior, Unif(0, 10), was used for ω_{ν}. Residual variances for models 1 and 2 were σ_1^2 and σ_2^2, respectively (diffuse uniform priors, Unif[0, 10], were used for σ_1 and σ_2).

Model selection used a Bayesian formulation. For each site, a model indicator z_i was introduced to select estimates from either model 1 ($z_i = 1$) or model 2 ($z_i = 0$; Li et al. 2012). The posterior frequency of selecting the common trend model was obtained by $f_i = P(z_i = 1|\mathrm{data})$, where a small value of f_i indicates that the trend for site i is unlikely to follow the common trend (i.e., lower values of f_i suggest that a site is unusual). Model choice occurred by fitting each model separately and allowing a mixture model with indicator z_i to compare the model fits at each Markov chain–Monte Carlo iteration, which selected either model 1 or model 2. We assumed a Bernoulli(0.95) prior for z_i, which reflects the fact that we anticipated relatively few unusual trends a priori; however, we also investigated the sensitivity of our results to this prior by performing the analysis with $z_i \sim$ Bernoulli(0.5). We considered sites with f_i-values of 0.05 or less to be “unusual” (note that 0.05 here is *not* the same as an α-value used in a null hypothesis framework). See the Supplement available in the online version of this article for model code.

All models were fitted by using WinBUGS (Lunn et al. 2000) executed from within R (R Development Core Team 2015). WinBUGS was used due to the availability of the “car.normal” function for implementing the RW(1) prior. Three parallel chains, each with 70,000 iterations, were run with different initial values to generate 210,000 samples from the posterior distributions. The first 40,000 samples of each chain were discarded and every third sample was retained, resulting in a total of 30,000 samples (i.e., 10,000 samples/chain). To assess convergence, we examined the scale reduction factor (a convergence statistic) for each parameter as well as examining trace plots and posterior distribution plots.

Relating $\mathrm{f_i}$ *to a site covariate.*—We were interested in relating the f_i value (i.e., the probability that a site would follow the common trend) to site-specific covariates. Thus, we fitted a beta regression model to relate f_i to (1) site depth, calculated as the midpoint of the water column depth for each gill-net set, (2) the order in which each site was visited during each year, and (3) the total catch over the time series for each site. We chose site depth because potential distributional shifts in Yellow Perch could change the proportion of the population that inhabits shallow or nearshore areas. In general, water column depth is an important habitat component, and this information was available for each Oneida Lake site. Site visit order was examined because sites were sampled in the same order each year, meaning that the potential existed for a seasonality effect to interfere with what we would otherwise interpret as actual spatial differences. Finally, total catch was examined simply to address the question of whether sites with relatively high or relatively low catches were also those identified as unique sites.

In beta regression, the response variable must be greater than 0 and less than 1; therefore, we replaced f_i with $[f_i \cdot (n-1) + 0.5]/n$, where n is the number of sites (Smithson and Verkuilen 2006). We used a logit link to relate the conditional mean to the predictor variable. Thus, we assumed that f_i followed a beta distribution with a mean modeled as a function of site depth, site visit order, or total catch. Diffuse normal priors (Norm[0, 1,000]) were used for the slope and intercept parameters. We fitted the models by using JAGS (Plummer 2013) executed from within R. Three parallel chains, each with 50,000 iterations, were run with different initial values to generate 150,000 samples from the posterior distributions. The first 30,000 samples of each chain were discarded and every third sample was retained, resulting in a total of 20,000 samples. We examined the scale reduction factor for each parameter, trace plots, and posterior distribution plots to assess convergence. All estimates are reported as posterior means and associated 95% credible intervals (CIs).

RESULTS

On average, gill-net catches of Yellow Perch declined substantially over time in Oneida Lake (Table 1; Figure 2). However, 6 of the 15 sampled locations displayed temporal patterns that we judged to be inconsistent (i.e., site-specific $f \leq 0.05$) with the overall temporal pattern suggested by the aggregated data. Three sites (sites 1, 2, and 4) generally produced catches that were (1) higher than the common model predictions for early years of the time series and (2) lower than the common model predictions for recent years. Thus, 50% of the sites identified as unusual displayed a period of more recent decline than predicted from the common model. In contrast, sites 8 and 9 displayed relatively consistent and high variability in catches throughout the entire surveyed time period, with relatively little temporal pattern. Therefore, those two sites were unusual for their lack of a temporal decline. Lastly, site 15 showed a decline over time, which appeared somewhat consistent with the common pattern, but it produced an unusual number of low catches that were concentrated in the middle of the time series. During the most

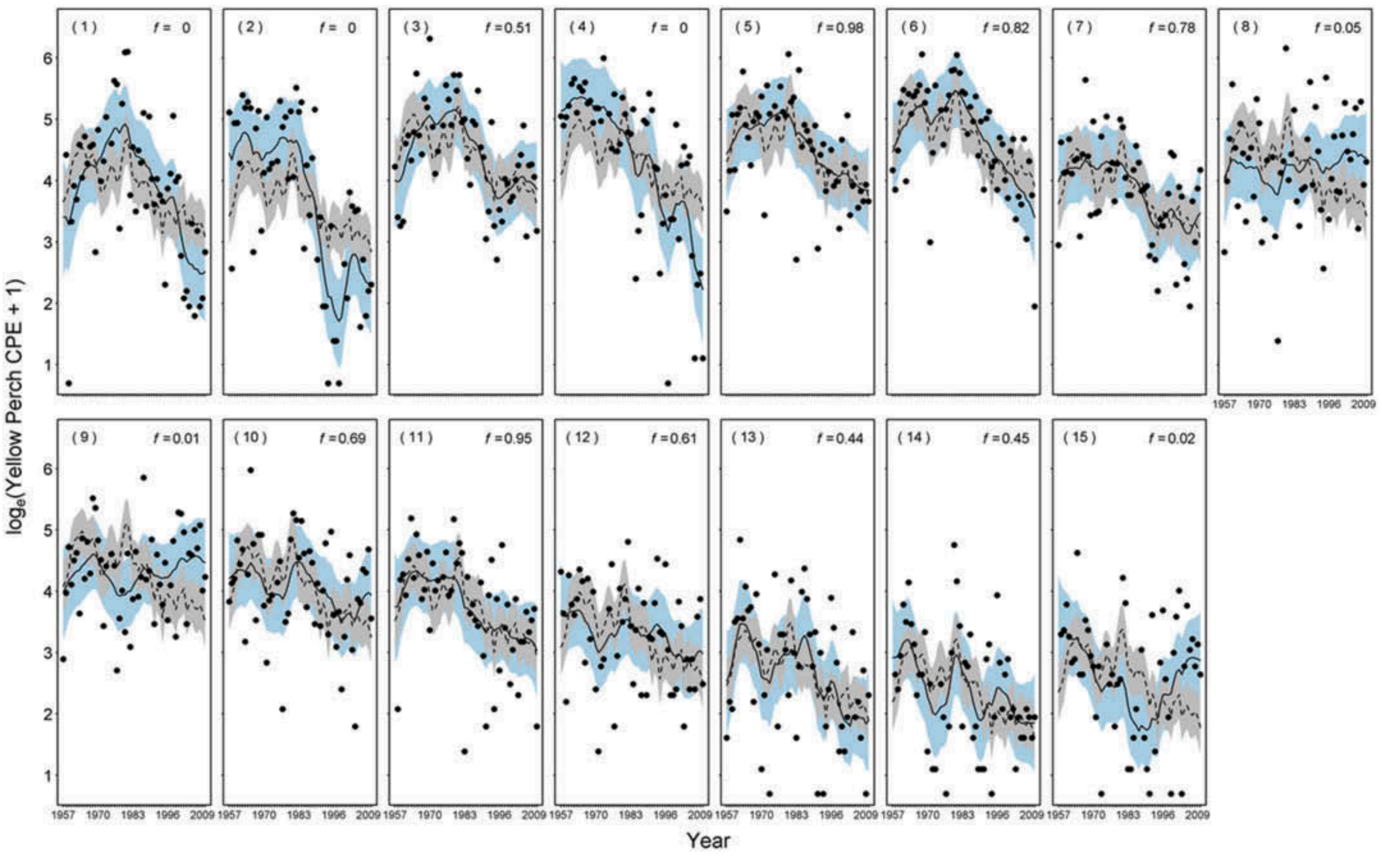

FIGURE 2. Temporal trends in $\log_e$-transformed Yellow Perch catch (catch per effort [CPE] = number per gill-net set; solid circles) at 15 sites in Oneida Lake, New York, 1957–2010. Posterior mean fitted lines are from two models: one that assumes a common trend for all sites (dashed line; gray-shaded area = 95% credible region); and one that estimates a unique trend for each site (solid line; blue-shaded area = 95% credible region). The number in parentheses on each panel is the site number (defined in Table 1). The *f*-value refers to the probability that a site will follow the common trend; a small *f*-value indicates that the trend for a specific site is unlikely to follow the common trend.

recent decades, catches at site 15 returned to the scale of observations from the beginning of the time series (i.e., were often large relative to the low catches observed during the 1970s and 1980s). Overall, the magnitude of deviation between site-specific temporal patterns and the common temporal pattern varied across sites, as would be expected based upon *f*-values (Figure 3).

Once the *f*-values were obtained for each site, we used beta regression to relate those values against site-specific characteristics so as to further illustrate how *f*-values might be useful for managers in attempting to evaluate spatial differences. A modest relationship was found between the posterior probability of adhering to the common trend and a measure of water column depth at the site (Figure 4). The relationship between the probability of a site having a trend similar to that of the common trend was positively related to the middepth of the gill-net set (estimated slope = 0.74; 95% CI = 0.35, 1.4); shallower sites tended to depart from the common pattern. No relationship was found for site visit order (estimated slope = 0.31; 95% CI = –0.36, 1.01) or total catch (estimated slope = –0.12; 95% CI = –0.86, 0.59), suggesting that differences in catch among sites were not having an undue influence on *f*-value determination. The selected value for the Bernoulli prior for z_i had little apparent effect on the results. Changing the prior from 0.95 to 0.50 did not affect the sites that were identified as unusual (*f*-values $\leq$ 0.05; Supplementary Figure S.1).

DISCUSSION

Using a Bayesian model choice procedure, we were able to identify six gill-net sites in Oneida Lake that displayed unique long-term temporal dynamics in Yellow Perch catches, in contrast with nine sites that exhibited a common temporal pattern when considered across the nearly 60-year time series. We also quantified the difference between common and unique trends in order to describe the magnitude of differences from an average temporal pattern for sites that were identified as unusual. Because the data considered here were collected over many decades, we expected that minor or few annual deviations from model 1 would not carry much weight in model

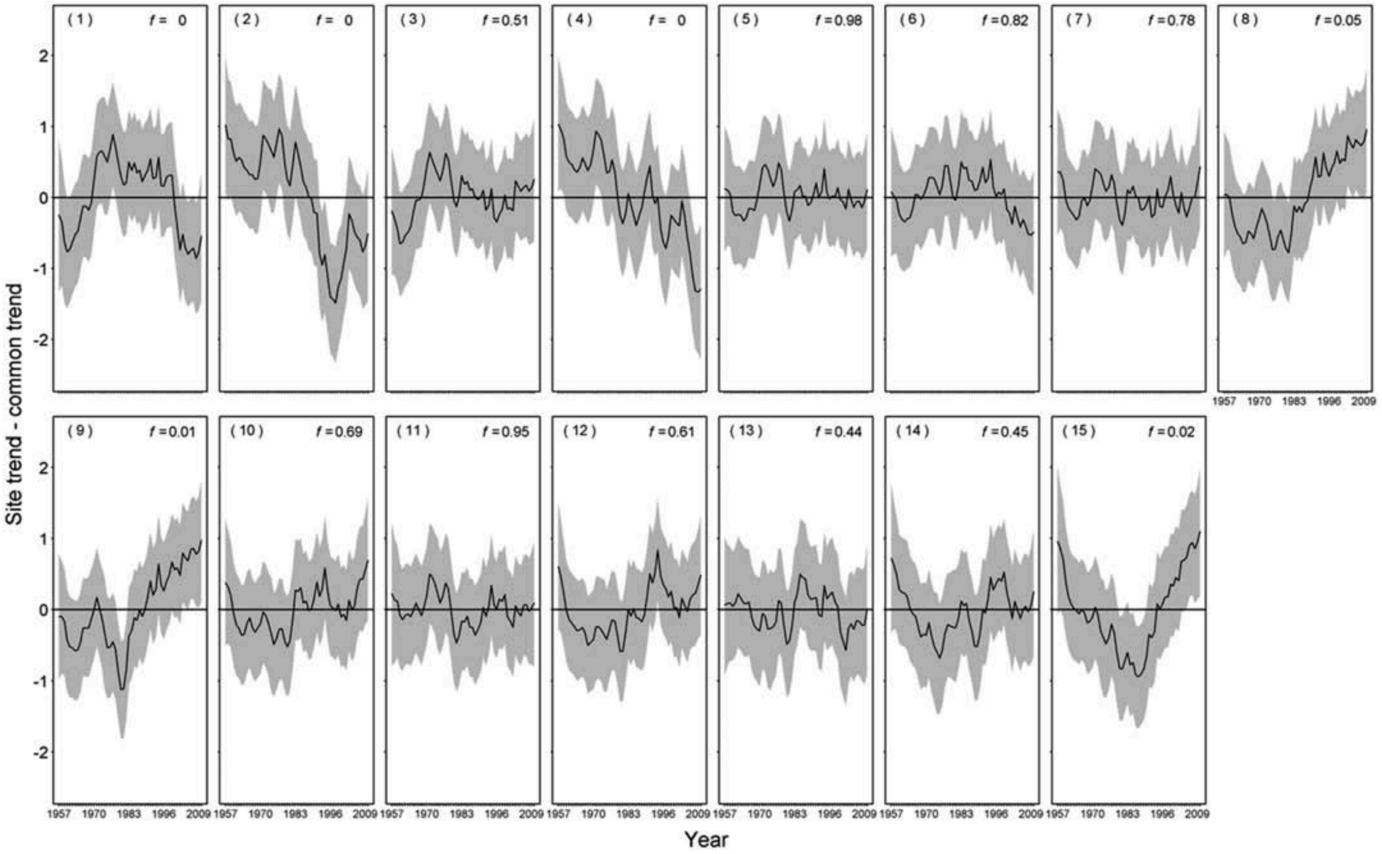

FIGURE 3. Difference between the estimated posterior mean site-specific trend and the estimated common trend (solid line) in $\log_e$-transformed Yellow Perch catch at 15 sites in Oneida Lake. The shaded area is the 95% credible interval for the difference between estimated trends. The number in parentheses is the site number (defined in Table 1). The *f*-value refers to the probability that a site will follow the common trend; a small *f*-value indicates that the trend for a specific site is unlikely to follow the common trend.

selection and that substantial evidence would be needed to classify a site as unusual. However, Yellow Perch in Oneida Lake are generally considered to be a distributed single stock (Forney 1974; Clady 1976; Irwin et al. 2009), although some homing to spawning locations may occur (Clady 1977). Thus, for this case study example, any interpretation of unique site-specific temporal patterns as representing dynamics of truly unique subpopulations that persist over time should be made with caution. Rather, we interpret the detection of unusual sites as likely representing intra-annual spatial variability, some of which may be changing over time in relation to habitat alterations and other ecological changes that occurred in Oneida Lake during the sampling period (Mayer et al. 2001; Zhu et al. 2006). For instance, we found some evidence that water column depth partially explained the probability that a site would display a unique temporal pattern, and this relationship was stronger than that observed for either sampling order or a site's cumulative catch. Furthermore, half of the unique sites recently displayed a steeper decline in catch than was observed with the common model. In this regard, the availability of certain habitat types (e.g., forage or refuge areas) and the preference of Yellow Perch for those habitat types may be shifting over time.

The sensitivity of the Yellow Perch's spatial distribution within Oneida Lake to habitat and food web changes remains an area worthy of further study. Our results were not sensitive to a substantial change in the Bernoulli prior on z_i, suggesting that the sites we identified as unusual were not sensitive to our prior belief regarding the proportion of sites that would be considered unusual. In a broader sense, the methodological approach described here could be informative to natural resource managers who are interested in identifying both the location and the magnitude of spatial differences in temporal patterns. However, our analysis took advantage of a standardized fishery-independent time series, so depending on the source of catch-per-effort time series data (e.g., commercial catch data), additional steps may be required to develop a standardized index of abundance that accounts for factors such as differences in boat size (Deroba and Bence 2009).

In Oneida Lake and elsewhere, Yellow Perch have been noted to be variable in abundance, particularly at early ages (Forney 1971). Yellow Perch are the primary forage of many

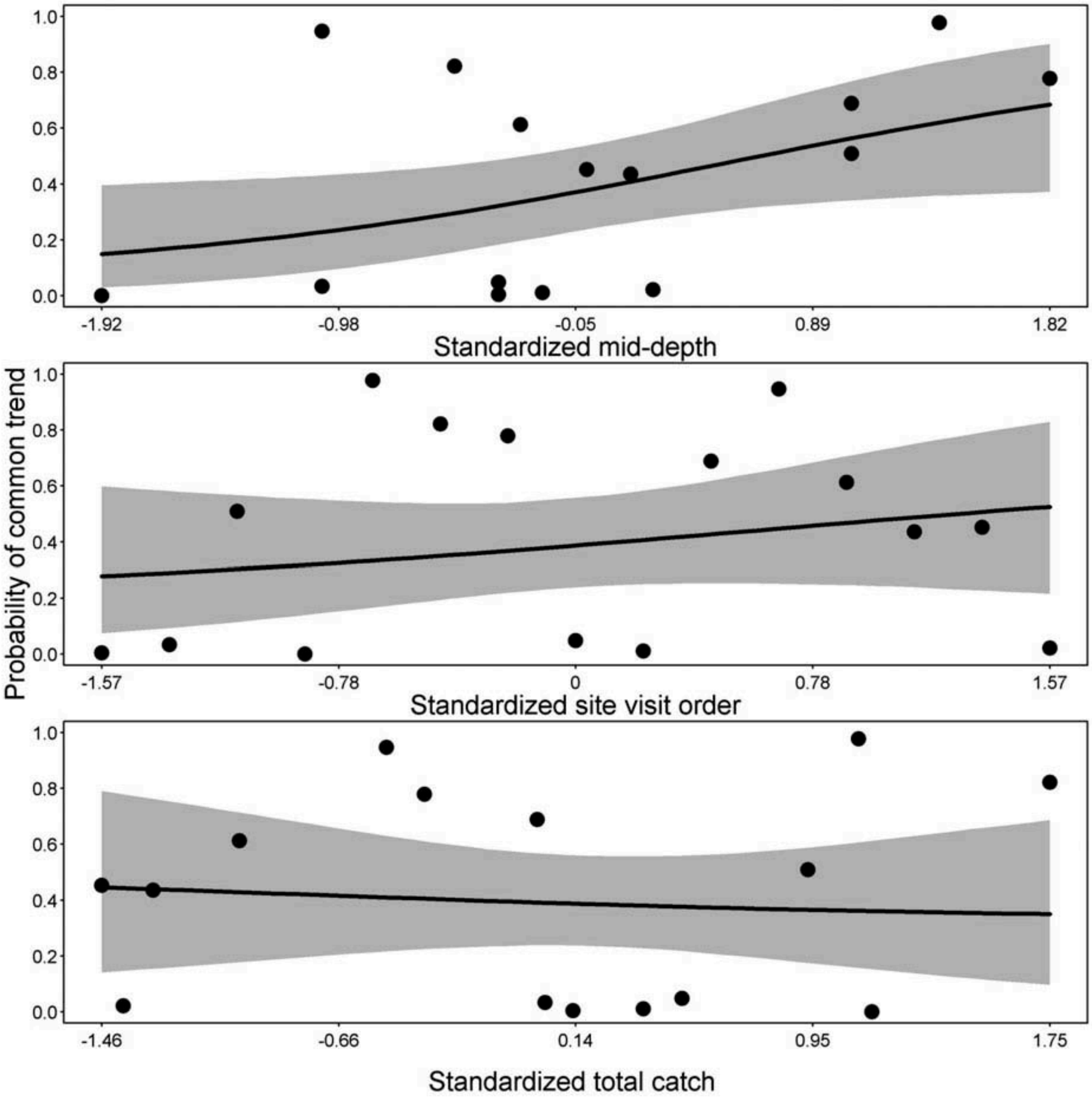

FIGURE 4. Relationship between the probability that a site will display a trend in Yellow Perch catch that follows the common trend (f_i; solid circles) and the standardized middepth of the gill-net set (upper panel), the standardized site visit order, and the standardized total Yellow Perch catch in Oneida Lake. The solid line represents the estimated posterior means from a beta regression model, and the shaded area is the associated 95% credible region.

piscivorous species, and they exhibit strong predator–prey dynamics with Walleyes (Rudstam et al. 1996). The common temporal pattern we detected for Yellow Perch was one of fluctuating catches (but no substantial overall trend) until the late 1980s, after which the Yellow Perch catch continued to be variable but trended lower by the end of the data set. In recent decades, White Perch *Morone americana*, Gizzard Shad *Dorosoma cepedianum*, zebra mussels *Dreissena polymorpha*, and double-crested cormorants *Phalacrocorax auritus* have all been investigated as potential drivers of ecosystem change in Oneida Lake. Irwin et al. (2016) found lower Yellow Perch catches during the years after zebra mussels were established; however, other studies also noted the potential for substantial impacts of predation on Yellow Perch—for instance, from Walleyes, anglers, and double-crested cormorants (Forney 1974; VanDeValk et al. 2002; Rudstam et al. 2004). We did not explicitly include predator–prey dynamics or introduced species covariates to our model, but these changes to Oneida Lake may have differentially impacted small-scale Yellow Perch density or distribution within the lake.

The use of Bayesian model selection for detecting temporal dynamics in fisheries data comes with several considerations that should be accounted for on a case-by-case basis. The first consideration is the length of the time series that the model will be describing. Fisheries data (particularly catch) are often highly variable, and over very short time series, the variability in the data may prohibit the confident estimation of patterns. However, this concern is not unique to Bayesian model selection and is therefore not a weakness of this particular method. The present modeling approach may also be used in situations where long-term data or multiple systems are being investigated and when the question has more to do with the inherent differences among spatial units. A second consideration is that the *f*-value is cumulative, meaning that low *f*-values (unusual sites) are not necessarily exhibiting recent deviations from the common dynamic. It is possible, however, to derive temporal differences between site-specific trends and the common trend in order to further examine the magnitude of differences for smaller periods of time (e.g., Figure 3).

As with many trend detection analyses, we envision Bayesian model selection not necessarily as an endpoint for resource managers but rather as a tool in the decision making process. For example, knowledge of which sites differ from a common trend may be important, but the results may also have to be viewed in terms of larger changes in the community; drivers such as introduced species, predator–prey dynamics, and climate change can impact the catch and abundance of species. However, knowing which sites are behaving differently from an overall system dynamic may help to elucidate the relative impact of other drivers. The Bayesian aspect of this model selection procedure also frees us from the constraints of critical values and permits greater flexibility in the interpretation of results. For example, although we selected an *f*-value cutoff of 0.05, any defensible value may be selected. We identified a natural break in the distribution of *f*-values at around 0.05, but this value can be adjusted based on knowledge of the particular system or can be set at a level deemed appropriate by managers or stakeholders. Another flexibility of the *f*-values is that they can be ordinated for interpretation. Therefore, rather than identifying a threshold *f*-value, all sites can be ranked from "most unusual" to "most common"—an interpretation that may be practical if resource managers are limited to a specific number of sites or if managers are interested in a specific percentage of most unusual sites. Likewise, we expect that identification of unique temporal patterns might be of broad interest for cases in which the responses do not manifest quickly as changes in the overall global average condition. It may also be useful to use explanatory covariates to further characterize the *f*-values, as was done in this study. We found modest evidence that water column depth helped to explain the uniqueness of Yellow Perch catch at sites within Oneida Lake; however, we see this aspect of the model as having greater appeal for use with systems where more covariate information can be explored.

Detection of temporal trends remains highly important in fisheries science because the observed trends often influence a suite of management decisions ranging from determining annual differences in stocking programs to developing strategies for management in the face of large-scale regime or ecosystem shifts. Owing to this broad application and the limited resources that are typically available to managers, temporal trend detection and description constitute a growing area in fisheries and will likely increase in importance as additional long-term data are made available and as managers with limited capacity identify their need to re-assess and prioritize sites for management, remediation, or further study. Additionally, spatial heterogeneity is ubiquitous in aquatic habitats, and applications of Bayesian model selection can easily extend to a wide range of management needs, such as the selection of marine protected areas, prioritization within endangered species management, and toxicological and site remediation scenarios, among others.

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