11-23-2013

Managing for resilience: early detection of regime shifts in complex systems

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Clean Techn Environ Policy
DOI 10.1007/s10098-013-0687-2

ORIGINAL PAPER

Managing for resilience: early detection of regime shifts in complex systems

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Received: 30 March 2011 / Accepted: 9 November 2013

Abstract The broad implications of catastrophic regime shifts have prompted the need to find methods that are not only able to detect regime shifts but more importantly, identify them before they occur. Rising variance, skewness, kurtosis, and critical slowing down have all been proposed as indicators of impending regime shifts. However, these approaches typically do not signal a shift until it is well underway. Further, they have primarily been used to evaluate simple systems; hence, additional work is needed to adapt these methods, if possible, to real systems which typically are complex and multivariate. Fisher information is a key method in information theory and affords the ability to characterize the dynamic behavior of systems. In this work, Fisher information is compared to traditional indicators through the assessment of model and real systems and identified as a leading indicator of impending regime shifts. Evidenced by the great deal of activity in this research area, it is understood that such work could lead to better methods for detecting and managing systems that are of significant importance to humans. Thus, we believe the results of this work offer great promise for resilience science and sustainability.

Keywords Regime shift · Leading indicator · Fisher information · Resilience · Environmental management

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Introduction

Complex systems are multivariate and often characterized by nonlinear dynamics. While these systems are not implicitly designated by multiple regimes, many complex systems do in fact display this structure (Garmestani et al. 2009a). A regime can be identified by the variables that define the system, and the periodicities associated with that regime (Fath et al. 2003). The range of possible movements within a dynamic regime that can occur without generating a regime shift is the domain of attraction (Ludwig et al. 2002). Over time, resilient systems exhibit self-organized patterns with a particular degree of dynamic order. However, it is possible for a system to shift from one regime to another resulting in a temporary loss of dynamic order denoting system reorganization (Karunanithi et al. 2008). These regime shifts are typically associated with significant consequences (e.g., declining fish stocks, loss of water quality, economic downturn).

Threshold methods (e.g., TITAN) and models are being explored as tools to aid in identifying thresholds in ecological systems (Baker and King 2010; Cuffney et al. 2011; King and Baker 2011; Qian and Cuffney 2012). Results from these efforts are compelling as they provide insight on change point identification in trends related to individual taxa and highlight the importance of model alternatives. Although thresholds and regime shifts appear to be quite closely related concepts, these phenomena are quite distinct. In particular, thresholds are defined as a point where small changes in underlying system variables produce large scale system wide responses and result in sudden and dramatic changes in key properties and system quality (Groffman et al. 2006). On the contrary, regime shifts do not require abrupt tipping points but can be the result of long periods of system reorganization. However, while thresholds do not automatically imply regime shifts, threshold approaches may provide insight into pertinent trends in key variables that coincide with a regime shift.

Understanding regime shifts is critical to system resilience and sustainability (Pawlowski and Cabezas 2008). Research in this area initially focused on the detection of regime shifts in complex systems, and a substantial literature has developed on the subject. The new thrust of research is concerned with predicting regime shifts before they occur. Recent research shows that there are system-specific conditions that indicate that a system is losing resilience and approaching a regime shift (Brock et al. 2008). For example, a shift from an oligotrophic to a eutrophic regime in a shallow lake may be preceded by an increase of the periphyton-layer covering the macrophytes and a reduction in the proportion of piscivorous fish (Brock et al. 2008). Other researchers have found that fishing pressure can increase population variability in fisheries that are not yet characterized as "overfished," and these results indicate that fishing pressure can reduce the resilience of a fishery and make it more vulnerable to perturbations (Hsieh et al. 2006).

There are several suggested mechanisms that may indicate that a regime shift is imminent. For instance, divergence in the spatial variance of ecological models has been shown to predict regime shifts, but this is limited to the fidelity of the model. Further, researchers have reported similar results in the variance spectrum of their model of North Atlantic Ocean circulation (Oborny et al. 2005; Kleinen et al. 2003). Their model showed that the variance spectra for system variables demonstrated lower frequencies and longer wavelengths as the system approached a regime shift (Kleinen et al. 2003). Carpenter and Brock (2006) report that the variability in the concentration of phosphorous in lake ecosystems was detectable before a regime shift. They simulated this response and assert that rising standard deviation in the data acts as a signal that a regime shift is imminent.

Brock and Carpenter (2006) also report that it is possible to predict regime shifts in spatial data. They tracked the rise of spatially broad-scale pollutant emissions and the associated decline in ecosystem services. They assert that a variance index computed as the maximum eigenvalue of the covariance matrix of the time series data rises (peaks) in advance of a regime shift, and requires no detailed knowledge about the drivers of the regime shift for the index (Brock and Carpenter 2006). van Nes and Scheffer (2007) propose that the rate of recovery from small perturbations operates as an indicator of system resilience. In their model, the rate of recovery from small perturbations decreases as the system nears a regime shift (i.e., "critical slowing down") (van Nes and Scheffer 2007). Dakos et al. (2008) found that "critical slowing down" was ubiquitous in historical climatic regime shifts. Chisholm and Filotas (2009) report that "critical slowing down" also operates as a predictor of a Hopf bifurcation in predator–prey models where prey are regulated by predation rather than density dependence, and in competition models where the dynamics of rare species operate at different temporal scales than those of common species. In addition to "critical slowing down," increasing variance and red shift in the frequency spectrum are considered to be predictors of impending regime shifts (van Nes and Scheffer 2007). Biggs et al. (2009) suggested that changes in ecological time series data could also serve as an indicator of an impending regime shift. In particular, increasing variability, skewness, kurtosis, autocorrelation, and slow rates of recovery from perturbations, may all serve as leading indicators of impending regime shifts. However, increases in these indicators only occur at the onset of the regime shift and typically too late for effective management actions (Biggs et al. 2009). Further, Scheffer et al. (2009) noted that traditional indicators have shown great promise in signaling regime shifts in simple systems; however, work is still needed to determine whether these indicators provide early warning signals in real complex systems. Quantifying and classifying regime shifts in complex systems requires the task of tracking multiple system variables simultaneously over time. An integrated indicator which compiles multiple variables into a single index may provide meaningful insight into assessing these types of systems. As previously described, the variance index is one such measure and another is Fisher information.

Fisher information (FI) is a key method in information theory and affords the ability to collapse the behavior of multiple variables that characterize a complex system into an index that captures overall system dynamics to include regimes and regime shifts (Fath et al. 2003). It has been employed to derive core equations of thermodynamics, proposed and applied as a sustainability metric, used to explore the organizational dynamics of complex systems and implemented as a quantitative indicator for the detection and assessment of regime shifts (Cabezas and Fath 2002; Mayer et al. 2006; Karunanithi et al. 2008, 2011; Eason and Cabezas 2012; Eason and Garmestani 2012, Gonzalez-Mejia et al. 2012a, b). Although Fisher information has been used to detect regime shifts, its behavior has not been explored as an early warning signal of impending transitions. Hence, the objectives of this paper are to (1) empirically investigate the relationship between Fisher information and traditional measures of critical transition to include: variance, skewness, kurtosis and critical slowing down and (2) explore the use of both traditional and integrated indicators (i.e., the variance index and FI) for detecting impending regime shifts. In the initial study, we simulated two model systems: a time-varying sinusoid as a simple pedagogic example and a two species predator–prey system and used the Spearman rank order correlation (SROC) test to assess the relationship between FI and traditional indicators. We then explored the use of both traditional and integrated indicators for detecting impending regime shifts by evaluating a shallow lake model and a real complex system: the Bering Strait marine ecosystem.

Characteristics of the traditional regime shift indicators under study

Variance, skewness and kurtosis are standard statistical measures and have been noted by numerous researchers to display an increasing trend prior to a shift (Kleinen et al. 2003; Oborny et al. 2005; Carpenter and Brock 2006; Biggs et al. 2009). Critical slowing down has also been suggested as a warning signal of an impending regime shift (van Nes and Scheffer 2007; Dakos et al. 2008; Biggs et al. 2009; Scheffer et al. 2009). Dakos et al. (2008) and Scheffer et al. (2009) indicated that as a system approaches a critical threshold, it slows in its recovery from perturbations. This slowing is reflected as a decreasing rate of change over time and consequently, an increase in autocorrelation. In the literature, critical slowing down is assessed by computing the lag-1 autocorrelation coefficient (AR1) of the data over time (Dakos et al. 2008; Biggs et al. 2009; Scheffer et al. 2009) and shifts are identified when there is an increasing trend in AR1.

Variance index

Brock and Carpenter (2006) explored the impact of spatially distributed pollutant emissions and declining ecosystem services by developing a model system to simulate dynamic changes in two regions. The variance index (computed as the maximum eigenvalue of the covariance matrix of the time series data) was used to collapse the behavior of multiple variables into an index and was noted to peak prior to a regime shift (Brock and Carpenter 2006).

Fisher information

Fisher Information was developed by statistician Fisher (1922) as a measure of the information present in a data set being used to fit an unknown parameter (Mayer et al. 2007). It is a fundamental quantity from which many known laws of nature (Frieden 2004) can be derived and has been shown to follow the second and third laws of thermodynamics (Karunanithi et al. 2008). The form of Fisher information used in this work was developed by Fath et al. (2003) and Mayer et al. (2007) as a measure of dynamic order:

$$I = \int \frac{\mathrm{d}s}{p(s)}\left[\frac{\mathrm{d}p(s)}{\mathrm{d}s}\right]^2, \tag{1}$$

where $p(s)$ is the probability density of the system being in a particular state s. This expression was developed such that Fisher information could be either computed analytically (Fath et al. 2003; Mayer et al. 2007) or estimated numerically (Karunanithi et al. 2008). We derive the numerical approach to computing the index by replacing the probability density $p(s)$ in Eq. (1) with its amplitude (i.e., $q^2(s) \equiv p(s)$) in order to minimize calculation errors for very small $p(s)$. Next, $\mathrm{d}p/\mathrm{d}s$ is solved as a function of q, such that:

$$\frac{\mathrm{d}p}{\mathrm{d}s} = 2q\frac{\mathrm{d}q}{\mathrm{d}s} \therefore \left(\frac{\mathrm{d}p}{\mathrm{d}s}\right)^2 = 4q^2\left(\frac{\mathrm{d}q}{\mathrm{d}s}\right)^2. \tag{2}$$

Equation (2) is substituted into Eq. (1):

$$I = 4\int \left[\frac{\mathrm{d}q(s)}{\mathrm{d}s}\right]^2 \mathrm{d}s. \tag{3}$$

Since our goal is to assess real systems, we adapted Eq. 3 for use with discrete data by using a summation to approximate the integral, giving the final expression:

$$I = 4\sum_{i=1}^{n}\left[q_i - q_{i+1}\right]^2. \tag{4}$$

This form of Fisher information (hence more noted as FI) does not require detailed knowledge of system structure or dynamics and can be used to characterize the dynamic order of model or real systems (Fath et al. 2003; Karunanithi et al. 2008).

From Eq. (1), note that FI is proportional to $\mathrm{d}p/\mathrm{d}s$. In the context of order, systems can exist within two idealized extremes, perfect disorder and perfect order. The perfect disorder case occurs when a system is unbiased toward any particular state (s). In other words, there is the same probability of being in one state as any other given state, i.e., $p\,(s) = p\,(1) = p\,(2) = \ldots p\,(n)$ and the PDF is flat and uniform (Fig. 1a). Accordingly, the system lacks order in that it can appear quite different from one observation to the next, and the resulting FI approaches zero, $\mathrm{FI} \propto \mathrm{d}p/\mathrm{d}s \to 0$ (Fath et al. 2003). Perfect order occurs when repeated measurements of the system result in the system being in the same state over time. This more structured system has high order and is biased toward a particular state or states. Accordingly, the PDF has a very steep slope and FI approaches infinity (Fig. 1b), $\mathrm{FI} \propto \mathrm{d}p/\mathrm{d}s \to \infty$. However, real systems typically function between these two system extremes (e.g., Fig. 1c).

Evaluating the dynamic behavior of a system entails obtaining information on its state over time. The condition or state of a system can be described by its n measurable

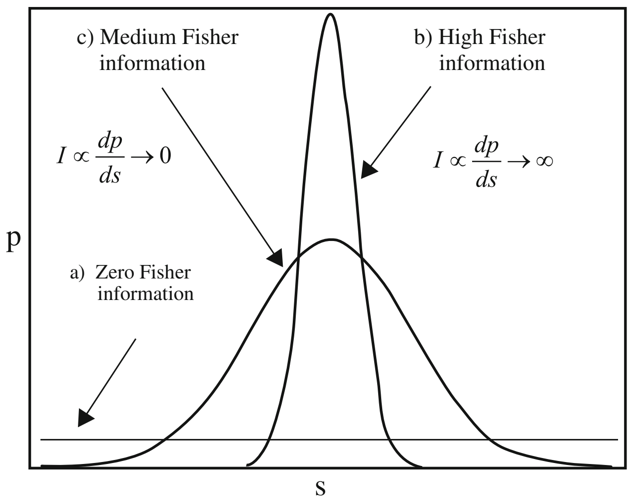

Fig. 1 Fisher information is proportional to dp/ds (adapted from Pawlowski and Cabezas 2008). **a** A system that has an equal probability of being in any state lacks order; accordingly, $I \to 0$ and represents the perfect disorder case. **b** The perfect order case occurs when a system is biased toward a state (or finite number of states). Since this system is more orderly, $I \to \infty$. **c** However, most systems exist between these two extremes

variables, such that a time-varying system has a trajectory in a phase space defined by n-dimensions (x_i) and time (t). Each point in the trajectory is defined by specific values for each of the variables (i.e., pt_i: [$x_1(t_i)$, $x_2(t_i)$ $x_3(t_i)\ldots x_n(t_i)$]). Since there is an inherent uncertainty in any measurement, each state s of the system is actually a region bounded by the uncertainty (Δx_i) for each variable not a single point, such that if $|x_i(t_i) - x_i\ (t_j)| \leq \Delta x_i$ is true for all variables then the two points at times i and j are indistinguishable and are noted as being in the same state of the system. Given this conceptual description of systems and states, the probability $p(s)$ of a system being in a particular state (s) can be estimated by counting the number of points inside the state affording the ability to designate all possible states of the system over time.

The Sustainable Regimes Hypothesis encompasses the conceptual ideas governing the use and interpretation of FI as a measure of order and stability applied to sustainability (Cabezas and Fath 2002; Karunanithi et al. 2008). Eason and Garmestani (2012) drew from this hypothesis and adapted it to provide guidance on using FI to assess the resilience of system regimes. In summary, the hypothesis states that: (1) a system in an orderly dynamic regime fluctuates within a natural and acceptable range of variation, however, the overall condition does not change over time; hence, $\mathrm{FI} > 0$ and $(\mathrm{d}\langle \mathrm{FI}\rangle/\mathrm{d}t \approx 0)$; (2) steadily decreasing FI signifies a progressive loss of dynamic order and denotes a system that is changing more quickly (or speeding up), losing functionality and thus resilience; (3) steadily increasing FI indicates that the system is changing at a lower rate, becoming more ordered and continuing to maintain function; and (4) a significant and often abrupt decrease in FI between two stable dynamic regimes (i.e., $\mathrm{d}\langle \mathrm{FI}\rangle/\mathrm{d}t \approx 0$) denotes a regime shift. The caveat regarding transitioning to a new regime is that there is no assurance that the latter regime is more humanly desirable that the former. Because FI affords the ability to assess aspects of the system condition related to resilience and not the quality of the condition, the underlying variables must be evaluated to compare and determine the human desirability of the system regimes (Eason and Garmestani 2012). As a note, both conditions of statement 1 must be true for a system state to be considered stable and sustainable. In other words, a completely disorganized system has no order over time. It has a $\langle \mathrm{FI}\rangle \approx 0$ and although $\mathrm{d}\langle \mathrm{FI}\rangle/\mathrm{d}t \approx 0$, the system is constantly changing, unpredictable, and not resilient. Note that the revision of the hypothesis presented here does not modify the interpretation of FI in terms of what changes in dynamic order infer about the resilience of system states, however, it adjusts the supposition (in line with theoretical and empirical knowledge) regarding the speed of change implied by increasing or decreasing FI.

The general methodology employed to compute FI for a system is as follows: (a) divide the time series into a sequence of time windows, (b) bin points into states within each time window, (c) use the binned points to generate a probability density function (PDF) for each time window, and (d) calculate FI from the PDF for each time window. In order to detect regime shifts using FI, we compute FI in overlapping time windows and compare those values over time. A sharp decrease in FI denotes not only system disorganization but also indicates an increasing likelihood of a regime shift. A simple example for calculating FI is provided in Cabezas and Eason (2010) and the algorithm for computing FI was coded in Matlab (Release 2011b, Mathworks Inc.)

Investigating the relationship between FI and traditional indicators

To explore the relationship between FI, variance, skewness, kurtosis, and critical slowing down, two models were simulated: (a) a time-varying sinusoid and (b) a 2-species predator–prey model. Once the regime shift indicators were computed for each model, SROC coefficients (two tailed with $\alpha = 0.05$) were calculated in order to evaluate the relationship between FI and the other parameters. In the first case, we were interested in evaluating a time series with increasing variance and considered a number of functions and parameter changes. Due to its simplicity, we decided to use a time-varying sinusoid: $f(t) = (\alpha + \beta t)\sin(2\pi t)$ with smoothly increasing amplitude and $\alpha = \beta = 1$

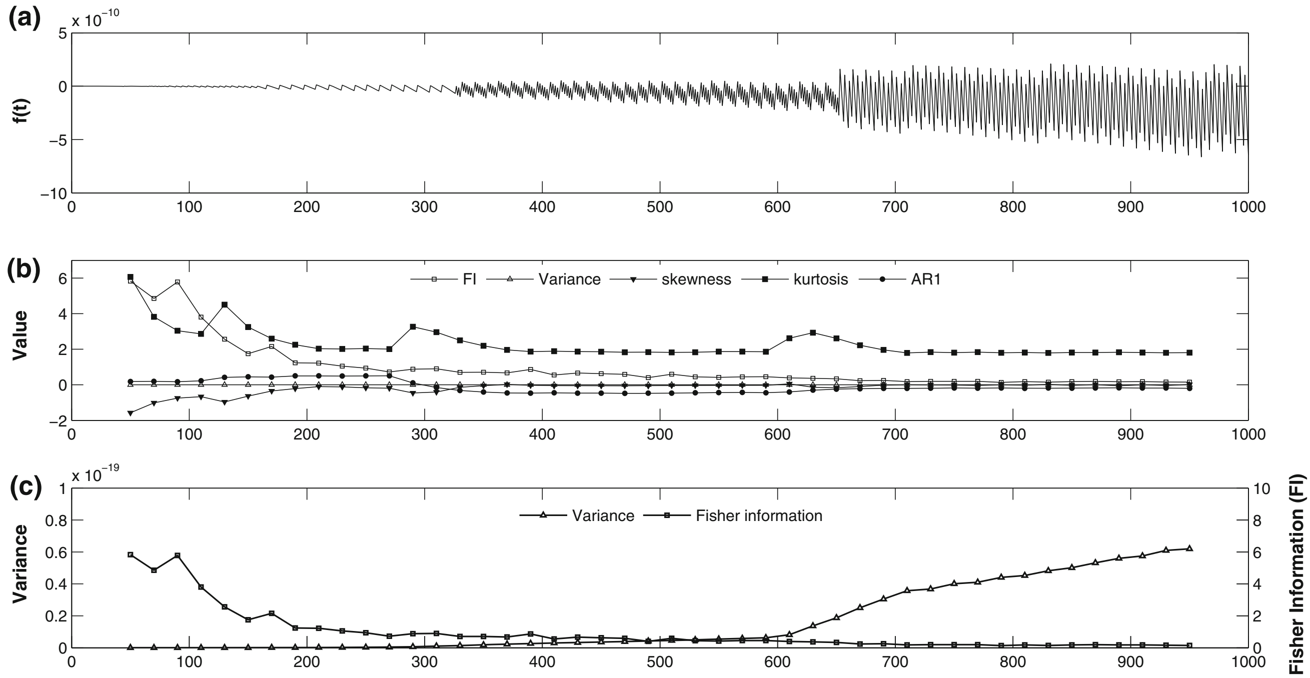

Fig. 2 Dynamic behavior of a time-varying sinusoid. **a** Plot of $f(t)$ versus time. **b** Fisher information has a positive correlation with both kurtosis and AR1, is negatively correlated with skewness and **c** has a strong negative correlation with variance

(Fig. 2a). The regime shift parameters were computed over a 100 time step integration window with an overlap of 20 time steps (Fig. 2b). Since the scale of the variance is significantly less than skewness and kurtosis, we provided a two-axis plot of FI and variance (Fig. 2c). Note that as the variability of the time series increases, the FI decreases. Further, the SROC test revealed that FI is positively correlated with kurtosis ($\rho = 0.81$, p value $= 1.35\text{E}{-11}$) and AR1 ($\rho = 0.34$, p value $= 0.02$), and negatively correlated with both skewness ($\rho = -0.78$, p value $= 1.95\text{E}{-10}$) and variance ($\rho = -0.98$, p value $= 4.11\text{E}{-33}$).

We further investigated the relationship between the regime shift parameters by examining a predator–prey ecosystem model. Equations 5 and 6 are conventionally adapted first order Lotka–Volterra differential equations describing the predator–prey population dynamics used to characterize the state of the system (Fath et al. 2003):

$$\frac{\mathrm{d}y_1}{\mathrm{d}t} = g_1\left(1 - \frac{y_1}{k}\right)y_1 - l_{12}y_1y_2\left(\frac{1}{1+\beta y_1}\right) \tag{5}$$

$$\frac{\mathrm{d}y_2}{\mathrm{d}t} = g_{21}y_1y_2\left(\frac{1}{1+\beta y_1}\right) - m_2y_2 \tag{6}$$

where y_1 is the prey species, y_2 is the predator species, g_1 is the prey growth rate, l_{12} is the rate of prey loss due to predatory feeding, g_{21} is the predator feeding rate, m_2 is the predator mortality rate, k is the prey density dependence, and β is a predator satiation term.

The system of ordinary differential equations was simulated with parameter settings: $\beta = 0.005$, $m_2 = 1$, $g_{21} = 0.01$, $l_{12} = 0.01$, and $g_1 = 1$ from time 0 to 5,000. Figure 3 is the phase space plot of the model with a time-varying prey density dependence ($k = 1 + 0.5\ t$). All of the regime shift parameters were computed over a 200 time step integration window with an overlap of 100 time steps and are plotted in Fig. 4. Each of the regime shift indicators appear to reflect some change in the behavior of the system near time = 1,000. However, the interpretation is somewhat unclear for the traditional indicators. For example, (a) there are two peaks of decreasing magnitude in skewness and kurtosis for variable 2 prior to the shift after which both indicators converge to zero (Fig. 4c, d); (b) the variance has a small increase near time = 1,000, larger spike near time = 1,500 and increases for the remainder of the simulation period. Each of these increases is relatively small and essentially invisible given the scale of the variance values for the time series (Fig. 4b); and (c) only variable 2 (y_2, predator species) shows an increasing trend in AR1. Conversely, FI indicates that the system was initially relatively stable, underwent a regime shift, reorganized into another dynamic regime, and then moved to a less orderly regime. In order to evaluate the relationships between the regime shift parameters, we focused our assessment on the period up to time = 1,000 where there were key changes in the parameters and found that FI had statistically significant correlations with the variance ($\rho = -0.74$, p value $= 0.004$), skewness ($\rho = 0.59$, p value $= 0.004$),

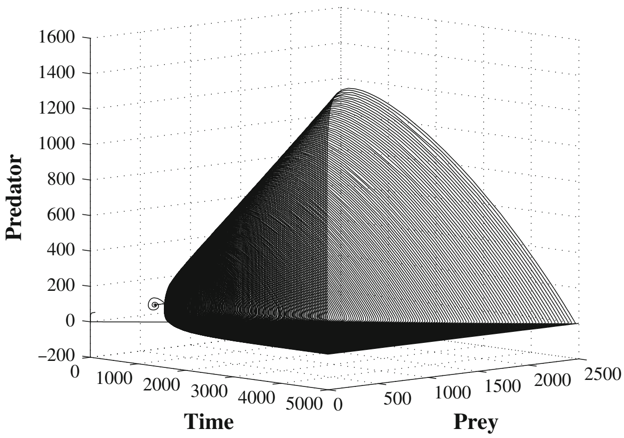

Fig. 3 Two species predator–prey model with time-varying prey density dependence, $k = 1 + 0.5\ t$

kurtosis ($\rho = 0.68$, p value $= 0.01$), and AR1 ($\rho = -0.68$, p value $= 0.01$) computed for the predator species (y_2).

One critical note to be made is that when a system is characterized by many variables, the regime shift indicator must be calculated for each variable. The danger, as shown in the exercise above, is that there may be changes in one variable, yet not in others. So what can truly be said about the dynamic behavior of the overall system? Simply calculating the statistics (e.g., variance, skewness, kurtosis, and AR1) of a multivariate system does not intuitively aid in assessing its regimes or regime shifts. As such, integrated indicators are key in evaluating real systems. The variance index was also computed for the system (Fig. 4f) and while the index was able to detect the initial shift, much like variance, it simply continued to increase after

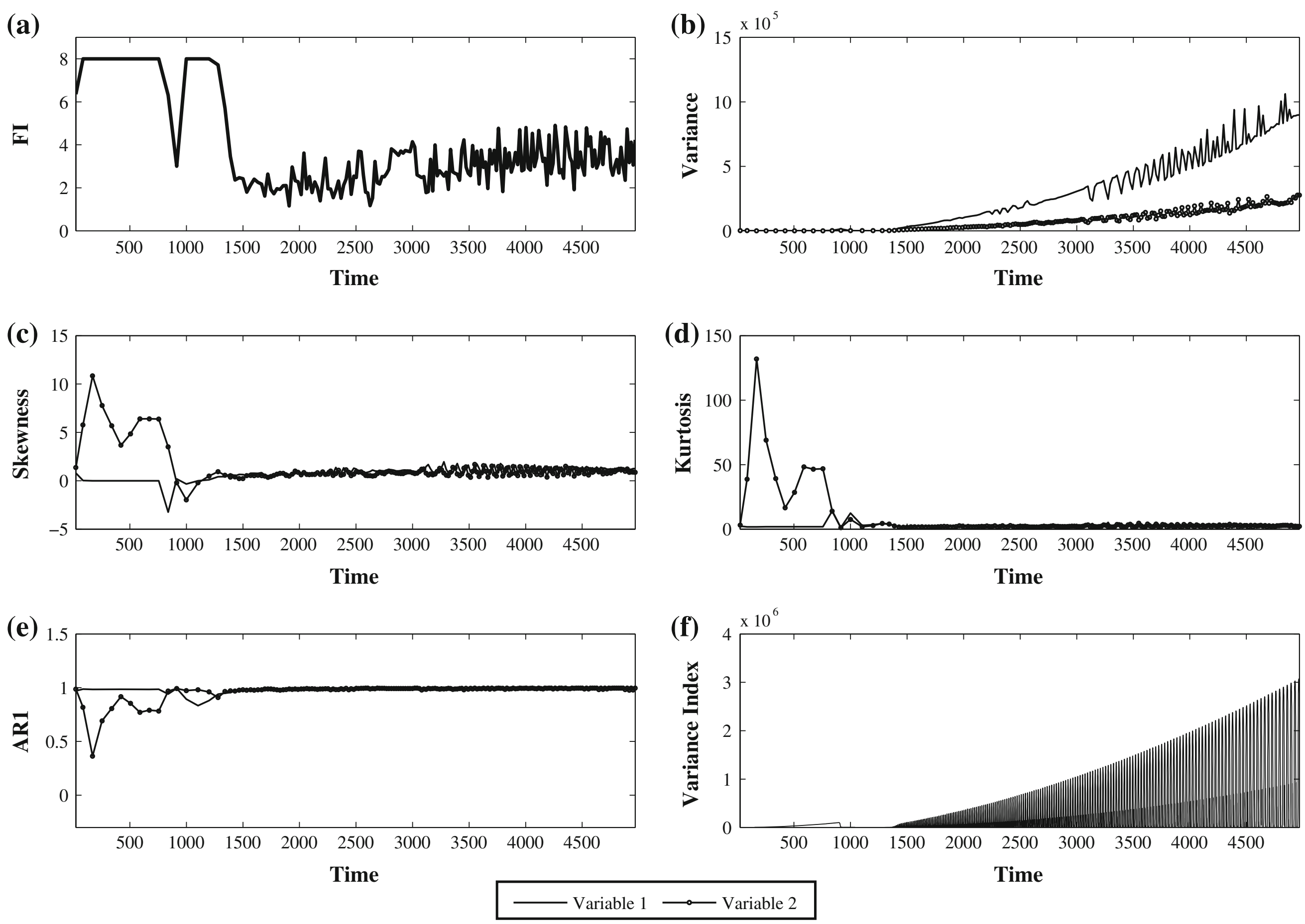

Fig. 4 Regime shift parameters for the two species predator–prey model. **a** FI reflects that the system underwent a regime shift (around time = 1,000) between two stable regimes and then transitioned into a less orderly regime. While the other regime shift indicators denoted changes in the system around time 1,000, the interpretation is not completely clear. **b** The variance has a larger spike near time = 1,500 and increased for the remainder of the simulation period. **c** The skewness of variable 2 has two peaks of decreasing magnitude prior to the shift, whereas the skewness of variable 1 increases up to the period of the shift before both converge to zero after the shift. **d** Similarly, the kurtosis of variable 2 has two peaks of decreasing magnitude prior to the shift and variable 1 is essentially zero except in the region of the shift. **e** There is an increasing trend in AR1 for only variable 2. **f** The variance index displayed a small spike indicating the regime shift and increases for the remainder of the period

the initial shift. FI, on the other hand, captured the nuanced changes in dynamic behavior of the system over time.

In summary, the SROC results reflected a strong and consistent correlation between FI and both variance and kurtosis for the model systems under study. These correlation results are in line with the expected relationships. For example, FI is high when there is low variability in the condition of the system and a high probability of a system being in a particular state. High FI implies that the system is biased toward a particular state; hence, the probability distribution would display more "peakedness" or positive kurtosis. Conversely, FI is low when the probability curve is flat indicating high variability in the system condition and a system that is constantly changing. As such, we expected to find that FI is negatively correlated with variance and positively correlated with kurtosis.

On the contrary, the SROC results regarding to the relationship between FI, critical slowing down, and skewness were inconsistent from the two studies (e.g., weak positive correlation between FI and AR1 in the time-varying sinusoid model ($\rho = 0.34$, p value $= 0.02$) and moderately negative for the Lotka–Volterra system ($\rho = -0.68, p$ value $= 0.01$). Finding consensus in the correlations may have been hampered by the conditions of the systems chosen or that fact that the Lotka–Volterra system had more than one variable each with distinct dynamics. In theory, we would expect that as FI increases (i.e., the system is becoming more stable), the skewness would decrease indicating less deviation from the mean. Regarding critical slowing down, it has been noted that as autocorrelation increases (i.e., approaches one), variance tends to infinity (Scheffer et al. 2009). Since an increasing trend in AR1 and a sharp drop in FI are both indicators of a regime shift, it is expected that AR1 is negatively correlated with FI as the system moves toward a regime shift. Hence, as indicated in the Lotka–Volterra example and supported by Scheffer et al. (2012), critical slowing (as evidenced by increasing AR1) and FI are positively related.

Another important finding from this study is the clear illustration that complex systems characterized by multiple variables require that the regime shift indicator must be calculated for each variable. As demonstrated in the assessment of the Lotka–Volterra system, there were changes in one variable, yet not in others. These conflicting results made it impossible to draw a conclusion about the behavior of the overall system, thereby highlighting the importance of using integrated indicators in assessing complex multivariate systems.

Exploring Fisher information as a leading indicator of regime shifts

In order to explore the use of FI for detecting impending regime shifts, we began by examining a classic bifurcation in a shallow lake shifting from oligotrophic to eutrophic due to the inflow of phosphorus. Unlike typical regime shifts which are often driven by large perturbations or catastrophic shifts in underlying drivers, a bifurcation is a qualitative change in dynamic behavior triggered by slow, smooth changes in system parameters (Biggs et al. 2009). We used a simple model to describe this type of behavior in a shallow lake system:

$$x_{t+1} = x_t + ae^{Z_t} - bx_t + \frac{x_t^2}{1 + x_t^2} \tag{7}$$

$$z_{t+1} = pz_t + \varepsilon_t \tag{8}$$

where x is the concentration of phosphorous in the lake, a is the rate of phosphorous input and b is the phosphorous removed from the lake over time through such processes as sedimentation, outflow, or biomass sequestration (Carpenter 2003). This type of model affords the ability to see the changes visually (Karunanithi et al. 2008) and is similar to systems that have been studied by others (Karunanithi et al. 2008; Pawlowski and Cabezas 2008; Carpenter 2003; Carpenter et al. 1999). To simulate the system dynamics, we set $b = 0.58$ and $Z = 0$ (no noise) and varied the input concentration of phosphorous (a) such that there are two shifts denoted by step increases:

$$\begin{array}{lll} 0 < t < 200 & a = 0.02 & \\ 200 < t < 210 & a = 0.02 + \left(\frac{t-200}{10}\right) \times 0.06 & \text{(shift 1)} \\ 210 < t < 500 & a = 0.02 + 0.06 & \\ 500 < 1,800 & a = 0.08 + \left(\frac{t-500}{1300}\right) \times 0.06 & \text{(shift 2)} \\ 1,800 < t & a = 0.08 + 0.06 = 0.14 & \end{array}. \tag{9}$$

The system was simulated for 3,000 time steps and the resulting phosphorous concentration is plotted in Fig. 5a (shaded sections indicate the shift periods). While the first shift appears to be a small, yet sudden shift, the second is characterized by periodic increases in phosphorous input and is therefore more gradual. All of the regime shift indicators were computed over a 100 step integration window and an overlap of 10 time steps (Fig. 5). While each parameter exhibited changes in behavior around the time of the first regime shift, FI detected the second shift earlier and continued to decrease reflecting the disorganization of the system corresponding to the step increases in phosphorous. The other indicators only displayed small spikes at the beginning and end of the shift. Note that after the second shift, FI begins to increase over 500 time steps prior to the system regaining order and shifting into its new regime. Accordingly, FI is sensitive to both abrupt and slow moving fluctuations in the system. Further, the changes in dynamic order (i.e., FI) served as an indicator that a regime shift was imminent. As such, we postulate that it is possible to "red

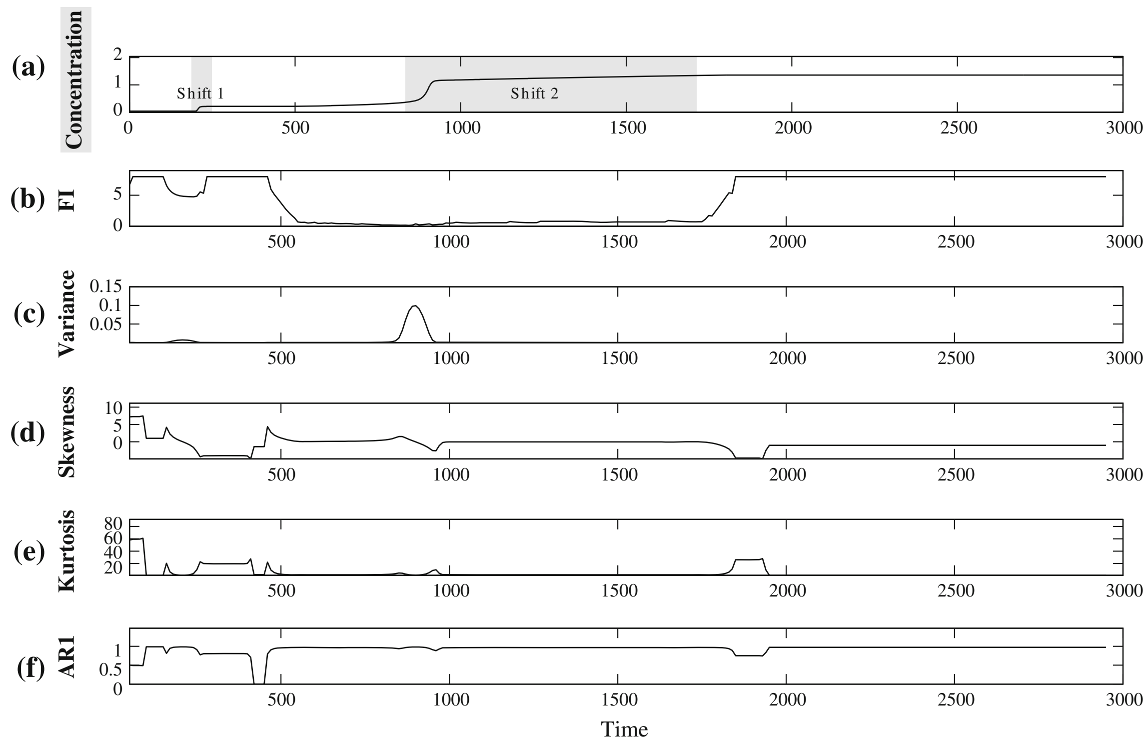

Fig. 5 Regime shift parameters for the shallow lakes model. **a** Lake phosphorous concentration. Each indicator detected the 1st regime shift in the same general time period. **b** However, FI detected the 2nd shift early, decreased in accordance with the step increases in phosphorous input and then began increasing over 500 time steps prior to the system regaining order and shifting into its new regime, while (**c–f**) variance, skewness, kurtosis, and AR1 only exhibited small changes at the beginning and end of the shifts

flag" an impending regime shift by assessing the changes in FI.

Detecting impending regime shifts in real systems

Further exploring the use of FI in detecting impending regime shifts, we assessed the Pacific Ocean Bering Strait marine ecosystem. The Pacific Decadal Oscillation (PDO) is one of the key changes in atmospheric conditions in the Pacific and relates to sudden transitions in physical conditions that according to Hilborn et al. (2003) may last 20–35 years and result in a regime shift. It is widely accepted that biological populations in marine systems respond to climate change (McGowan et al. 1998; Hsieh et al. 2005; Harley et al. 2006). Moreover, regional climate and biological changes in the Bering Strait have been documented in numerous studies (McGowan et al. 1998; Graham 1994; Miller et al. 1994; Francis and Hare 1994; Francis et al. 1998; Hare and Mantua Hare and Mantua 2000; McGowan et al. 2003; Grebmeier et al. 2006). A regime shift occurred in this system in 1977 and another in 1989 as identified by Hare and Mantua (Hare and Mantua 2000; Scheffer et al. 2001). Karunanithi et al. (2008) previously studied the Bering Strait system and was able to use FI to detect both regime shifts.

In this study, the Bering Strait ecosystem was used to compare the behavior of FI to that of the other regime shift parameters (i.e., variance, skewness, kurtosis, AR1 and the variance index) when assessing a real, complex system. We used time series data compiled by Hare and Mantua (2000) which characterizes the activity in the system. Of the 100 time series they assembled, not all were complete time series sets. Thus, our final dataset was limited to the variables with complete time series and contained 35 biological and 30 climate variables from 1965 to 1997. From Fig. 6a, it is clear that in a system with many variables, no assessment about ecosystem dynamics can be made by viewing the time series alone. The same is true of the traditional indicators as values of each regime shift parameter must be computed for each variable (e.g., Fig. 6b, c). Accordingly, integrated indicators (i.e., indices) are pertinent for evaluating any multivariate system and in particular, real systems typically characterized by complex dynamics and multiple, disparate variables. FI and the variance index were computed with a 10 year integration window and 5 year overlap (Fig. 6d, e). While both metrics reflect changes in the system, FI drops in accordance with the 1977 and 1989 regime shifts, whereas the variance index peaks at multiple points during the time period, making it difficult to interpret the dynamics of the system.

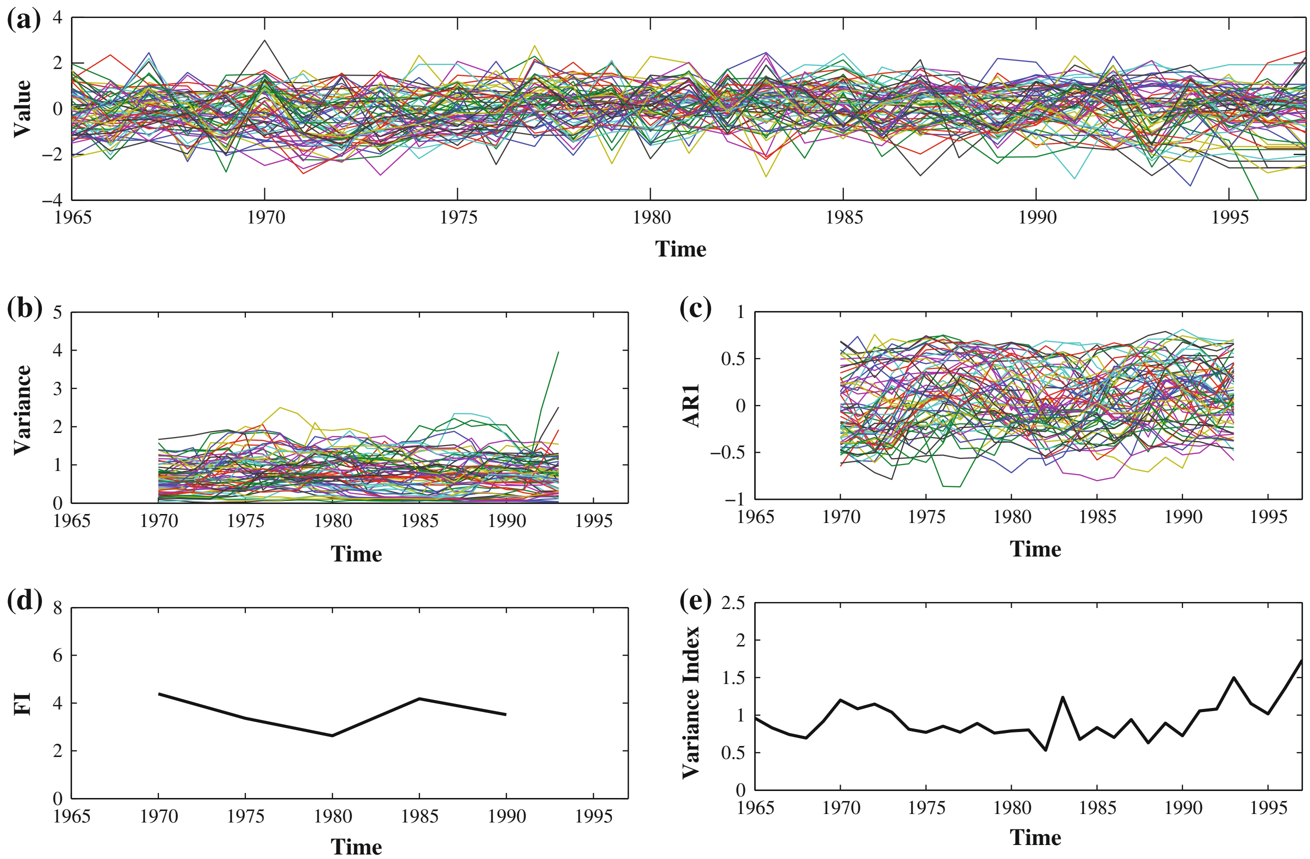

Fig. 6 Dynamic behavior of the Bering Strait ecosystem. In viewing the plot of **a** the time series data, as well as, traditional regime shift indicators, e.g., **b** variance and **c** AR1, no assessment about ecosystem dynamics can be made by viewing these alone. While both **d** FI and **e** the variance index denote changes in the system, the results from the variance index are inconclusive. FI, on the other hand, identifies the regime shifts when they occurred (i.e., 1977 and 1989)

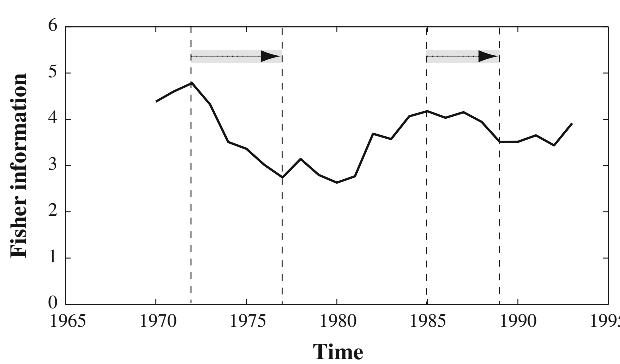

Fig. 7 Detection of impending regime shifts in the Bering Strait ecosystem using FI. Decreases in FI many years prior to the regime change warn that a shift is imminent and provides a window of opportunity to implement management options

When FI was computed with a 10 year integration window and a 1 year overlap (Fig. 7), progressive decreases in FI denoting loss of order and function were found about 5 years prior to an actual regime shift. Accordingly, there is a window of time in which FI detected changes in system condition, thereby warning of an impending regime shift.

Discussion

In this paper, we compared FI to traditional regime shift indicators for multiple systems and found that FI typically identified the shifts at nearly the same time or often before the other indicators under study. Using model systems, we confirmed that as a system approaches a regime shift, FI decreases and is negatively correlated with variance and positively correlated with kurtosis. Although there was no consensus on the relationship between FI, skewness, and AR1 from the empirical studies, based on theoretical understanding of the indicators, we postulated that FI is negatively correlated with both skewness and AR1. However, the mathematical relationships should be further explored.

It is evident that no true insight is provided by traditional indicators when assessing multivariate systems (Figs. 5, 6). Moreover, Seekell et al. (2011, 2012) noted that there is evidence of conflicting patterns in autocorrelation, variance, and skewness as a system approaches a regime shift. In particular, they indicated that while some systems displayed increasing trends in these indicators others were characterized by decreases. Hence, they proposed the use of conditional heteroscedasticity which captures patterns of variance clustering (low or high). Although this approach shows promise, thus far, applications have focused on changes in a small number of system variables and require that the condition be checked for each variable separately. Accordingly, additional testing and adaptation of this method are necessary for assessing shifts in complex multivariate systems.

The multivariate systems evaluated in this study afforded the ability not only to explore the use of FI as a leading indicator of impending regime shifts but also served as a mechanism for highlighting the importance of integrated indicators. FI was shown to be effective at evaluating complex systems characterized by multiple variables, is demonstrably sensitive to both fast and slow changes in system dynamics and is able to capture patterns of change in system variables (including periods of low and high variability). Further, when evaluating a real system (i.e., Bering Strait), while both FI and the variance index detected changes in the system, the variance index results were inconclusive. FI, on the other hand, identified the regime shifts when they occurred (i.e., 1977 and 1989) and gave warning of impending shifts many years prior to the actual regime shifts.

More research must be conducted in order for predictors of regime shifts to be effective for environmental management. This is particularly relevant when the drivers of regime shifts are subtle and internal, compounding the difficulties associated with the phenomena (Biggs et al. 2009). Previous interpretation of regime shifts using FI related primarily to locating minima in the datasets. However, based on the results presented in this paper, we believe that it is possible to "red flag" an impending regime shift by assessing the significance of declines in the dynamic order (i.e., FI) of a system prior to the actual regime shift occurring.

The window of opportunity to effectively manage an impending regime shift is typically small but critical (Biggs et al. 2009). In order to manage for resilience, policy should be focused upon slowly changing variables (e.g., land use, biodiversity), as the uncertainty of predictions based on these variables is much lower than trying to predict perturbations (e.g., hurricanes, pest outbreaks) that can generate dramatic but more obvious regime shifts (Scheffer et al. 2001). Therefore, the best way to deal with regime shifts is via monitoring, leading indicators, and a suite of policy instruments (Garmestani et al. 2009b). Based on the results presented in this study, integrated indicators, such as FI, appear to be a powerful tool for managing for resilience. Accordingly, we propose that FI be further explored as a leading indicator of impending regime shifts in complex systems and an important metric in sustainability and resilience science.

Acknowledgments The authors would like to thank William A. Brock for his insightful comments on an earlier version of this manuscript. The views expressed in this paper are those of the authors and do not necessarily represent the views or policies of the U.S. Environmental Protection Agency. Mention of trade names or commercial products does not constitute endorsement or recommendation for use.

Conflict of interest The authors declare that they have no conflict of interest.

References

Baker ME, King RS (2010) A new method for detecting and interpreting biodiversity and ecological community thresholds. Methods Ecol Evol 1:25–37

Biggs R, Carpenter SR, Brock WA (2009) Turning back from the brink: detecting an impending regime shift in time to avert it. Proc Natl Acad Sci 106:826–831

Brock WA, Carpenter SR (2006) Variance as a leading indicator of regime shift in ecosystem services. Ecol Soc 11(2):9. http://www.ecologyandsociety.org/vol11/iss2/art9/

Brock WA, Carpenter SR, Scheffer M (2008) In: Norberg J, Cumming G (eds) Complexity theory for a sustainable future regime shifts. Columbia University Press, New York, pp 180–206

Cabezas H, Eason T (2010) Fisher information and order. In: Heberling MT, Hopton ME (Eds.) San Luis basin sustainability metrics project: a methodology for assessing regional sustainability. EPA Number: EPA/600/R-10/182, pp. 163–222

Cabezas H, Fath BD (2002) Towards a theory of sustainable systems. Fluid Phase Equilib 194–197:3–14

Carpenter SR (2003) Regime shifts in lake ecosystems: pattern and variation. Excellence in ecology series 15. Ecology Institute, Oldendorf

Carpenter SR, Brock WA (2006) Rising variance: a leading indicator of ecological transition. Ecol Lett 9:311–318

Carpenter SR, Ludwig D, Brock WA (1999) Management of eutrophication for lakes subject to potentially irreversible change. Ecol Appl 9:751–771

Chisholm RA, Filotas E (2009) Critical slowing down as an indicator of transitions in two-species models. J Theor Biol 257:142–149

Cuffney TF, Qian SS, Brightbill RA, May JT, Waite IR (2011) Response to King and Baker: limitations on threshold detection and characterization of community thresholds. Ecol Appl 21:2840–2845

Dakos V et al (2008) Slowing down as an early warning signal for abrupt climate change. Proc Natl Acad Sci 105:14308–14312

Eason TN, Cabezas H (2012) Evaluating the sustainability of a regional system using Fisher information, San Luis Basin, Colorado. J Environ Manag 94:41–49

Eason T, Garmestani AS (2012) Cross-scale dynamics of a regional urban system through time. Region et Developpement 45:55–77

Fath BD, Cabezas H, Pawlowski CW (2003) Regime changes in ecological systems: an information theory approach. J Theor Biol 222:517–530

Fisher RA (1922) On the mathematical foundations of theoretical statistics. Philos Trans R Soc Lond 222:309–368

Francis RC, Hare SR (1994) Decadal scale regime shifts in the large marine ecosystems of the north-east Pacific: a case for historical science. Fish Oceanogr 3:279–291

Francis RC, Hare SR, Hollowed AB, Wooster WS (1998) Effects of interdecadal climate variability on the oceanic ecosystems of the NE Pacific. Fish Oceanogr 7:1–21

Frieden R (2004) Science from Fisher information: a unification. University Press, New York

Garmestani AS, Allen CR, Gunderson L (2009a) Panarchy: discontinuities reveal similarities in the dynamic system structure of ecological and social systems. Ecol Soc 14. http://www.ecologyandsociety.org/vol14/iss1/art15/

Garmestani AS, Allen CR, Cabezas H (2009b) Panarchy, adaptive management and governance: policy options for building resilience. Neb Law Rev 87:1036–1054

Gonzalez-Mejia AM, Eason TN, Cabezas H, Suidan MT (2012a) Assessing sustainability in real urban systems: the greater Cincinnati metropolitan area in Ohio, Kentucky, and Indiana. Environ Sci Technol 46:9620–9629

Gonzalez-Mejia AM, Eason TN, Cabezas H, Suidan MT (2012b) Computing and interpreting Fisher information as a metric of sustainability: regime changes in the United States air quality. Clean Technol Environ 14:775–788

Graham NE (1994) Decadal-scale climate variability in the tropical and North Pacific during the 1970s and 1980s: observations and model results. Clim Dyn 10:135–162

Grebmeier JM et al (2006) A major ecosystem shift in the northern bearing sea. Science 311:1461–1464

Groffman PM et al (2006) Ecological thresholds: they key to successful environmental management or an important concept with no practical application? Ecosystems 9:1–13

Hare SR, Mantua NJ (2000) Empirical evidence for north pacific regime shifts in 1977 and 1989. Prog Oceanogr 47:103–145

Harley CDG et al (2006) The impacts of climate change in coastal marine ecosystems. Ecol Lett 9:228–241

Hilborn R, Quinn TP, Schindler DE, Rogers DE (2003) Biocomplexity and fisheries sustainability. Proc Natl Acad Sci 100:6564–6568

Hsieh C, Glaser SM, Lucas AJ, Sugihara G (2005) Distinguishing random environmental fluctuations from ecological catastrophes for the North Pacific ocean. Nature 435:336–340

Hsieh C et al (2006) Fishing elevates variability in the abundance of exploited species. Nature 443:859–862

Karunanithi AT, Cabezas H, Frieden BR, Pawlowski CW (2008) Detection and Assessment of ecosystem regime shifts from Fisher information. Ecol Soc 13 http://www.ecologyandsociety.org/vol13/iss1/art22/

Karunanithi AT, Garmestani AS, Eason T, Cabezas H (2011) The characterization of socio-political instability, development and sustainability with Fisher information. Global Environ Chang 22(1):77–84

King RS, Baker ME (2011) An alternative view of ecological community thresholds and appropriate analyses for their detection: comment. Ecol Appl 21:2833–2839

Kleinen T, Held H, Petschel-Held G (2003) The potential role of spectral properties in detecting thresholds in the earth system: application to the thermohaline circulation. Ocean Dyn 53:53–63

Ludwig D, Walker BH, Holling CS (2002) Models and metaphors of sustainability, stability and resilience. In: Gunderson LH, Pritchard L Jr (eds) Resilience and the behavior of large-scale systems. Island Press, Washington, pp 21–48

Mathworks Inc. (2012) MATLAB Software: the language of technical computing version 7.8.0.347: Release R2011b Natick, MA

Mayer AL, Pawlowski CW, Cabezas H (2006) Fisher information and dynamic regime changes in ecological systems. Ecol Model 195:72–82

Mayer AL, Pawlowski CW, Fath BD, Cabezas H (2007) Applications of Fisher information to the management of sustainable environmental system. In: Frieden BR, Gatenby RA (eds) Exploratory data analysis using Fisher information. Springer, London, pp 217–244

McGowan JA, Cayan DR, Dorman LM (1998) Climate–ocean variability and ecosystem response in the North Pacific Ocean. Science 281:210–217

McGowan JA, Bograd SJ, Lynn RJ, Miller AJ (2003) The biological response to the 1977 regime shift in the California current. Deep-Sea Res II 50:2567–2582

Miller AJ, Cayan DR, Barnett TP, Graham NE, Oberhuber JM (1994) The 1976–1977 climate shift of the Pacific Ocean. Oceanography 7:21–26

Oborny B, Meszena G, Szabo G (2005) Dynamics of populations on the verge of extinction. Oikos 109:291–296

Pawlowski CW, Cabezas H (2008) Identification of regime shifts in time series using neighborhood statistics. Ecol Complex 5:30–36

Qian SS, Cuffney TF (2012) To threshold or not to threshold? That's the question. Ecol Ind 15:1–9

Scheffer M, Carpenter S, Foley JA, Folke C, Walker B (2001) Catastrophic shifts in ecosystems. Nature 413:591–596

Scheffer M et al (2009) Early-warning signals for critical transitions. Nature 461:53–59

Scheffer M et al (2012) Anticipating critical transitions. Science 338:344–348

Seekell DA, Carpenter SR, Pace ML (2011) Conditional heteroscedasticity as a leading indicator of ecological regime shifts. Am Nat 178:442–451

Seekell DA, Carpenter SR, Cline TJ, Pace ML (2012) Conditional heteroskedasticity forecasts regime shift in a whole-ecosystem experiment. Ecosystems 15:741–747

van Nes EH, Scheffer M (2007) Slow recovery from perturbations as a generic indicator of a nearby catastrophic shift. Am Nat 169:738–747