**The Regime Shift Detector: a model to identify changes in dynamic rules governing populations**

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**Abstract**

1: Environmental factors may interact with internal rules of population regulation, sometimes perturbing systems to alternate dynamic states. Yet, pinpointing when sustained state changes occur in naturally fluctuating populations is difficult. An analytical approach that can identify the timing and magnitude of such changes, or “regime shifts”, would facilitate understanding of abrupt ecological transitions with potential to inform management of species of economic or conservation concern.

2: We develop a generalizable model, the “Regime Shift Detector” for detecting changes in the parameters of a simple density dependent model governing the temporal fluctuations of a population. The model is a generalizable tool comprised of a suite of functions for examining population time series data for the presence, location, and magnitude of shifts. The model uses an iterative approach to fitting subsets of time series data, and then ranks the fit of a particular break point combination using model selection. We examined the performance of this model with simulated data and two real-world case studies each with >20-years of data: one species with an invasion dynamic, the multicolored Asian ladybeetle (*Harmonia axyridis*), and one that has been declining, the eastern monarch butterfly (*Danaus plexippus*).

3: We found that under low environmental/sampling error, the regime shift detector accurately identified two or more break scenarios with >90% accuracy, one break scenarios with 80% accuracy, and no shift scenarios with approximately 60% accuracy; yet, the model’s performance declined as sampling error increased. In our case study examining the invasion process of Multicolored Asian Ladybeetle (*Harmonia axyridis*), the regime shift detector identified shifts in population cycling associated with known variation in prey availability. However, the results for the eastern monarch population were more ambiguous, within greater uncertainty about the number and location of breaks in the time series data, suggesting that multiple super-imposed processes are likely involved in the decline of this species.

4: When interpreted in the context of known species biology, the regime shift detector has the potential to aid management decisions and identify critical drivers of change in species’ dynamics. In an era of rapid global change, such tools can increase understanding of the conditions under which population dynamics can shift to other states.

**Introduction**

Population dynamics are governed by internal, biotic rules and also abiotic factors, often leading to both stochastic and deterministic forces governing abundance patterns (Bjørnstad and Grenfell 2001). External perturbations to population processes can lead to regime shifts, where the internal rules that govern fluctuations in population abundance transition to another state (Hare and Mantua 2000, Carpenter et al. 2008). Understanding how and when external environmental factors interact with internal density dependent regulation remains a fundamental challenge in population ecology (Sutherland et al. 2013, Eason et al. 2016).

Density dependent tools for modelling population time series were developed and championed during the 1950s and 60s. Examples include the Ricker and Beverton-Holt models, which were initially developed for fisheries management (Ricker 1954, Beverton and Holt 1957) and describe the expected population size in year *t* as a function of the population size in year *t-1*. The accuracy of these simple density dependent models is generally highest for populations fluctuating around their carrying capacity (Sabo et al. 2004), with compensatory density dependence, and a short development period to minimize the effect of stage-structured lags (Bjørnstad and Grenfell 2001). Although this deterministic approach to population modelling has largely fallen out of favor for more complex strategies involving nonlinear stochastic elements (May 1976, Bjørnstad and Grenfell 2001, Barraquand et al. 2017, Boettiger 2018), these models remain useful, in large part due to their simplicity and ecologically meaningful interpretations (Gadrich and Katriel 2016). Differences in parameter values between populations, or a change within a single population, can suggest differences in environmental constraints governing a population, providing a quantitative measure of environmental change impacts (Forchhammer and Asferg 2000, Berryman and Lima 2006, Zipkin et al. 2009, Bahlai, vander Werf, et al. 2015).

Although theoretically well-described, identifying abrupt transitions in ecological systems is challenging using real-world data due to a lack of systematic approaches (Bestelmeyer et al. 2011). In many cases, transition points are applied to time series data *ad hoc*, based on data visualization or specific hypotheses surrounding factors affecting population fluctuations (Hare and Mantua 2000, Toms and Lesperance 2003, Weimerskirch et al. 2003, Berryman and Lima 2006, Knapp et al. 2012), creating the potential for biases in selecting break points. Break point analysis tools eliminate this bias by locating change points with a variety of optimization strategies, including linear and moving average methods (Braun and Muller 1998, Zeileis et al. 2001, Killick and Eckley 2014, Priyadarshana and Sofronov 2015). However, these methods do not work on data with internal, density dependent structure inherent to population time series data. Density-dependence population growth has the potential to mask transition points. For example, transient dynamics occurring immediately after a temporary disturbance can result in a change in population size, but not necessarily in the rules governing population fluctuations. Wavelet analysis has been applied to population time series to address changes in cycling patterns (Jenouvrier et al. 2005) but this method also does not account for density-dependence processes as an explicit mechanism governing changes in abundance (Cazelles et al. 2008). A robust, unbiased tool for identifying regime shifts would simultaneously allow us to identify when shifts in population cycling processes occur and further quantify the specific changes to the underlying dynamic driving population size changes.

In this paper, we develop a generalizable tool for detecting shifts in dynamic regimes within density-dependent populations using time series data. We illustrate our approach using the Ricker model because of its simplicity and high performance under a variety of realistic environmental scenarios. Yet, the techniques described in our paper can be readily adapted for other model structures, including more complicated processes such as seasonal periodicity or lag effects. We describe the basic structure of our model and how it can be used to evaluate the presence, location, and magnitude of shifts in the population parameters governing population dynamics. We demonstrate the utility our model through a series of simulations and apply the model to real-world case studies of two populations of conservation and economic concern. First, we examine the invasion process of the multicolored Asian ladybeetle (*Harmonia axyridis*), a cosmopolitan invasive, in the two decades following its arrival in Midwestern US agricultural ecosystems. Then, we examine the declining eastern monarch butterfly (*Danaus plexippus*) population using census data collected on its overwintering grounds in Mexico over a similar two decade period.

**The Regime Shift Detector model**

We assume that the population of interest follows a Ricker model structure such that the population size in time t+1, , is dependent on the population size in time t, , the carrying capacity of the system, , and the per-capita annual growth rate, (Turchin 2003):

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We further assume that observed annual population abundance is partially stochastic and may be influenced by either environmental variation and/or sampling error. As such, we include an error term , which follows a normal distribution centered around zero with a variance of . The parameters K, r, and are estimated from the population timer series data (N1, N2, … N*t*). The Ricker model is a useful starting point for breakpoint analyses because 1) it does not rely on any external information (other than the previous year’s population size; 2) only three parameters need to be estimated, and those parameters have ecologically meaningful interpretations; and 3) it is an extremely flexible distribution, taking a variety of forms, from linear to compensatory to over-compensatory, and thus has a wide range of applications across a wide variety of taxa (Ricker 1954, Brook and Bradshaw 2006).

To build the Regime Shift Detector, we use an iterative, model-selection based process to determine if, and when, shifts in parameter values occurred within a given time series. To achieve this, we first fit the Ricker model to the entire time series of available data. Then the population time series is subdivided into all possible combinations of 2, 3, …, n subsets of sequential data points (hereafter, ‘break point combination’) and the Ricker model is fitted to each of the subsets produced for each break point combination. We constrain break point combinations to only include subsets with at least four sequential data points to avoid over-fitting.

After fitting each subset for a given break point combination, we evaluated the model’s Akaike Information Criteria for small sample sizes (AICc) by calculating AICc values for each segment and sum them together (Hall et al. 2013). AICc values were used to rank fits for each break point combination, and fits for break point combinations with lower AICc values were considered to have better performance. When AICc values differed by two units or less, models were considered equivalent (Burnham and Anderson 2002).

The ‘regime shift detector’ is implemented as a series of R functions to enable a user to quickly generate a report on the fit of the model and the location of break points with their own data. Users provide the model with a data frame of population observations at standard time intervals. The model (and all subsequent simulations and case studies) were scripted and run in R Version 3.3.3 (R Development Core Team 2017) . All data manipulations, analyses and figure scripts, including the complete development history, are publicly available in a Github repository at <https://github.com/cbahlai/monarch_regime>. We summarize the role of each function in the supplemental files (see S1), but readers can download the script file directly for implementation details.

*Simulation study*

We conducted a series of simulations to test the accuracy of the regime shift detector under a variety of scenarios. For a given time series, the regime shift detector produces both a top break point combination, and a set of equally performing break point combinations for cases in which model fits produce equivalent AICc values (i.e. within 2 units of the best-performing fit). We achieved this by altering the Ricker parameters to simulate changes in dynamic rules. First, we selected a starting a base scenario with a starting population *Nt* of 3000, and a starting values of *r* and *K* as 2 and 2000, and a duration of 25 years, to start the scenario in a known, stable dynamic. We then modified *r* and *K* individually by 10% intervals from their starting values (0%, 10%,…,90%) while holding all other parameters constant. We also evaluated how the magnitude of stochasticity in the system (as measured by the error term ) influenced model performance. For generalizability of our simulation results, we simulated error as a percentage of the mean population size, rather than as absolute value (described in the model above). For each (true) annual population size in the simulated dataset, a random value was selected from a normal curve of mean 0 and standard deviation of (where = 1, 5, 10%, and every 10% thereafter to 90% of the true mean population size over the complete time series)*.* To scale the standard deviation to the population size used in the simulations, and the expected value of N(t+1) was multiplied by this value to simulate error σ. Each of these scenarios was run on 1000 simulated datasets for breakpoint combinations with 0, 1, 2 and 3, respectively. We also tested the impact of time series length by modifying length of the simulated time series at two year intervals (over a range from 25 – 33 years) while holding other parameters constant. In cases where the top selected break point combination did not match with the data generation process, we examined what errors had occurred (described in more detail in Appendix S2).

We examined the regime shift detector’s performance from two perspectives. First, we evaluated the type II error rate, or how often the regime shift detector failed to detect a shift in model parameters when a shift was indeed present (Fig 1). Then, we evaluated the type I error rate, or how often the regime shift detection falsely inferred a shift in the time series when no shift was present.

In general, scenarios with a higher number of breakpoints (two or more) were more likely to be identified correctly by the regime shift detector (Fig. 1). The regime shift detector correctly identified break point combinations in >90% of scenarios initiated with two or more break points and in approximately 80% of scenarios initiated with one break point under low noise conditions (Fig. 1 A), although accuracy decreased with increasing noise in the data. Zero break scenarios were identified within the set of equivalent break points produced by the model in approximately 60-80% of input scenarios, increasing in accuracy with increasing experimental noise. The regime shift detector correctly identified shifts most frequently in cases with moderate changes to *K* (30-60%; Fig. 1 B), and smaller changes to *r* (<25%; Fig. 1 C). This result is somewhat counter-intuitive, as we would generally expect larger shift in parameters to be more easily detected. However, because the Ricker model produces chaotic dynamics with high values of r (r > 2.3) and has the potential for large deviations from equilibrium with high K values, a large shift in parameters could potentially result in a situation where multiple break point fits would perform equally well. Finally, the likelihood that the regime shift detector accurately identified scenario conditions decreased as scenario length increased, likely because of the factorial increase in potential break point combinations with additional data in the time series (Fig. 1 D).

Conversely, when we examined regime shift detector for its false positive rate, we found that we could be most confident in model results which found no breakpoints, and those that found 3 or more breaks at low sample error rates (<10% of the sample mean; Fig. 2). When the regime shift detector found no breaks, it reflected a simulation scenario with no breaks in virtually all cases (Fig. 2 A). When the model identified scenarios with one or two breaks as the top model, this reflected the scenario conditions ~65% of the time, and decreasing with simulated error (Figs. 2 B, C). A similar pattern was observed for scenarios identified to have three breaks, however, accuracy was generally quite high with this output, with ~90% accuracy observed (Fig. 2 D).

**Applications**

We tested the performance of the regime shift detector model with two cases using population time series data from field observation studies. Both case studies involve approximately two decades of observations of economically or culturally important insect species: one case examines an invasion process and the other examines a population decline, both occurring over the same time period in recent history.

Multicolored Asian ladybeetles in southwestern Michigan

The 1994 invasion of multicolored Asian ladybeetles to southwestern Michigan, United States was documented in monitoring data collected on agriculturally-important Coccinellidae (ladybeetles) in landscapes dominated by field crops. Population density of ladybeetles is monitored in 10 plant communities weekly over the growing season using yellow sticky card glue traps starting in 1989 at the Kellogg Biological Station at Michigan State University. We used data on the captures of adults at the site from 1994-2017, culled at day of year 222 (August 10) to minimize the effect of year-to-year variation in the sampling period. We then calculated the average number of adults captured per trap, across all traps deployed within a sampling year, and used this value as the dependent variable in our analysis. Detailed sampling methodology is available in previous work (Bahlai et al. 2013, Bahlai, Colunga-Garcia, et al. 2015, Bahlai, vander Werf, et al. 2015).

Two break points, one occurring after 2000 and one occurring after 2005, were observed in the best break point combination model (Fig. 3 A). The shift from ‘phase A’ to ‘phase B’ in 2000 is characterized by substantial increases in the fitted values for K and r, with approximate increases of 75% and 40% over their initial estimates, respectively (Table 1). The shift from 'phase B' to 'phase C' in 2005 is characterized by a return to parameter estimates that were nearly identical to those observed for ‘phase A’ (Table 1, Fig. 3 B). Although the regime shift detector ranked several break-point combinations similarly by AICc, the top-ranked break point combination (2000, 2005) was also selected by AIC.

Dynamics of the ladybeetle invasion appear to be closely coupled with prey availability (Bahlai and Sears 2009, Heimpel et al. 2010, Rhainds et al. 2010, Bahlai, Colunga-Garcia, et al. 2015), which, in turn, is driven by documented pest management practices (neonicotinoid insecticide use; Bahlai, vander Werf, et al. 2015) leading to relatively simple pulsed changes in dynamics. The first shift in the dynamics of the Asian ladybeetle*,* after 2000, corresponds to the well documented arrival and establishment of a preferred prey item from its native range, soybean aphid, to North America (Ragsdale et al. 2004, Wu et al. 2004). The invasion of this aphid dramatically increased resources available to *H.axyridis* in habitats where the beetles were already well-established (Bahlai et al. 2013), supporting both a higher carrying capacity and a greater intrinsic growth rate. The second shift, after 2005, is more difficult to directly explain, as the prey item still persists in the landscapes where *H. axyridis* occurs. However, landscape-scale use of neonicotinoid insecticides decreased prey numbers, particularly during the spring when aphids are colonizing new hosts, which could be limiting early season reproduction of ladybeetles(Bahlai, vander Werf, et al. 2015)*.*

Monarch butterflies in Mexican overwintering grounds

The eastern population of the North American monarch butterfly (*Danaus plexippus*) is migratory, with the majority of individuals overwintering in large aggregations in Oyamel fir forests within the transvolcanic mountains in the central region of Mexico (Urquhart and Urquhart 1978). Monarchs are highly dispersed over their breeding season, occupying landscapes throughout the agricultural belt in central and eastern United States and southern Canada (Flockhart et al. 2017). As such, estimates of the overwintering population size can provide a convenient and inclusive annual metric of the size of the eastern migratory population (Prysby and Oberhauser 2004). We used data on the total area occupied by monarchs from 1995 to 2017 (based on early winter surveys conducted in December), compiled by the World Wildlife Fund Mexico (available at MonarchWatch; Lovett 2017).

The regime shift detector estimated that the best break point combination fit for the monarch overwintering density data was a single break after 2003 (Fig. 4). The shift corresponds with a >50% reduction in K and a 15% reduction in r (Table 2; Fig. 4 B). However, model selection results were somewhat ambiguous, and ranked two additional models as functionally equivalent: one with a break after 2003 and an additional break after 2008, and another one-break model at 2006. The regime shift detector ranked these three break point combinations of different structures similarly by AICc (i.e., AICc for top model: 120.2; identical AICc for the latter two models: 121.9), but varied in rank when using AIC. By AIC, the two-break combination of 2003, 2008 was strongly favored (AIC=106.9), followed in rank by the one-break fit at 2003 (AIC=114.6) and the one break fit at 2006 (AIC=116.3).

Abiotic drivers of monarch population dynamics are complex and can interact at local, regional, and continental scales (Saunders et al. 2017). Loss of milkweed hostplants due to changing agricultural practices on Midwestern breeding grounds (Hartzler 2010, Pleasants and Oberhauser 2013) is hypothesized to be a major cause of the decline. However, other studies have implicated climate (Zipkin et al. 2012), extreme weather events (Brower et al. 2004), changing habitat availability on wintering grounds (Vidal and Rendón-Salinas 2014), and mortality during the fall migration (Imanine et al. 2016?) as possible factors influencing monarch population dynamics. With many super-imposed drivers, monarch dynamics are likely to be driven by both press and pulsed processes, making the detection of discrete break points associated with regime shifts more difficult.

Although we observed a shift in dynamic after the 2003 overwintering season, conclusions about best models may change with the information criterion used to rank them (Table 2). If AIC is used instead of AICc to rank break point combinations, the top model becomes a two-break model with shifts after 2003 and 2008, with stepwise declines in carrying capacity at each points. There is biological support for both of these models. For example, changing herbicide use practices in central North America have largely eliminated milkweed hostplants from agricultural field crops, with fairly consistent, low levels of milkweed on the landscape starting from about 2003-2005 (Zaya et al. 2017). Although glyphosate tolerant soybeans and maize were introduced to the US market in 1996 and 1998 respectively (Duke and Powles 2009), actual glyphosate use lagged behind, with dramatic increases in use of the pesticide in 1998- 2003 in soybean, and 2007-2008 in maize (Baker 2017).

**Discussion**

The regime shift detector provides a novel and objective tool for evaluating changes in parameters, such as carrying capacity and growth rates, that govern natural populations. The regime shift detector allows for comparisons of population processes over time and between ecosystems. As illustrated with our case studies, model results not only identify and quantify parameters changes, but can provide insight into the potential drivers in the systems under study and help focus the time frames that should be examined more closely.

The model in the regime shift detector is a compromise between sensitivity and simplicity. Yet, we find that the information criteria used and decision rules for cutoff can impact model results, and thus should be considered critically before drawing conclusions from model results. Additionally, we recommend users carefully consider the limitations of the tool in the context of the raw data presented: if phases of change are close together (e.g., less than 3-4 years or time periods), the resultant variation may reduce the model’s sensitivity for detecting shifts in the data. For instance, we use the discrete form of the Ricker model, with a yearly time step, but end users can modify model structure and temporal resolution appropriate to their systems and available data. As is, the results of the model should be interpreted with caution in populations undergoing rapid change in their environments or internal dynamics.

At low and intermediate numbers of breaks, the regime shift detector’s most common error was to over-estimate, i.e. to ‘find’ breakpoints where they did not occur. About one third of the scenarios identified as one break in the top-ranked break point combination were initiated under zero break conditions, a similar number of scenarios identified as two-break were initiated under one and two break conditions. However, break-point combinations with higher numbers of break points are subject to greater penalties in the calculation of AICc. Thus, a user can have high confidence in an accurate detection of break points if the regime shift detector model indicates either zero, or ≥3 breaks in a time series, because these scenarios must have very good fit to achieve either ranking. In the more intermediate scenarios where one or two breaks are identified, the set of similarly-ranked models should be considered when interpreting the results from the model, as illustrated by our case studies.

The Ricker model used in the regime shift detector could be changed or modified to incorporated more complicated population processes as well as covariates (for example, if a population had a known response to temperature or another environmental variable). We used AICc to rank break-point combination models. AICc allows for a more conservative selection of break-point combinations compared to AIC, by down weighting the selection criterion for models with many break points. However, this more conservative approach negatively affected the model’s ability to detect shifts even in dynamic in low sampling error scenarios, as evidenced by the higher type I error we observed for one and two break scenarios (Fig 2 B, C), because the penalty term for increasing the complexity of the model dramatically increases with AICc. The ambiguity and differences in system complexity we observed from our case studies allow us to illustrate the important impact of model selection criterion choice on the ultimate output of the Regime Shift Detector model, and how criteria optimize models for different outcomes (Burnham and Anderson 2002). AICc-based ranking of models produced sets of equivalently performing break point combinations in both of our case studies, presenting a practical problem. Thus, we used AIC to aide in the interpretation of the results set, as it does not penalize more complex model structure as heavily as AICc (Ripplinger and Sullivan 2008). If it is reasonable to assume that the population data being subjected to the regime shift detector has a low associated sampling error and the regime shift detector ranks a one or two break scenario as its top output, a user may wish to use less conservative information criteria (i.e. AIC) to rank break point combination models or resolve ambiguities in ranking within sets of very different break point combinations.

We used simulations to understand how changing various inputs affected the likelihood of the regime shift detector in identifying the conditions under which the data were produced. Performance of the regime shift detector model declined rapidly with increasing levels of stochasticity, or error, in the data (Fig. 2), a behavior that is expected of any statistical tool. Nevertheless, whenever possible, the sampling error of the data should be estimated to help evaluate the model’s results in the context of variation within the data due to sampling error. The error rate of the regime shift detector in detecting initial conditions varies with output, but in low-sampling-error scenarios amongst top-ranked break point combinations, an output of zero or three or more break points by the script is generally greater than 90% accuracy, while outputs of one or two breaks have a lower rate of accurately detecting input conditions, at just under 70%. The lower accuracy in these one and two break top outputs is primarily explained by over-estimating the number of breaks (ie., the model assigning breaks where there are none). This may occur because of an insufficient penalty to ‘finding’ extra breaks for these intermediate scenarios, whereas when a break point combination with three breaks rises to the top rank despite substantial penalty for model complexity, it is indicative of an excellent fit. Nevertheless, in scenarios initiated with 1-2 breaks, the set of equivalent break point combinations indicated by the regime shift detector contained the initiation conditions of the scenario in >80% of cases (Fig. 1).

Other input conditions also impacted the performance of the regime shift detector model. The effect of dynamic shift size was dependent on which parameter was changed and by how much (Figs. 2 B, C). Although larger shifts in regression parameters would, intuitively, lead to a higher likelihood of detection, these larger shifts would also be more likely to induce large variations in transient dynamics in the years immediately following the shift, potentially making the timing of shifts more difficult to pinpoint. Similarly, longer time series yielded results that were more error prone (Fig. 2 D). This likely because, firstly, there were simply more possible break-point combinations for the model to select from, and secondly, because the penalty for increasing parameterization (i.e. AICc) would decrease as sample sizes grew, leading to increasing likelihood of identifying extra breaks.

When interpreted in the context of known species biology, the regime shift detector model has the potential to aide management decisions and identify, and rank critical drivers of change in internal dynamics of a population. Our modeling framework should be useful in this era of rapid global change affecting species dynamics, as it can help evaluate population changes relative to internal regulators.

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**Table 1:** Ricker model fits for each phase between break points resulting from fitting population data of *Harmonia axyridis* from Kellogg Biological Station, 1994-2015. Regression parameters r represent the per capita yearly intrinsic rate of increase and K the carrying capacity, based on population numbers expressed as average number of adult *H. axyridis* captured per trap, per year. The ‘Phase’ column gives a shorthand for referring to the data subsetting structure indicated by the regime shift detector model.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Data**  **structure** | **Phase** | **Years in subset** | **r ( ± SE)** | **K ( ± SE)** |
| 1994-2017 | A | 1994-2000 | 1.3 ± 0.3 | 0.31 ± 0.02 |
|  | B | 2001-2005 | 2.3 ± 0.3 | 0.43 ± 0.03 |
|  | C | 2006-2013 | 1.6 ± 0.3 | 0.27 ± 0.03 |
|  |  |  |  |  |

**Table 2.** Ricker model fits for each phase between break points resulting from fitting population data documenting the area occupied by overwintering Monarch butterflies in their winter habitat in the Mexico, 1995-2016. Regression parameters r represent the per capita yearly intrinsic rate of increase and K the carrying capacity, in units of hectares occupied. The ‘Phase’ column gives a shorthand for referring to the data subsetting structure indicated by the regime shift detector model.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Data structure** | **Phase** | **Years in subset** | **r ( ± SE)** | **K ( ± SE)** |
| One break | A | 1995-2003 | 1.0 ± 0.5 | 10.1 ± 1.9 |
|  | B | 2001-2015 | 0.8 ± 0.3 | 4.1 ± 0.7 |
|  |  |  |  |  |

**Figure captions**

Figure 1: **Performance the regime shift detector model under varying conditions.** Proportion of results where initial conditions were detected by the top model (circles) or within the equivalent model set (squares) under A) varied noise (in the form of standard error) B) varied % changes in the K constant in the Ricker model C) varied % changes in r, the intrinsic rate of increase in the Ricker model and D) simulated time series length. Sets of 0, 1, 2 and 3 break points were randomly generated from within the set of possible values each scenario was iterated 1000 times.

Figure 2: **Observed outcomes of the regime shift detector model relative to simulation conditions.** Proportion of results with a given outcome under varied simulation length in years. Sets of 0, 1, 2 and 3 break points were randomly generated from within the set of possible values, and data were simulated with a 20% shift of r and a 40% shift of K at the given break point. Each series consisted of 25 years of simulated data and each scenario was iterated 1000 times. Lines joining points represent a third order polynomial GAM representing the best fit, with standard error. Data are plotted here by output of the regime shift detector script under varied standard error as a proportion of the mean (i.e. % noise) and input break point combination conditions, where A) proportion of scenarios where zero breaks were detected; B) proportion of scenarios where one break was identified; C) scenarios with two break points identified; and D) scenarios where three breaks were identified by the regime shift detector script.

Figure 3: **Regime shift detector breaks and Ricker model fits for an invasive ladybeetle**. Population data documenting the invasion of *Harmonia axyridis*, a ladybeetle native to eastern Asia, to plots at the Kellogg Biological Station in southwestern Michigan, USA, 1994-2015 A) Time series documenting average number of adults captured, per trap, per year. Vertical blue lines indicate timings of shifts in dynamics, as indicated by the regime shift detector model. B) Ricker fits of phases of population dynamics as indicated by the regime shift detector model.

Figure 4: **Regime shift detector breaks and Ricker model fits for a species of conservation concern.** Population data documents the area occupied by overwintering Monarch butterflies in their winter habitat in the Mexico, 1995-2017. A) Time series documenting raw data of estimated area occupied by overwintering monarchs by year. Vertical blue line indicates timing of a shift in dynamics, as indicated by the regime shift detector model. B) Ricker fits of phases of population dynamics as indicated by the regime shift detector model.