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

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**Abstract**

1: Understanding how and when environmental factors interact with density dependent population regulation remains a fundamental question in ecology. Pinpointing when sustained state changes occur in naturally fluctuating populations has remained unresolved. An analytical approach which allows the identification of timing and magnitude of such changes, or “regime shifts”, would advance our understanding and have the potential to direct the management of species of economic or conservation concern.

2: We develop a generalizable model, the “Regime Shift Detector” for adapting a simple density dependent model to detecting shifts in the dynamic regime observed in population time series data. This model was developed to be used as a generalizable tool comprised of a suite of functions for examining population time series data for the presence, location, and magnitude of shifts, using an iterative approach to fitting the Ricker model on subsets of time series data, and ranking the fit of the break point combination using model selection. We examined the performance of this tool with simulated data and two real-world case studies involving 20-year population time series datasets documenting species of conservation and economic concern.

3: We found that under low sampling error conditions, the regime shift detector model accurately identified no shift scenarios in approximately 60% of cases, and identified shifts in 1, 2 and 3 break scenarios in ≥80% of cases, although its performance declined as sampling error increased. In our case study examining the invasion process of common name (*Harmonia axyridis*), the regime shift detector identified shifts in population cycling associated with prey availability. However, in the case study examine population cycling in Monarch butterflies, the regime shift detector tool’s results were more ambiguous, suggesting that multiple super-imposed processes are 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 aide management decisions and identify and rank critical drivers of change in a species; dynamics. In an era of rapid global change affecting species dynamics, it is critical to use tools which allow better understanding of changes to internal regulators of population, and not base management decisions on population numbers alone.

**Introduction**

Population dynamics are governed both by internal, biotic rules, and abiotic influences, leading to equally important weighting of stochastic and deterministic forces governing population fluctuation patterns (Bjørnstad and Grenfell 2001). External perturbations of dynamic population processes can lead to population or trophic regime shifts, where the internal rules that govern a population’s fluctuations transition to another state (Hare and Mantua 2000, Carpenter et al. 2008). Understanding precisely how and when environmental factors interact with density dependent internal population regulation remains a fundamental challenge in ecology (Sutherland et al. 2013). The practical challenge of pinpointing when sustained state changes occur in naturally fluctuating populations has, to date, remained unresolved. An analytical approach which allows identification of timing and magnitude of regime shifts would advance our understanding and have the potential to direct the management of species of economic or conservation concern.

Density dependent tools for modelling population time series were developed and championed during the 1950s and 60s. Examples of these models include the Ricker and Beverton-Holt stock and recruitment models, which were initially developed for fisheries management (Ricker 1954, Beverton and Holt 1957). The accuracy of these simple density dependent models is regarded as highest for populations fluctuating around their carrying capacity (Sabo et al. 2004), with strong over-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), these models remain useful, in large part due to their simplicity and ecologically meaningful interpretations (citations). When parameter estimates produced by fitting these models differ between populations, or change in a single population, it suggests differing environmental constraints are occurring on the population, providing a quantitative measure of an effect of environmental changes (Forchhammer and Asferg 2000, Berryman and Lima 2006, Bahlai, vander Werf, et al. 2015).

A diagnostic, data-driven approach to model selection can be used to bypass assumptions about data structure when fitting simple density dependent models with time series data to gain insight into environmental constraints (Berryman 1999). However, the choice of break points in the time series are often applied *ad hoc*, based on data visualization or specific hypotheses surrounding factors affecting population fluctuations (Hare and Mantua 2000, Weimerskirch et al. 2003, Berryman and Lima 2006, Knapp et al. 2012), creating the potential for observer bias in selecting the break points themselves. Break point tools developed for other fields eliminate this bias by approaching locating change points with a variety of optimization strategies (Braun and Muller 1998, Priyadarshana and Sofronov 2015), but for data series without the internal, density dependent structure inherent to population time series. Wavelet analysis has been applied to population time series to determine changes in cycling pattern, (Jenouvrier et al. 2005), but this method also does not explicitly account for density-dependence. A robust, unbiased tool for identifying these shifts prior to explicitly quantify changes occurring in shifts between phases is warranted.

In this paper, we develop a generalizable tool for adapting a simple density dependent model to detect shifts in dynamic regimes within population time series data. We describe the basic structure of our model and how it can be used to examine population time series data for the presence, location, and magnitude of shifts in dynamic regimes, and examine the performance of this tool with simulated data and real-world case studies of two populations of conservation and economic concern.

**Methods**

A model script, simulations, and two case studies using population data from insect population monitoring were scripted and run in R Version 3.3.3 “Another Canoe” (R Development Core Team 2017) run within the RStudio Integrated development environment 1.0.136 (RStudio Team 2015). 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>.

*The model*

For our purposes, we use the Ricker model to describe the dynamics within a system (Turchin 2003).

The Ricker model is a single-variable discrete time model in which N(t+1), the population at time t+1, is a function of N(t), where N(t) is the measure of population size in year t, and the parameters K and r (the carrying capacity and per capita yearly rate of increase respectively) are estimated for the population during the time period modeled. The Ricker model was selected for our purposes because 1) it does not rely on any external information, other than population data over time, to be fit; 2) only two parameters need to be estimated, and those parameters have ecologically meaningful interpretations, and 3) in our experience, the model simply fits insect population data well.

We used an iterative, model-selection based process to determine if, and when, shifts in dynamic regime had occurred within a given time series. To achieve this, we first fit the Ricker model to the entire population time series, then the population time series was subdivided into all possible combinations of 2, 3, …, n subsets of sequential data points (hereafter, ‘break point combination’). For example, a twelve year series with a break point combination of 4, 8 would be broken into subset 1 = 1, , 2, 3, 4; subset 2 = 5, 6, 7, 8; subset 3 = 9, 10, 11, 12) and the Ricker model was fitted to each of the subsets produced for each break point combination. Break point combinations were constrained to only include subsets with more than three sequential data points to avoid over-fitting.

After fitting each subset for a given break point combination, the Akaike Information Criteria for each subset were summed together, providing an overall AIC for the fit. To further account for the effect of small series sizes, we calculated AICc (AIC correction for small samples) by using the total number of parameters estimated for the fit (where nparameters = 3 (nbreaks + 1), because for each fit, r, K and error were estimated), and this factor was added to the total AIC for each break point combination. 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, model performance was considered equivalent (Burnham and Anderson 2002), so when models were found with equivalent performance, the simplest model (ie: the one with fewest parameters and break points) was selected for further analysis. If the top-ranked models had the same number of parameters, the one with the numerically lowest AICc was considered best-ranked for the purpose of further analysis.

*Technical implementation*

The ‘regime shift detector’ was implemented as a series of R functions to enable a user starting with a data frame of population observations at a standard time intervals to quickly generate a report on the fit of the model described above to their own data. We summarize the role of each function in S1, but we encourage the reader to download the script file directly from <https://github.com/cbahlai/monarch_regime/blob/master/regime_shift_detector.R> for the details of implementation, included as line-by-line comments in the script.

*Simulations*

We conducted a series of simulations to test the accuracy(?) for the regime shift detector under a variety of scenarios. Specifically, we evaluated the impact of different size regime shifts by creating scenarios where the % change in r and K were individually modified at 10% intervals from 0 to 90%, the impact of length of time series was examined by extending the length of the time series by 2 year intervals from 25 to 33, and the impact of sampling error was tested at 1, 5, 10%, and every 10% interval thereafter to 90%. Each of these scenarios was run on simulated data with 0, 1, 2 and 3 break point combinations, and each scenario by break point combination was iterated 500 times with newly simulated data.

*Case studies*

We used two case studies to test the performance of the regime shift detector script on population time series data produced under natural conditions as parts of observational experiments. Both case studies involve approximately two decades of observations of economically or culturally important insect species, however, one case examines an invasion process, and another examines a population decline, both occurring over the same time period in recent history.

*Harmonia axyridis* in southwestern Michigan

The 1994 invasion of *Harmonia axyridis* to southwestern Michigan, United States was captured as part of 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 xx at the Kellogg Biological Station at Michigan State University. Detailed sampling methodology is available in previous work (Bahlai et al. 2013, Bahlai, Colunga-Garcia, et al. 2015, Bahlai, vander Werf, et al. 2015). The invasion process observed for *H. axyridis* inspired the need for a regime shift detector (Bahlai, vander Werf, et al. 2015).

Raw sampling data documenting the captures of adult *H. axyridis* at each sampling point, during each sampling week were extracted from the database (<https://github.com/cbahlai/monarch_regime/blob/master/casestudydata/kbs_harmonia94-15.csv>). Dates were converted to day-of-year format, and data were culled at day-of-year 240 to minimize the effect of variation in sampling period between sampling years (Bahlai, vander Werf, et al. 2015). We then calculated the average number of *H. axyridis* adults captured per trap, across all traps deployed within a sampling year were computed. We implemented our model using data from 1994-2015.

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, Wassenaar and Hobson 1998). 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 eastern migratory population (citation). Since the 1995 overwintering season, various groups have monitored the total area occupied by overwintering monarch colonies each season as a proxy for raw population counts, to minimize disturbance to the butterfly aggregations themselves. We used data documenting observations of area occupied from the winter of 1995 to the winter of 2017, compiled from these surveys by MonarchWatch.org (note that the northern hemisphere overwintering season overlaps two calendar years, in this study we have used the year in which the winter started, i.e. 1995 from the winter of 1995-1996, to define the year of observation). Data are available directly from MonarchWatch (Lovett 2017).

Monarch overwintering population data were subjected to the RSdetector function. Because the time series data also suggested the possibility of a simple linear decline in K (i.e. a linear decline in the mean population) data were also modelled this way, and the information criteria produced from this simpler model was used to compare to the performance of the RS detector.

**Results**

*Simulations*

Simulations were conducted by modifying one critical parameter at a time from a base scenario to determine how modifying each parameter affected the findings of the model. When varied sampling error was simulated as ‘noise’ (Fig. noise\_sim), the script’s ability to detect starting conditions dropped as percent noise increased, with the exception of no-break scenarios, which were generally correctly identified at a rate of approximately 60%, regardless of simulated sampling error (Fig. noise\_sim A). Outcomes involving the script finding extra breaks were most common in scenarios initiated with only one break (Fig. noise\_sim B), while outcomes where one break was missed by the script only occurred in scenarios initiated with three breaks, increasing with sampling error, and then plateauing at about 20% of outcomes above 30% sampling error (Fig. noise\_sim C). Outcomes identifying the correct number of breaks but misidentifying one break’s location peaked at around 20% sampling error in scenarios initiated with three break points, and at approximately 40% sampling error in scenarios initiated with two break points (Fig. noise\_sim D), and total failure to identify initial conditions generally increased with sampling error, with the exception of scenarios intiated with no break points (Fig. noise\_sim E).

Modifying the length of time series that a scenario affected the ability of the model to identify the starting conditions (Fig. Nyears), with model performance decreasing slightly with length of time series (Fig. Nyears A). In general, increasing time series length increased the probability that the script would correctly identify the break points from the initial conditions, but also ‘find’ additional break points (Fig. Nyears B) or find a break in a scenario that was not initiated with any breaks (Fig. Nyears E). Other erroneous results were rare (Figs. Nyears C, D).

The effect of modifying regime shift size on the model’s ability to detect conditions with which the scenarios were initiated was examined by modifying the % change in r and K at the given break point combination (Figs. changeK, changeR). The script was best able to identify initial conditions when the value for K was shifted by approximately 40% (Fig. changeK A) with extra breaks more frequently detected in scenarios initiated with larger changes of K at break points (Fig. changeK B). Complete failure to identify break points was most common in scenarios with small shifts in K (Fig. changeK E); missed breaks occurred rarely in 3 break scenarios regardless of the shift in K (Fig. changeK C) and misidentified breaks occurred occasionally in scenarios with 2 or 3 breaks and very large or very small shifts in K (Fig. changeK D.) The efficiency of the model responded differently to modifications of the size of shifts in r: instead of an intermediate optimum shift as observed for K, smaller shifts involving changes in r were most easily detected by the model (Fig. changeR A). The model was more likely to erroneously find additional breaks, miss breaks, or misidentify breaks as the percent change in r increased (Fig. changeR B, C,D). Complete failure to identify correct break combinations increased slightly with increases in r for scenarios initiated with 1, 2, or 3 break points, but error rates remained constant regardless of shift in r in the zero-break scenarios (Fig. changeR E)

To aide in the interpretation of regime shift detector model outputs in a situation where the conditions under which the data were produced are unknown (i.e. any ‘real’ population data), we also examined the scenarios where sampling error was varied in the converse way- by the proportion of input scenarios resulting in a given observed outcome (Fig. obs\_outcomes). When the regime shift detector model indicated that it had found no breaks in the data, this result generally reflected input scenarios with more than 80% accuracy when sampling error was below 50% (Fig. obs\_outcomes A). When the script identified scenarios with one or two breaks, sampling error affected the accuracy of outcomes more negatively, with accuracy dropping to approximately 60% at levels of sampling error approaching 25% (Figs. obs\_outcomes B, C). A similar pattern was observed for scenarios identified to have three breaks, however, accuracy was generally higher with this output, with >80% accuracy observed even at a sampling error rate of 25%.

*Case study- Harmonia axyridis*

The sampling error (in the form of standard error of the mean) for population samples of *H. axyridis* was estimated at about 6% from the raw data.

When the regime shift detector script was run using the *H. axyridis* population data from 1994-2013, as was used in the previous study, the script produced identical results to the previous implementation (Bahlai, vander Werf, et al. 2015) when break point combinations were ranked by AICc and AIC. Only one break point combination was identified by the regime shift detector: no break point combinations with equivalent fit were identified. Two break points- one occurring after 2000, and one occurring after 2005 were observed in this ‘best’ break point combination model (Fig. harmonia\_fit A). In this truncated data, the shift from ‘phase A’ to ‘phase B’ at the year 2000 was characterized by substantial increases in the fitted values for K and r (Table 1, ‘original’ data structure), followed by a return to parameter estimates nearly identical to those observed for ‘phase A’ in the post-2005 shift from ‘phase B’ to ‘phase C’ (Table 1 ‘original’ data structure, Fig. harmonia\_fit B).  
  
However, when the regime shift detector was applied to updated *H. axyridis* population data, which included two additional sampling years, the results were strikingly different. The two new observations, but 2015 observation, in particular, broke from the trend in dynamics observed in 2006 and after (Fig. harmonia\_fit A, data to the left of black vertical dashed line), and the regime shift detector script only located the post-2000 break in these data (Table 1, ‘updated’ data structure, Fig. harmonia\_fit B). In this case, the resultant regression parameters estimated for the period combining all apparent phases from 2001 on were intermediate in value, with greater standard error, than those estimated for phases B and C from the fits resulting from the shorter time series (Table 1, ‘updated’ data structure , Fig. harmonia fit B, dashed curve).

*Case study- Monarch butterflies*

Sampling error could not be estimated for this population measure as it is only reported as a single value- total area occupied by overwintering monarchs.

The regime shift detector script found three different break point combinations that were deemed to have equivalent performance by their respective AICcs, two models with a single break after 2003 and 2006 respectively, and a third with breaks at 2003 and 2008. However, when ranked by AIC, the two-break model substantially out-ranked both of the single-break models. Similarly, the population dynamic was modelled as a linear decline in carrying capacity K produced a fit that was ranked best of all scenarios tested by AICc, but second best after the two break point model by AIC (Table 2). The break point combination as ranked by AIC, the two break model is represented graphically by the solid lines in Fig. monarch\_fit (A, B) but the fit of the one break model is also given by the dashed line in Fig. monarch\_fit B.

**Discussion**

*Regime shift model structure*

The implementation of the model described here used the Ricker function because it presented an ideal compromise of simplicity and fit for the populations we wished to model. However, the method presented here could easily be adapted to population processes better described by other models, and incorporating other dependent variables which may be available (for example, if a population had a known response to temperature or another environmental variable). Similarly, this approach is not necessarily limited to population processes: a regime shift detector script could be developed to identify changes in any ecological dynamic with a well-defined internal rule governing its fluctuations. The sensitivity and precision of the approach could also be adjusted in these future implementations by adjustment of decision rules regarding selecting models of equivalent and best fit.

AICc was the information criterion used to rank break-point combination models, with all models ranked within two units of the lowest AICc considered to have equivalent performance, however, just a single ‘best’ model from the set of equivalent models was used for comparison in the simulations. The decision to only include one ‘best’ fit represented a compromise between accuracy, simplicity of script outputs, and computational intensity when running many simulation iterations. Overall script performance would likely have a higher rate of detecting all initial conditions if the set of all equivalently fitting models, instead of just the top-ranked, had been considered when comparing the performance of the script to the input conditions. In response to this observation, we developed the ‘modelspecification’ function so that a user may manually produce regression statistics associated with similarly ranked fits and interpret those values in the context of the known biology of the species under evaluation.

With regards to selection of information criteria, AICc was used for decision-making in the regime shift detector script rather than AIC because it allowed for a more conservative selection of break-point combinations while minimizing overfitting in higher sampling error scenarios- essentially by down weighting the selection criterion for models with many break points. However, this more conservative approach negatively affected the script’s ability to detect higher break frequency in low sampling error scenarios, particularly for one and two break input scenarios, because the penalty term for increasing the complexity of the model dramatically increases with AICc. Thus, if it is reasonable to assume that the population data being subjected to the regime shift detector script has a low associated sampling error, a user may wish to use less conservative information criteria (i.e. AIC) to rank break point combination models.

Because the model uses a single datum to represent the population in a given year, the model had to be constrained to avoid over-fitting to short time series. Unfortunately, this limitation means that shifts in dynamic regime occurring less than four time steps apart will not be detected by this modelling approach. In populations undergoing rapid change in their environments or internal dynamics, thus, the results of the script should be interpreted with caution, because a single-variable discrete time step model like the Ricker may not fully leverage available information. In these cases, using a model that allows, for example, within season dynamics to be measured may be more useful.

Regardless of model used to form the basis of the regime shift detector script, it is important that the model’s fitting function is set with some understanding of the data’s structure to prevent fitting or convergence issues. For example in our case, the rickerfit function was set to have a starting value of r at 1.5. For populations with dynamics that are expected to deviate from this value dramatically, setting this value to one closer to the expected value will aide in model convergence.

*Simulations*

Using the decision rules as set, simulations were performed to understand how changing various inputs affected the likelihood of the regime shift detector script identifying the conditions under which the data were produced. Simulations indicated that the performance of the regime shift detector script declined rapidly with increasing levels of sampling error (Fig. noise\_sim), a behavior that is, in general, expected of any statistical tool. Nevertheless, whenever possible, the sampling error of the data subjected to the script should be quantified to help evaluate the script’s results in the context of variation within the data due to sampling error. The error rate in detecting initial conditions varies with output, but in low-sampling-error scenarios, an output of zero or three or more break points by the script is generally approaching 90% accuracy, while outputs of one or two breaks have a lower rate of accurately detecting input conditions, at just under 80%.

Other input conditions also effected the performance of the regime shift detector script. The effect of changing the magnitude of the shift was dependent on which parameter was changed and by how much (Figs. change, changeR). 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 chaotic dynamics in the years immediately following the shift, potentially making the timing of shifts more difficult to pinpoint. Similarly, longer time series yielded regime shift detector script results that were more error prone (Fig, Nyears A), 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 (AICc) would decrease as sample sizes grew, leading to increasing likelihood of identifying extra breaks (Fig. Nyears B).

*Case studies*

Our case studies represent two different biological processes- invasion and a population decline, in two very well studied insect species, allowing us to interpret the outputs of the regime shift detector script in the context of known biology. The two species represent ideal test case studies because they also represent cases with differing complexity in population drivers. In the case of *H. axyridis*, dynamics of this predacious species is believed 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 (Bahlai, vander Werf, et al. 2015)- leading to relatively simple pulsed changes in dynamics. With Monarch butterflies, drivers of population dynamics are complex and result from drivers at local and continental scales (Saunders et al. 2017): previous studies have implicated climate (Zipkin et al. 2012), specific weather events (Brower et al. 2004), changing land use and habitat availability (Vidal and Rendón-Salinas 2014), and management practice (Pleasants and Oberhauser 2013) in their population dynamics. With many super-imposed drivers, we would predict the changing dynamics of this species would be driven by both smooth and pulsed processes, making the detection of discrete break points associated with regime shifts more difficult.   
  
In the *H. axyridis* case study, the regime shift detector script detected identical shifts to those observed in the previous study, when applied to the 1994-2013 data used in that study: specifically, shifts after 2000 and after 2005 corresponding to the invasion, and subsequent control of a prey item, with neonicotinoid insecticides (Bahlai, vander Werf, et al. 2015). However, when updated data, including observations from 2014-2015 were included in analysis, the post-2005 regime shift was no longer detected. Examination of the time series data suggests that a new dynamic emerging in these additional years of data may be the cause (Fig. harmonia\_fit). These two additional years deviate considerably from the population pattern observed in 2006-2013, in fact, they appear to be more similar to the dynamic observed during 2001-2005, when prey populations were uncontrolled by neonicotinoids. Because the regime shift detector script is unable to detect shifts with three or fewer years of data to minimize overfitting, these new data are constrained to be part of the previous, less explosive dynamic, so the script finds that the new, post 2006 phase integrating the 2014-2015 data does not differ from the explosive dynamics of 2001-2005. Thus, it seems probable that the script’s performance was compromised in this situation with the very earliest signs of a new shift in dynamic regime.

There are several possible biological explanations for *H. axyridis’* return to explosive population dynamics relating to prey availability. The resultant dynamic could be indicative of changing use patterns in neonicotinoids in central North America. Indeed, neonicotinoid insecticides are a subject of considerable controversy implicated with environmental impacts (Goulson 2013), so it is possible that farmers and land managers simply began using less of these insecticides in 2014 in response of this controversy. Alternately, extreme rainfall early in the growing season in the US Midwest in 2015 may have compromised the efficacy of neonicotinoid seed treatments. Finally, we may be observing the early signs of insecticide resistance among the field crop pests targeted by neonicotinoid seed treatments (Nauen and Denholm 2005, Puinean et al. 2010, Herron and Wilson 2011). Additional years of observation will be essential in determining if this apparent emerging shift is rooted in biological or management drivers, or simply represented a ‘blip’ in *H. axyridis’* dynamics.

The findings of the regime shift detector script on the Monarch overwintering population is, as expected, more ambiguous than that for *H. axyridis*, but still provides useful information in interpreting the timing of events effecting population density and cycling of the butterfly. Multiple models for describing the dynamics of monarchs were ranked similarly, and the conclusions reached about ‘best models’ depended highly on the information criterion used to rank them (Table 2). Using AICc, a more conservative decision rule down-ranking more complex models, a model assuming the carrying capacity was undergoing a linear decline was favored over all break-point models tested by the regime shift detector script, but only slightly so. Yet, using AIC allowed the script to be more sensitive to apparent shifts in dynamics, and in this case, a two-break model with shifts after 2003 and 2008 were observed, with stepwise declines in carrying capacity at these points and roughly consistent, although perhaps slight growth in the intrinsic rate of increase at the first shift. However, there is biological basis to support either of these favored models, and the reality faced by monarch butterflies is likely a super-imposition of both.

A smooth decline in carrying capacity for monarchs could be driven by a variety of factors which we know to have occurred: increasing deforestation in their overwintering grounds or loss of prairie breeding habitat in central North America would likely leave this particular signature on the overwintering data because these drivers are progressive and not reversible in the short term. Indeed, changes of these kinds are well-documented. Although the monarch’s overwintering habitat has been protected by various conservation strategies directed by the Mexican government dating back to 1980 (Vidal et al. 2014), illegal logging activity in the overwintering zone has occurred as recently as 2015 (Brower et al. 2016). Systematic prairie loss in the monarch’s breeding habitat has also been implicated with their decline (Mueller and Baum 2014), however, this loss has largely plateaued in recent decades (Zaya et al. 2017). Climate change, in the form of gradual shifts to less favorable conditions for overwintering, breeding, or feeding is also probable (Batalden et al. 2007), and could also manifest in an observed smooth decline.

Pulsed changes in carrying capacity would be observed due to specific climatic events and changing land management practices. Several extreme climate events affecting monarch overwintering survival have been documented in the past decades (Brower et al. 2004, 2015, Zalucki et al. 2015). However, assuming conditions largely return to previous averages after the climate event, we would not expect any one single extreme climate event to have lasting, multiple year impacts on the internal dynamic rule governing monarch population fluctuations. Indeed, we observe population densities at an outlying low density in 2013-2014 (as described in (Vidal and Rendón-Salinas 2014)) return to previous dynamics in subsequent years. Changing herbicide use practices in central North America, however, represent pulsed changes to new management states, and have largely eliminated milkweed from agricultural field crops (Zaya et al. 2017). This change in management, brought about by the introduction of glyphosate resistant soybeans and maize, has had the effect of dramatically reducing the density of agricultural weeds, including milkweed, within agricultural fields. Indeed, although glyphosate tolerant soybeans and maize were introduced to the US market in 1996 and 1998 respectively (Powles 2010), actual glyphosate use lagged behind, with dramatic increased in use of the pesticide in 1998- 2003 in soybean, and 2007-2008 in maize (Baker 2017). This pulsed increase in glyphosate use roughly correspond to shifts detected by our script, and glyphosate use in these crops has been implicated in monarch decline by multiple previous authors. Thus, findings from our regime shift detector tool could be used to pinpoint thresholds of herbicide use or critical areas of adoption in future investigations.  
  
**Conclusions**

The regime shift detector model provides an objective tool for examining population regulation pattern shifts in natural populations. 253

The regime shift detector tool, as is, represents a compromise between sensitivity and simplicity. We illustrated through case studies how the information criteria used and decision rules for cutoff have a dramatic impact on the results of the model, and thus should be considered critically before drawing any conclusions by the use of this tool. Similarly, we recommend a user carefully consider the limitations of the tool in the context of the raw data presented: if phases of change are too short to be detected by the model, its ability to detect these shifts will be limited, and the resultant variation may reduce the script’s sensitivity for detecting other shifts in the data. As we have demonstrated herein, alternate dynamics should be considered, and compared to outputs, for a holistic interpretation.

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 a species internal dynamics. In an era of rapid global change affecting species dynamics, it is critical to use tools which allow better understanding of changes to internal regulators of population, and not base management decisions on population numbers alone.

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**Table 1:** Regression parameters 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. Analyses were performed on a subset of the data, from 1994-2013 to compare to previous use of this approach (Bahlai, vander Werf, et al. 2015), and then again on the updated data including two additional sampling years. Note that the information criteria cannot be compared between the two data structures here, as they represent two different sets of independent variables; these criteria represent the ‘best’ of those that were used to rank competing break point combinations tested within the given data structures. The ‘Phase’ column gives a shorthand for referring to the data subsetting structure under the most complex scenario represented here.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Data**  **structure** | **AIC** | **AICc** | **Phase** | **Years in subset** | **r ( ± SE)** | **K ( ± SE)** |
| Original, to 2013 | -13.5 | -7.5 | A | 1994-2000 | 1.3 ± 0.3 | 0.33 ± 0.03 |
|  |  |  | B | 2001-2005 | 2.2 ± 0.2 | 0.46 ± 0.02 |
|  |  |  | C | 2006-2013 | 1.5 ± 0.2 | 0.29 ± 0.02 |
|  |  |  |  |  |  |  |
| Complete, to 2015 | -36.8 | -16.8 | A | 1994-2000 | 1.3 ± 0.3 | 0.33 ± 0.03 |
|  |  |  | B+C | 2001-2015 | 1.6 ± 0.4 | 0.43 ± 0.05 |
|  |  |  |  |  |  |  |

**Table 2.** Model performance of top-ranked models of differing structures fit to population data documenting the area occupied by overwintering Monarch butterflies in their winter habitat in the Mexico, 1995-2016. One break and two break models are for best break point combinations selected by regime shift detector script, while ‘linear K’ model assumes a linear decline of carrying capacity K and a single constant intrinsic rate of increase r. The ‘Phase’ column gives a shorthand for referring to the data subsetting structure under the most complex scenario represented here.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Model structure** | **AIC** | **AICc** | **Phase** | **Years in subset** | **r ( ± SE)** | **K ( ± SE)** |
| One break | 114.6 | 120.2 | A | 1995-2003 | 1.0 ± 0.5 | 10.1 ± 1.9 |
|  |  |  | B+C | 2001-2015 | 0.8 ± 0.3 | 4.1 ± 0.7 |
|  |  |  |  |  |  |  |
| Two break | 106.9 | 121.9 | A | 1995-2003 | 1.0 ± 0.5 | 10.1 ± 1.9 |
|  |  |  | B | 2004-2008 | 1.6 ± 0.2 | 5.6 ± 0.3 |
|  |  |  | C | 2009-2016 | 1.2 ± 0.4 | 2.8 ± 0.5 |
|  |  |  |  |  |  |  |
| Linear K | 112.9 | 118.5 | A+B+C | 1995-2016 | 1.3 ± 0.3 | - |
|  |  |  |  |  |  |  |

**Figure captions**

Figure ChangeK: **Performance of Regime Shift Detector Script under conditions of varying K.** Proportion of results with a given outcome under varying % changes in the K constant in the Ricker model at four simulated break point scenarios. Sets of 0, 1, 2 and 3 break points were randomly generated from within the set of possible values, and data were simulated with random 5% sampling error and a 20% shift of r at the given break point. Each series consisted of 25 years of simulated data and each scenario was iterated 500 times. Lines joining points represent a third order polynomial GAM representing the best fit, with standard error. Possible outcomes were A) Successful identification of all break points; B) One extra break point identified; C) One break point missed; D) Correct number of breaks found, but one or more break points misidentified; and E) Complete failure to identify the correct break point combination by the regime shift detector script.

Figure ChangeR: **Performance of Regime Shift Detector Script under conditions of varying r.** Proportion of results with a given outcome under varying % changes in the r constant in the Ricker model at four simulated break point scenarios. Sets of 0, 1, 2 and 3 break points were randomly generated from within the set of possible values, and data were simulated with random 5% sampling error 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 500 times. Lines joining points represent a third order polynomial GAM representing the best fit, with standard error. Possible outcomes were A) Successful identification of all break points; B) One extra break point identified; C) One break point missed; D) Correct number of breaks found, but one or more break points misidentified; and E) Complete failure to identify the correct break point combination by the regime shift detector script.

Figure noise\_sim: **Performance of Regime Shift Detector Script under conditions of varying sampling error.** Proportion of results with a given outcome under varying % in sampling error (‘noise’), modeled as randomly generated values selected from a continuous interval within a given % noise, for each observation generated in a simulation. 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 500 times. Lines joining points represent a third order polynomial GAM representing the best fit, with standard error. Possible outcomes were A) Successful identification of all break points; B) One extra break point identified; C) One break point missed; D) Correct number of breaks found, but one or more break points misidentified; and E) Complete failure to identify the correct break point combination by the regime shift detector script.

Figure Nyears: **Performance of Regime Shift Detector Script under varied time series length.** 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, generated with a 5% random noise to simulate sampling error. Each series consisted of 25 to 33 years of simulated data and each scenario was iterated 500 times. Lines joining points represent a third order polynomial GAM representing the best fit, with standard error. Possible outcomes were A) Successful identification of all break points; B) One extra break point identified; C) One break point missed; D) Correct number of breaks found, but one or more break points misidentified; and E) Complete failure to identify the correct break point combination by the regime shift detector script.

Figure obs\_outcomes: **Observed outcomes of Regime Shift Detector Script 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 500 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 sampling error (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 Harmonia: **Regime shift detector breaks and Ricker model fits for an invasive ladybeetle**. Population data documentis 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 pf apparent regime shifts as observed by Bahlai et al 2015. When data from 2014-2015 are included in the analysis (data following the black dashed line), the shift after 2005 is no longer detected by the model. B) Ricker fits of phases of population dynamics as determined by Bahlai et al 2015 (solid lines) and the new fit indicated by two additional years of sampling data (black dashed line).

Figure Monarch: **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, 1995-2016 A) Time series documenting raw data of estimated area occupied by overwintering monarchs by year. Vertical blue lines indicate timings of apparent regime shifts as indicated by the regime shift detector script. B) Ricker fits of phases of population dynamics as indicated by the regime shift detector script. Between each phase, the carrying capacity K decreased by about 50% from its former value, while r increased slightly in the transition from phase A to phase B. An alternate fit associated with a one break model that combine phases B and C, is given by the black dashed line.