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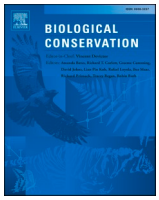

A systematic approach for detecting abrupt shifts in ecological timeseries

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ABSTRACT

Conservation efforts and sustainable use of natural populations often seek to reach or maintain viable abundance levels for a target population. Yet, this goal can be undermined by a number of events resulting from out-of-equilibrium dynamics, including large and sudden changes in abundance. The dynamical properties of such temporal changes are valuable indications about population's capacity to cope with environmental changes. Correctly identifying past or anticipating impending occurrences of temporal abrupt shifts in ecological systems is thus of major importance to adjust conservation and management strategies. Despite many available abrupt shift detection methods, few offer the possibility to compare and agree on the best model among linear, nonlinear, or abrupt models. By combining several existing methods, we develop an approach that classifies any timeseries to a trajectory type – no change, linear, nonlinear (quadratic), abrupt – and confirms the occurrence of potential abrupt shifts. We assessed the classification performances using a set of simulated data for which we had deterministic predictions for each type of trajectories. We used various levels of noise and perturbation events to make the simulations more realistic. This classification can be of particular interest when comparing dynamics of many populations across space or time. We show this by applying this classification approach to three different temporal datasets commonly used in conservation: catch tonnage, bird index, and insect occupancy timeseries. With this tool, we hope to promote conservation and management practices that explicitly take into account the likelihood of out-of-equilibrium trajectories and especially abrupt shifts in ecological systems.

1. Introduction

A common goal in conservation is to sustain viable abundance levels for populations and maintain them at a certain equilibrium despite the increase of prominent – and sometimes unpredictable – pressures on organisms (Wiens and Hobbs, 2015). However, natural populations are dynamical systems characterized by temporal changes that can be strong and persistent (Scheffer et al., 2001) – or fluctuations that can be periodic or completely irregular (Bjørnstad and Grenfell, 2001). Moreover, it is generally assumed that populations respond to environmental conditions and anthropogenic disturbances in a predictable and gradual manner, although equilibrium and predictable situations are rarely encountered in nature (Hastings et al., 1993; Clark and Luis, 2020). Instead, population dynamics are often out-of-equilibrium, driven by stochastic events, and their fluctuations are hard to predict (Dennis et al., 2001; Hsieh et al., 2005). If conservation strategies ignore the out-of-equilibrium and nonlinear nature of dynamics that are pervasive across taxa (Clark and Luis, 2020), or are unable to prioritize the least stable populations, they face a high risk of failure in sustaining viable populations.

Sudden, high amplitude, and large-scale shifts have been documented for a long time in ecological systems (Folke et al., 2004). The causes of such abrupt shifts are not unique and can arise in systems responding linearly to a sudden change in the environmental conditions, or from systems crossing a critical limit leading to a different equilibrium (Scheffer et al., 2001). The latter case is often called "regime shift" as the abrupt transition corresponds to deeper structural and compositional changes and leads to persistent change that can even be irreversible. Systems subject to regime shifts or other out-of-equilibrium dynamics may appear unstable and unpredictable (Mori, 2011), and given the intensifying climate change those dynamics would apply to an increasing number of natural systems (Garcia et al., 2014). Shifts towards a degraded equilibrium – e.g., lake eutrophication (Carpenter et al., 1999), collapse of fisheries (Levin and Möllmann, 2015) – could be deleterious for ecological and socio-economical processes (Biggs et al., 2018). The recent history of ecological science has spectacular examples

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of the detrimental effects of overlooking potential abrupt shifts, notably in fisheries management with the emblematic case of the Atlantic cod (*Gadus morhua*) (Möllmann et al., 2021) or the large ecosystem shift in the Black Sea (Daskalov et al., 2007). Despite the considerable implications of abrupt shifts, practical implementation of programs aimed at documenting and predicting shifts into biodiversity monitoring remain scarcely performed (Hewitt and Thrush, 2019).

Detecting abrupt shifts (also called changepoints or breakpoints depending on the field of study) has been a growing and transdisciplinary topic during the last few decades. As a result, a wealth of methods has been developed and applied in earth and biological sciences especially in climatology (Feng et al., 2010), paleontology (Bagniewski et al., 2023), as well as in ecology (Andersen et al., 2009; Bestelmeyer et al., 2011). The majority of the methods are designed to detect shifts in the mean of a focal variable, among which various approaches can be distinguished (Rodionov, 2005). Some of the methods involve curve fitting (Fong et al., 2017), parametric or nonparametric tests (Ross, 2015), Bayesian statistics (Lindeløv, 2020a), or other approaches (Boulton and Lenton, 2019). Some methods are suitable to detect multiple shifts, by testing all possible numbers and combinations of shifts (Bahlai and Zipkin, 2020), or require to indicate the number of shifts expected (Lindeløv, 2020a; Zeileis et al., 2002), while other can only detect a single one (Fong et al., 2017). A summary of the most recent breakpoint methods implemented in R can be found in Supplementary Table S1, whereas a complete overview is given by Lindeløv (2020b).

In ecology, like in other disciplines, the challenging task of detecting and locating abrupt changes has drawn a lot of attention (Andersen et al., 2009), especially abrupt changes in the mean value of a focal variable. However, knowing the location of a shift does not cover all aspects of the properties of a trajectory that could be useful to inform conservation strategies. Qualitative classifications of timeseries based on whether abrupt shift occurred in the past could be especially relevant for risk assessment of surveyed populations (Williams et al., 2011) and may prove easier to interpret than fully quantitative frameworks not suited to detect shifts – like generalized additive models (Buckland et al., 2005; Ficetola and Denoël, 2009). Given the wealth of abrupt shift detection methods, the number of practical studies trying to compare, validate, or integrate the outcome from different algorithms is surprisingly low (see Blöcker et al., 2023 for an example of integrated used of several models). Similarly, there is very little work on proper comparison of abrupt shift models with alternative non-abrupt models or cross-validation with other methods (Beaulieu and Killick, 2018). For instance, breakpoints might be detected in portions of the timeseries where only smooth nonlinear change is occurring, and thus abusively identified as a shift. Some comparative frameworks for classifying timeseries have already been developed for specific (Berdugo et al., 2022; Vert-pre et al., 2013) or more general (Rigal et al., 2020) systems, but come with a certain number of limitations. First, indications of uncertainty regarding the choice of the model or the timing of shift are rarely provided by classical methods (Vert-pre et al., 2013). Second, empirical timeseries usually available in conservation have often limited length, and abrupt shift detection frameworks are not always practically applicable or relevant for too short timeseries. Yet, the minimal length of applicability or relevance for most abrupt shift detection methods is rarely specified (Hewitt and Thrush, 2019). Last, when new classification and breakpoint detection methods are introduced they are not always thoroughly evaluated against simulated data (Shi et al., 2022). This prevents any detailed evaluation of the performances of the methods to detect abrupt shift dynamics in controlled conditions. Even when simulated data are used, abrupt shifts are often generated by post hoc transformations of non-abrupt timeseries (e.g., adding a constant or a trend), which may prove poorly realistic (Topal et al., 2016).

The goal of this paper is to develop a classification of timeseries into abrupt and non-abrupt (constant, linear, nonlinear) trajectories with immediate application for conservation. To do so, we combined existing methods to propose a classification of trajectory shapes focusing especially on the detection of abrupt shifts. We assessed the performance of our trajectory classification approach using simulated population timeseries and estimated the classification reliability with three independent metrics. Finally, we applied our classification approach to empirical examples representative of a large fraction of ecological timeseries relevant for conservation.

2. Methods

2.1. Trajectory classification

2.1.1. Four different trajectory shapes

The shape of a timeseries trajectory (i.e. the overall pattern of fluctuations over time) reflects the state of the study system (e.g., population, resource, climate), but describing the overall trajectory over a given time period can be challenging. Here, we assigned any timeseries (e.g., abundance, biomass) to a trajectory shape based on three properties of the best-model fitted on the timeseries: i) linearity, ii) trend, and iii) abruptness.

Trajectories best-fitted by a linear model with or without a significant slope were classified either as “linear” or “no change” respectively. Nonlinearity was assessed using a model of second order polynomial following Rigal et al. (2020), and such timeseries were classified as “quadratic”. If a timeseries was best-fitted by a step change (suggesting the possibility of a regime shift), it was classified as “abrupt”. Thus, based on whether a timeseries was better described by linear/nonlinear, with/without a significant trend, abrupt/nonabrupt, we were able to define four trajectory shapes, i.e. “no change”, “linear”, “quadratic”, and “abrupt” (Fig. 1A).

2.1.2. Description of the classification procedure

We classified timeseries following a sequence of three operational steps: 1) model choice, 2) model validation, and 3) classification reliability.

Step 1: Model choice

To choose among the four possible trajectory shapes considered, we followed a comparative approach. The classification started by modeling the relationship between the state variable and time (1) using different models associated with the four different shapes (Fig. 1B).

$$y(t) = f(t) + \varepsilon(t) \tag{1}$$

with y the state variable, f a function that can be linear, quadratic, or abrupt, both vary with time t, and $\varepsilon(t)$ the error term of the model.

According to the trajectory shape the function f followed one of the forms (2)–(5):

$$f(t) = \alpha_0 + \varepsilon(t) \tag{2}$$

$$f(t) = \alpha_1 t + \alpha_0 + \varepsilon(t) \tag{3}$$

$$f(t) = \alpha_2 t^2 + \alpha_1 t + \alpha_0 + \varepsilon(t) \tag{4}$$

$$f(t) = \alpha_0 + \beta_0 I(t > e) + \varepsilon(t) \tag{5}$$

with α_0, α_1, α_2, β_0 coefficients of the models and e the threshold parameter with $I(t > e) = 1$ when $t > e$ and 0 otherwise. Four statistical models were fitted on each timeseries. Linear models without and with slope were associated with “no change” (2) and “linear” (3) shapes respectively, second order polynomial model with “quadratic” (4) shapes, and step model with “abrupt” (5) shapes. Linear and polynomial models were fitted using *lm* functions in R, and step model with only one breakpoint using the *chngpt* R package (Fong et al., 2017).

We selected the most parsimonious model for each timeseries by comparing values of the Akaike Information Criteria corrected for small sample size (AICc) of each fit. The values of AICc were computed using

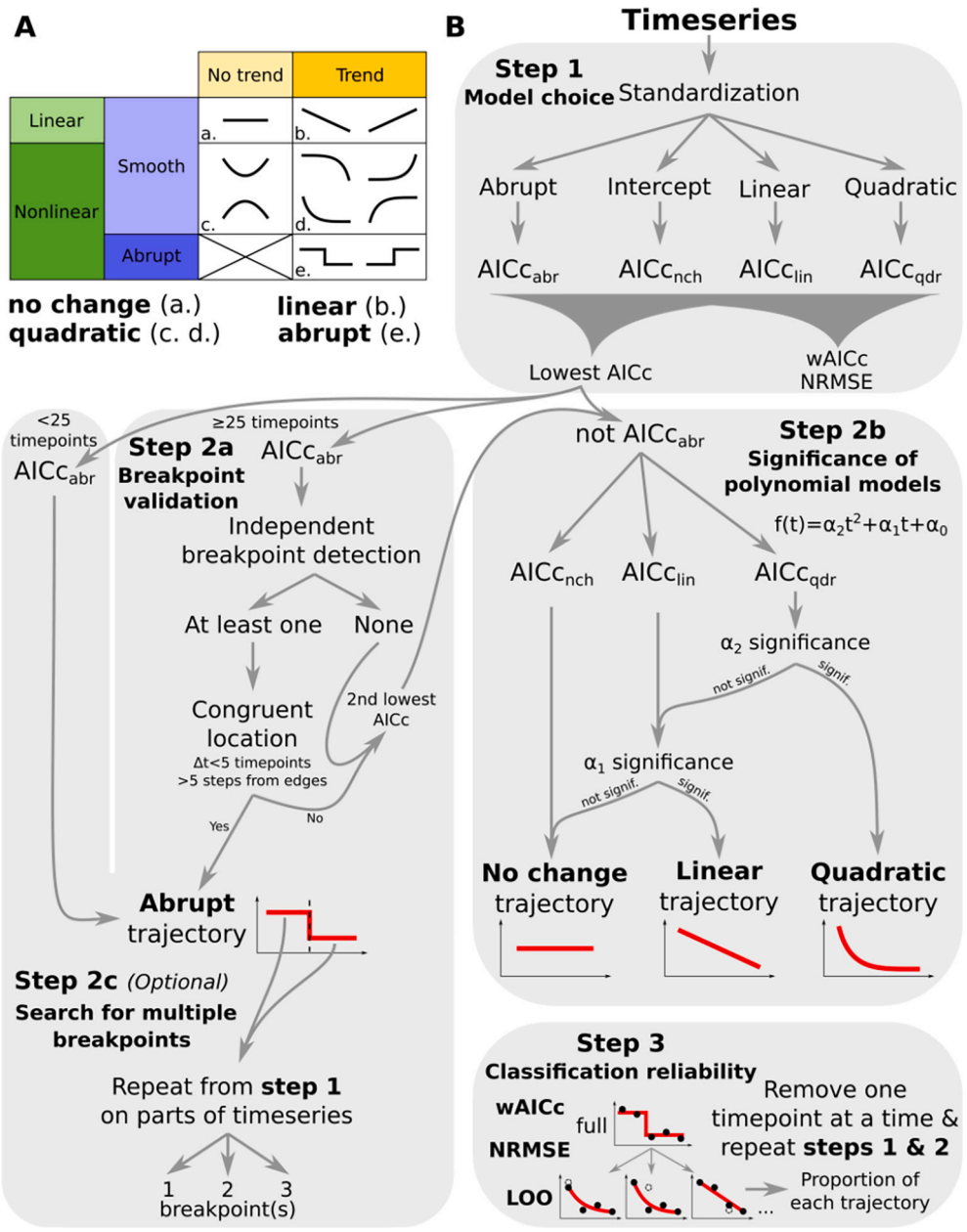

Fig. 1. Trajectory shapes (or classes) with associated properties (**A**) and trajectory classification step by step (**B**). Four models are fitted to the timeseries (including threshold regression, second order polynomial and linear models) for which corrected Akaike Information Criteria (AICc), AICc weights (wAICc), and normalized root mean square error (NRMSE) are computed (step 1, see main text for details). According to the best trajectory found in terms of AICc, the shape is validated either with another breakpoints detection method (step 2a) or by checking the significance of the coefficients (step 2b). To classify a timeseries as "abrupt", break dates detected by both methods need to be congruent and not too close to the start or the end. For "abrupt" trajectories, an optional extra step aims at finding multiple breakpoints (step 2c). The reliability of the classification is then assessed by a leave-one-out procedure (LOO, step 3) that consists in repeating steps 1 and 2 on the original timeseries to which one timepoint is omitted sequentially. From these, the most influential points can be detected and the proportion of LOO trajectories the same shape as the full timeseries can be computed.

the 'AICc' function from the *MuMIn* package (Bartoń, 2023). The best model was the one with the lowest AICc defined as follows (6):

$$AICc = -2log(L) + 2k + \frac{2k(k+1)}{N-k-1} \quad (6)$$

with L the likelihood of the data given the parameters, k the number of parameters, and N the length of the timeseries. The number of parameters varies according to the shape associated with the model. There is only one parameter for "no change" shape (intercept), two for "linear" shape (intercept and slope), and three for both "quadratic" (intercept, first and second order coefficients) and "abrupt" (two step values and the location of the breakpoint). We used AICc instead of AIC as recommended when the length of the timeseries is low ($N/k < 40$ according to Burnham and Anderson (2004) which is the case for most available ecological timeseries.

Step 2: Model validation

According to the best model obtained in step 1, the classification of the timeseries was confirmed in two alternative sub-steps, step 2a or step 2b (Fig. 1B).

Step 2a: Breakpoint validation

If step 1 found an "abrupt" shape as the best model, step 2a aims at validating the existence and location of the breakpoint using the *asdetect*

package (Boulton and Lenton, 2019), which is an abrupt shift detection method independent to the one used in step 1. This step is aimed at improving the reliability of the classification as "abrupt" by reducing the risk of spurious classifications as "abrupt" (false positive rate).

To identify breakpoints, *asdetect* is based on searching for anomalous rates of change in a timeseries. The method started by separating the timeseries into sections of predetermined length and fitted linear regression models through each section. An anomalous rate of change is defined as a gradient that is more than three median absolute deviations (corrected for asymptotically normal consistency) away from the median gradient. On a "detection timeseries" the same length as the original timeseries, a value of one was added or subtracted (depending on the direction of the anomaly) for each timepoint involved in an anomalous section. This process was repeated for all whole number section lengths ranging from five timepoints for the regression to be meaningful up to one third of the total length of the timeseries to have at least three values to compute the median absolute deviation. The "detection timeseries" was then divided by the number of section lengths used to give the proportion that a timepoint was considered part of an abrupt shift. Whether an abrupt shift was detected or not was based on the maximum absolute value of the detection timeseries above a given threshold. If those maxima spread over successive timepoints then the location of the shift was chosen as the integer part of the median date. The temporal range of such flat maxima was regarded as uncertainty of the breakpoint date. We set the detection threshold to 0.15, meaning that the breakpoints needed to be involved in anomalous sections in at least 15 % of the section lengths. This threshold is low compared to previous uses of *asdetect* (e.g., 0.4 in Boulton et al., 2020) but is reasonable since the breakpoint algorithm was not used alone but as a validating method aimed to be conservative enough.

Unlike the step change model from step 1, the *asdetect* method was able to detect multiple breakpoints on the same timeseries. To avoid uncertain shifts due to lack of hindsight, we discarded breakpoints within five timepoints from the start or the end of the timeseries. If at least one breakpoint was detected, the agreement with the step change was checked and the difference between both breakpoints needed to be five timepoints or less to be accepted. Note that all those thresholds and limits values can be easily adjusted by the user. If none or incongruent breakpoints were found with the *asdetect* method, the trajectory shape with the second lowest AICc was chosen.

Step 2b: Significance of the polynomial models

If step 1 found a smooth shape as best-fitted model or the breakpoint was not validated in step 2a, step 2b validated the degree of complexity of the model (i.e. linear or quadratic). This was done by checking the significance of the higher order coefficient (p-value<0.05) associated with the model found in step 1 (i.e. significance of the second order coefficient for "quadratic" shapes or of the slope for "linear" shapes following Rigal et al. (2020). At the end of step 2b, the trajectory retained corresponded to the one with the lowest AICc and the highest significant order.

Step 2c: Search for multiple breakpoints

If an "abrupt" shape was found and validated, an optional step 2c searched for additional abrupt shifts in order to refine the description of trajectories preceding and following the first identified shift found in step 2a. To do so, the classification steps (1-2a-2b) were repeated on the parts of the timeseries before and after the shift (included in both parts of the timeseries), if they were long enough (15 timepoints or more). Even if no additional breakpoint was found, this step allowed to specify the trajectory before and after the shift.

Step 3: Classification reliability

We used three different indices to assess the reliability of the classification generated by the workflow presented above. One measure for the relative support of data for each fitted model i is the AICc weight ($wAICc_i$) (Hobbs and Hilborn, 2006), which required to calculate the difference Δ_i of AICc between each model i to the best one (7):

$$\Delta_i = AICc_i - min(AICc) \tag{7}$$

The weight for each model ranges from zero to one and was calculated as follows (8):

$$wAICc_i = \frac{e^{-0.5\Delta_i}}{\sum_{j=1}^{4} e^{-0.5\Delta_j}} \tag{8}$$

We used the *wAICc* to check how better was the best model compared to the rest.

To assess the reliability of the classification and identify the timepoints that were most influential on the definition of the trajectory shape we implemented a leave-one-out cross validation procedure (LOO). The procedure consisted in repeating the classification steps (1-2a-2b) on the original timeseries while one timepoint was removed each time for all timepoints of the timeseries. For each of the four trajectory shapes, we computed the proportion of LOO timeseries attributed to each trajectory. The proportion of the best shape found for the complete timeseries gave an indication of the robustness of the classification to specific points.

Lastly, we computed the root mean square error normalized by the standard deviation (NRMSE) for each model as an absolute measure of goodness-of-fit. The NRMSE is comprised between zero and one with low values indicating that the model explains most of the variation.

For the "abrupt" trajectories, we also computed the standardized measure of the abruptness, as the difference in the mean before vs. after the breakpoint divided by the average standard deviation before and after the breakpoint (Bathiany et al., 2020).

2.2. Simulated timeseries

2.2.1. Building trajectory shapes

We built a library of simulated biomass timeseries to test the classification on timeseries for which we knew the "true" underlying trajectories (Fig. 2). To do so, we generated timeseries using a discrete Ricker-type population model (Ricker, 1954). This is a widely used model for population dynamics for a variety of organisms that can exhibit different types of bifurcations frequently found in ecological systems (Dakos et al., 2017). The model simulated the biomass of a population driven by a logistic growth and a mortality term. Overall, we produced eight deterministic trajectory scenarios that corresponded to four distinct trajectory shapes that we aimed at classifying (Fig. 2). The total length of timeseries was set to 100 timepoints. To match realistic trajectories, we considered three sources of stochasticity: demographic stochasticity, environmental stochasticity, and a jump process. Ecological timeseries are of limited length and this length constraint could have an impact on the classification performances. To test the effect of timeseries length while keeping the trajectory shapes unchanged, we subsampled one point out of two and up to five consecutive timepoints from the "complete" 100 timepoints timeseries we generated timeseries of length 50, 33, 25, and 20 points. In total, the timeseries library generated consisted of eight mortality scenarios, each for 12 noise level combinations, repeated 100 times independently, from which five different timeseries lengths have been produced. This corresponded to a library of 48,000 timeseries. We also tested the effect of five different types of data transformation on our classification approach. The parameter values of the full model and the deterministic scenarios, together with the default values of the classification approach, can all be found in Supplementary Table S2. Further details about the population model, stochasticity, data transformation, and subsampling processes are given in Supplementary text S1.

2.2.2. Assessment of performances

Knowing the expected trajectories allowed to tell whether the shapes were correctly classified or not. The performances of the classification were quantified by building confusion matrices, which are contingency

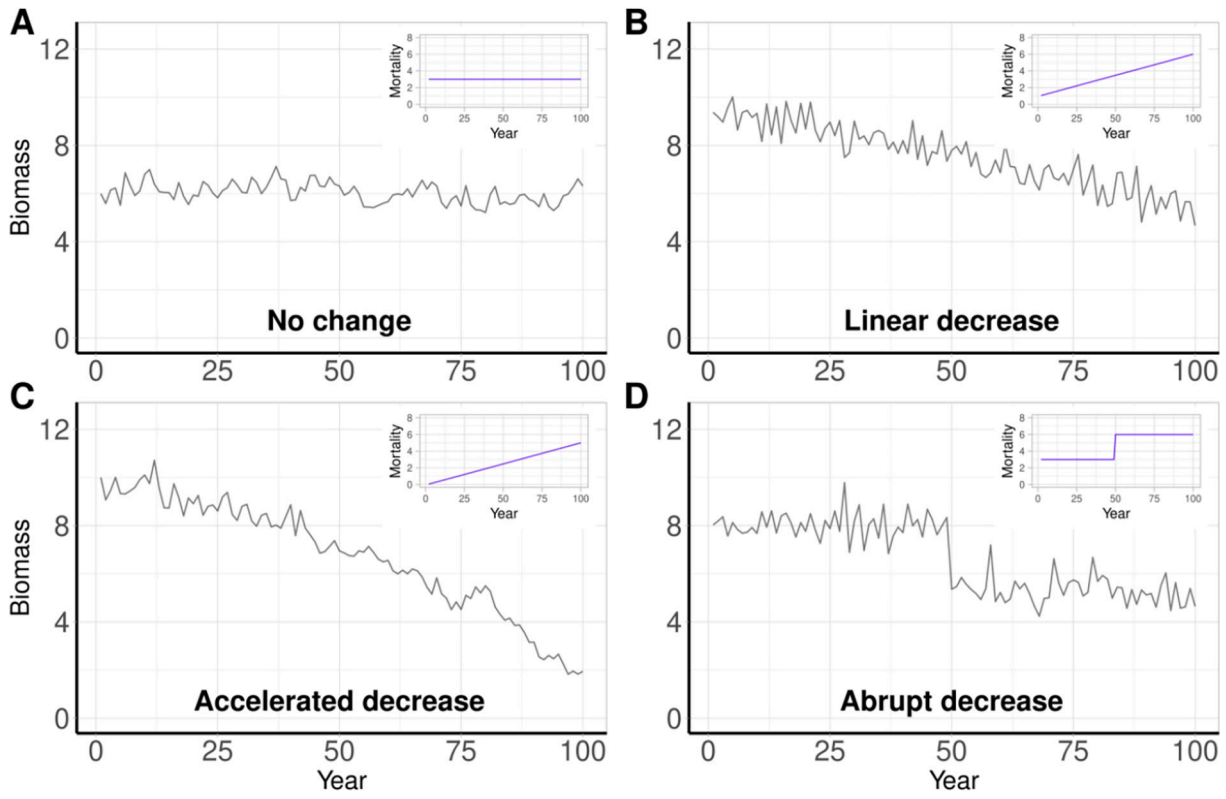

Fig. 2. Examples of simulated timeseries covering the four different trajectory shapes, "no change" (**A**), "linear" (**B**), "quadratic" (**C**), and "abrupt" (**D**). The solid black line show examples of biomass timeseries with low demographic stochasticity ($\sigma_r = 0.025$) and the solid blue line in the small panels show timeseries of maximum mortality rate F driving the biomass trajectories. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

tables that display the frequency distribution of the classification results (predictions in rows) according to expected classes (in columns). A binary classification (e.g., abrupt vs. smooth) can lead to four outcomes depending on whether the prediction is correct (true positive, *TP*, or true negative, *TN*) or incorrect (false positive, *FP*, or false negative, *FN*). Correct predictions are located in the diagonal of the matrix. More formally, we calculated the true positive rate $TPR = TP/(TP + FP)$, and false positive rate $FPR = FP/(TP + FP)$, which are measures of sensitivity and specificity of the classification. When in our case we consider four classes, we have four pairs of *TPR* and *FPR* associated with each of the classes when considering the other three as negative. Confusion matrices were generated using the 'confusionMatrix' function from the *caret* package (Kuhn, 2008).

We estimated the effect of adding the breakpoint validation step compared to the model choice alone in terms of classification performances. We also tested different detection thresholds in the *asdetect* method on the classification performances for abrupt vs. smooth timeseries. To do so, we built Receiver Operating Characteristic (ROC) curves that represent the performances of a binary classifier in terms of *TPR* and *FPR* for different thresholds. One curve was drawn for each timeseries length by running the classification for all possible thresholds between zero and one with a 0.01 increment and only considering the outcome as abrupt or smooth.

2.3. Empirical timeseries

We tested our classification approach on empirical timeseries of various types and organisms. Three datasets were chosen for illustrative purposes because they had long enough timeseries, they were relevant for conservation, and were readily available online. The first dataset consists in worldwide timeseries for fish stocks and were downloaded from the RAM Legacy Stock Assessment Database (https://www.ramlegacy.org/database/, RAMLDB v4.61) that gathers current and historical timeseries for various variables including catch, biomass, and mortality (Ricard et al., 2012). We applied the classification to catch timeseries with a length of 25 years or more and no missing years. The second dataset involves European common bird indices with timeseries ranging from 1980 to 2021 from the PanEuropean Common Bird Monitoring Scheme (Brlík et al., 2021). The third dataset comprised the odonate occupancy index from Britain from 1980 to 2012 (Termaat et al., 2019).

All simulations and analyses were performed with R (version 4.2.1) (R Core Team, 2022). The code and data of the classification approach can be downloaded at https://github.com/matpelissie/abrupt_shifts_ecological_timeseries_classification. The code also includes an Rshiny app for users to test the classification on their own timeseries.

3. Results

3.1. An example of a classification output

The classification of one or several timeseries was performed by our function 'traj_class'. This wrapper function took as input a list of timeseries and gave as output the best trajectory shape found for each of them and the main descriptive properties related to the different models (model coefficients, associated *p*-values, number and location of breakpoints, relative support of each model given by AICc weights, NRMSE, and LOO scores). Most of those properties were displayed on a summary figure (Fig. 3) that showed the four different fitted models in four different panels. The panel with the best shape ("abrupt" in the illustrated example) was highlighted in blue (Fig. 3D). The trajectory found was "abrupt" because this model had the lowest AICc among the four compared (AICc = 173.45) and the locations of breakpoints detected (at $t = 49$ for *chngpt* in blue, and at $t = 48$ for *asdetect* in red)

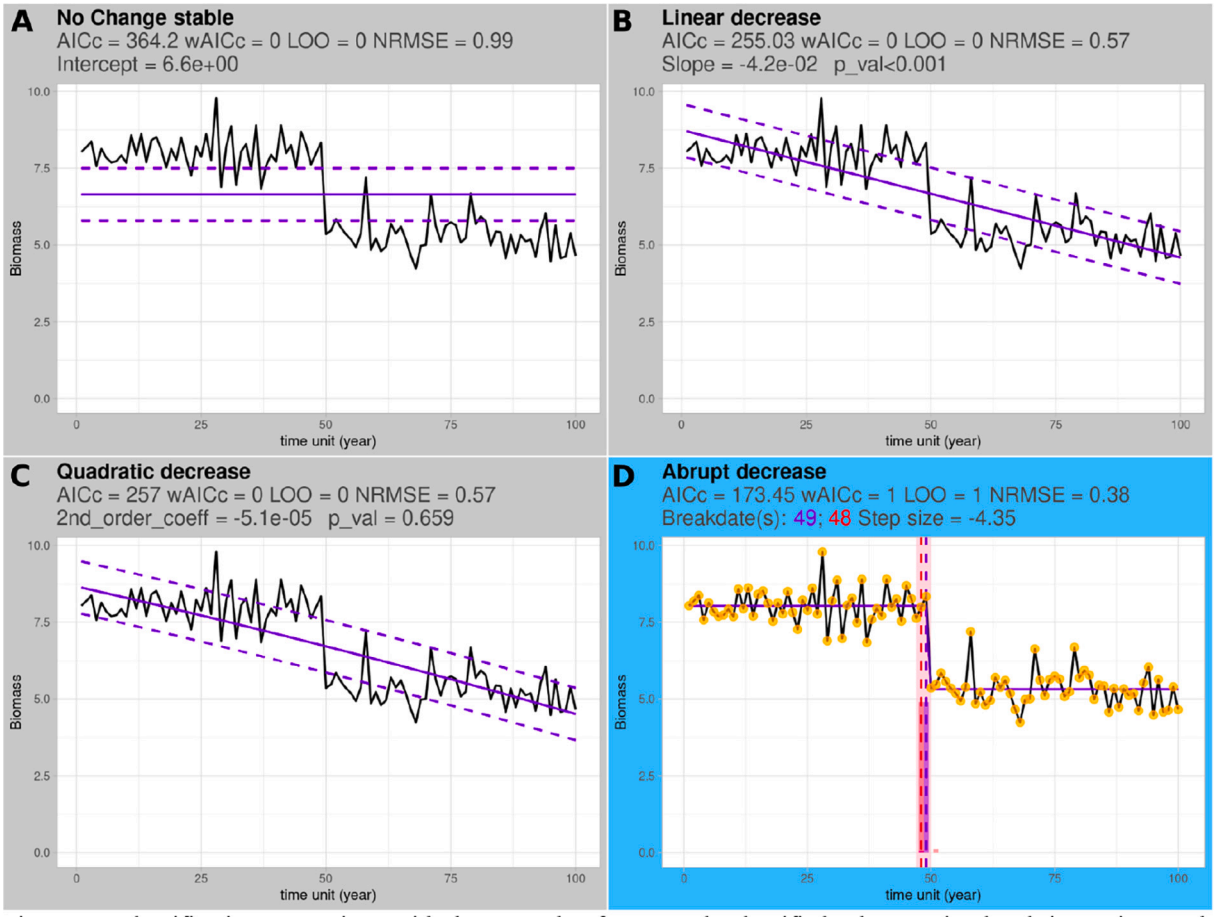

Fig. 3. Classification output in R with the example of a correctly classified "abrupt" simulated timeseries. Each of the four panels (**A**–**D**) describes the shape and trend of the trajectory: the same timeseries is shown (black line) with a different fit (solid blue line) and standard deviation (dashed lines for all panels except "abrupt" fit). In the "abrupt" panel **D**, the location of breakpoints is indicated by vertical dashed lines (in blue from *chngpt* – step 1, in red from *asdetect* – step 2a), the pink background corresponds to the uncertainty of asdetect breakpoints, and the distribution of breakpoint locations from Leave-One-Out (LOO) timeseries are represented by colour bars. Timepoints that if removed in the LOO process result in a specific shape are highlighted by orange dots in the corresponding panel. The panel with the best shape is highlighted in blue. Panel subtitles show AICc score, AICc weight (wAICc), LOO, and normalized root mean square error (NRMSE). Trajectory-specific values are also displayed: the intercept of the "no change" model (6.6), the slope (−4.2e-2) and associated p-value (<0.001) of the linear model, the second order coefficient (−5.1e-5) and associated p-value (0.659) of the quadratic model, the location of breakpoints (in blue from *chngpt* at $t = 49$, in red from *asdetect* at $t = 48$) and abruptness (the standardized magnitude of the abrupt shift equal to −4.35 here). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

were less than five timepoints apart. To examine the reliability of the best trajectory choice the value of the AICc weight, LOO score, and NRMSE were also displayed on each panel. In this example, both wAICc and LOO were equal to one for the "abrupt" trajectory, which indicates the abrupt model had far more support than the others and no particular timepoint affected the trajectory classification. Timepoints that if removed in the LOO process led to a different classification are highlighted by orange dots in the corresponding panel. In this example, as the removal of any individual timepoint still led to an "abrupt" trajectory, all orange dots were located in the "abrupt" trajectory panel (Fig. 3D). The NRMSE for the "abrupt" trajectory was 0.38 meaning that 38 % of the variation remained unexplained by the model.

3.2. Trajectory classification performance on simulated timeseries

Classification with only AICc comparison (step 1) on long timeseries (100 timepoints) yielded "abrupt", "quadratic", and "linear" timeseries most often correctly classified with 94 %, 96 %, and 96 % correct classifications respectively, but far less for "no change" timeseries with 53 % correct classification while 43 % were misclassified as "abrupt" (Fig. 4A). This overall picture remained for shorter timeseries (Fig. 4B–C), but with a decrease in the proportion of "linear" timeseries correctly classified with 70 % and 73 % correct classification, while 20 % and 17 % were misclassified as "abrupt" for timeseries length of 50 and 20 points, respectively. For 20 points timeseries, the proportion of "no change" timeseries correctly classified was higher than for longer timeseries with 84 % correct classification.

Classification with both AICc comparison and the breakpoint validation (step 2a) reduced the proportion of "no change" timeseries misclassified as "abrupt" from 43 % to 9 %, 43 % to 14 %, and 12 % to 2 % for timeseries length of 100, 50, and 20 points, respectively (Fig. 4D–F). However, it increased only marginally the proportion of "no change" timeseries correctly classified from 53 % to 70 %, 51 % to 69 %, and 84 % to 91 % for timeseries length of 100, 50, and 20 points, respectively. Compared to AICc only (step 1), the proportion of correctly classified "abrupt" timeseries was slightly decreased at 90 % and 86 % (from 94 % and 93 %) for timeseries length of 100 and 50 timepoints, and more severely at 61 % (from 87 %) for timeseries length of 20 timepoints. In the case of the 20 points timeseries length, "abrupt" trajectories were misclassified as linear for 34 % of the timeseries with breakpoint validation (Fig. 4F) compared to only 10 % without (Fig. 4C).

The level of noise applied on simulated timeseries had overall a

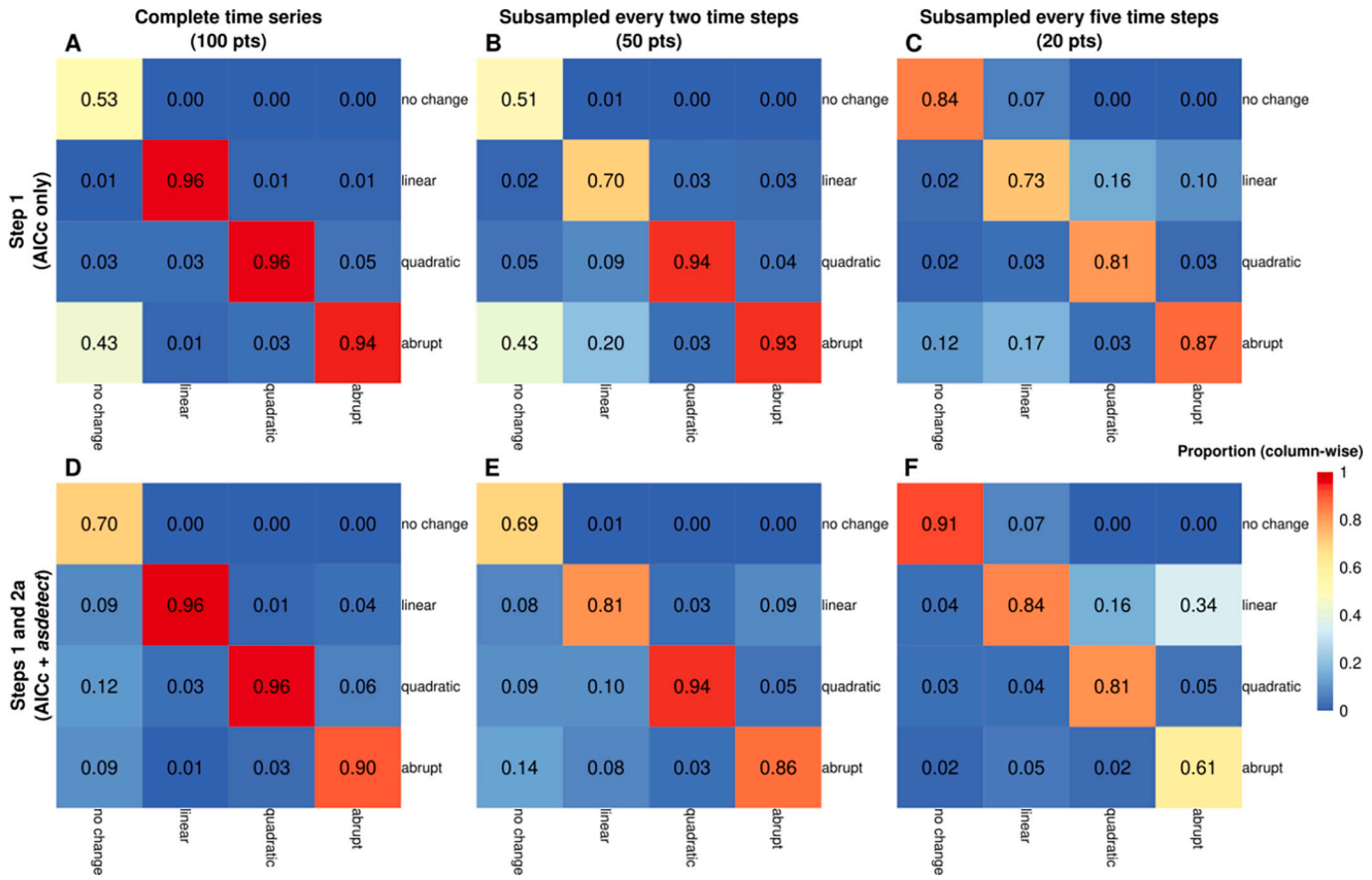

Fig. 4. Confusion matrices for simulated timeseries classified with step 1 – AICc only (**A**–**C**), or steps 1 and 2a – AICc + asdetect (**D**-**F**). For each row, the different matrices correspond to different timeseries length, 100 (**A**, **D**), 50 (**B**, **E**), or 20 (**C**, **F**) timepoints. Expected trajectory classes are in columns and predictions are in rows, numbers are the proportions by reference (expected) classes. For instance, in panel **A** for complete timeseries (100 points) classified with step 1 only, 53 % of the timeseries simulated to be "no change" were correctly classified, 1 % was misclassified as "linear", 3 % as "quadratic", and 43 % as "abrupt". The diagonal in each matrix corresponds to the proportion of correctly classified timeseries.

limited effect on the proportion of correct classifications especially for long timeseries (100 timepoints) regardless whether the breakpoint validation (step 2a) was used (Supplementary material, Fig. S1) or not (Supplementary material, Fig. S2). Increasing the standard deviation of demographic stochasticity from 0.001 to 0.075, in the absence of random jumps, which was enough to lead to significant qualitative timeseries noise (see examples in Supplementary material, Fig. S3) decreased the proportion of correctly "classified" abrupt trajectories from 97 % to 78 %, from 96 % to 67 %, and from 83 % to 43 % for timeseries length of 100, 50, and 20 points, respectively (Supplementary material, Fig. S1). However, the magnitude of random jumps had hardly any influence on classification performances with the proportion of "abrupt" trajectories correctly classified from 97 % to 96 %, from 96 % to 95 %,and from 83 % to 70 % for timeseries length of 100, 50, and 20 timepoints, respectively (Supplementary material, Fig. S1). "Abrupt" trajectory shape was the most sensitive shape to noise level, especially for shorter timeseries for which only half of the timeseries were correctly classified at the highest noise levels. In addition, the proportion of quadratic timeseries misclassified as linear tend to increase with noise especially for shorter timeseries while the opposite is not observed.

The effect of the detection threshold from the breakpoint validation step on the classification of abrupt vs. smooth trajectories is summarized on ROC curves for different timeseries length (Supplementary material, Fig. S4). Using the classification with the *asdetect* breakpoint validation was relevant only for timeseries above 25 timepoints. With the parameters chosen, the *asdetect* method required at least 15 timepoints to be used (to compute median absolute deviation from at least three sections of length five), and thus for timeseries below 25 timepoints we advise not to use the validation method and consider only the outcome from step 1, which can be done by specifying the argument in the function. The values of wAICc, LOO, and NRMSE scores help to assess the reliability of each classification. Their distribution according to whether the timeseries were correctly classified or not is provided in supplementary material (Supplementary material, Fig. S5).

We performed all classifications on "raw" (untransformed) timeseries. Testing classification results with three types of data transformations (rescaling, standardization, scaling by the mean) were identical to the "raw" timeseries. Only the absolute values of AICc were different, but wAICc, LOO, and NRMSE remained unchanged compared to the "raw" timeseries. However, logarithm and square root transformations changed the classification results as well as the wAICc, LOO, and NRMSE (Supplementary material, Fig. S6) and slightly improved the proportion of correct classification for "abrupt" timeseries.

Timeseries with two step changes were also simulated and classified. In most cases the trajectory selected was either "linear" or "quadratic" but not "abrupt" (Supplementary material, Fig. S7).

3.3. Empirical ecological timeseries

We applied our classification on three empirical examples for timeseries of fish catch, bird abundance, and odonate occupancy indices of >25 years (one timepoint per year). The three datasets contained timeseries classified as "abrupt", "quadratic", and "linear" (Fig. 5). The values of one in both wAICc and LOO scores in tuna and wheatear timeseries (Fig. 5A–B) indicated good support for their respective "abrupt" and "quadratic" trajectory compared to other trajectories

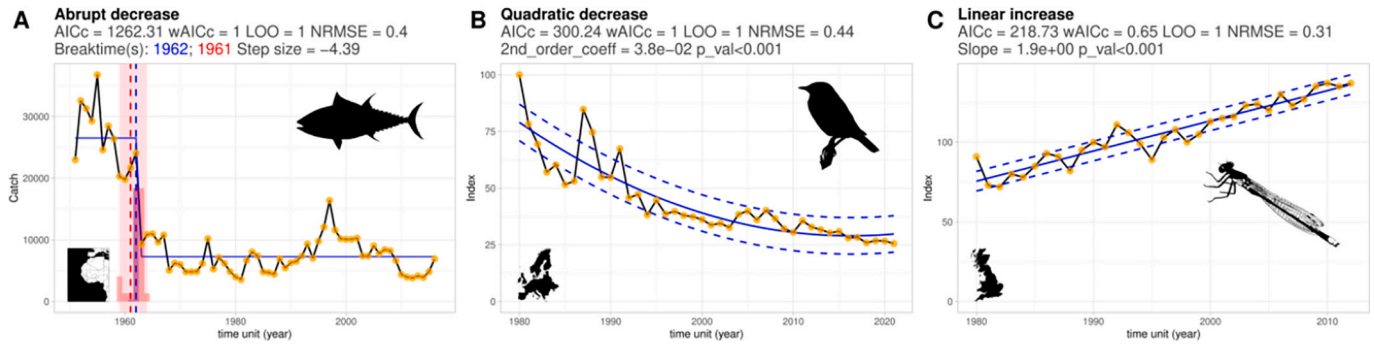

Fig. 5. Three empirical timeseries classified either as "abrupt", "quadratic", or "linear" following our classification approach, namely, (**A**) Atlantic bluefin tuna (*Thunnus thynnus*) catch in Eastern Atlantic (source: RAM Legacy Data Base), (**B**) Northern wheatear (*Oenanthe oenanthe*) abundance in Europe (source: EBCC/BirdLife/RSPB/CSO), and (**C**) Red-eyed damselfly (*Erythromma najas*) occupancy in Britain (source: Termaat et al., 2019). The location of breakpoints is indicated by vertical dashed lines (in blue from *chngpt*, in red from *asdetect*), the pink background corresponds to the uncertainty of *asdetect* breakpoints, and the location of breakpoints from LOO timeseries are represented by colour bars. Timepoints highlighted by orange dots indicate that if removed in the LOO process the best trajectory would remain the same as the complete timeseries. Animal silhouettes come from https://www.phylopic.org/. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

considered. In the case of the damselfly timeseries (Fig. 5C), the wAICc score was 0.65, which indicated that the fit from other shapes, notably "quadratic", were almost equally good. For the tuna timeseries, the distribution of breakpoints from LOO timeseries was unimodal and consistent with the location of both *chngpt* and *asdetect* from the complete timeseries suggesting no other shift in the timeseries. The NRMSE scores are below 0.5, which indicates the models explained most of the variation of the timeseries. Additional examples of classified timeseries with multiple breakpoints or smooth trajectories are provided in supplementary material (Supplementary material, Fig. S8).

4. Discussion

In this article, we develop a simple and straightforward classification of ecological trajectories based on their shape and trend to describe ecological dynamics in a meaningful way for developing conservation strategies. Our approach takes into account the transient and persistent changes that ecological systems out-of-equilibrium and in non-stationary environments experience (Ryo et al., 2019; Wolkovich et al., 2014) by accounting for abrupt and nonlinear shapes in addition to the typically used linear ones. As shown before (Gonzalez et al., 2023; Rigal et al., 2020), such temporal descriptions of ecological trajectories can contribute to decision-making in conservation and biodiversity assessments for identifying populations with highest need of conservation and for tracking the effects of conservation measures. We validated the classification performance and the limits of our approach against realistic simulated population timeseries. We also showcased the generality of our classification approach with examples of empirical population timeseries of different data types and origins.

In contrast to most breakpoint detection methods, the main feature of our classification approach is that it detects abrupt shifts along a trajectory and compares it to linear and nonlinear alternatives. Compared to other nonlinear fitting methods alone (e.g., GAMs Ficetola and Denoël, 2009), our approach focuses on providing the most prevalent shape of a trajectory rather than aiming at maximizing model fit. Thus, the fitted model trajectories of our classification are not meant to reflect the system's "equilibrium", as the observed timeseries result from changing environmental conditions that likely involve delays leading to transient and out-of-equilibrium dynamics in addition to sources of process and measurement error (Dornelas et al., 2013). Instead, our classification approach aims to describe such out-of-equilibrium trajectories through model comparison of the most parsimonious trajectory shapes. Such best-guess description of a population's dynamics is a prerequisite to effective conservation measures. For instance, acknowledging the occurrence of abrupt shifts enables to prevent future collapses in order to adapt conservation accordingly. The interpretation of a given trajectory shape depends on the system considered (see Supplementary material, Table S3 for potential ones) and using organism lifespan or generation time as time unit could improve the interpretation of the trajectories (Bestelmeyer et al., 2011). The structure of the classification approach allows the user to understand the reason for the trajectory found through visual and informative outputs. The main output (Section 3.1) provides the user with means to assess the quality of the classification by displaying the alternative shapes tested and through scores indicative of the level of confidence. In addition, high flexibility is allowed to control the classification steps. For instance, the detection threshold could be increased to remain rather conservative in the detection of "abrupt" trajectories, or conversely, the validation step could be skipped to minimize the risk of missing abrupt shifts. By testing the classification on a library of simulated timeseries, we were able to clarify the limits of our approach (Section 3.2). With the default set of classification parameters, the timeseries with no change were the most often misclassified, meaning that a slight trend or shift could sometimes be found from noise. Still, we consider this high sensitivity to be more in line with the precautionary principle that should prevail in conservation management (Cooney, 2004). Our tests show that the classification is reliable for timeseries of at least 25 timepoints, with the possibility to use it for shorter lengths without the breakpoint validation step (step 2a). This lower bound is congruent with those already suggested to detect tipping points with confidence of at least 15 to 20 years (Hewitt and Thrush, 2019). We also evidenced that the classification is rather robust to noise input and only some kinds of usual data transformation have an impact on the classification output.

Yet, we do not expect our classification to be suitable to any type of timeseries. Our aim is to remain rather simple and only single breakpoint models are supported. In the case of multiple shifts or high-frequency periodicity, other methods could be more relevant depending on the question asked. Notably, the Bayesian *mcp* method infers the location of breakpoints with segment specific regression models but the number of breakpoints needs to be known a priori (Lindeløv, 2020a). In case of timeseries exhibiting a clear seasonal component, the proposed classification could be preceded by an appropriate deseasoning step, but we advise to compare the result with other methods like *bfast* (Verbesselt et al., 2010) or bayesian version *Rbeast* (Zhao et al., 2019) that are specifically suited for such cases as they look for breakpoints in periodic systems after decomposing the signal into trend, seasonal, and noise components. In general for our classification, poor model fit would be evidenced by high normalized root mean square error (NRMSE) indicating that the model explains little variation, low AICc weight meaning that other models describe equally well or better the timeseries and low

Leave-One-Out score suggesting that the trajectory found is not robust to the removal of individual timepoints. The warning values of each score depends on the trajectory shape considered (Supplementary material, Fig. S5). In such case, the classified trajectory should be treated with caution. In addition, our classification approach is designed to describe not only the location of breakpoints but the full extent of timeseries, thus all changes along the timeseries are likely to influence the trajectory. Lastly, in our classification approach, only one type of breakpoints is targeted, referred to as the "step" threshold effect (Fong et al., 2017). We acknowledge the existence of other types of breakpoints (e.g., change of slope, change in variance) but assume that most detectable abrupt shifts in ecological systems are best approximated with abrupt step-changes. Still, our classification could be adapted to integrate more specific trajectory types by adding other nonlinear or breakpoint fitting methods.

The main interest of the proposed trajectory classification approach also remains in the possibility to be applied to a large number of timeseries without necessary analyzing each of them individually. Consequently, the approach we develop can foster a more systematic identification of abrupt dynamics in timeseries for conservation science (Biggs et al., 2018) and even beyond. As an example, in fisheries science, management practices still largely rely on fixed target indicators (so-called biological reference points) to trigger management actions, which may prove unreliable under changing conditions (Silvar-Viladomiu et al., 2021). Thus, considering trajectory classification for some of the main stock variables (e.g., abundance and productivity) could complement the classical stock assessment procedure. This could be a way forward to include regime shift and non-equilibrium perspectives into fisheries stock assessment, that are currently largely overlooked (King et al., 2015). More generally for populations monitored over mid- to long-term a nonlinear classification would allow to evidence transient dynamics (e.g., trend inversions, inflection points) that could for instance warn about the early stages of a larger decline or the onset of population recovery. Such nonlinear changes are transitory and could be detected only after they started to be noticeable (Andersen et al., 2009). A valuable advance would be to explore the delay in the detection of such change using a classification like the one we develop here when the timeseries is updated on a regular basis.

Out-of-equilibrium dynamics and nonlinearity are ubiquitous from populations of most taxa (Clark and Luis, 2020) and up to the scale of ecosystems (Guichard and Gouhier, 2014). The trajectory classification approach we developed here could help to promote conservation and management practices that explicitly take into account nonlinear responses and the likelihood of abrupt shifts in ecological systems. Yet, the dynamics of an ecological system can't be only summarized by describing the shape of a single timeseries. A more complete description could be reached by considering trajectories of multiple system components in parallel. This could apply to understanding dynamics across space for spatially-structured communities (Pedersen et al., 2020) or to considering trajectories of environmental drivers that influence the ecological trajectories (Gonzalez et al., 2023; Spake et al., 2022). Integrating a multiple trajectory classification in our approach could represent a way forward for improving the monitoring and management of ecological systems.

CRediT authorship contribution statement

All authors: conceptualization; MP: analyses; MP: writing first draft; All authors: review and editing.

Declaration of competing interest

The authors declare that they have no conflicts of interest and that this article is an original manuscript not submitted to any other journal. They also attest to comply with all ethical requirements as well as to have correctly indicated the funding of the work.

Data availability

The code and data can be downloaded at https://github.com/matpelissie/abrupt_shifts_ecological_timeseries_classification.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2023.110429.

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