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Journal of Applied Ecology
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Journal of Applied Ecology 2014, **51**, 1050–1056 doi: 10.1111/1365-2664.12263

User-friendly and evidence-based tool to evaluate probability of eradication of aquatic non-indigenous species

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Summary

1. The gap between practitioners and conservation or environmental management science is difficult to bridge. Managers sometimes use limited scientific information in their decision-making process, mainly because they have little time to review primary literature before making a decision. Making data readily available to managers is expected to improve the overall efficiency of management interventions. Here, we present an approach to develop user-friendly applications for evidence-based management and illustrate the concept by presenting a simple computer program designed to evaluate the probability of eradication of aquatic non-indigenous species.

2. We conducted a review of case studies that attempted to control aquatic non-indigenous species and used a statistical model to relate the outcome (eradication or non-eradication) to characteristics of the populations and interventions conducted. Based on a few key variables, the model returned accurate probabilities of eradication as evaluated with a receiver operating characteristic curve and jackknife and cross-validation procedures.

3. We packaged the statistical model in a user-friendly computer program that can be used by managers to (i) rapidly calculate the probability of success of a planned intervention with associated uncertainty, (ii) compare the success probabilities of different possible interventions and (iii) prioritize what information should be collected to increase the reliability of estimates.

4. *Synthesis and applications*. Our decision support tool is easy to implement, statistically flexible and could be used for any type of conservation or management intervention, given a sufficient number of case studies available in the literature. We recommend that scientists develop such tools whenever they conduct reviews of effectiveness of intervention. This is likely to result in greater use of data by practitioners, increased reliability of cost–benefit analyses and an overall increase in efficiency in conservation and environmental management.

Key-words: conservation, decision support tools, invasive species, management, predictive model

Introduction

Management decisions concerning environmental issues are often based on information coming from the manager's experience and/or from expert advice (Pullin *et al.* 2004; Pullin & Knight 2005; Cook, Hockings & Carter 2010). Management would be better informed if scientific data were incorporated in decision-making through the implementation of evidence-based management (Pullin & Knight 2001; Sutherland *et al.* 2004), but a manager may not have time to review the science before taking action (Pullin *et al.* 2004; Pullin & Knight 2005). Making the evidence readily available, particularly through development of tools to enhance the use of data, is essential to improve efficiency. Systematic reviews of conservation actions allow managers to quickly judge whether a particular technique has been effective elsewhere (e.g. Stewart, Coles & Pullin

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2005; Davies & Pullin 2007; Smith *et al.* 2010), but do not provide information about probability of success if the technique is to be applied in a new context. In addition, to intervene in the most cost-effective manner, managers should be able to compare the effectiveness of different options (Segan *et al.* 2010). Evidence-based tools to inform decision-making are being developed for specific situations. For example, using Bayesian belief networks or various numerical models allows predicting the behaviour of a system under different management scenarios (Newton *et al.* 2007; Raymond *et al.* 2011; Holzkämper *et al.* 2012). However, the scope of inference of these models may be narrow, which impedes applicability to other systems.

Every management action taken represents an unreplicated and uncontrolled manipulative experiment (Sutherland *et al.* 2004). By itself, the outcome of an individual intervention is statistically meaningless for prediction, but a collection of quantified case studies represents a statistically valid data set with independent data points. The outcome of each observation depends on (i) what action was taken, (ii) the system upon which the action was taken and (iii) what is unknown about the system. This provides the necessary ingredients for a statistical model: the dependent variable (outcome) depends on independent variables and covariates (what action was taken and characteristics of the system upon which the action was taken), and variability inherent to the statistical model (unknown). Such models have been used often to identify factors influencing success of different interventions (e.g. Brooks *et al.* 2006; Padgee, Kim & Daugherty 2006; Stewart *et al.* 2009; Smith *et al.* 2010; Pluess *et al.* 2012), but publication formats (e.g. reporting summary statistics rather than estimated coefficients) may make it difficult or impossible to use the information to estimate probability of success for a new situation. Here, we show that simple statistical models can be used to obtain reliable probabilities of successful management. We illustrate how such models can be used to develop user-friendly management tools by developing a simple computer program that predicts the probability of eradication of aquatic non-indigenous species.

Our general approach is to conduct a review of case studies dealing with a particular problem and use that information to predict the outcome in a new situation. A list of selected characteristics (i.e. factors considered to have the potential to influence the outcome) and a measure of success is recorded for each case study. A statistical model is fitted to the data set to relate the outcome to the various factors. The predictive power of the statistical model is then evaluated. Using the statistical model allows estimating the probability of success of a proposed intervention by entering its characteristics as factors. Once packaged in a user-friendly way, this framework allows the user to rapidly and quantitatively evaluate the intervention's chances of success, in relation to the known predictive power of the model.

Throughout the world, projects are underway to prevent ecological and economic harm caused by non-native species (Mack *et al.* 2000), with the ultimate goal of eradicating the unwanted species from an invaded area (Simberloff 2009). A quantitative analysis relating various factors to success of eradication attempts in terrestrial systems identified population extent as the main predictor (Pluess *et al.* 2012). In aquatic systems, qualitative *a posteriori* analyses of case studies pointed to factors potentially affecting success. For example, time to response following detection and the level of operational preparedness were identified as key elements (Anderson 2005; Williams & Grosholz 2008). The history of documented attempts to control aquatic non-indigenous species provides a unique opportunity to test and implement our approach.

Material and methods

LITERATURE REVIEW

We reviewed available literature dealing with attempted control of aquatic non-indigenous species. Note that we did not intend to conduct a systematic review (*sensu* Pullin & Stewart 2006); a complete review and an evaluation of factors influencing control success are underway (B. Beric, University of Windsor, pers. comm.). Instead, we focused on a few factors we considered likely to influence success and included only reports for which information on all these factors was available. For each case study, we recorded characteristics of the target system: (i) the broad taxonomic grouping of the target species (plant/algae, invertebrate or vertebrate), (ii) the habitat (marine intertidal, marine subtidal, river/stream or lake/pond), (iii) the area occupied by the population (m^2) and (iv) the population status ('introduced' if no evidence of reproduction, 'established' if reproducing or 'invasive' if causing economic or ecological harm). We also recorded information about the attempted control program: (i) the type of control method used (mechanical, chemical, biological or a combination of methods), (ii) containment ('yes' if actions were taken to prevent natural or anthropogenic dispersal to or from the target area, and 'no' if no action was taken) and (iii) the duration of the program, including post-intervention surveys (years). Life history of target species (e.g. longevity, dormant stage, etc.) and duration of post-treatment surveys varied widely among case studies. It was therefore difficult to establish a formal criterion for declaring eradication. We thus considered two possible outcomes: 'eradication' when no individuals were detected in post-treatment surveys and 'non-eradication' when individuals were detected. Note that 'eradication' corresponds to an 'apparent eradication' as there is uncertainty related to probability of detecting remaining individuals, if any, during the post-treatment surveys. When multiple independent interventions were reported in the same article or report (e.g. different water bodies), they were recorded as separate data points. Studies testing control methods and not targeting an entire population were excluded.

STATISTICAL MODEL

The statistical model used was a generalized linear model, with the 'logit' link function, and outcome of each case study (eradication = 1 and non-eradication = 0) as the binary dependent variable. The independent variables Area (log10-transformed) and

Duration were continuous whereas Taxonomy, Habitat, Status, Method, and Containment were categorical . The model selected for prediction was the most parsimonious main effect model; from all combinations of variable inclusion, we chose the model with the lowest Akaike information criterion (AIC) value. The model selection was confirmed using the area under the curve (AUC) from receiver operating characteristic (ROC) curves fitted for each model; we made sure no model had an AUC considerably greater than the most parsimonious model (i.e. the difference in AUC was <0·01). The predictive power of the final model was assessed in three different ways: assessment of true- and false-positive rate at different probability thresholds, jackknife procedure and cross-validation.

First, a ROC curve was built for the final model and the optimal threshold was determined. From there, the true-positive rate (proportion of case studies that resulted in eradication with a fitted value above the threshold) and false-positive rate (proportion of case studies that resulted in non-eradication with a fitted value above the threshold) were determined. Given that model selection procedures can result in overoptimism (Harrell, Lee & Mark 1996), we computed a custom 'null' ROC curve instead of the usual straight line passing through the middle of the plot. We used a randomization procedure in which (i) the observed outcomes (a vector of 0s and 1s) were randomly assigned to the different measured combinations of independent variables, (ii) the most parsimonious model was determined using the AIC model selection procedure described above, and (iii) a smoothed ROC curve was fitted for the model. Modified from the procedure described in Macskassy and Provost (2004), this was repeated 1000 times, and the average true-positive rate (y axis) was determined for different false-positive rates (x-axis). We finally calculated 95% confidence intervals by retaining the 2·5th and 97·5th percentiles of true-positive rates for each examined false-positive rate.

Secondly, we conducted a jackknife evaluation. Each datum was successively removed from the data set, and models were fitted using the remainder of the case studies. We used these models to obtain an independent prediction of the probability of eradication for each case study. We evaluated the discriminatory power of the model by comparing the independently predicted probability of eradication and the known outcome; we used a Mann–Whitney U-test to compare the median predicted probability between eradications and non-eradications.

Thirdly, we used a bootstrapped cross-validation procedure (Harrell, Lee & Mark 1996). We randomly selected 100 case studies (training subset) that were used to calibrate a model including the independent variables retained in the final model. A ROC curve was built for this model, and the optimal threshold determined. We used the remaining case studies as the testing subset; for each of these, we calculated the predicted probability of eradication and associated confidence limits. We calculated the proportion of case studies that were correctly classified as eradication (proportion of case studies with a calculated probability greater than the optimal threshold that ended up in eradication) and non-eradication (proportion of case studies with a calculated probability smaller than the optimal threshold that ended up in non-eradication). Since case studies with a predicted probability of eradication close to the optimal threshold usually have broad confidence limits (uncertainty), we also calculated correct classification probability for case studies with confidence limits lying above and below the optimal threshold. This was repeated 1000 times, and we calculated the mean proportion of correct classification for the different outcomes.

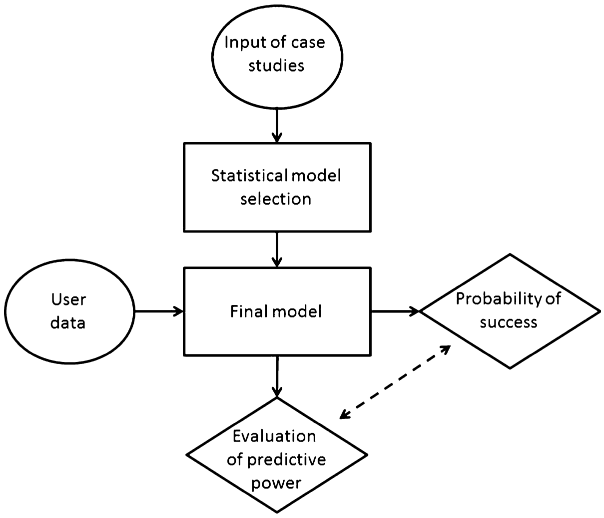

Fig. 1. Flowchart presenting the approach for development of evidence-based management tools based on statistical models fitted to meta-analysis data. Circles represent inputs, rectangles represent actions performed by the software, and diamonds show outputs returned to user.

SOFTWARE DEVELOPMENT

To make the predictions from the statistical model easily and quickly accessible to managers, we developed Model Informing Probability of Eradication of aquatic non-indigenous species (MIPE) using the MATLAB® r2012b programming language (Mathworks®, Natick, Massachusetts, USA). The literature review data, all code, stand-alone executable file and a user manual are available online (see Data accessibility section). The structure of the program is depicted in Fig. 1; the application retrieves the data file, fits and selects the best statistical model, and evaluates the predictive power of the model (vertical path on flowchart; Fig. 1). It also retrieves the information about the current situation faced by a manager and calculates the probability of eradication with associated confidence intervals (horizontal path on flowchart; Fig. 1). For ease of use, we developed graphical user interfaces with (i) a main window where the user selects the data file and inputs the characteristics of the current situation (Fig. 2a) and (ii) a main result window summarizing the output (Fig. 2b). On the main result window, we provided a graph showing the predicted probability of eradication (from the jackknife procedure) for case studies that resulted in eradication and non-eradication. This allows the user to compare the current output with what happened in the past. From the main result window, the user can access other useful options: (i) the test of main effects, (ii) plots of main effects, (iii) the model selection information, including the variables retained in the final model, and (iv) the results can be exported to a spreadsheet to facilitate communication of results.

Results

The final data set contained 143 case studies recorded in 79 articles or reports; out of these, 52% resulted in

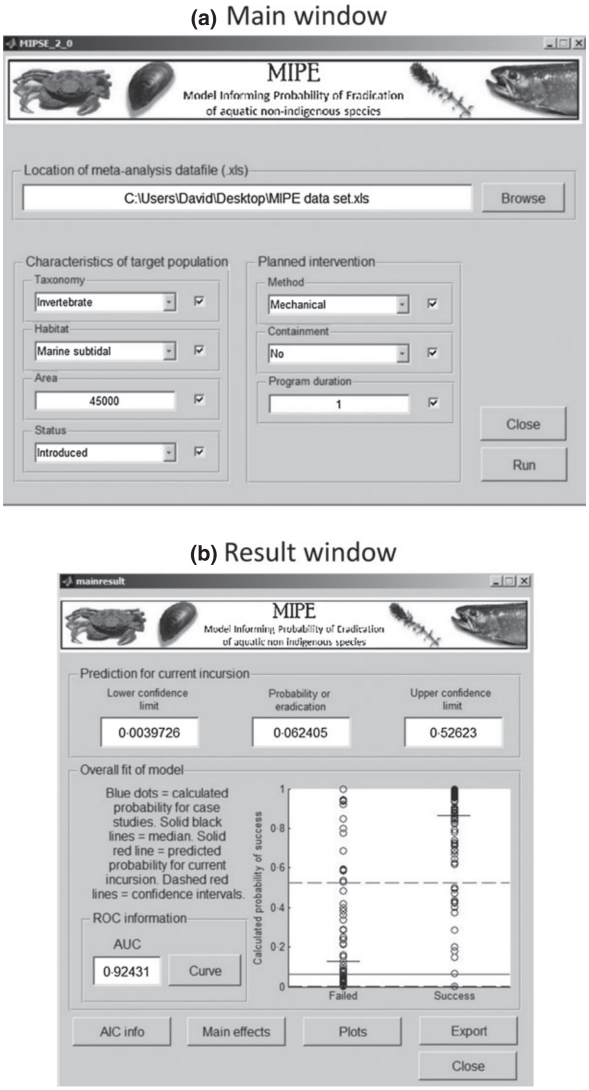

Fig. 2. Screenshots of the software developed to predict the probability of eradication of aquatic non-indigenous species. (a) Main window where the user selects the data file of case studies and inputs the characteristics of the current situation, and management options. (b) Main result window where the probability of success, in relation to predictive power of the model, is reported.

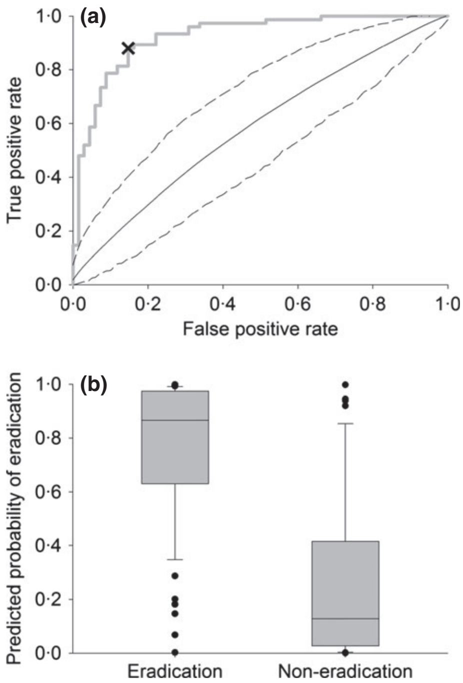

Fig. 3. Predictive power of a statistical model developed to calculate probability of eradication of aquatic non-indigenous species. (a) Receiver operating characteristic curve (thick solid line); area under the curve was 0·92. The optimal probability threshold (0·52, with 0·88 true-positive and 0·15 false-positive rates) is represented by the cross. The thin solid line and dashed lines represent the expected values and confidence intervals if the model predictions were no better than random (i.e. 'null' curve). (b) Box plot showing predictions for each case study evaluated with a jackknife procedure. Boxes show median and 25th and 75th quantiles, whiskers are 5th and 95th quantiles, and dots are outliers.

eradication. All independent variables and covariates other than Containment (Taxonomy, Habitat, log Area, Status, Method, and Duration) were included in the final model. The predictive power of the model, as evaluated by all three procedures, is excellent. The area under the ROC curve built for the final model (Fig. 3a) was 0·92, meaning the model ranks eradications higher than non-eradications 92% of the time (Hanley & McNeil 1982). With the calculated optimal threshold probability of 0·52, the true- and false-positive rates were 0·88 and 0·15, respectively. The ROC curve lays well above the confidence intervals of the 'null' curve (Fig. 3a). From the jackknife procedure, the calculated probability of success of case studies that resulted in eradication and non-eradication differed markedly (median = 0·87 and 0·13, respectively; Mann–Whitney U-test: $Z = 7{\cdot}64$, $P < 0{\cdot}00001$; Fig. 3b). There are, however, a few outliers; in some cases, an intervention that our model indicated to have a high probability of success failed in real life for unknown reasons, and a few with low calculated probability of success were actually successful. Finally, when considering all case studies in the testing subsets, the cross-validation procedure correctly classified 75·4% of eradications and 76·4% of non-eradications. When excluding case studies whose confidence limits included the optimal threshold, the model correctly classified 90·0% and 93·1% of eradications and non-eradications, respectively. A full analysis of what factors influence success is outside the scope of this article and will be dealt with in an ongoing meta-analysis (B. Beric, pers. comm.). Once that is available, the data set will be updated and more independent variables may be added to the model and software.

Discussion

APPLICATIONS TO CONTROL OF AQUATIC NON-INDIGENOUS SPECIES

The decision to intervene when a new species is discovered in an area, and the planning of the intervention, should be driven by the ratio of costs and benefits. McEnnulty *et al.* (2001) developed a decision framework based on primary and secondary costs and benefits from both a monetary and ecological point of view (with the two aspects weighted by societal value). The option with the lowest ratio should be attempted first. Tools are being developed to evaluate potential problems linked with non-indigenous species (e.g. risk assessment; Kolar & Lodge 2002; Leung *et al.* 2012) and the potential costs of control attempts (Martins *et al.* 2006; Crombie, Knight & Barry 2008). However, the magnitude of the cost/benefit ratio is highly dependent on the probability of success. If the eradication attempt fails and the population spreads, all the costs are incurred but none of the benefits are earned, thus the realized ratio goes to infinity. Until now, the probability of success was estimated based on managers' experience or expert opinion. Managers now have access to a reliable quantitative probability of success, with associated uncertainty, that will enhance the precision of the cost/benefit analyses. MIPE is only designed to evaluate probability of eradication. This needs to be kept in mind because many recorded interventions, although they failed at eradicating, significantly reduced the population size. These cases still succeeded in the sense that they likely reduced the rate of spread of the species and mitigated the negative economic and ecological impacts, at least in the short term. Conversely, some cases considered successful had important collateral damages on the target ecosystems. Therefore, MIPE should not be used indiscriminately; it is simply a tool to assist cost–benefit analyses.

USE OF STATISTICAL MODELS IN EVIDENCE-BASED MANAGEMENT

A major challenge for environmental and conservation scientists is to provide managers with tools that incorporate data in their decision-making process (Sutherland & Freckleton 2012). Statistical models have proven useful; for example, population viability and minimum viable population analyses (Boyce 1992) provide a probabilistic basis to management of endangered species. Also, species distribution models can be used to locate populations of rare species, plan reintroduction programs or design reserves (Guisan & Thuiller 2005). Statistical models can also be used to predict invasiveness of introduced species (Miller *et al.* 2007). In the realm of outcome of interventions, meta-analyses and statistical models have been used to determine whether techniques are efficient (e.g. Stewart & Pullin 2008; Smith *et al.* 2010, 2011) and identify factors influencing success (e.g. Brooks *et al.* 2006; Padgee, Kim & Daugherty 2006; Smith *et al.* 2010; Pluess *et al.* 2012). With our approach, we go one step beyond these by providing managers with a quantitative prediction, in a new context, that is quick and easy to obtain. Our approach bypasses the tedious process of obtaining a prediction when only model parameters are published. Furthermore, when only summary statistics are reported, predictions are impossible to compute in the classical meta-analysis approach.

Our data set, dealing with success or failure, is well approximated by a generalized linear model with a binary response variable and 'logit' link function. This statistical procedure would not necessarily be adequate to other types of interventions. However, the general approach is easily adapted to different types of data. For example, generalized linear models with Poisson distribution would be adequate for population counts of a rare species, whereas other variables with normal distributions would be better analysed with a general linear model.

LIMITATIONS OF APPROACH

A major limitation of our approach is that it relies on a review of published accounts of management actions. First, conducting a literature review and analysing the results is a major time investment. We are not suggesting that such an endeavour should be undertaken by managers after a problem is detected. Instead, we advocate for the proactive development of easy-to-use tools whenever scientists conduct reviews of factors affecting the success of management actions. This way, managers could select the proper tool from an existing 'bank' or 'toolbox' when facing a new problem. Secondly, the approach is vulnerable to publication biases. We believe success stories are published more often than failed attempts, that failed attempts are more likely to be published for projects with large budgets and that attempts are more likely to be published when scientists are involved as principals or team members than when conducted by resource managers alone. Thirdly, even for management of aquatic non-indigenous species, a field where a wealth of information is available in usable published form, the case studies reviewed are likely a minor fraction of what has been attempted globally. Like Sutherland *et al.* (2004, 2013), we urge managers to quantify the outcome of every action they take and make their results available to the scientific community. At the moment, it is likely that not enough empirical data would be available to develop statistical models and identify key predictors for many fields of application. On the other hand, with the development of an internet-based central data base of outcomes of management actions [as proposed by Sutherland *et al.* (2004), http://www.environmentalevidence.org], predictive tools could be developed for any type of intervention. There is also a danger that managers could use these tools indiscriminately. It is therefore important to insist that these are only one more tool in a toolbox that includes proper cost–benefit analyses, learning through experience, adaptive management (Rist, Campbell & Frost 2012) and expert knowledge of a system (Fazey *et al.* 2006). Managers with little statistical training may see these tools as black boxes. Potential users unsure of the mechanics should consult with statisticians or scientists to understand the limitations of the approach for their specific application.

STRENGTHS OF APPROACH

A key feature of our framework is that it adapts to the case studies included in the data set. This is possible because all steps (model fitting, selection and evaluation) are executed every time the user runs the application. For example, end users with years of experience managing a particular species could replace all the information in the data file with their own case studies. The software would then fit a model that is highly specific to their particular situation. Also, as more case studies are published, or end users add their unpublished attempts to the data set, the model evolves accordingly. A larger data set could allow inclusion of interaction terms and random factors. At the moment, only fixed effects are evaluated and interactions are not considered. For example, submodels could be estimated for each taxonomic group, describing interaction between taxonomy and other factors, or a random factor could be added when multiple interventions were made on the same species. With future expansion of the data set and more parameters added, the predictive power and the accuracy of estimates would be expected to increase.

In addition to providing a quantitative probability of success of a planned project, our approach also allows the user to weigh and compare management options. As an example, a manager dealing with a newly established fish species in a medium-sized lake would quickly realize that trying to eradicate it using mechanical methods, such as nets and electrofishing, is far less likely to succeed than by chemical methods, such as rotenone or antimycin. Also, a user could test different proposed durations of the intervention to estimate how long it would take to reach an acceptable probability of eradication.

In the situation, where incomplete information is available, our framework allows a user to prioritize acquisition of data. Consider a situation where the user does not know (i) whether a species is introduced or established and (ii) whether containment is possible. Both factors would require effort to obtain information, such as sampling for presence of larvae in the water and/or examining gonads in adults to determine reproductive status and reviewing and/or field sampling the life history and dispersal of the species and the characteristics of dispersal vectors to assess containment. By successively excluding each factor from the model selection routine, the user could compare the fit of the model. The one factor that influences the reported AUC the most would be the highest-priority knowledge gap.

CONCLUSIONS

Since the first calls were made for evidence-based management (Pullin & Knight 2001; Sutherland *et al.* 2004), a great deal has been accomplished to increase the use of scientific information in conservation and environmental management. A journal was founded with the aim of encouraging publication of results of management actions by non-scientists (Sutherland *et al.* 2013). Great efforts were made to collate evidence for the effectiveness of interventions and disseminate the information online (http://www.environmentalevidence.org). The main tool of evidence-based management, namely systematic review and meta-analysis, is largely inspired by the medical model where a wealth of solid experimental work is available (Fazey *et al.* 2004). This results in the exclusion of a large number of unreplicated and uncontrolled studies, and often, the conclusion is that not enough evidence is available to judge effectiveness (e.g. Davies *et al.* 2008; Martínez-Abraín *et al.* 2010). An alternative is to conduct a meta-analysis where the replication unit is the case study, allowing inclusion of more information. In such work, the statistical models used to evaluate influence of various factors on the outcome of intervention can be used to obtain predictions of probability of success in a new situation. As we demonstrated, the evaluation of probability of success can be made available in a quick and intuitive manner with basic programming skills. Overall, we think our approach is an important step forward in the development of evidence-based management tools and will enhance the use of scientific information in managers' decision-making process. Our approach is flexible in terms of statistical methods and types of data and provides invaluable information to a manager such as probability of success, comparison of different options and prioritization of information acquisition. Similar applications could be developed to deal with any type of management/conservation interventions. The biggest issue is data availability; we prompt managers to quantify their work and make their experience available to the scientific community.

Acknowledgements

Funding for this project was provided by the Canadian Aquatic Invasive Species Network (CAISN II) of the Natural Science and Engineering Research Council (NSERC) of Canada. M.A.L. gratefully acknowledges a Canada Research Chair, NSERC Discovery and Accelerator grants and a Killam Research Fellowship. We are grateful to three anonymous reviewers for critical comments, to Fisheries and Oceans Canada's Gulf Region Aquatic Invasive Species Rapid Response Working Group for useful discussions and comments, to Boris Beric for help building the data set, and to Jean-Sébastien Lauzon-Guay for proofing and improving the code.

Data accessibility

Literature review data, user manual, Matlab code and executable file: DRYAD entry: http://dx.doi.org/10.5061/dryad.1rh77 (Drolet *et al.* 2014).

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Received 14 September 2013; accepted 31 March 2014
Handling Editor: Marc Cadotte