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Authors

Henry Travers[1,*], Matthew Selinske[2,3], Ana Nuno[4], Anca Serban[5], Francesca Mancini[6], Tatsiana Barychka[7], Emma Bush[8], Ranaivo A. Rasolofoson[9], James E.M. Watson[10,11], E.J. Milner-Gulland[1]

1. Interdisciplinary Centre for Conservation Science, Department of Zoology, University of Oxford, New Radcliffe House, Radcliffe Observatory Quarter, Woodstock Road, Oxford, OX2 6GG, UK
2. Interdisciplinary Conservation Science Research Group, School of Global, Urban and Social Studies, RMIT University, GPO Box 2476, Melbourne, VIC, 3001, Australia
3. ARC Centre of Excellence for Environmental Decisions, The University of Queensland, Room 525, Goddard Building, St Lucia, QLD, 4072, Australia
4. Centre for Ecology and Conservation, College of Life and Environmental Sciences, University of Exeter, Penryn, Cornwall, TR10 9FE, UK
5. Department of Geography, University of Cambridge, Downing Place, Cambridge CB2 3EN, UK
6. School of Biological Sciences, University of Aberdeen, Zoology Building, Tillydrone Avenue, Aberdeen AB24 2TZ, UK
7. Centre for Biodiversity and Environment Research, Department of Genetics, Evolution and Environment, University College London, Medawar Building, London WC1E 6BT, UK
8. Biological and Environmental Sciences, Faculty of Natural Sciences , University of Stirling, Stirling, FK9 4LA, UK
9. Gund Institute for Environment, University of Vermont, 617 Main Street, Burlington, VT 05405, USA
10. School of Earth and Environmental Sciences, University of Queensland, St Lucia QLD 4072, Australia;
11. Wildlife Conservation Society, 2300 Southern Boulevard, Bronx, New York 10460, USA

*Corresponding author (henry.travers@zoo.ox.ac.uk)

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Abstract:

If efforts to tackle biodiversity loss and its impact on human wellbeing are to be successful, conservation must learn from other fields which use predictive methods to foresee shocks and pre-empt their impacts in the face of uncertainty, such as military studies, public health and finance. Despite a long history of using predictive models to understand the dynamics of ecological systems and human disturbance, conservationists do not systematically apply predictive approaches when designing and implementing behavioural interventions. This is an important omission because human behaviour is the underlying cause of current widespread biodiversity loss. Here, we critically assess how predictive approaches can transform the way conservation scientists and practitioners plan for and implement social and behavioural change among people living with wildlife. Our manifesto for predictive conservation recognises that social-ecological systems are dynamic, uncertain and complex, and calls on conservationists to embrace the forward-thinking approach which effective conservation requires.

Introduction

Conservation science has been defined as a crisis discipline (Soulé 1985, Kareiva & Marvier 2012) because of the alarming rate of biodiversity loss and its impacts on ecosystem functions and people's livelihoods (Cardinale et al. 2012). Yet, despite international recognition of the need for action (for example, the Strategic Plan for Biodiversity Aichi targets and the Sustainable Development Goals (Leadley et al. 2014)), and increasing global and national expenditure on research to find solutions (Stroud et al. 2014), the overall trend of rapid biodiversity loss persists (WWF 2016). Conservation needs a range of new, forward-looking approaches to solve current and future challenges. Prediction, a powerful but currently undervalued tool, can form a vital component of such an approach.

In the field of ecology, there have been a number of recent calls for predictive approaches to move beyond developing theories to applications that improve management of natural systems (Mouquet et al. 2015, Pennekamp et al. 2017). This is welcome. However, many of the challenges facing conservation scientists and practitioners are inherently social, revolving around human behaviour and its, often ignored, impact on natural systems. The threats that people generate and their responses to conservation interventions are complex, dynamic and often context-specific. Hence, focusing predictive approaches on improving the management of ecological systems will not be sufficient to change the trajectory of biodiversity loss. Similarly, the prior experience and intuition of practitioners are unlikely to be reliable guides to how certain interventions are likely to perform. Predictive approaches can help understand how humans might behave in the future and ensure that conservation interventions are framed, designed, implemented and evaluated to better account for and respond to those changes. Predictive science can provide the evidence required to inform decision-makers and practitioners, for whom an understanding of future changes in the systems they manage is essential.

There are different ways to conceptualise prediction (e.g. Mouquet et al. (2015). Here we divide approaches to prediction into three types (Table 1); mechanistic models of system dynamics based on existing understanding, which can be used to explore how systems would respond to new circumstances (such as models of human responses to climate change); empirical approaches that make use of observational or experimental data, such as from stated-preference surveys (which ask people about their potential behaviours under different circumstances or preferences for different potential futures); and conceptual models of how a system may behave under different future circumstances (such as used in scenario planning, or theories of change). We contrast these predictive approaches to conservation with explanatory approaches, which might, for example, statistically describe how the livelihoods of local people impact on wildlife habitat, or model (either conceptually or mechanistically) the state of the system as it is. Although many of methods that can be used to make predictions can also be used for explanatory analyses, the results of explanatory analyses only allow conservationists to design their interventions based on current circumstances and understandings. This is not to say that explanatory approaches do not provide useful information, but rather that predictive approaches can be used to complement the information from explanatory analyses, enabling interventions to be designed based on how the intervention may change system behaviour in the future, in the context of external factors. Prediction is therefore a powerful addition that allows conservation practitioners to either pre-empt change or develop responses to it, rather than be caught blind when it occurs.

Our perception, as conservation scientists working at the interface between research and practice, is that, while researchers may publish papers which use predictive approaches, conservation practice is largely based on explanatory approaches, which are by their nature reactive rather than proactive (Milner-Gulland & Shea 2017). This contrasts with fisheries science, for example, which is heavily reliant on predictive mechanistic and statistical models to guide management (Haddon 2011). This disconnect is particularly unfortunate because the foundations of quantitative conservation biology lie in explicit predictive models. Lebreton (1978) formulated a stochastic population model to assess the risks faced by wild swans in France, and used it to evaluate alternative management options. Similarly, Shaffer (1981) used stochastic population models to develop the idea of minimum population sizes and explore future scenarios for grizzly bears, evaluating the risks of extinction within specified time frames. Since that time, there have been numerous applications of predictive models in conservation, evaluating proposed harvesting scenarios, the impacts of planned agricultural development and forest harvesting scenarios, and the consequences of anticipated urban expansion (see journals such as *Natural Resource Modelling* for examples). In rare cases, these models build in the interactions between human behaviour and ecological processes. For example, Bunnefeld et al. (2013) used a management strategy evaluation framework, which incorporated population dynamics and harvesting decisions, to evaluate alternative investment and harvesting strategies for the management of mountain nyala. Nevertheless, despite the availability of methods and examples, our observation is that many conservation decisions do not make explicit use of predictive models of any kind. A particular gap lies in the lack of use of predictive approaches to human behaviour (rather than models of biological dynamics; Milner-Gulland 2012).

Without predictive approaches, the practice of conservation assessment, planning and action is stuck in the cycle of reactively implementing interventions after each new crisis has taken hold, never proactively trying to avoid them (Putman et al. 2011). In this paper, we show how predictive approaches can be systematically applied to all four stages of the cyclical process for creating good environmental policy (Dovers 2005); problem framing, policy or intervention framing, implementation and evaluation. By emphasising the learning potential of these approaches (e.g. by producing expectations about what might happen and comparing these with actual outcomes), the complementary power of a priori prediction and post hoc explanation is harnessed (Hofman et al. 2017). This integrated approach aligns with scientific best practice in other fields, such as military science, public health and public financial policy, for which it is common practice to apply predictive approaches to anticipate the emergence of crises. Our intention here is not to provide a comprehensive review of the methods that can be used to make predictions but to highlight why they are useful and the contexts in which they can be used.

## The unrealised potential of predictive approaches

Outside of conservation, prediction is a rapidly developing science, responding to the need to deal proactively with future and emerging challenges. Examples include the Stock-Watson's experimental recession index, used to estimate the probability of economic recession (Stock &

Watson 1993); the Collier-Hoeffler econometric model, used to predict the probability of a civil war (Collier & Hoeffler 2002); and epidemiological models used in public health (Table 2). As in conservation, the success of predictions in other fields varies. However, as the application of predictive methods is more advanced, the associated impact is greater. This is particularly true in relation to behaviour change, where theories from social psychology, such as the theory of planned behaviour (Azjen 1985), can be used to identify predictors of human behaviour (Armitage & Connor 2001; Hardeman et al. 2002). As methods develop and sources of validated data grow, the potential for prediction in ecology and conservation has never been greater (Sutherland & Freckleton 2011, Pennekamp et al. 2017, Maris et al. 2018). Predictive approaches can be used to navigate trade-offs in decision-making and, when coupled with further data, can provide real-time monitoring of the outcomes of an intervention. Furthermore, predictive approaches can help to frame and design interventions, by providing probabilistic assessments of likely outcomes, anticipating unexpected behaviours (Liu et al. 2001) and understanding and explicitly accounting for uncertainty (Ascough et al. 2008). These tools can also identify criteria for success and provide predictions against which to evaluate the success of interventions (Mondal & Southworth 2010), thereby informing on-going improvements in the implementation of interventions. This should lead to better design, and therefore to more successful conservation interventions.

Prediction is also a fundamental part of 'active' adaptive management, in which the impact of interventions is first predicted and then measured during implementation, enabling interventions to be adapted before the cycle begins again (Salafsky et al. 2001). However, although adaptive management has often been cited as necessary for conservation, in theory, it is still rarely used in practice (Keith et al. 2011). Where it is applied, adaptive management is most commonly 'passive', only reviewing past and current performance of conservation activities rather than actively applying alternative approaches to improve learning (Grantham et al. 2010). Adopting predictive methods in a staged way could therefore provide a stepping stone towards greater use of 'active' adaptive management. Conservation challenges are not always predictable, and therefore may not appear at first sight to be amenable to adaptive management. However, predictive approaches have also played a role in real-time responses to unexpected events, by improving mechanistic understanding of the system and exploring potential outcomes of different interventions (Ferguson et al. 2001, Keeling et al. 2003). In public health, they have also been used as a communication tool to engage local communities and decision-makers (Roeder et al 2013), and within a framework of adaptive management, they have helped in evaluating disease control measures and informing updates (Shea et al. 2014; Table 2).

Predictive approaches at multiple stages of conservation interventions

We consider the benefit of predictive approaches at four main stages of conservation interventions: "problem framing" refers to the identification and definition of a conservation issue; "policy/intervention framing" refers to the identification of the action or process that is carried out to influence what happens; "implementation" refers to the execution of a conservation plan or decision; and "impact evaluation" refers to the monitoring and assessment of intervention outcomes, leading to the continuation, adaptation or termination of a specific conservation intervention (Fig. 1). Elements of the predictive approach are already widely used in conservation, often in an informal way by conservation managers on the ground; our contention is that formalising this approach would both change the mindset of donors, implementers and researchers, and bring new and underused tools and approaches (such as those laid out in Table 1) more into the mainstream of conservation practice.

*Problem framing*

How a problem is identified and defined ultimately determines both its solution and the approach taken in trying to implement that solution. Consequently, problem framing is a crucial step for understanding the values and positions of multiple stakeholders, broadening the range of solutions considered and finding the most effective ways to address certain issues (Johnson et al. 2013). Application of predictive approaches at this stage could significantly improve conservation outcomes. Failing to anticipate environmental problems creates a lag between the emergence of a problem and provision of a conservation response (Sutherland & Woodroof 2009). This lack of foresight can result in poor prioritisation of interventions (Dolman et al. 2012), naive assumptions about contexts or trends (Siegel 1996), subjective and arbitrary decision-making (Game et al.

2013) and failure to identify actual or emerging threats (Sutherland & Woodroof 2009, Putman et al. 2011).

Applying predictive approaches at the problem framing stage can lead to better informed and well supported conservation decisions about which threatening processes to address, and in what order (Game et al. 2013). This can generate better stakeholder buy-in and trust (Tompkins et al. 2008), as well as greater awareness about other potential confounding factors and more resilient decision processes (Murray-Rust et al. 2013). For example, horizon scanning has been used to identify emerging issues for conservation as a whole (e.g. Sutherland et al. 2018), as well as for specific issues, such as invasive species (e.g. Dehnen-Schmutz et al. 2018). These approaches have also been used at finer scales, such as the use of scenarios and backcasting to engage diverse groups of stakeholders in short-term regional environmental threat planning (Cook et al. 2014) and incorporating risk assessments to quantify the probabilities of future bio-security risks in Australia (Walshe & Burgman 2010). Promisingly, the Intergovernmental Science-Policy Platform for Biodiversity and Ecosystem Services (IPBES) recently called for greater integration of policy with predictive approaches (e.g. models and scenarios), developing pre-emptive policy responses to forecasted future threats to biodiversity and ecosystems services (IPBES 2016).

*Intervention framing*

Conservation management often involves developing interventions in the context of complex social-ecological systems (Nuno et al. 2014), when knowledge of these systems is incomplete and outcomes are uncertain. Despite, or perhaps because of this, the design of interventions remains largely based on personal experience or subjective judgements (Pullin et al. 2004, Sutherland et al. 2004, Ferraro & Pattanyak 2006), which can be subject to significant bias (Burgman et al. 2011). In this context, predictive approaches represent an additional means of dealing with uncertainty and complexity, exploring the consequences of management alternatives and identifying and evaluating uncertainty in different proposed conservation interventions. This is not to suggest that the use of prediction should supplant personal experience or judgement, but that predictive methods can provide an additional source of evidence on which to design interventions. Not only can this lead to improved outcomes for conservation but it can also provide greater security for policy makers and donors when they are evaluating which options offer the greatest potential value for money.

Where conservation interventions aim to alter human behaviour, predictive approaches can be used to navigate uncertainty and assess the likely impact of alternative management actions. For example, the development of a theory of change for how different interventions can be used to address illegal wildlife trade allows practitioners to identify which types of interventions are most likely to be appropriate in a given context (Biggs et al. 2016). In another example, in the Western Ghats of India, interventions involving the restitution of tree rights to local coffee growers, which were proposed to promote the intercropping of native tree species with coffee plantations, were empirically tested using a role-playing game modelling approach (Garcia 2013). The findings revealed that, contrary to their original aim, the proposed interventions risked speeding up the transition to a landscape dominated by the exotic silver oak *Grevillea robusta* rather than promoting native species. This represents a good example of how predictive approaches enable conservation programmes to be tested against unforeseen behaviour, allowing for better decision-making and design for interventions.

*Implementation*

In many instances, the first stage of implementation of a conservation intervention or policy is a small-scale pilot or demonstration project. Yet the power of such projects to establish that an intervention will prove effective is typically limited by issues of scale and complexity in comparison to the problem being addressed (Wells 1995). The temporal scales at which desired ecological and social impacts are detectable can make evaluating outcomes, and therefore determining the likely result of a scaled up programme, challenging (Kapos et al. 2008). However, it is often necessary to start small and scale up later due to critical capacity constraints (Wells 1995), which can add to the uncertainty regarding whether a piloted intervention will work at scale. Here again, predictive methods can aid implementation by assessing the likely outcomes of multiple alternatives in advance to ensure that only those interventions with the greatest probability of success are piloted

(Travers et al. 2011). This can either be achieved through the interpretation of existing evidence through a predictive lens or the collection of new data aimed explicitly at testing potential interventions (e.g. through the use of behavioural games or scenario interviews). Where an intervention is piloted based on prior predictive work, and if the results of the pilot are in line with the predictions, this gives confidence that the intervention will work.

Successful implementation of conservation interventions is also often dependent on a number of exogenous factors beyond the control of practitioners, particularly in countries experiencing rapid economic growth and undergoing significant social change (McShane et al. 2011). The uncertainty created by such factors may affect decision-making and undermine any interventions attempted. Although adaptive management can be used to redesign interventions to improve conservation outcomes (Salafsky et al. 2001), such approaches largely react to the consequences of changing conditions rather than the changes themselves, with the result that opportunities to respond pre-emptively may be missed. Predictive approaches can be used to identify and test the impact of exogenous factors on which the successful implementation of interventions may depend. For example, Travers et al. (2016) applied a scenario-based interview approach to predict how forest clearance by smallholder farmers living inside Cambodian protected areas would change in response to an increased or decreased trend in the price of cassava (the primary cash crop). The results of this approach showed that if cassava prices rose, illegal clearance would increase significantly in accessible villages but would be unlikely to change in more remote villages where farmers would be unable to capitalise on increasing prices. Hence, managers at the site are in a position to adaptively allocate resources where they are most needed as and when cassava prices change, rather than waiting to react to the resulting patterns of clearance.

*Evaluation*

The evaluation of the impacts of conservation programmes is an essential component of conservation practice and is founded on assumed relationships between interventions and outcomes (Maron et al. 2015). Those relationships are assumed in turn to operate through a theory of change, which comprises the causal pathways between interventions and outcomes

(Woodhouse et al. 2015). The theory of change is based on the best understanding of the system prior to an intervention. However, before interventions take place, predictive approaches can be used to develop a stronger theory of change whose validity can be tested during and after interventions by doing impact evaluation.

In recent years, in the face of increasing calls for more robust evidence (Ferraro & Pattanyak 2006), the evaluation of conservation programmes has increasingly used a counterfactual approach, in which impact is defined as the difference between the outcome with intervention and the outcome in the absence of the intervention under evaluation. The main challenge in the counterfactual approach is that it is impossible to observe what would have occurred in absence of the intervention because the intervention did actually occur. Therefore, the counterfactual must be predicted. In that sense, approaches used to construct the counterfactual are predictive. A recent example of this is Young et al. (2014), who explored the difference conservation has made to threatened species by constructing a post-hoc counterfactual for the red list status of these species in the absence of conservation. Depending on the rigor required, such an approach may offer advantages over other counterfactual evaluation designs, such as randomised control trials or quasi-experimental methods, that estimate the counterfactual by observing a control group, particularly in cases where the resources required for data collection are high, it is difficult to identify a suitable control, or there are ethical concerns around collecting control data.

Greater application of predictive approaches in constructing meaningful counterfactuals would move impact evaluation from a retrospective discipline to a prospective one. This move is challenging because in addition to predicting what would happen without the intervention (the counterfactual), researchers have to predict what will happen in the presence of the intervention. However, steps toward prospective impact evaluation have been made. For example, Visconti et al. (2015) investigated the potential impacts of different strategies proposed to achieve one component (endangered species representation) of the Strategic Plan for Biodiversity Aichi target 11 of expanding terrestrial protected area coverage to 17% of the globe’s land area by 2020. They predicted the extent of suitable habitat available for terrestrial mammals, with or without (the counterfactual) this expansion, under different socio-economic scenarios. The results vary as a function of the proposed expansion strategy and socio-economic scenario.

<u>Challenges in the application of predictive approaches</u>

Much as with the adoption of more rigorous approaches to assessing the impact of conservation interventions and the greater use of evidence-based decision-making in general, we recognise that there are a number of challenges to the more widespread use of predictive methods. It is often noted that there is a divide between conservation science and practice (Pullin et al. 2004; Sunderland et al. 2009; Milner-Gulland et al. 2010; Gardner 2012) but we do not believe that arguing for *the use of evidence* in conservation *is* contradictory to advocating for more use of predictive methods. The use of predictive methods can also contribute to bridging the science-practitioner divide. The wider application of predictive methods could prove fertile ground for furthering collaborations between conservation scientists and practitioners. In general, external advice may be particularly relevant during the selection of appropriate methods, which will vary depending on the level of capacity and data requirements, the stage of the intervention, the type and precision of the prediction being made. For example, while the technical expertise required to carry out some predictive methods is likely to be found within a typical conservation programme (e.g. scenario interviews), other methods may be better suited to collaborations between conservation practitioners and external experts.

In many cases, the data required to make predictions may not be readily available and will need to be collected. Here the complexity of the predictions is likely to play a significant part in the level of data collection and analysis required. For example, where the aim of an intervention is to reduce forest clearance or illegal hunting, predicting how a given intervention is likely to lead to behavioural change by its specific target audience may be sufficient. In this case, scenario interviews with the relevant people, to inform a Theory of Change, might be a way forward. However, in cases where the interaction between a conservation intervention and desired outcome is more indirect (e.g. a specified increase in the population of the conservation target as a result of an alternative livelihoods intervention), the data requirements of suitable predictive approaches are likely to be greater. In this case a population model of the conservation target may need to be parameterised and behavioural games may be the best way to understand how people respond to different incentive structures.

We also recognise that some decision-makers may be sceptical of the accuracy of predictions or uncomfortable with the level of uncertainty associated with them. Despite the multiple benefits of predictive approaches, applying them without fully understanding their inputs, outputs and underlying assumptions can lead to misleading results. For example, how people say they intend to respond to certain conditions may differ from how they actually behave (Webb & Sheeran 2006). A frequent criticism is that small deviations in initial conditions can have large influences on the outputs of mechanistic models, which are designed to inform policy (Crooks & Heppenstall 2012). As models become larger and more complex, the challenges of testing and validating them increase (Crooks & Heppenstall 2012). There are several cases where ill-informed models have led to suboptimal conservation outcomes. For example, fisheries models that overestimated initial stock sizes informed policies that resulted in overfishing and the collapse of Canadian stocks of Atlantic cod, triggering an environmental disaster with significant social and economic impacts (Walters & Maguire 1996).

Acknowledging and communicating uncertainty when using predictive approaches to inform management is a critical consideration (Milner-Gulland & Shea 2017). Predictive approaches should be treated as informative tools that can provide new insight for policy as part of adaptive management, rather than the source of definitive answers. A multidisciplinary team with inputs from multiple stakeholders is likely to be key for enhancing success of predictive approaches, ensuring that the social and ecological contexts are used to formulate predictions and interpret outcomes, thereby improving their reliability (Subrahmanian & Kumar 2017). While communicating prediction and its associated uncertainty to stakeholders can be challenging, this is increasingly common for climate change science and ecological modelling at multiple policy levels. Gaining the trust of decision-makers will be instrumental in integrating predictions into decisions-making frameworks. In this sense, some predictive methods, such as agent-based models, are particularly suited as tools for engaging with decision-makers, as they can demonstrate the potential consequences of different policy or management decisions (An 2012). “Black swan” events, defined as events which are extremely difficult to predict and have profound consequences (May et al. 2008), are another reason why predictive approaches need to be combined with more traditional explanatory approaches to conservation and effective monitoring. This provides a backstop so that management is able to continue and to respond quickly when unexpected events occur.

The ethical implications of predicting social and human behaviour also require consideration. In criminology, for example, the use of machine learning algorithms to observe crime patterns and aid in crime prevention, has been underpinned by historical biases, and led to discriminatory policing of African American communities in the US (Perry 2013). Similar concerns might arise in the use of predictive methods to identify groups most likely to respond to particular interventions, which could lead to discrimination (either in terms of additional policing or exclusion from benefits). These risks are is likely to be true in any scenario, irrespective of the use of prediction, but risk being exacerbated through the use of predictive methods. It will therefore be important for the conservation community to ensure that decisions related to predicting the future actions of the individuals and communities we work with are taken in a fair and transparent manner.

## Manifesto

Despite many potential benefits throughout the policy cycle, predictive approaches remain underused in conservation, representing missed opportunities with important consequences for both biodiversity and livelihoods. In this manifesto for predictive conservation, we therefore call for greater use of predictive approaches by both scientists and practitioners to aid decision-making and conservation practice. This will allow for the implementation of pre-emptive and more effective interventions. We recognise the existing use of predictive approaches in conservation ecology, and therefore focus our emphasis particularly on situations where conservation science can inform interventions aiming to change human behaviour. Movement towards a predictive, proactive and preventative conservation will be of the utmost importance in addressing current and future challenges, by revolutionising how these are tackled throughout all intervention stages and even before they occur.

We therefore call on all conservation actors to move towards a more predictive approach to conservation. This entails:

1. Using the best available tools to predict changing circumstances prior to their emergence (Table 1), providing the space for more objective prioritisation and development of responses.
2. Exploring the consequences of different management options in advance, in order to reduce the associated uncertainty and support more informed decision-making.
3. Identifying the factors upon which the success of interventions depend, in order to facilitate adaptive management as changes in these variables occur.
4. Developing counterfactuals in advance, against which the success of conservation interventions can be evaluated.
5. Embracing and clearly articulating uncertainty when undertaking these predictive approaches.

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Table 1. Examples of predictive approaches that could be more widely used in conservation science.

| Approach | Example of use | Source |
|---|---|---|
| Mechanistic model | Management strategy evaluation in fisheries management | Dichmont & Fulton 2017 |
| Mechanistic model | Protected area planning under scenarios of future climate change | Singh & Milner-Gulland 2011 |
| Mechanistic model | Predicting changes to ecosystem structure and functioning due to habitat loss and/or fragmentation | Bartlett et al. 2016 |
| Mechanistic model | Predicting how a common pool resource system will react to perturbations under different management strategies | Mancini et al. 2017 |
| Empirical | Discrete Choice Experiment to understand elasticities on utility of different attributes of a system (including interventions) | Moro et al. 2013 |
| Empirical | Scenario approaches for understanding how behaviour would change under different future circumstances | Cinner et al. 2009, Travers et al. 2016 |
| Empirical | Behavioural games to understand future responses to alternative conservation interventions | Travers et al. 2011, Garcia et al. 2013 |
| Conceptual model | Scenarios of different possible futures at the system level, horizon scans | Sutherland & Woodroof 2009, IPBES 2016 |
| Conceptual model | Theory of change for how an intervention will go from input to impact | Biggs et al. 2016 |

Table 2. Examples from public health of how predictive approaches have been used at all stages of the management cycle to inform and improve intervention design and outcomes.

| Cycle stage | How predictive approach was used | Benefit of this approach | Study |
|---|---|---|---|
| Problem framing | By combining Bayesian phylogeography techniques and landscape resistance models, the authors were able to predict unexpected invasion routes of the vampire bat rabies virus. These predictions were then validated by real-time livestock rabies mortality data. | These predictions will allow affected countries to prepare for and mitigate possible future outbreaks by developing preventative vaccination of livestock, education campaigns and control measures. | Streicker et al. 2016 |
| Intervention framing | During the foot-and-mouth disease outbreak among Great Britain's livestock in 2001, predictive modelling enabled the anticipation of the spatio-temporal pattern of disease spread. | Predictions from the models enabled the design of real-time culling and vaccination strategies. | Ferguson et al. 2001, Keeling et al. 2003 |
| Implementation | In the eradication of rinderpest virus in the 2000s, stochastic epidemiological models were able to predict | These predictions played an important role in the implementation of the intervention by creating a | Mariner et al. 2005, Roeder et al. 2013 |

| | | | |
|---|---|---|---|
| | unexpected outcomes, by showing how suboptimal vaccination was worse than no vaccination. These models were then used as a communication tool to engage decision-makers in visualising epidemiological processes and choices. | consensus for a strategy of focused vaccination as a necessary action to achieve eradication, therefore contributing to the success of the eradication programme. | |
| Evaluation | A study based on the 2001 outbreak of foot-and-mouth disease in the UK showed the advantages of using predictive tools within an adaptive management framework. | The approaches used in the UK FMD epidemic were estimated to have saved up to £20 million in terms of lower livestock losses to culling. The same study also calculated that a similar approach could have led to 10,000 averted cases in the measles outbreak observed in Malawi in 2010. | Shea et al. 2014 |

Figures

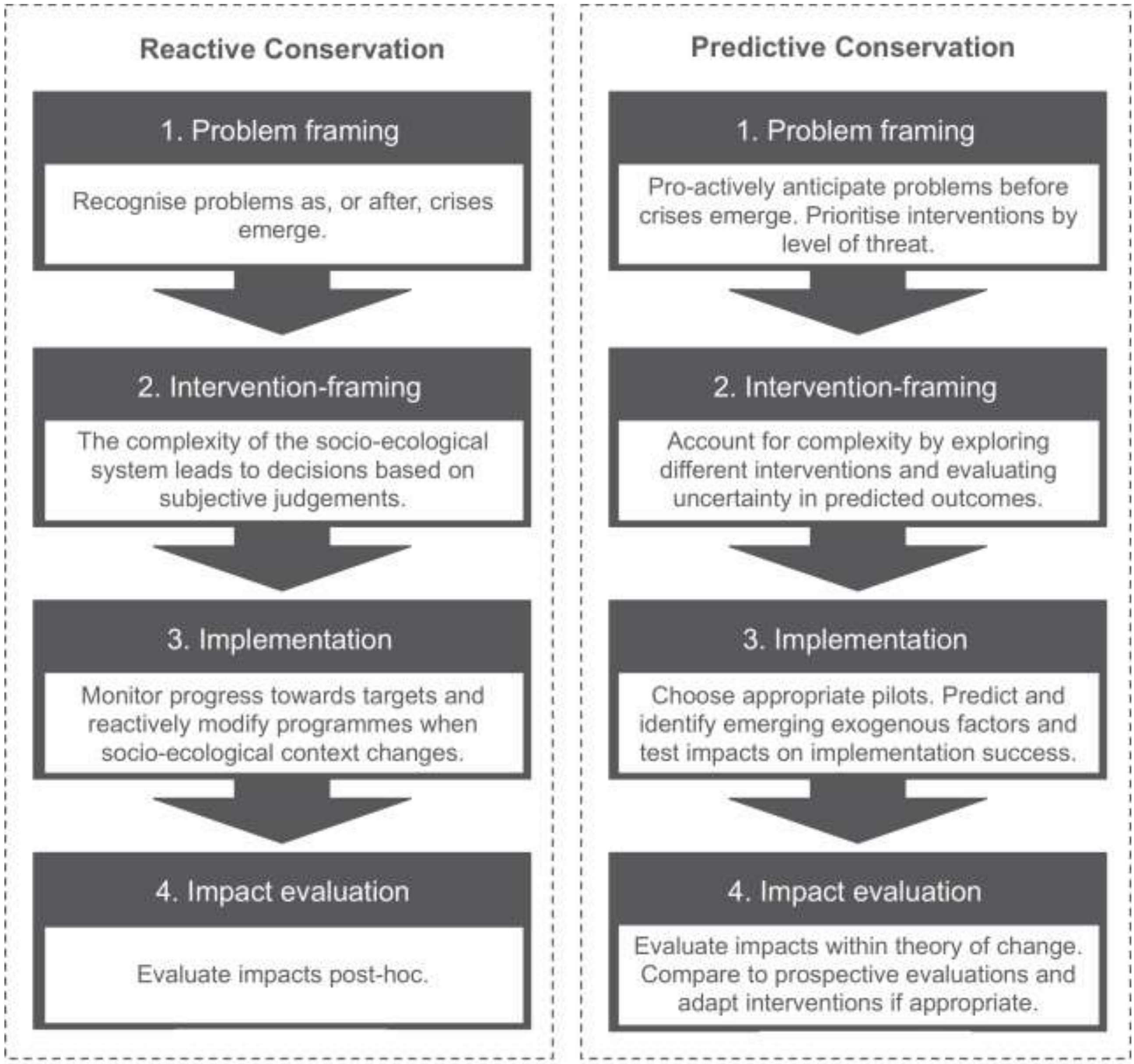


Figure 1. A caricature comparison of predictive and reactive approaches to conservation; in reality conservation practice will combine elements of both.