Conservation in a changing world needs predictive models.

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As conservationists we need to predict how biological systems will respond to environmental change, and how such responses may be affected by conservation interventions (Clark *et al*., 2001). Environmental change can create novel environmental conditions; for example, climate change has generated new extremes in patterns of temperature and precipitation, whilst the human-assisted spread of exotic species has created novel species assemblages and interactions. Conservation organisations may also intervene to alter environmental conditions experienced by animals; for example at the Wildfowl & Wetland Trust we have created a network of reserves to provide undisturbed feeding and roosting areas for waterbirds (Rees & Bowler, 1996). Currently, many approaches to prediction are based on observed relationships between a biological property of conservation interest (e.g. species distribution) and one or more environmental variables (reviewed in Sutherland, 2006). However, such relationships, typically measured for a narrow range of environmental conditions, may not hold as conditions change, especially given the complex, non-linear responses shown by ecological systems (Stillman *et al*., 2015a).

Calls for conservation to become more predictive (Clark *et al*., 2001; Sutherland, 2006; Pennekamp *et al*., in press) have led to the development of models that base predictions on fitness maximization decision-rules, including individual-based models, dynamic energy budget models, and mechanistic species distribution models (Kearney & Porter, 2009; Sousa *et al*., 2010; Stillman *et al*., 2015a). Such models allow us to predict key conservation outcomes including the numbers and distributions of animals, their physiological state, demographic rates, and interactions between individuals and species (Grimm & Railsback, 2005). The decision rules of fitness-maximizing models are based on adaptive behaviour and so are not expected to change even if the environment changes, and are thus more likely to maintain their predictive power as environmental conditions change than are the empirical relationships of traditional correlative methods (Sutherland & Norris, 2002; Stillman *et al*., 2015a). This basis for prediction enables such models to produce accurate, robust predictions outside of the range of environmental conditions for which they were parameterized (Wood, Stillman & Goss-Custard, 2015).

As conservation practitioners we have used predictive models to inform our responses to a range of conservation problems. For example, we recently used a fitness-maximizing model to predict how the carrying capacity of a key stopover site for migratory waterbirds would be affected by projected sea level rises, changes in food resources, and increased anthropogenic disturbance (Stillman *et al*., 2015b). Predictive models typically require both the specialist computational skills of scientists, as well as the practitioners' detailed knowledge of the system being modelled (Wood, Stillman & Goss-Custard, 2015). Hence, conservation practitioners and scientists need to collaborate and communicate effectively to develop predictive models (Cartwright *et al*., 2016).

Pennekamp *et al*. (in press) found that low data availability limited the use of predictive models in conservation, as such models need relatively large amounts of data to run and test. When developing our own models, we have found that such data are often not available in the literature, and may not always be practical to collect in the field. As practitioners, we need scientists to make better use of existing data, as well as greater use of our expert knowledge. For example, model parameter values and their uncertainty can be estimated using Bayesian approaches informed by pooled expert knowledge of conservation practitioners (Martin *et al*., 2012). Approaches that increase the speed and spatial scale of data collection, including remote sensing and citizen science, can aid model development (Janssen & Ostrom, 2006; Robinson *et al*., 2007). Better synthesis of available data (e.g. Roberts *et al*., 2016), and archiving of such data where it can be searched for and accessed, would enable more efficient estimation of parameter values from incomplete data. Allometric scaling methods have proven useful for estimating species- and system-specific values for parameters for which data are not available or measurable. Additionally, missing parameter values can be estimated from model simulations in a calibration process, with starting values informed by practitioners' knowledge (Grimm & Railsback, 2005).

Due to the difficulty of measuring lifetime reproductive success directly, proxies such as energy-maximization have been used to implement the fitness-maximization decision-rules in predictive models (Grimm & Railsback, 2005). However, the identity of the most appropriate proxy is often unclear. The development of a wider suite of decision-rules and model currencies, and understanding the systems for which each is most applicable, would allow predictive models to be implemented for a broader range of conservation issues (McLane *et al*., 2011). For example, for some herbivores nitrogen or predator avoidance may be more important than energy, due to the relatively low N content of vegetation and higher predation risk of herbivores, respectively (Inger *et al*., 2006). To incorporate budgets based on alternative currencies, including macronutrients such as nitrogen, we need physiological information including the rates of gain and loss of such currencies. The availability of such information is currently limited for model currencies other than energy.

Conservation scientists and practitioners can co-create predictive models; for example the expert knowledge of practitioners can inform the ranges of parameter values used to build and test models using Bayesian or traditional calibration approaches. Scientists can also create tools to allow practitioners to use models directly. Generalized software that minimizes system-and species-specific assumptions (e.g. MORPH; Stillman, 2008) can allow the development of models without having to start from scratch. These packages provide a software “shell” containing only general processes (e.g. food consumption), but no system-specific parameters or processes. Instead, parameters and equations are contained in parameter files external to the software itself, allowing detailed models of wide-ranging systems to be developed without the time cost of programming new software. Furthermore, general modelling software, such as NetLogo (http://ccl.northwestern.edu/netlogo/), allows the development of complex models more rapidly with little programming experience.

Predictive models can take many years to develop, yet as practitioners we need to address conservation problems urgently (Stillman *et al*., 2015a). Our article highlights the need of practitioners for the insights of predictive models, and how conservation scientists can work with practitioners to overcome obstacles that can prevent their implementation. Without the concerted efforts of scientists and practitioners to implement these steps, predictive models will not fulfil their potential.

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