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PRACTITIONER'S PERSPECTIVE

Co-creation of individual-based models by practitioners and modellers to inform environmental decision-making

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Introduction

Effective environmental decision-making, in the form of evidence-based management and policy, is a key prerequisite to help balance nature conservation, natural resource management and human socio-economic activities (Sutherland *et al*. 2004). To aid such decision-making, the need for predictive tools that are accurate, robust and parsimonious has arguably never been greater. The Earth is currently in a time of environmental change unprecedented in human history, due to climate change, growing human population size and resource use, land-use changes and intensification, habitat loss and fragmentation, pollution and invasive species. Thus, the ability to predict how biological systems will change over time is as fundamental to research ecologists as it is to practitioners engaged in environmental decision-making (Evans 2012). As the competition between people and other organisms for space and resources intensifies with continued human population growth, public support for environmental management and policy can only be retained if environmental decision-making is scientifically sound.

Yet, it is widely recognized that ecologists need to be better at prediction, as current approaches are inadequate (Evans 2012). The use of empirical relationships between biological properties and explanatory factors, typically measured for a narrow range of environmental conditions, may not hold as conditions change. Hence, predicting beyond the empirical range may not offer a sound basis for environmental management and policy. In contrast, individual-based models (IBMs), also known as agent-based models (ABMs), predict the behaviours of individual organisms and their population-level consequences on the basis of simple decision rules, such as fitness maximization (Stillman & Goss-Custard 2010). Fitness may be a measure of reproductive success or a short-term proxy such as rate of energy gain. The decision rules which form the basis of IBM predictions are not expected to change even if the environment changes. This basis means that IBMs can produce accurate, robust predictions outside of the range of environmental conditions for which the model was parameterized (Grimm & Railsback 2005). Hence, IBMs are key decision support tools to inform environmental management and policy and facilitate evidence-based decision-making (DeAngelis & Mooij 2005; McLane *et al*. 2011).

An ever-growing number of IBMs have been developed by modellers, who aim to aid practitioners and inform a range of issues related to conservation, natural resource management, wildlife management and human socio-economic activities (Grimm & Railsback 2005). Such applications of IBMs include the following: (i) wading bird conservation within commercial fisheries (Stillman *et al*. 2003), (ii) assessing the impacts of river restoration on fish populations (Railsback *et al*. 2009), (iii) examining the dynamics of mangrove forests (Berger *et al*. 2008), (iv) interactions between humans and large carnivores (Ahearn *et al*. 2001) and (v) managing herbivore grazing (Wood *et al*. 2014). The range of practitioners using IBMs to inform their decision-making processes include statutory authorities with responsibilities in environmental and natural resource management, non-governmental organizations such as conservation charities and those interested in the sustainable use of natural resources. Thanks to advances in computational power, data availability and ecological theory, increasingly complicated, sophisticated IBMs can be produced. Yet, this does not mean that these models will be more useful in informing environmental decision-making. IBMs typically require specialist computational knowledge to build and refine the model and analyse the model outputs, and so practitioners are unlikely to have the requisite skills to use IBMs directly.

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Conversely, practitioners may have greater knowledge of the system being modelled, so their input into the modelling process is highly desirable. Thus, it is important that modellers and practitioners collaborate effectively to develop models which can address the key questions that practitioners are interested in. In this paper, we highlight the uses of IBMs in environmental decision-making, identify potential obstacles to their successful use and discuss how such obstacles can be overcome. We aim to help practitioners understand the potential benefits of IBMs and to help modellers to understand how to develop IBMs which will better aid practitioners and inform environmental management and policy. We refer to a coastal bird IBM case study, from which general lessons can be learned.

Using models in practice: managing coastal bird populations

IBMs can inform decision-making on a wide range of environmental issues, including fisheries, forestry, conservation and agriculture (Grimm & Railsback 2005). In this section, we explore the development and use of an IBM to help reconcile nature conservation with economic activities within coastal areas.

The conservation of coastal birds within protected areas is threatened by a range of issues including climate change, anthropogenic disturbance, changes in fisheries practices and habitat loss due to coastal development (Stillman & Goss-Custard 2010). In response, practitioners including environmental and fisheries managers needed tools to help predict their consequences on bird populations. Since the mid-1990s, IBMs have been developed to advise bird conservation and environmental management within coastal areas (e.g. Stillman *et al.* 2003; Stillman & Goss-Custard 2010). In particular, IBM predictions are used by fisheries managers to inform the setting of annual quotas of quarry species, such as the shellfish that species of coastal wading bird, such as the oystercatcher *Haematopus ostralegus*, feed upon. This evidence-informed process allows fisheries managers to set quotas which enhance the economic potential of the fishery without threatening the conservation of birds. Such models are needed to predict how changes in the environment and fisheries practices would affect either population size or the demographic processes that determine population size.

The coastal bird IBM was developed from the long-term study of the oystercatcher in the Exe Estuary in southern England (Stillman *et al.* 2003). Subsequently, it has been applied to a wide range of sites around the world and to species and issues other than oystercatchers and shellfisheries (Stillman & Goss-Custard 2010). The growing range of site- and species-specific applications led to the development of a general IBM software package called MORPH, which made few system-specific assumptions and hence can potentially be applied to any system (Stillman 2008). Subsequently, MORPH has been used to develop a number of different IBM applications, including a model to inform the management of overgrazing by herbivores (Wood *et al.* 2014). In working closely with practitioners to use IBMs to inform environmental management and policy, we have encountered a range of problems, and solutions, which we discuss in the remainder of the paper.

Co-creation of IBMs by practitioners and modellers

We propose a framework to allow practitioners and modellers to co-create IBMs to inform environmental decision-making (Fig. 1). Our proposed framework is based on our experiences of developing IBMs with practitioners in over 35 coastal systems, to assess the conservation impact of processes including sea level rise, habitat loss, shellfishing, disturbance from humans, tidal barrages, wind farms, nuclear power stations, and changes in agriculture and hunting (Stillman & Goss-Custard 2010; Table 1).

WHAT IS THE QUESTION?

The first step is to identify the question of interest to practitioners. To avoid a mismatch between the IBM that modellers develop and the predictions that practitioners want, practitioners must be involved in the first stages of IBM development. Furthermore, engaging practitioners too late can make them feel that they have no say in the

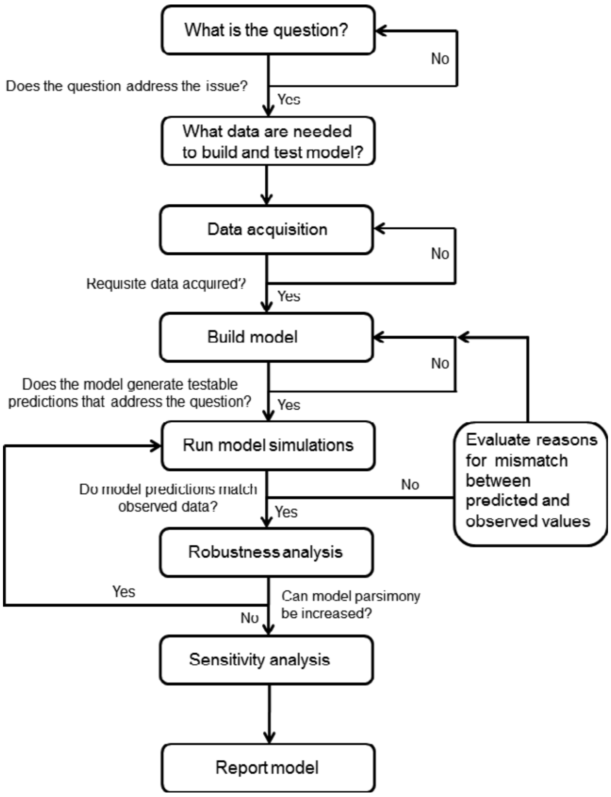

Fig. 1. Our proposed framework to guide modellers on developing, using and communicating individual-based models to aid practitioners in environmental decision-making.

modelling process and can lead to practitioner involvement being viewed as tokenistic. Where the aim of the IBM is to test the efficacy of different management options for a given focal species or study system, close collaboration will help the modellers understand which options are practical and will thus avoid wasted effort testing unrealistic options.

Recent experience has shown that by discussing model development and data eligibility with all relevant groups of practitioners and other stakeholders, in advance of generating model predictions, modellers can increase the chances that model predictions will be accepted by everyone (e.g. Elston *et al.* 2014). There are various ways in which practitioners can be engaged, although to date, there is little understanding of which approaches are most effective at achieving and maintaining such engagement. For example, modellers can use a series of workshops to discuss the conception, development and results of an IBM. Ideally, such workshops should involve participants from all of the relevant groups of practitioners. Alternatively, a modeller might be seconded into a practitioner group, or vice versa, in order to better understand what those practitioners need from an IBM. Again, such an approach must ensure that key practitioner groups are not excluded.

WHAT DATA ARE REQUIRED?

Once the question of interest has been identified, the next step is to identify the data that will be required to parameterize, run and test the model. Practitioner involvement at this stage is essential due to their expertise of the study system and its environmental issues. This is a critical step because a barrier to building and using IBMs is the relatively high requirement for data. The types of data required are likely to vary depending on both the question and study system of interest. For example, the data needed for a model of landscape dynamics of forests (e.g. Berger *et al.* 2008) will differ from a model of avian herbivory (e.g. Wood *et al.* 2014). The IBMs used to manage coastal bird populations typically require information on (i) species bioenergetics, including daily energy requirement; (ii) foraging behaviour, including estimates of intake rates for different prey species and densities; (iii) interactions with other foragers, as well as predators and parasites; (iv) food quantity, quality, availability and spatial configuration; and (v) the availability and spatial configuration of different habitat types (Stillman & Goss-Custard 2010).

DATA ACQUISITION

Whilst IBMs have a relatively high requirement for data for parameterization and testing, a range of data sources are typically available. To estimate the parameters, such sources include the following: (i) contemporary and historical field data, (ii) values derived from allometric relationships and (iii) values inferred statistically. Additional site-specific data are likely to be required to run and test the model, such as the physical specifications of the patches and the starting population sizes. This information can be obtained from contemporary and historical field data. Particular caution is needed in using historical data, as such values may no longer be appropriate. Close collaboration between practitioners and modellers is key to understanding what data are available given the requirements of the model. Practitioners also have knowledge of useful unpublished literature.

MODEL CONSTRUCTION

In order to address the question of interest to practitioners, the IBM must make explicitly testable predictions of the relevant biological properties or phenomena, such as the survival probability of animals within a population. Many IBM packages include a graphical user interface (GUI) that allows practitioners to visualize the model and its components (Fig. 2), and which can aid the practitioner's understanding of how the model works. Our experience is that IBMs can be communicated much more effectively when shown as a visual animation, for example showing patches being exposed and covered by the tide, and birds moving between patches in response to changes in food abundance and availability through the tidal and day/night cycle. These animations make much more 'intuitive sense' than IBM descriptions in reports or papers.

To increase the use of IBM approaches among researchers and practitioners, modellers must develop IBMs that are more intuitively used and user-friendly. Already, IBM software packages exist that do not require specialist programming skills, such as MORPH (Stillman 2008) and WaderMORPH (West *et al.* 2011). General modelling platforms such as NetLogo (http://ccl.northwestern.edu/netlogo/) also allow inexperienced programmers to develop IBMs.

MODEL PREDICTIONS

After model construction, testing of predictions against real-world data can begin through a process of model validation. The degrees of accuracy and precision in the predictions should be agreed with practitioners and will likely vary depending on the question. The confidence of practitioners in the predictions will be undermined if the model is not adequately tested and shown to give accurate, robust predictions (Bart 1995). Unless tested, a model is useless to decision-makers as they have no way of knowing whether the model is producing reasonable predictions. The predictions of IBMs should be tested rigorously using the pattern-oriented modelling (POM) approach developed by Grimm & Railsback (2012). POM is a well-established strategy for designing and testing models of complex systems by comparing model predictions and observations of multiple processes, at multiple levels, from the individual to population and community

Table 1. The sites and issues for which coastal bird individual-based models have been co-created with practitioners

Sites	Issues	Practitioners
Burry Inlet and Three Rivers, UK	Shellfishing, site quality	Countryside Council for Wales, Natural Resources Wales, Welsh Government
Bridgwater Bay, UK	Nuclear power station outflow	Centre for Environment, Fisheries and Aquaculture Science, Royal Society for the Protection of Birds, Natural England
Caerlaverock, UK	Habitat change	Wildfowl and Wetlands Trust
Cardiff Bay, UK	Habitat loss	British Trust for Ornithology
Chichester Harbour, UK	Human disturbance	Solent Forum, Natural England, Royal Society for the Protection of Birds
Dee estuary, UK	Shellfishing	Environment Agency, Natural Resources Wales
Exe estuary, UK	Shellfishing, disturbance, site quality, sea level rise	Natural England
Humber estuary, UK	Sea level rise, port development, habitat loss, site quality	Associated British Ports Marine Environmental Research
Liverpool bay, UK	Wind farms, habitat loss, disturbance	Crown Estates
Menai Straits, UK	Shellfishery management	Countryside Council for Wales, Shellfishing industry
Morecambe Bay, UK	Shellfishery management	Royal Society for the Protection of Birds
Poole Harbour, UK	Sea level rise, site quality, shellfishing, invasive species	English Nature, HR Wallingford, British Association for Shooting and Conservation
Baie de Seine, France	Port development, habitat creation	Syndicat Mixte Baie de Somme
Solway Firth, UK	Shellfishing	Scottish Natural Heritage, Royal Society for the Protection of Birds
Baie de Somme, France	Hunting, shellfishing, sedimentation, site quality, Spartina encroachment	Syndicat Mixte Baie de Somme
Severn Estuary, UK	Tidal barrage and lagoon development	Natural England, Countryside Council for Wales, Royal Society for the Protection of Birds, British Trust for Ornithology
Southampton Water, UK	Port development, habitat loss, site quality, human disturbance	Associated British Ports Marine Environmental Research, Solent Forum, Natural England, Royal Society for the Protection of Birds
Strangford Lough, UK	Shellfishing	Department for the Environment Northern Ireland
Wash, UK	Shellfishing, site quality	English Nature, Eastern Sea Fisheries Joint Committee

(Grimm & Railsback 2012). To achieve this, modellers should design IBMs to predict multiple patterns observed in nature at different scales and levels of organization. Such a strategy will reduce the risk that an IBM will predict the correct pattern for the wrong reason because in nature, different patterns are interlinked in ways that reflect the systems' internal organization. Within the POM approach, each pattern serves as a filter for falsifying unsuitable versions of submodels and unsuitable parameter combinations. The accuracy and precision of model predictions may be improved through an iterative process of model calibration, until the quality of predictions satisfies the practitioners (Grimm & Railsback 2005).

ROBUSTNESS ANALYSIS

Models ought to contain sufficient complexity to predict a biological phenomenon to within an acceptable margin of error. Additional complexity is therefore unnecessary. When developing models, one must keep in mind that the aim is to generate an accurate, robust prediction of a given biological property or phenomenon in order to answer a question, not to maximize complexity. A robustness analysis is a process of model simplification that can help to identify unnecessary parameters and processes, i.e. those that do not improve the accuracy or robustness of model predictions, by systematically varying model structure and processes (Grimm & Railsback 2005).

SENSITIVITY ANALYSIS

Sensitivity analyses are useful tools to quantify the range of parameter values over which the IBM can generate accurate predictions (Grimm & Railsback 2005). There are a range of methods for sensitivity analyses, the most commonly used of which is the 'one-at-a-time' method in which the values of key parameters are varied, either based on knowledge of parameter variation or a fixed value, over successive simulations (Grimm & Railsback 2005). A thorough sensitivity analysis lets practitioners know the range of conditions over which the model predictions are likely to be valid. Such analyses are particularly useful in helping practitioners understand the uncertainty associated with predictions where parameter values are associated with large natural variation or measurement error.

REPORTING THE MODEL

A major barrier to the effective use of IBMs is that they can be viewed as complicated 'black boxes' (Topping,

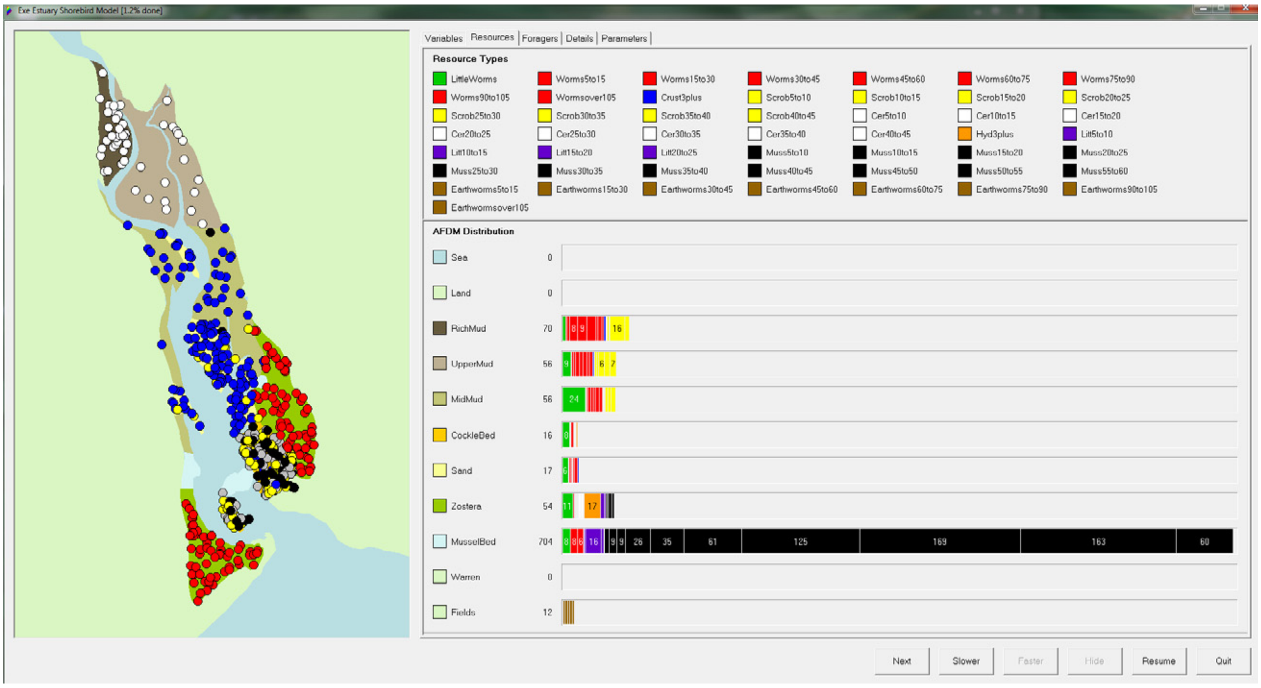

Fig. 2. An example of the graphical user interface (GUI) associated with the MORPH software, showing an individual-based model of waders foraging on intertidal invertebrates. The distribution of patches and foragers (circles) is displayed to the left (different types of forager are represented in different colours). Tabs to the right display the values of state variables (food resources in this example) graphically. The details tab shows the numerical value of each global-, patch-, and forager-state variable during each time step. Individual foragers can be selected by double-clicking either in the display or on the details tab; the forager can then be followed through the simulation. Buttons at the bottom right allow the simulation to be paused, slowed down or sped up, or progressed one time step at a time.

Høye & Olesen 2010). The notion of black boxes discourages use of such models and undermines confidence in the entire approach. However, there is no reason why an IBM, with full and clear reporting, cannot be made intelligible to the non-specialist, including practitioners. The use of GUI-enabled models can be particularly useful in model communication to stakeholders, as these allow practitioners to visualize the model and its constituent processes and parameters (Fig. 2). Furthermore, one should keep in mind that even the most complex model is less akin to a black box than the 'expert judgement' which currently underpins most environmental decision-making (Sutherland *et al.* 2004). Whilst the modelling process can be made transparent through adequate reporting, human decision-making is a biased, subjective internal process.

The predictions of an IBM, however accurate and robust, are likely to form only part of the evidence considered by practitioners during decision-making. To ensure that IBM-based predictions are seen as a viable part of the evidence base available to practitioners, the IBMs must be reported clearly. Helpfully, there is an established, standardized protocol for describing IBMs (Grimm *et al.* 2006) which should be more widely used. Reporting of the IBM should include a full description of the model structure and parameter values, including how such values were derived. Clear reporting is particularly important where complex statistical techniques have been used to infer parameter values, as such techniques may be unfamiliar to practitioners. Finally, publication of the model and its applications in peer-reviewed scientific literature will increase the scientific credibility of that model, which in turn can improve confidence in that model among practitioners (Bart 1995).

A further benefit of close collaboration between modellers and practitioners is increased awareness of model predictions among the practitioner community. Evidence has shown that practitioners do not routinely consult peer-reviewed journal articles to directly inform management actions; indeed, Sutherland *et al.* (2004) reported that the primary scientific literature accounted for only 2·4% of the total sources of information that conservation practitioners in England used to make management decisions.

Final remarks

Clearly, there is more that could be done to improve the development of effective decision support tools. In particular, development will benefit from approaches that make it easier to collect the relatively high amounts of data required for an IBM, at increasingly high spatial and temporal resolutions. Data collection approaches that allow data to be gathered over relatively short periods of time would allow models to be developed more rapidly to meet the demands of practitioners. In this regard, the rise of approaches such as remote sensing and citizen science could become increasingly useful. More generally, we need to understand better how modellers and practitioners can work together given the pressures on time, money and other resources that affect both groups. Despite these areas for improvement, we believe that IBMs are powerful tools to inform environmental debates, which are best created through the close collaboration between modellers and practitioners.

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Data accessibility

Data have not been archived because this article does not contain data.

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Biosketch

Kevin A. Wood is a researcher who has spent most of his career to date developing individual-based models (IBMs) of bird populations to aid environmental decision-making. These models have addressed how populations of swans, geese and oystercatchers respond to environmental change and altered management regimes. **Richard A. Stillman** is an applied ecologist with an interest in predicting how environmental change and management influence animal populations. His research aims to advise policymakers, conservationists and industry on the best ways of reconciling the interests of wildlife with those of humans. **John D. Goss-Custard** has spent over 40 years as a professional shorebird and estuary scientist and consultant and is currently a Visiting Professor at Bournemouth University. All three authors are present or past members of Bournemouth University's individual-based ecology research group (http://individualecology.bournemouth.ac.uk/index.html).