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Combining socio-economic and ecological modelling to inform natural resource management strategies

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Abstract: Effective management of natural resources requires understanding both the dynamics of the natural systems being subjected to management and the decision-making behaviour of stakeholders who are involved in the management process. We suggest that simulation modelling techniques can provide a powerful method platform for the transdisciplinary integration of ecological, economic and sociological aspects that is needed for exploring the likely outcomes of different management approaches and options. A concise review of existing literature on ecological and socio-economic modelling and approaches at the interface of these fields is presented followed by a framework coupling an individual-based ecological model with an agent-based socio-economic model. In this framework, each individual of the species of interest is represented on a spatially-explicit landscape, allowing the incorporation of individual variability. The socio-economic model also simulates inter-agent variability through the assignment of different attitudes and decision-making options for different agents; these may represent farmers, estate managers, policy-makers, the general public and/or other stakeholders. This structure enables variation in attitudes and circumstances of individual stakeholders, together with interactions between stakeholders, to be simulated. We discuss strengths and limitations of such an approach, and the information requirements for building a robust model to inform a real management situation.

Keywords: artificial neural networks; decision-making; machine learning; simulation modelling

1. INTRODUCTION

1.1 Background

Natural resources are provided by and embedded within often complex networks of ecological processes [Largoüet et al. 2012]. Human decision-making depends on social and economic valuations and influences as well as perceptions of natural systems and their intrinsic value [Beratan 2007; Siebert et al. 2006; Valbuena et al. 2010b]. Hence a transdisciplinary approach [Evely et al. 2010] is needed, where ecological, social and economic considerations are taken into account. Collaboration between these three research fields has been hindered by various barriers [Barlow et al. 2011; Lélé & Norgaard 2005]. However, in recent times more studies have crossed disciplinary boundaries to address interdisciplinary issues [for examples of projects, see Keough & Blahna 2006].

Modelling methods can provide a powerful tool for exploring the likely outcomes of different management approaches and options, especially when based on reliable data from empirical studies [Bunnefeld et al. 2011; Frederiksen et al. 2001]. The construction of models has long been employed in all three fields as a tool for improving understanding of respective systems [Richiardi et al. 2006, Wan et al. 2002; Jongejans et al. 2008]. Modelling approaches differ between the disciplines but are not without overlap. Before attempting to combine aspects of these fields of research into a single model for exploring management strategies, it is necessary to have an understanding of the aims and methodologies currently used within the different fields.

We begin by presenting a concise review of the literature on ecological and socio-economic modelling and approaches at the interface of these fields. We then present a framework for coupling an ecological and a socio-economic model. We give details on the decision-making process and discuss strengths and limitations of this approach. We conclude with some reflections on the information requirements for building a robust model of a real management situation.

1.2 Ecological Models

Ecological modelling has proceeded over time from simple verbal models to more or less complex statistical and simulation models. The focus of this section of the paper is on population models as these are most related to the modelling framework being described here. A wide range of different models types have been developed for predicting population dynamics, including mean field models based on mathematical equations, structured models such as matrix models and individual-based and agent-based models.

Mean field models such as the Hassell-Comins model [Hassell & Comins 1976] and the Ricker model (see, for example, Domokos & Scheuring 2004, Sun & Yang 2000) have been widely used and have formed a foundation for modelling ecological population dynamics. These models, and those that have followed them, incorporate mathematical equations to describe biological processes. They assume that all individuals in the population are identical – they model average population densities and not individuals. These have progressed from simple models assuming exponential population growth (see Jongejans et al. 2008) to complex formulations including density-dependence (such as the Hassell-Comins model; Hassell &Comins 1976). In addition to models of within-population dynamics, models of movement and dispersal have been constructed to take into account spatial aspects of population effects (for example, Ovaskainen et al. 2008).

Matrix models enable more biological detail to be incorporated into population models [Jongejans et al. 2008] than mean field approaches. Importantly, the population is categorised into age or stage classes, each with their own survival and reproduction rates [Ellner & Rees 2006; Jongejans et al. 2008]. Stochasticity can be incorporated to allow for demographic or environmental variation [Frederiksen et al. 2001]. A matrix framework allows the use of numerous analytical tools for extracting information about population dynamics and the importance of different population parameters with regard to population trends [Ellner & Rees 2006; Jongejans et al. 2008]. However, the assigning of categories can produce artificial divisions in the population, giving rise to error and incompatibilities in intra- and inter-specific comparisons of sensitivities and elasticities [Ellner & Rees 2006].

Individual-based and agent-based models (IBMs and ABMs, respectively) provide yet more flexibility; they facilitate the development of mechanistic models of populations based on the ecology and behaviour of the species, allowing variation between individuals through variation in characteristics and stochasticity in different behaviours and biological processes [Grimm *et al.* 2006; Travis et al. 2011]. The flexibility of IBMs makes them useful in situations where spatial complexities need to be incorporated into the model [Travis et al. 2011], which may be true of many case studies, including situations where there are clear spatial patterns in the attitudes of stakeholders towards the species. Analytical models, which are likely to be faster and produce clearer results, can provide a useful complement for verifying IBM results and produce more strategic advice for management practices [Travis et al. 2011].

1.3 Socio-Economic Models

Similarly to the field ecological modelling, the history of sociological and economic modelling is large and diverse. Here we focus on literature that relates to human decision-making since this is key to simulating management action and reaction in human communities [Grothmann & Patt 2005; Lal et al. 2001]. Approaches which overlap with models of human attitudes, especially towards other humans and wildlife, are central in the development of the socio-economic aspect of the management modelling framework. Within social sciences, economists are more in favour of quantitative methods and mathematical models than other disciplines [Lélé & Norgaard 2005]. Hence developments in this field are likely to be more directly applicable to the development of computational models than is the case for other social science disciplines that also need to be incorporated into our general modelling framework.

Traditional methods in economics have involved the use of linear technical analysis methods in forecasting in the financial markets [Castillo & Melin 2002]. More recently, economic research and development has adopted a diversity of models based on machine learning algorithms and concepts (Castillo & Melin 2002; see Fasli & Kovalchuk 2011, García-Crespo *et al.* 2011, Zhang & Wan 2007 for examples). These methods enable predictions to be made in the presence of nonlinear dynamics [Caraiani 2012; Lisi & Schiavo 1999] and near-unlimited numbers of factors influencing the outcome [García-Crespo *et al.* 2011]. Such methods have particular relevance in modelling human decision-making, where relationships between decisions and internal and external states may be masked and complicated by the lack of understanding of the human mind and the dynamic state of internal states such as attitudes to different management incentives or to particular species.

Although quantitative methods are generally held in higher regard among economists than they are among other social scientists [Lélé & Norgaard 2005], modelling approaches have been utilised to some extent in a broad range of fields. For example, social scientists studying human social networks have long been interested in network models [Lusseau et al. 2008; Newman 2008] and an agent-based computational model has been developed to explore the emergence of social relationships [Sutcliffe & Wang 2012].

A benefit of agent-based models is that a system's properties and patterns emerge from the behaviour of individual components ("agents") without the need to specify or even expect the emergence of these patterns [Leombruni & Richiardi 2005]. The inclusion of adaptive decision-making (*i.e.* which may change over time) of agents

[Wan *et al.* 2002] allows different strategies or attitudes of agents to be explored without the need for *a priori* knowledge about which strategy is most optimal.

Early agent-based models in economics include Smith's Experimental Market where agents were represented by students [Smith 1962]. Later models have explored the role of information on share price in stock markets [Wan *et al.* 2002]. Although ABMs have been treated with scepticism by economists [Leombruni & Richiardi 2005] – as indeed they were by ecologists (see Grimm et al. 1999) – there is now recognition of the need for such methods which allow emergent aggregate behaviours of systems to arise [Leombruni & Richiardi 2005; Richiardi et al. 2006]. Hence agent/individual-based models have now been embraced to some extent in both natural and social sciences, and we believe they offer the ideal approach for an interdisciplinary modelling framework.

Network science is a field which has also crossed the disciplinary boundaries with regard to modelling approaches. Beginning with work by social scientists and mathematicians [Newman 2008], interest in networks has spread to physics, biology, ecology, computer science [Proulx *et al.* 2005; Newman 2008] as well as economics [Pin 2011]. Ecological applications include exploration of food webs [Newman 2008], disease transmission networks [Boots et al. 1999, 2004; Proulx et al. 2005] and animal social networks [Lusseau et al. 2008]. Network analysis has also been applied to modelling of disease transmission in humans (*e.g.* Meyers 2007). In the context of our framework, we can model social networks where linkages and influences between individuals or other entities might not be correlated with space and/or time. A wide range of tools and methods for describing networks and extracting useful information from them exist [Newman 2003, 2008] and network approaches may thus represent a powerful approach for modelling human communities and populations where social structuring is strong.

1.4 Combined models

Work on models combining human and environmental or ecological systems has taken a variety of forms; from statistical mapping of the risk of human-wildlife interactions [Merkle et al. 2011] to numerical models adapted from the Lotka-Volterra predator-prey model [Helldén 2008] to agent- or individual-based models [Bennett et al. 2009; De Almeida et al. 2010; Valbuena et al. 2010a, b]. Here, we briefly highlight a few recent examples of agent-based approaches.

Agents with learning behaviour have been used in modelling land-use/cover change (LUCC), and a generic framework for this was introduced by Valbuena et al. [2010b]. In this framework, agents are described by their willingness to carry out certain action (*e.g.*buy or sell land) and their ability to so. These internal factors affect options, decisions and actions of the agent which can also be influenced by external factors reflecting social networks and interactions with other agents and with institutions [Valbuena et al. 2010b]. The influences of institutions and social networks on agents, *via* policies and subsidies, demand for goods and services, and advice, in response to land-use changes, provide a regional-scale feedback mechanism for agent behaviour, in addition to the internal feedback based on previous actions [Valbuena et al. 2010b]. The decision-making process of an agent is probabilistic, with the probabilities of the different options available being modified by the aforementioned factors [Valbuena et al. 2010b]. Monticino et al. [2007] have presented a different land-use model, where agents are also characterised according to types which dictate the options available to them. However, decision-making is approached differently, *via* the use of utility functions, with agents selecting the action with the highest expected utility [Monticino et al. 2007]. Uncertainty is incorporated into the decision-making through a probability for each consequence for each action. Both models incorporate interactions with other agents, with actions of one agent possibly influencing actions of other agents [Monticino et al. 2007, Valbuena et al. 2010a].

We present here a framework which is motivated by the ambition to (1) further develop previous work using agent-based models to model human stakeholders; (2) integrate the potential of network approaches for modelling social linkages, in order to (3) couple human socio-economic models with individual-based ecological models for exploring natural resource management strategies.

2. FRAMEWORK

The framework we present combines, at the simplest level, an individual-based model for a single species with an agent-based model simulating a community of humans.

2.1 The Socio-Economic Sub-model

Agents represent individual humans or groups of like-minded humans with an interest in the natural resource ("stakeholders"). Examples of possible categories include farmers, estate managers, policy-makers and the general public. The characterisation of agents builds on the categorisation by willingness and ability proposed by Valbuena et al. [2010b]. The "willingness" parameters of an agent [Valbuena et al. 2010b], here termed "attitudes" since these reflect the values and intentions of the agent, describe the internal likelihood of an agent taking each particular action available to it. The actions available, the "options" or "abilities" of the agent, depend on the type of stakeholder the agent is representing. The agent type will also affect its attitudes. Each agent is characterised by a preference function, which describes the agent's values (1).

$$P_i = \sum_{j=0}^{n} w_{ji}\, k_{ji} \qquad (1)$$

Where *Pi* is the preference function for agent *i*, k_{ji} is the *j*th attribute (out of the *n* attributes considered by agent *i*) on which agent *i* places some value (for example, wealth or a species of wildlife) and w_{jj} is the weight given by agent *i* to that attribute *j*. The weight, therefore, indicates the attitude of the agent towards that attribute. This preference function is then applied to the decisions the agent makes, and can be influenced by internal and external factors.

An example of a specific decision that a landowner agent might have to make is whether to cull wild animals on his/her land (Figure 1). In this case, the output could be a value along a continuous scale, corresponding to the number to be killed, or a binomial decision for each animal encountered. The probability of killing, or the number to be killed, is the output from an algorithm which has as its inputs internal and external factors: these would include the agent's estimate of the number of wild animals on the land, and possibly its *perception* of the total population size (which would serve as an indicator of how well the species is thriving, and hence its conservation importance). Other factors could include the economic income for the year or for the previous year and the size of the agent's land (economic considerations). The output is selected such that the value of the preference function is maximised.

Rather than trying to fit linear regressions to predict the best outcome, we suggest the use of machine learning algorithms to deal with multiple inputs and the possibility of non-linear and complex relationships between the best action to take and the values of each factor [Castillo & Melin 2002; Tourenq et al. 2001]. Machine learning algorithms such as artificial neural networks (ANNs) can adjust the weights of different inputs over time based on previous experience to simulate learning [Mitchell 1997].

Stakeholders in the real world are likely to be influenced by the actions of other stakeholders (for relevant examples, see Valbuena et al. 2010b). The strength of the influence might be spatially correlated; *i.e.* individuals might be more influenced by what their neighbours do than by what people in a different community do. However, especially in the light of present-day technology, this is not necessarily the case. Hence we propose the use of a network structure where the influence *l* of each agent *j* on a decision of one agent *i* is weighted according to the strength of the relationship between the agents, as described by the *z* number of chosen factors *b* and their weights *a* (2).

$$l_{ij} = \sum_{m=0}^{z} a_{mi} b_m \tag{2}$$

The influence can be simply determined by the Euclidean distance between the agents, whereby there would be only one factor *b*: the distance. The weight *a* would be set as negative to reduce influence with distance. If there are multiple factors (for example, political affiliation, work relationship and/or friendship) these can be weighted differently according to importance perceived from the empirical evidence. In case studies where detailed, robust data is available, weights could be varied between individuals or stakeholder types to reflect the different levels of influence different types of relations would have on people in different work-life situations and with different attitudes to nature and economic aspects. These linkages can be assigned *via* a matrix in the model where rows and columns denote the agents who influence and who are being influenced, respectively, with the value in the cell corresponding to the linkage sign and magnitude.

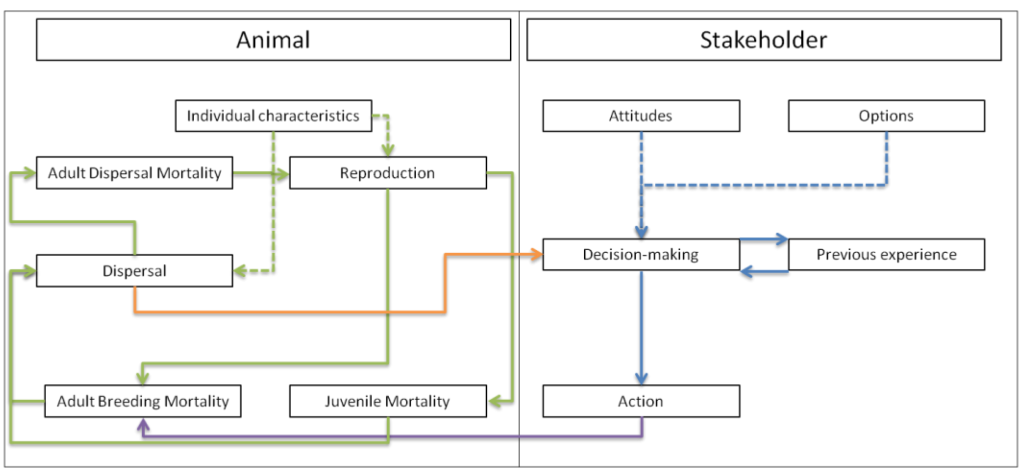

Figure 1. Flow diagram to represent an example of links and scheduling in the combined socio-ecological model. Arrows correspond to movement from one step in the model to the next. Green arrows represent movement from one process in the ecological (animal) individual-based model (IBM) to another in the same IBM. Blue arrows represent movement between socio-economic (stakeholder) agent-based model (ABM) processes. Orange arrows denote transfer from the IBM to the ABM, and the reverse is shown with purple arrows. Dashes arrows show where characteristics of individuals/agents influence processes but are not processes themselves.

The ecological IBM simulates the dynamics of the natural resource, in this example a single animal population with processes of dispersal, reproduction and mortality. This figure only shows links between a single animal and a single stakeholder; for social influences, see Figure 2.

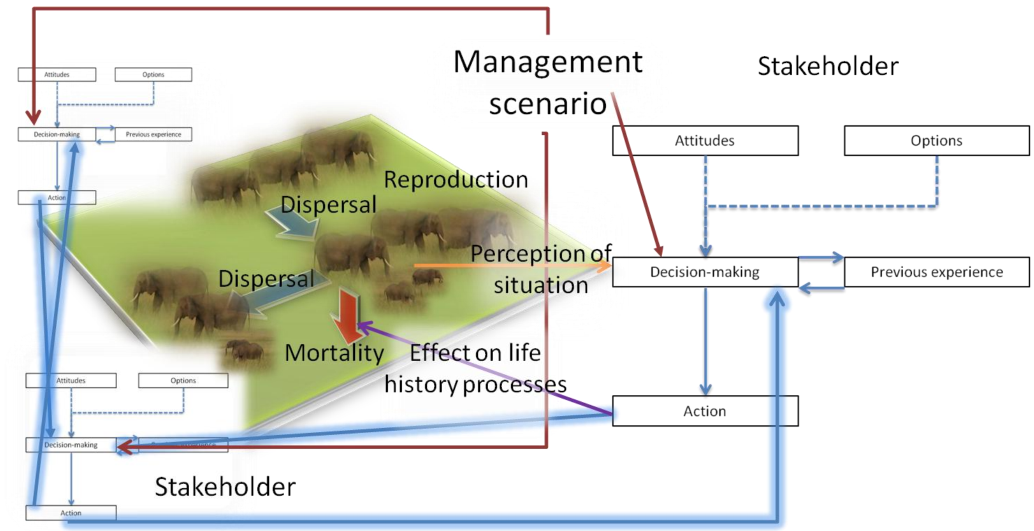

Figure 2. Illustration of an example of links and scheduling between agents and processes and within agents in the combined socio-ecological model. Here, the individual animals (represented by elephants as an illustration only) disperse, reproduce and die on a spatial landscape. Individual stakeholder agents perceive the situation within their range of observation at each time step and choose an action from the options available to in order to maximise the value of their preference function (as defined by the attitudes of the agent) but influenced by available options, previous experience and external factors. Actions depend on decisions but incorporate some level of stochasticity.

Arrows correspond to movement from one step in the model to the next. For an explanation of the symbology, see Figure 1. Highlighted blue arrows illustrate transfer of information from (and hence influence of) the actions of one stakeholder agent to the decision-making process of another. This may happen in the same time step (continuous updating) or from the actions taken in one time step to the decision-making in the next time step. Red arrows illustrate information flow from imposed management strategies (such as culling or conservation programmes introduced by the government) on the decision-making of each stakeholder agent in the model.

2.2 The Ecological Sub-model

The ecological model is intended to be flexible to allow for wide applications of the model to a range of different species. We envisage a spatially explicit IBM where individual animals (or other organisms) disperse and reproduce in each time step (Figure 1). Possible incidents of mortality include dispersal and breeding mortality, as well as mortality of juveniles or offspring (Figure 1). The complexity of the modelled processes of dispersal, reproduction and mortality would depend on the species and the level of knowledge about its biology and behaviour.

The model can also include a landscape. A discrete grid of cells storing information about the environment has been used to represent the landscape in both theoretical and applied work (for example, Anderson et al. 2009; Travis et al. 2009)

2.3 Links and Scheduling

An example of how the combined model would run and how the two sub-models might be linked is provided here to illustrate the framework. The time step begins with the dispersal of individuals of an animal population to new breeding sites (Figure 1). When the individuals settle in their new locations (*e.g.* territories), stakeholders gather or obtain information about the new situation; for example, how many wild animals are on their land. This information is fed into the decision-making algorithm, together with the other inputs and the algorithm uses weights calculated for each input from previous experience to produce an output decision [Mitchell 1997; Figure 1].

Further extensions of the framework can include the incorporation of multiple species. A dynamic landscape can be used to simulate land-use patterns as affected by agents and individual animals. The socio-economic model can also have status hierarchical structure; agents who affect and are directly affected by the animal or plant species would form the first level of contact – for example, farmers whose crops are destroyed by wildlife. At another level would be agents who have an interest (either sociological, economic or both) in the situation or are affected by it, but do not come into direct contact with the species. However, their decision-making processes can affect those of the 'front-line' agents, and *vice versa*. This could represent a local authority body. Further layers can be added to simulate different levels of influence. This could be political, social or economic. The actual 'level' of an agent might be represented in terms of the scale of influence; a high-level agent might implement legislation or other changes that influence the abilities and perhaps willingness of numerous agents and hence a large part of the landscape and/or animal population(s).

3. CONCLUSIONS AND RECOMMENDATIONS

The framework presented here is general and conceptual. It is intended to be applicable for a wide variety of resource management situations, and to be of use in developing theory on coupled human-nature systems (CHANS; An 2012). Different types of organisation (spatial, network and hierarchical) have been identified as important fields of ecosystem management research where multi-agent systems (MAS) – analogous to the ABMs in the context of computer software modelling – are a useful tool [Bosquet & Le Page 2004]. This framework provides options for exploring effects of these three aspects through the formulation of different forms of structures; for example, spatial structure and temporal and spatial autocorrelation can be incorporated through a spatial landscape on which the animals move; a strategy often employed in ecological modelling (see, for example, With & King 1997). Different stakeholder groups represent a secondary hierarchical structure, encompassing the elements of the lower level (individuals) as a simple nested hierarchy [Bosquet & Le Page 2004]. These are different from the status hierarchies envisaged in Section 2.3, and the proposed framework can be used as a tool in exploring how the structure and interactions between these groups arise from the behaviour and interactions of individual stakeholders [Bosquet & Le Page 2004; Hogeweg & Hesper 1983]. Incorporation of a network structure enables analysis of the sensitivity of systems to changes in social links and information flow between stakeholder agents.

However, this framework has not yet been tested or validated. One of the disadvantages of a complex, multipart model is the difficulty in performing an independent validation of the model. In this case, what would ideally be required would be a case study where the original state and changes in the natural resource (in this case, probably an animal population) have been documented over time, together with spatial (and possibly temporal) distributions of the attitudes and types of stakeholders involved, and any policies, incentives or legislation implemented. This would allow the testing of the model in the light of the management scenarios applied and the outcomes in terms of the fate of the natural resource. Such detailed case studies may be difficult to obtain, so less robust examples which nevertheless cross the boundaries between human attitudes and actions and changes in nature may have to be relied upon. Separate validation of the IBM and the ABM with no overlap could hardly be considered adequate since such a method does not consider the direct and/or indirect interactions between the two systems, which are the focus of the combined modelling approach. A possible case study to use for validation is the case of the red grouse *Lagopus lagopus scoticus* in Scotland, where information on both the ecological and socio-economic systems exists, including some information on how stakeholders (estate managers) make decisions [Redpath and Thirgood 1997]. Other methods for validation include comparisons between results from different types of models to look for consensus between different approaches [Bosquet & Le Page 2004; Travis et al. 2011].

Like all IBMs and ABMs, models based on the proposed combined socio-ecological framework will be highly complex and therefore may be very slow to run [Travis et al. 2011]. Advances in computing power may render this to be less of a problem in many cases, but where populations are large and social networks are large and complex, this may hinder progress considerably.

Machine learning algorithms like ANNs provide a flexible decision-making approach which is robust to noise in the data. One disadvantage of using this algorithm is the complexity and following obscurity regarding how decisions are actually made, resulting in a ‘black box’ which makes it more difficult for the observer to interpret results. We suggest the ANN framework because it is likely to be more familiar to those working on building ecological models than other machine learning algorithms.

Data requirements for a robust model vary considerably depending on the level of detail that is desired. We plan to apply this model framework to the conflict between commercial hunting of red grouse and conservation of the hen harrier *Circus cyaneus* in the United Kingdom (see, for example, Thirgood & Redpath 2008). Basic requirements involve data on the attitudes and activities of stakeholders across all types, and some method of categorisation of agents into discrete types. Data on the spatial distribution of agent types across the landscape is useful for incorporating spatial links with other agents and with the natural resource(s). For this case study, information exists on perceptions and preferences of stakeholder groups on opposite sides (hen harrier conservation vs. red grouse management or shooting; Marshall et al. 2007; Redpath et al. 2004) and of the general public [Hanley et al. 2010], although information on spatial distributions is scarce.

Knowledge about the main behavioural processes of the species (‘natural resource’) being simulated is required. Data on dispersal rates and strategies, as well as mating behaviour and average numbers of offspring are needed for building a sensible ecological model. Mortality rates at various stages in the time step are also important to include. For the hen harriers, such a model has been developed [Heinonen et al. in prep]. Furthermore, data on the stages which link the actions of the stakeholders with the species population processes provide the links between the inputs and outputs of the decision-making processes of the agents and the natural resource being managed. For the hen harrier – red grouse conflict, these can be modelled through variation in hen harrier mortality levels, simulating the level of illegal killing, and the numbers of hen harriers on the estate of a grouse manager can provide an input for the decision-making of a grouse manager agent, together with their own economic situation, while the general public and conservationists may obtain their perceptions of the status of both sides of the conflict through more indirect means.

Data requirements of combined models can vary considerably depending on the level of detail considered necessary and on the data available. We believe that this flexibility will allow this framework to be used to address a variety of natural resource management situations.

In conclusion, despite data requirements, we believe this framework provides a new step for building informative models for complex systems, exploring the effects of management decisions at different hierarchical levels and taking into account heterogeneity in attitudes and available options of individual stakeholders, which may affect compliance with management policies or incentives.

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