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The role of statistics in the analysis of ecosystem services†

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Operationalising the holistic approach implicit in an ecosystem services assessment is a challenge, incorporating social and economic considerations alongside the physical, chemical and biological function of ecosystems. The paper considers the role of statistics within a range of frameworks proposed for the analysis of ecosystem services. The use of different statistical techniques within the component parts of an ecosystem services assessment framework are discussed, including (1) data availability and sampling strategies, (2) statistical data analysis, (3) geography and spatial models, (4) meta-analysis, (5) environmental models, (6) societal models, (7) feedbacks and loop analysis, and (8) graphical models including Bayesian belief networks. Issues of value and the potential for a statistical contribution to multivariate non-monetary valuation are considered. We argue that statistics has an underpinning role by providing tools to link together the component elements along with their uncertainties for a thorough ecosystem services assessment, and should be an integral part of this developing inter-disciplinary research area. Copyright © 2011 John Wiley & Sons, Ltd.

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1. INTRODUCTION

The ecosystem services concept provides a challenge to those working in ecological and environmental research. Developing through the 1990s (see Dick *et al*., 2011a) ecosystem services came to greater prominence following the work conducted by the Millennium Ecosystem Assessment (MA) team and their published framework for assessment (MA, 2003). Ecosystem services are defined in the MA framework as the benefits people obtain from ecosystems, and this framework has proved helpful in focussing thoughts on different aspects of the ecosystem and its services (MA, 2005). Vital elements of an ecosystem are the interactions within the biological, physical and chemical constructs describing the environment, and between these and human society with its socio-economic development putting pressures on this planet's resources. This broader perspective challenges the notion that the traditional single focus approach to environment policy and management (including individual initiatives to promote agriculture, forestry, fishing, conservation, biodiversity, etc.) can deliver a sustainable future within such a complex system. Operationalising the ecosystem service concept will potentially lead to a major change in the relationship between environmental science and policy.

While ecosystem services have already claimed a prominent place in the environmental policy development arena (for example, with the setting up of an Intergovernmental Platform on Biodiversity and Ecosystem Services (IPBES) by the United Nations in 2010 (Larigauderie and Mooney, 2010)), there remain considerable challenges in operationalising the MA or other frameworks for specific studies (Alho, 2008; Ashworth *et al*., 2009; Griebler and Lueders, 2009; Liu *et al*., 2010). This paper gives an overview of the role statistics can play in the development of these concepts, looks at a range of recent applications relevant to ecosystem services assessment, and considers how a range of statistical tools assists with more rigorous assessments of the delivery of ecosystem goods and services from a landscape.

2. CONCEPTS

In addition to its focus on human-ecosystem interaction, the development of ecosystem services brings with it a series of ideas: (1) the possibility and importance of a holistic, or at least more holistic, approach to assessing and managing the environment; (2) the usefulness of valuing the consequences of a change to an ecosystem; and (3) the concept that the environment contains natural capital. The first concept effectively relates to interactions, feedbacks and multiple outcomes, and statistics has a range of standard data analysis tools to apply.

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However the design of data collection and sampling strategies to derive and test multiple outcomes from complex models is a challenge. The second concept focuses on identifying and measuring changes in flows from the ecosystem related to input or state changes, which may translate into trends for smoothly varying systems, and for more abrupt changes the detection of discontinuities or the estimation of the probabilities of state changes, as in the prediction of tipping points. The general notion of value introduces the idea of a relative importance between different aspects of the ecosystem with the potential for a statistical choice between alternative weighting systems through a multivariate approach. The third concept can appear to be similar to the second but there are some important differences. It relates to stocks within the ecosystem, so has some comparisons with census statistics in human populations or the application of geostatistics to assess oil reserves within a geological structure. While the ideas of stocks and flows are naturally linked in our understanding of ecosystems, in practice it is usually much easier to assess the environmental flows and much more difficult to assess the environmental stocks – which is a relevant factor when considering the statistics for undertaking an ecosystem services assessment.

The practical application of these concepts leads to the development of frameworks within which we have a combination of understanding ecosystem function, identifying services to humans, valuing these services (throughout this paper the word value does not equate to monetary value unless explicitly stated) and including human behaviour responses. Statistics provides the underlying theory to combine these information resources along with the quantification and linkage of the uncertainties, thus ensuring that the later stages of the assessment, including the valuation phase, correctly reflect the extent and limitations of the current knowledge base.

3. CHARACTERISTICS AND COMPONENTS OF ECOSYSTEM SERVICE FRAMEWORKS

There are many variants of the frameworks used to define an ecosystem service assessment. The simplest systems are linear where a model of ecosystem function is combined with a relatively simple service valuation phase; Figure 1 illustrates a framework derived from a scenario analysis (Figure 3.3, p. 36 in TEEB, 2008) applied to the issue of reduced grazing pressure resulting in establishment of more seedling trees in a catchment as observed in the long term monitoring site of the Environmental Change Network (ECN) in the Scottish Highlands (see Dick *et al*., 2011a for more discussion of this ecosystem change). More complex frameworks include the cascade (Haines-Young and Potschin, 2010) with a single feedback from the valuation phase through pressures and policy action to affect ecosystem function; Figure 2 shows this framework adapted for the tree re-colonisation example. The Integrated Science for Society and the Environment (ISSE) framework (Collins, 2007) was developed for the US Long Term Ecological Research network and concentrates on the disturbance effects on an ecosystem with pulses as short term events and presses as longer term changes; it includes bidirectional links between drivers and disturbance and a feedback from the services assessment through human outcomes and behaviour to influence the drivers (Figure 3). These different frameworks have much in common and consideration of the potential for statistical contribution is generic.

The ISSE framework as applied to the Cairngorm tree colonisation ecosystem change is discussed further in Dick *et al*. (2011a) and is used in this paper to illustrate where statistics can contribute to an ecosystem services assessment. The general ISSE structure is formulated as a completely looped system (Figure 3), so one way forward is to split it into parts which can be analysed sequentially – an approach which is encouraged by the identification of the six questions linked to the framework which are initially answered by a narrative but can also be quantified:

Q1: How do long-term press disturbances and short-term pulse disturbances interact to alter ecosystem structure and function?
Q2: How can biotic structure be both a cause and consequence of ecological fluxes of energy and matter?
Q3: How do altered ecosystem dynamics affect ecosystem services?
Q4: How do changes in vital ecosystem services alter human outcomes?
Q5: How do perceptions and outcomes affect human behaviour?
Q6: Which human actions influence the frequency, magnitude or form of press and pulse disturbance regimes across ecosystems, and what determines these human actions?

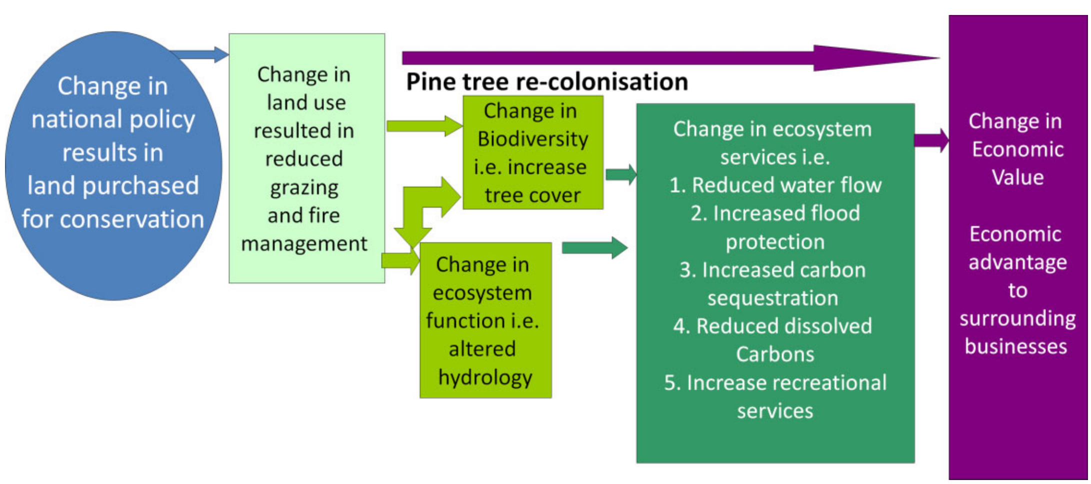

Figure 1. A simple linear ecosystem services framework derived for tree recolonisation following restrictions on grazing.

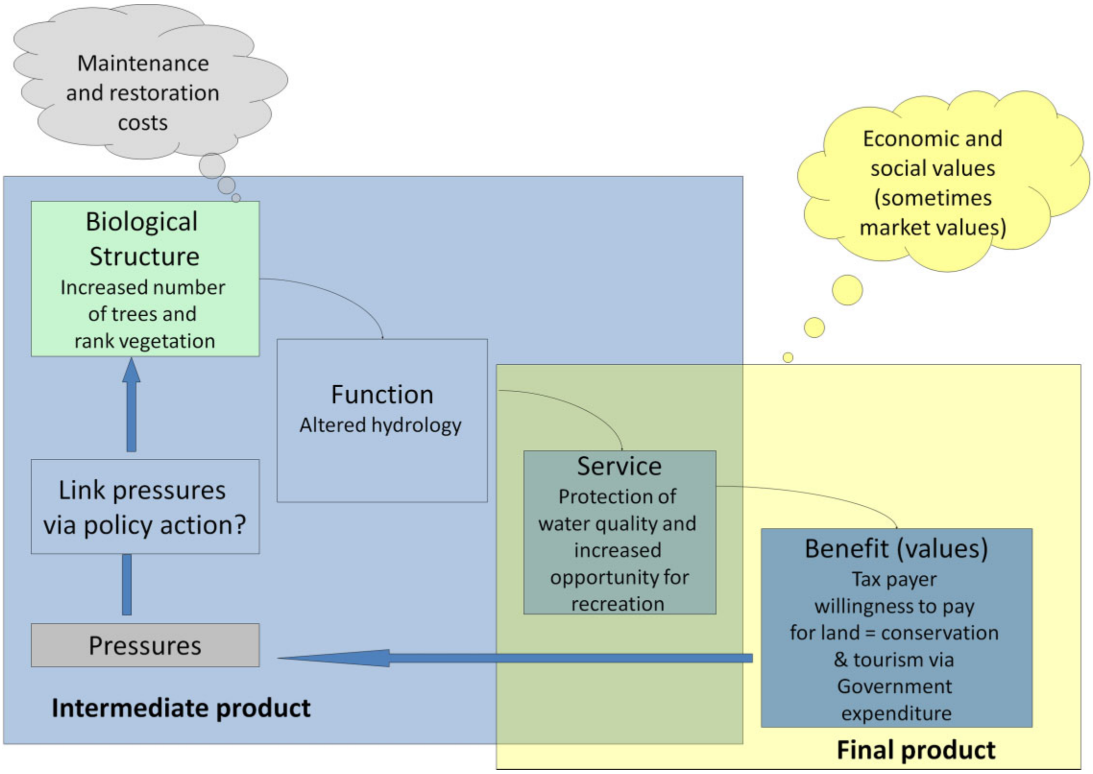

Figure 2. A modified cascade ecosystem services framework for tree recolonisation following restrictions on grazing derived from Haines-Young and Potschin (2010).

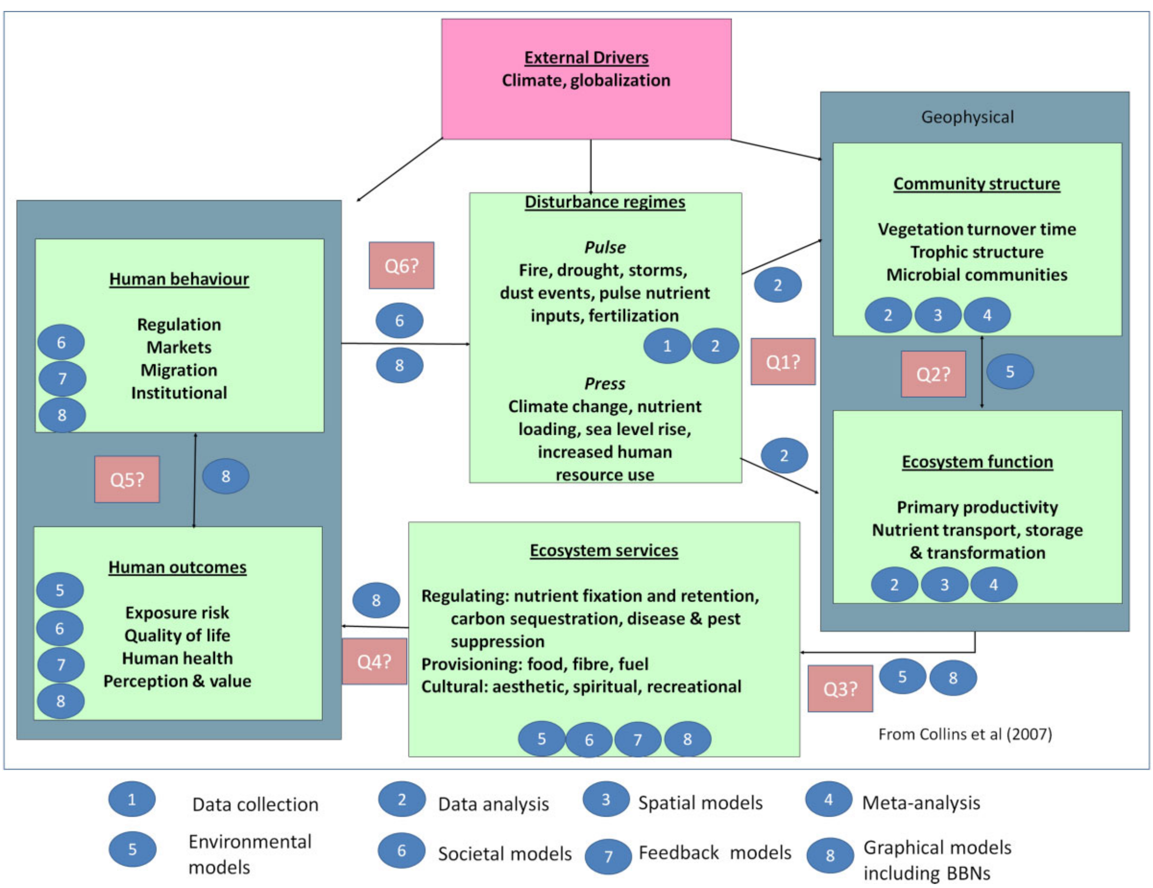

Figure 3. ISSE framework incorporating indicators to the components and statistical elements discussed in text.

The following sections consider that contribution statistics can make to each part of the process, using a gradual progression from data acquisition through to Bayesian belief networks using eight component headings:

(1) Data availability and sampling strategies
(2) Statistical data analysis
(3) Geography and spatial models
(4) Meta-analysis
(5) Environmental models
(6) Societal models
(7) Feedbacks and loop analysis
(8) Graphical models including Bayesian belief networks

Links between the components and the elements and questions of the ISSE ecosystem services framework are indicated on Figure 3 for illustrative purposes. Though these components are separated for convenience of discussion, there is a continuum within any ecosystem services assessment and none of the statistical techniques has a unique application in any one area.

3.1. Data availability and sampling strategies

A holistic assessment of even a relatively small ecosystem ideally should be based on a substantial data resource, and the availability of data will be a critical consideration when judging the value of any ecosystem service analysis. Commonly ecosystem service research will include both narrative and numerical data requiring the use of different statistical tools. The natural sciences tend to concentrate on continuous quantitative variates for primary information while there is a greater predominance of narrative data in social sciences, but there is no exclusive division of data types between the disciplines.

The primary focus at the initial stage of an analysis, common to all data types, is to assess the basic properties such as the statistical error and any bias in the collected information, which relates to applying the fundamental principles of sampling. Although an optimum sampling scheme can be used to collect data specifically for this work, commonly data from other studies form a substantial segment of the information for an ecosystem assessment. Monitoring schemes can be good data sources but their representativeness may not be ideal (Magurran *et al*., 2010), and recent work has looked at the power of such schemes to detect relevant change (e.g. Elston *et al*., 2011). The sampling strategies of contributory studies may not combine together neatly to provide an adequate coverage of the whole (statistical) population. This can be illustrated by considering the populations associated with the three perspectives for ecosystem services given in Haines-Young and Potschin (2008): the habitats perspective (e.g. the woodland grazing system considered as an example in Kuhnert, 2011), those where the service defines the system of interest (e.g. the bioremediation of sewage waste in Mangi *et al*., 2011; the coastal defence systems in Morse-Jones *et al*., 2011), and those developed from a place-based approach (e.g. the ecosystem services associated with the ECN sites in Dick *et al*., 2011b). The populations are all different and a sampling strategy for a habitat approach, for example, may not provide a satisfactory coverage to deliver adequate data for an apparently similar place-based assessment.

If there are deficiencies in the data resource, a choice will be made to rectify this either by further data acquisition, possibly through field work, or by incorporating models and expert opinion. A well developed literature on statistical procedures for eliciting and quantifying expert opinion and its uncertainty for a variety of practical studies exists (e.g. Garthwaite *et al*., 2005; Oakley and O'Hagan, 2007; Moala and O'Hagan, 2010). Kuhnert (2011) explores the use of expert opinion in four ecological case studies and argues that it has a place in ecological decision analysis. Estimating the statistical error along with the costs for the various options will help define the balance between the choices of using different information sources.

3.2. Statistical data analysis

In general numerical data are initially analysed using a statistical model (regression, analysis of variance, time series) or a more complicated variant (non-linear model, GLM, GAM, GLMM, etc.). These analyses consider the dependence of single or multiple responses on explanatory variables, identify relationships but not necessarily cause, and normally investigate only parts of the ecosystem. Similar approaches may be taken with narrative data, possibly with greater use of descriptive statistics in the initial stages. The aim within an ecosystem services assessment is to build from a series of statistical analyses, which focus on identifying process, function and capital (where appropriate) and provide a quantification of the linkages with their relevant uncertainty measures.

3.3. Geography and spatial models

Many ecosystem services studies use spatially referenced data, and developments in four areas of spatial analysis (geographic information systems, remote sensing, spatial trends and hierarchical models) are briefly discussed. Useful statistical developments in all these areas also point to more statistical research for developing the spatial aspect of ecosystem services and in particular quantifying the associated uncertainties.

The development of geographical information systems (GIS) has highlighted the uncertainty in geo-referencing, but other sources of statistical error are often embedded in these databases and may not be recognised. It is easy to include concentrations of air pollutants, for example, within a GIS without including the uncertainties from the models used to derive the values. Many social science and health related databases are referenced to an area, such as the postcode system in the UK, and depending on the scale of the ecosystem study the question of how to spatially apply that single value may become an issue. Jerrett *et al*. (2010) review the use of GIS methods in environmental and public health and discuss issues such as combining different risk elements and the conceptual framework of hazard, exposure and vulnerability, which are relevant to ecosystem service assessment.

With demand for more data across the environment there is increasing use of remotely sensed and satellite data. These data have their own uncertainties, with statistics making valuable contributions on pattern recognition for example, but the appropriateness and accuracy from ground-truthing for the ecosystem being studied are additional considerations. Again the evaluation of uncertainties in these inputs is an important aspect of an ecosystem assessment, and with ecosystems covering large areas this becomes a substantial task. Kohler and Huth (2010) illustrate some of the issues in their quantification of scale dependence of spaceborne estimates of the carbon stored in tropical rainforests.

Another statistical issue that is often overlooked occurs when combining trends from data series collected in different parts of the ecosystem. The strength of the trends will depend on the use of a realistic spatial correlation structure in any meta-analyses, potentially requiring re-analysis of the original data series. Shamsudduha *et al*. (2009) use a spatial structure following non-parametric seasonal trend decomposition to analyse groundwater trends for the Ganges-Brahmaputra-Meghna Delta and developments of these types of analyses may well be fundamental to ecosystem assessments on a larger scale.

In many frameworks it is recognised that ecosystem service assessments are dependent on the spatial scale and one approach is to consider nested regions for the assessment. The analysis may decide to ignore the upscaling/downscaling issue if it concentrates on different blends of ecosystem services at the different scales (e.g. considering tourism only at a National Park level while considering water quality only at the scale of catchments within the Park). However this is an unsatisfactory approach since it ignores the connectedness of the nested scales and hierarchical spatial models provide a method of accounting for spatial covariance at different resolutions. For example, Sahu *et al*. (2010) give an application of Bayesian hierarchical models to link scales by bringing together point measurements and a real model output to estimate wet deposition of sulphate in the eastern USA. Cressie (2010) reviews the assessment uncertainty in complex ecological models using hierarchical statistical models, presenting it as a coherent approach for including uncertainty from sampling, measurement, process specification, parameter, initial and boundary conditions, etc. but acknowledges the difficulties of practical implementation.

A coherent approach to the spatial element of ecosystem services assessment presents a considerable challenge. There are several examples of useful statistical techniques but these require further research and development before their routine application to ecosystem services.

3.4. Meta-analysis

If the assessment of an ecosystem service relates to a larger area or several sites, a second phase of the data analysis is some form of meta-analysis to bring the information together in a coherent way and to deliver a parsimonious but effective model for prediction. Meta-analyses have become increasingly common in the analyses of social and medical science studies where combining information across several studies has many benefits (Borenstein *et al*., 2009). There is evidence of its growing use in ecology, for example Philpott *et al*. (2009) used a meta-analysis to combine studies on bird predation of arthropods in agro-ecosystems in Central America and Benayas *et al*. (2009) looked at the role of ecological restoration across several studies. Stewart (2010) reviews the use of meta-analyses in conservation science and recommends that the more sophisticated statistical techniques used in other disciplines be applied.

Extending the meta-analysis analogy helps with understanding what is required to combine the information to build an ecosystem function framework. Meta-analyses can provide the consistent overview where different statistical techniques may have been used in the individual component analyses, and so this approach could be used to link outputs from individual statistical analyses into the ecosystem model. However for multiple outcomes and with increasing complexity in elements of ecosystem function, while meta-analysis provides a useful intermediate tool with good conceptual properties the development of models with more flexibility may be helpful.

3.5. Environmental models

Combining the understanding of parts of the system leads to the development of environmental models. Primarily environmental models rely on quantitative data, and qualitative or narrative information is often reassigned using a scoring system. Many environmental studies assume causal links, so if two measurements genuinely differ there will be underlying inputs and processes which can be investigated to explain the discrepancy. There are three main types of environmental model in common use, empirical, process-based and stochastic models, and these will be considered separately.

Empirical models rely on statistical relationships derived from data; they can readily reflect the uncertainty in their outputs, but are limited to the range of available explanatory variables and any extrapolation can be misleading. These models can be quite complex and informative, as, for example, with the development of a general statistical modelling approach to combine remotely sensed datasets, model output, and data assimilation products allowing the quantification of uncertainty on each parameter which was applied to the detection of ocean fronts from satellite data (Hopkins *et al*., 2010).

Process-based models rely on the underlying physical, chemical or biological principles to support the model structure and it is often argued that the reliance on basic principles allows these models to work outside the range of current conditions. While process-based models of simple systems can reproduce observations well, as the system becomes more complex the ability to match observed data tends to diminish and the uncertainties in both model structure and model predictions become important considerations (as with the legendary uncertainty of weather forecasts in some parts of the world). Statistical techniques are available to assess the uncertainty in model output, but they are often ignored or applied in a cursory fashion by practitioners. Examples of uncertainty assessment include the relatively simple application by van Oijen *et al*. (2005) and Ogle and Barber (2008) for crop-forest and tree physiology modelling ranging to the use of model emulators for complex computer models (Kennedy and O'Hagan, 2001) with a subsequent application to estimating carbon stocks in peat (Kennedy *et al*., 2008). Uncertainty in climate modelling provides a significant challenge with Rougier *et al*. (2009) deriving methods for multivariate outputs in general circulation models using an emulator approach while Crucifix and Rougier (2009) directly identify and use simplified versions of climate models.

Stochastic models are used for population dynamics, with as an example the exploration of climate change on seabirds such as the population consequences for Cassin's auklet off the Californian coast (Wolf *et al*., 2010). Increasing complexity in the models can introduce greater uncertainties with the links to multiple drivers becoming more difficult to estimate, so potentially models for different populations in an ecosystem may not be as well-coupled as would be desirable.

The assessment of a whole ecosystem function will bring together all these flavours of environmental models, each with their own strengths and limitations, to reproduce complexity; this structure has to accommodate the different qualities of error estimation, but there are statistical procedures available to achieve that goal when the information is available.

One advantage of the ecosystem function model is that it provides a tool to explore scenarios and therefore estimate responses to changes, such as the pulses and pressures in the ISSE framework (Collins, 2007). A major consideration is the spatial and temporal scale of an ecosystem along with the degree of complexity of the combined model. All the processes from the bacteria and soil microbes upwards cannot be accommodated realistically within a working ecosystem model, and, further, science may only be aware of and have investigated a very limited number of the processes and interactions in any ecosystem. One way to handle this is to restrict the models to specific spatial and temporal scales. This necessary step introduces artificial boundaries on the ecosystem model and should force adjustments to the complexity of the model elements. To estimate the functioning of a stream catchment on a monthly time step, for example, may require simplifying some models, e.g. the detail of generating water flow estimates every hour is not required, while increasing complexity in others, e.g. providing monthly estimates of water uptake by a tree when there is only an annual measurement available. The scale issue is obvious and quite basic, though it can be ignored by the temptation to always include the most complex models available. It is recognised within the ecosystem services literature by the nested approach to implementing the ISSE framework and within systems modelling by a considerable literature on upscaling and downscaling (e.g. Maraun *et al*., 2010).

3.6. Societal models

One can argue that there is no difference from a statistical perspective between the data used in the natural and social sciences, but the social science community have developed a different range of tools suitable for the integration of their numerical and narrative data. There is much greater use of narrative information in social studies, and the strong assumption from the physical sciences of underlying processes almost hard-wiring the direct influence of a change in variable A on variable B is less relevant, e.g. increased rainfall increases water quantity in a river while improving a transport link has a less predictable influence on the number of tourists. People change their mind following events so there are many more step changes in outcomes rather than smooth trends, and even with the detailed quantitative data and models in economics, changes in value can occur quite suddenly and may only in part be rooted in logical decisions, with sentiment and subjectivity often the major factors.

While the basic types of data analysis can be similar, there is more emphasis initially on identifying correlations. There is an acceptance of living with greater uncertainty in the analysis and of not necessarily being able to measure the underlying factors which are believed to control the responses. This leads to the use of latent variables in factor analysis and in various versions of structural equation or causal modelling, with the latter techniques also allowing the use of a proposed logical (deterministic) causal framework in place of the data-driven empirical relationships from standard regression. As with many environmental systems, effects can be related to multiple causes and establishing and quantifying the interaction structure is a major issue.

Group responses are often more amenable to analysis and provide better predictability than individual responses. Demography and the use of cohorts, for example in health studies, have been standard ways of providing an averaging process to provide coherent group responses. However as individuals we are part of the studied system, so our opinions influence our views on the reasonableness of the groupings chosen and how these relate to the responses, and therefore affect our individual beliefs on the validity of the outcomes of the study. A greater degree of objectivity may be sought by using the data to drive the groupings, such as the use of a typology derived from attitudes revealed in answering a questionnaire in the Scottish Environmental Attitudes and Behaviours Survey 2008 (Davidson *et al*., 2008) before an analysis using logistic regression.

Ecosystem services assessment will include information gained through public participation to assess the importance or value of a system, and the challenge is to convert perception and opinion to some qualitative or quantitative measure. Combining several perceptions together leads to structures like cognitive or mind maps where graphical representations are used to identify ideas and the links between them. This graphical approach is common to many methods for determining how the linkages operate from the available data. Fuzzy logic is one possibility and fuzzy cognitive mapping was used in implementing the European Water Framework Directive to bring together participatory data with economics to test water-pricing options (Mouratiadou and Moran, 2007). One driver for using ecosystem services assessment is to provide an input to decision-making, for example to weigh the benefits of building a dam against the environmental costs. Several economic ecosystem services assessments have used a cost-benefit paradigm, but there are alternative operational research or decision theoretic approaches with, for example, multi-criteria analysis allowing for use of both quantitative and qualitative data and searching for a balance between several objectives set on different criteria (CLG, 2009).

Agent-based modelling is another approach proposed for integrating socio-economic and ecological data (Matthews, 2006), where a community response is simulated by modelling a large number of individual agents operating a fairly simple rule set with the ability to learn and adapt. The group response then becomes an integration of the actions of individuals, so better reflecting societal structure. Again this is a computationally intensive approach for any sizeable system but it is one way of capturing human behaviour uncertainty.

Some of these societal models can include environmental variables, but in general an ecosystem services assessment will be combining information from many different types of analysis. From a statistical viewpoint, as well as providing a transparent method to track the levels of certainty we assign to the different elements, we also should consider the subjective decisions that have been made in constructing these environmental and societal analyses in our assessment of the value of the final outputs.

3.7. Feedbacks and loop analysis

Feedbacks occur within ecosystem services at two different levels. There can be feedbacks within ecological function where, for example, increased river flow can result in scouring of the river bed leading to further increases in river flow, introducing a dynamic element to the statistical model. The temporal detail for the application of fully dynamic multivariate models across an ecosystem is unlikely to be matched across all relevant variates in an ecosystem assessment and so some simplification or model reduction for feedback loops may be appropriate. For example, if the feedback operates at either a shorter or much longer temporal scale than the scale of the ecosystem assessment and is restricted to some components of the ecosystem function model, then it may be sufficient for the ecosystem function assessment to accommodate the feedback by an adjustment to the equations and parameters to approximate the effect of the dynamic component over the relevant time period. Standard Bayesian analyses of linear dynamic models on parts of the ecosystem function offer another possibility.

There is a second level of feedback in several frameworks (e.g. cascade (Figure 2)) and ISSE (Figure 3)) where the outcome of the whole function and service model then results in changes of policy or adaptation of an environmental pressure. Levins loop analysis is one method for modelling whole system feedbacks within ecological models. Levins (1966) opens with 'Modern population biology arises from the coming together of what were previously independent clusters of more or less coherent theory', a statement which could reasonably apply to ecosystem services, and then introduces his strategy for model building including a graphical diagram of the structure. The optimisation he proposed works on qualitative data, which he saw as a corrective balance to the 'one-sided analytical quantitative approach that is still dominant'. Ortiz and Wolff (2002) applied this approach to management strategies of benthic systems on three habitats and proposed it as a useful theoretical framework to assess the whole system complementing other available quantitative tools. Justus (2006) discusses the limitations of loop analysis in that it applies to a system close to an equilibrium state and it indicates only direction of response so requiring auxiliary information for interpretation, but concludes that the qualitative approaches including loop analysis have a continuing role to enhance understanding within scientific debate. However the limitations of this approach appear to restrict its potential usefulness in evaluating ecosystem services.

3.8. Graphical models including Bayesian belief networks

Graphical models using a probabilistic logic provide a statistically stronger approach to analysing complexity and uncertainty. The basic structure of a probabilistic graphical model is one of nodes containing random variables and edges or arcs linking the nodes that give association (undirected graph), dependence (directed graph) or a mixture of both (chain graph). The requirement in an ecosystem services framework to link together quantitative and qualitative data with expert knowledge favours a Bayesian approach, and the (BBN) is a directed acyclic graph developed in the last two decades and applied to explore ecosystem management options. The graphical structure of BBNs is similar to that used by other decision tools where differing criteria may be used for optimisation, including neural networks and fuzzy logic, and so they link well between the environmental and societal models. A few examples of the application of BBNs illustrate their potential.

Bacon *et al*. (2002) used decision software to assign cost-benefit criteria to parcels of land and then a belief network to assess the chances of land use change, combining farmer satisfaction scores with costs to allow an objective assessment of a land management issue including quantification of the uncertainty associated with the management decisions. In a later development Aalders (2008) used the BBN for the whole analysis to combine biophysical characteristics with a more detailed development of the social processes influencing land use management decisions. Hunter *et al*. (2009) use Monte Carlo modelling based on a BBN for a cost-benefit analysis to assess potential interventions to improve rural water supplies and note in their paper the more robust approach to uncertainty assessment provided by these methods compared to previous economic analyses.

Amstrup *et al*. (2008) forecast the future status of polar bears with a BBN. Using four arctic ecoregions, modelled climate change and sea ice projections are combined with a range of population stressors so this is an example of a more detailed representation of ecosystem function within a BBN and of using multiple outputs. The structure combines quantitative and qualitative data with expert opinion, and a significant portion of the work was on sensitivity, validation and ensuring uncertainties were assessed. Hamilton *et al*. (2007) generated a BBN of ecosystem function to model the risk of algal blooms and to identify significant knowledge gaps. In that case it proved difficult to distinguish between causative factors and in later work Hamilton *et al*. (2009) applied Bayesian model averaging to explore structural uncertainties and provide an ecologically interpretable model. Johnson *et al*. (2010a) develop an Integrated Bayesian Network to bring together multiple BBNs; in this case they further developed the ecosystem function BBN alongside an environmental management BBN and included a water catchment simulation model within the integrated structure. By using an object oriented approach they handle complexity by identifying sub-nets, which can be treated as conditionally independent objects with interface nodes to transfer information. Implementing this structured hierarchical approach allows the construction of complex and dynamic models with the dynamic element implemented by linking several time slices of an object oriented Bayesian network allowing the incorporation of temporal dependence in parameters and feedback loops.

Two significant questions when using these graphical approaches as a management tool are (1) where to set the boundary of the ecosystem, and (2) what to include on the nodes and links. These reflect the core concerns of any ecosystem services assessment, and several papers, e.g. Amstrup *et al*. (2008), point out that these decisions take many iterations between the groups involved taking a considerable time to reach a consensus. Johnson *et al*. (2010b) explicitly include this within an iterative Bayesian network development cycle they propose for cheetah relocation in southern Africa where they know the network will develop over time with new case studies and improved expert knowledge, and there are several sub-nets and multiple target nodes to be modelled and validated.

Several papers (e.g. Bromley *et al*., 2005; Chan *et al*., 2010) show the usefulness of developing a BBN within a participatory approach to environmental management as it enhances stakeholder understanding and contribution. Langmead *et al*. (2009) used a BBN to focus on the socio-economic drivers in the north-west Black Sea ecosystem showing successful integration of the information while avoiding the data intensive requirements of process-based models.

There are several developments in the more generic graph theory which facilitate inference where the BBN can face difficulties; for example Thwaites *et al*. (2008) use a transporter chain event graph as a more efficient approach when the state spaces are asymmetric and develops this further with causal networks (Thwaites *et al*., 2010). Feedback loops can also be handled without dynamic models by using local probability propagation (Weiss, 2000), but there are significant issues with inference if there are many loops within the overall graph (Nishiyama and Watanabe, 2009).

BBNs have been used for many aspects of ecosystem services modelling and so provide a potential unifying framework for these assessments, as well as linking naturally to the decision support aspects of environmental policy. Further developments to help assess complex spatial-temporal systems are required, but there is potential research to extend BBNs and overcome current limitations.

4. ECOSYSTEM SERVICE EVALUATION

The proceeding sections have considered the important role of statistics to inform ecosystem service studies. However, often such studies ultimately aim to evaluate the whole ecosystem in order to assess options for change and statistics can also help inform this task. Often economic valuation is favoured as it is considered a globally recognised metric, but non-monetary value has an important role to play in ecosystem services.

Value is a concept we understand, but actually quantifying a value is challenging both philosophically and practically. As individuals we use some ecosystem services (e.g. for food production) and thus have a clear idea of their value, but we may have no contact with other services (e.g. biodegradation of soil pollutants) and so find valuing them more difficult or impossible. We even may wish to give some aspects of the ecosystem infinite value (e.g. where the religious significance of a site precludes any change in the area). Economic history shows us that the monetary system we generally use gives transient rather than absolute values – the attempt to use absolute values for international trade by linking major currencies to the gold standard initially adopted by England in 1717 was finally dropped by the United States in 1971 after several notable failures including the 1929 depression. Modern currencies rely on flows of capital within the system to determine their value, giving the flexibility to respond to changing political and economic events (for example adjusting for the fact that labour costs in the developing world are not directly comparable to labour costs in the developed world). However to many the importance of the environment is in its long-term properties, so there is some contradiction in assessing these within a transient value paradigm. Therefore while we understand the concept of value of an ecosystem, quantification can be difficult and we should recognise that many aspects of value are actually local transient assessments rather than longer term absolute numbers.

Many of the initial examples of applying the ecosystem services framework have interpreted value as being purely economic value, with arguments that applying the economic approach is necessary to save the environment (e.g. Balmford *et al*., 2011). There are many papers recognising that this is not a completely satisfactory approach, and Bateman *et al*. (2011), while arguing from a strongly economic perspective, suggest an ecological standard could be used for occasions where a value cannot be established with any credibility and these would put thresholds onto the outcome – similar to a basic multi-criteria analysis approach. Daily *et al*. (2009) consider the possibility of non-monetary value as a separate metric in one of their examples while Málovics and Kelemen (2009) argue for participatory non-monetary valuation particularly if there is potential for groups in society having differing outcomes.

Statistics is in a strong position to contribute to this debate as it provides methodology for the combinations of different types of data in a more general framework than the purely economic and is comfortable with the concept of using multiple metrics. Statistical multivariate analyses provide many options for combining information, effectively generating weightings of the variables, with monetary valuation being just one way of providing such a weighting system. This area of ecosystem services assessment is still in its development phase and has been dominated by the notions that single value outputs are what people understand and that an economic metric is the relevant one. Possible progress on alternatives will only succeed alongside work on the public perception of risk and challenging the idea that people cannot cope with more than one number.

5. CONCLUSION

The ecosystem services framework brings together a range of environmental studies alongside socio-economic information to provide a holistic assessment of the value of the ecosystem. Statistics underpins many of these component parts, providing methodology for data collection, data analysis and the evaluation of process-based model uncertainty. Sampling strategy and the representativeness of the data are major factors in the applicability of the ecosystem services assessment, and this is an area where statisticians can provide valuable information to the other scientists involved. Statistics also provides the theoretical basis for tracking uncertainty through an ecosystem services assessment, which is an important factor in ensuring that society's valuation of the environment is soundly based. There is also an important role in statistical education to improve public perception of risk and value, potentially formalising the multi-faceted complexion of many, if not all, environmental outcomes and human decisions. While ecosystem services may prove to be a difficult concept to implement for environmental policy, there is an important role for statistics in these recent developments into a more comprehensive approach to understanding the environment and the human–environment interface.

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