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Uncertainty In Modelling Human-Landscape Interactions

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EXTENDED ABSTRACT

Recent involvement in designing and developing a simulation model to allow interaction between biophysical, economic and social processes has also led to interest in uncertainty and error propagation in models. This uncertainty exists in each of the biophysical, economic and social domains. With regard to the hydrologic processes there appears to be an indeterminacy principle that makes up-scaling difficult. When this is combined with the uncertainty in the other aspects of the model it would suggest that caution is needed in interpreting output from such models.

The uncertainty in biophysical, social and economic systems is a combination of uncertainty in; data input and model structure. As we build models where non-linearities due to the model structure are incorporated the relative uncertainty in the outputs will grow rapidly. Using a simple model where data input errors are either added or multiplied together we can see the consequences for the relative error in the output (figure 1). Suppose we have a process that results in a local (cell) parameter y_i with standard deviation σ_i and the area of the plot is a_i. We will assume that the same value and standard deviation occur in n other plots such that:

$$A_n = \sum_{i=1}^{n} a_i \tag{1}$$

and

$$Y_n = \sum_{i=1}^{n} y_i \tag{2}$$

or

$$Y_n = \prod_{i=1}^{n} y_i \tag{3}$$

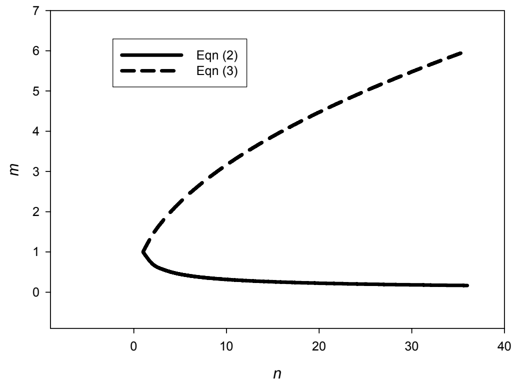

Figure 1. Relative error in an aggregated parameter as related to the number of cells (n). The aggregation process is either additive (equation 2) or multiplicative (equation 3).

The uncertainty present in models requires that when using the results of models that clients are made aware of the extent of these errors and their nature. We feel that policy makers should be made aware of the uncertainty when using such models. Decisions still need to be made and modelled scenarios provide inputs that help in make sense of the studied system. However, having made a decision to change a system monitoring of the results is required to determine if the desired response has occurred. Indeed, the dynamic between the uncertainties contained with the model and those in the minds of its clients is itself a social process that can be monitored and managed.

1. INTRODUCTION

Uncertainty in measurements arises due to bias, precision and environmental factors (including human). These we have learnt to control using standard practices of replication and reduction in environmental factors by experimental design. In development of models of biophysical, economic and social systems we often combine many parameters together to produce models with hundreds and even thousands of parameters. The uncertainty in these models arises not only from the uncertainty in the model inputs but also due to other more fundamental problems associated with our ability to model complex systems. Often in presenting model outputs we fail to adequately represent these uncertainties. In this paper we intend to explore some of the issues associated with uncertainty in coupled human/landscape modelling.

We need to heed the words of Prigogine (2005) "We live in a probabilistic universe. … The future is not given and therefore we have only a probabilistic description and there is no certainty" when we are looking at devising models of systems. What do we mean by uncertainty? The uncertainty we encounter has been classified as (Driebe and McDaniel Jr, 2005):

- *Lack of knowledge of a simple process* – this uncertainty is eliminated once the process is known or over time observed
- *Reduced dynamics of an open system* – we are only aware of part of the system and the coupling of this system to the surrounding environment creates "shocks" to the system. If the environmental dynamics can be discerned the uncertainty may be reduced or eliminated
- *Chaotic dynamics* – Characterised by exponential sensitivity to the initial conditions. Knowing the initial conditions gives us limited predictive power into the future
- *Irreducible complex dynamics with many degrees of freedom* – It is encountered with turbulence and the weather, and probably most economic and social systems of interest.
- *Reflexive dynamics* – This occurs when the system is composed of thinking agents that change their behaviour (thinking) as the system changes. This occurs in economic systems (Soros, 1987) and social systems.
- *Quantum dynamics* – Here only a probabilistic description is possible.

In human/landscape modelling we are faced with most of these forms of uncertainty apart from quantum dynamics. Here we will look at the uncertainties that face both the modeller and the interpreter of the outputs from such models who are often policy makers. Our past experience has been to use scientific methods and hierarchical control systems to reduce uncertainty. The validity of scientific inference is based on experimentation and is either preceded by prediction or followed by postdiction. Prediction is usually done using actual or mental models while the postdiction process often leads to a model. If we do not have a model then we often think that what we know is of limited utility. In physics this model is usually in the form of a set of mathematical equations.

Given uncertainty how can we as modellers help managers and other decision makers who are affected by the fundamental uncertainty that surrounds them? In the past we have a usually tried to deal with uncertainty by trying to reduce it or eliminate it by normalising the system. Reductionist approaches to science and hierarchical management structures are normalising techniques that have worked very successfully for small or slowly evolving dynamical systems. These techniques have also had failures when they are used outside of their "effective range".

2 GENERAL ASPECTS OF MODELLING

Models represent a hypothesis of how we think a system works. These models are often derived from some analysis of experimental data that leads to a set of equations. The parameters in the models are usually derived by experimentally fitting the model to data sets using regression techniques. However, as Venables and Dichmont (2004) clearly state these regressed parameters are only expected to apply to "a limited region about some central point in the design (or x- variable) space". Extrapolation beyond this range is fraught with unknown uncertainty in the results.

Bayesian approaches have become popular in modelling (Best et al., 2000; Goldstein, 2003). This approach uses a process known as elicitation to determine the prior probabilities of like solution pathways in the model. In Bayesian methods uncertainty is built in as the model is developed. However, the formulation of the model by elicitation, formulation of the prior probabilities and calculation of posterior probabilities (Gilks et al., 1996) can be difficult. The Bayesian approach can be loosely described as a structure approach to 'sense making' from diverse knowledge sources of a system.

2.2 Biophysical Models

The biophysical systems in landscape modelling generally consist of atmospheric, hydrological, soil/regolith, plant and animal sub-systems. The modelling of these can occur at any scale depending on the purpose(s) for which the model is to be used. A good frame for looking at the scale required by a model was provided by (Hoosbeek and Bryant, 1992) (figure 2). For simplicity here we will look at the one aspect of landscape modelling that is associated with hydrology.

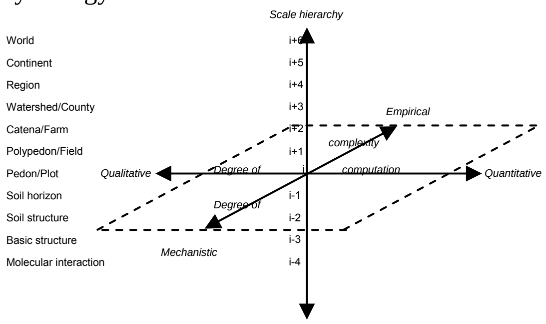

Figure 2. Framework for organising modelling activities after Hoosbeek and Bryant (1992).

Uncertainty in hydrologic modelling arises from many sources and also depends on the type (structure) of the model. Distributed process based models use physics based models for the energy balance and water transport at a point/plot scale and aggregate the values up to give catchment scale results (Beven and Feyen, 2002). For the water balance component Addiscott et al., (1995) have questioned the use of Richards equation based models for anything greater than areas of 1-10 m^2 due to uncertainty in parameterisation. The up-scaling of processes is unlikely to lead to a cascade of errors if the aggregation is additive (linear) but will lead to considerable error if the errors are multiplied through the upscaling process. The example below illustrates this point.

Suppose we have a process that results in a local (cell) parameter y_i with standard deviation σ_i and the area of the plot is a_i. We will assume that the same value and standard deviation occur in n other plots such that:

$$A_n = \sum_{i=1}^{n} a_i \qquad (1)$$

and

$$Y_n = \sum_{i=1}^{n} y_i \qquad (2)$$

or

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is where A_n is the area we want to know the aggregated value Y_n for. Then the relative error (m) in Y_n ($\pm m.\sigma_i$) for such a simple system as related to n are shown in figure 1. What this simple example shows is that models where the outputs from one cell multiply or divide those in other cells can generate large errors quickly and should be avoided. This kind of error propagation occurs with the non-linear processes which often occur in complex systems. The calculation of these errors could lead to unrealistic results, as there are some bounds on these errors, due to finite energy and mass balance constraints.

There have been some special editions of journals (see Jolma and Norton 2005; Beven and Feyen, 2002) where some of these issues have been discussed in detail. There are some (Beven and Feyen, 2002) who suggest that up-scaling in hydrology may be impossible until we have better understanding or find better ways to do this. This same comment could equally apply to ecological and social systems. There have also been suggestions that greater computer power will allow us to use data directly in modelling (Beven 2002); it will be interesting to see if this proves to be correct.

Lumped parameter models where the catchment behaviour is described by catchment scale parameters are common in hydrology. The lumped parameters are generally attributed to a physical entity and derived by fitting (tuning) the model to input and output data sets. However, as Beven and Freer (2001) have shown the parameter set obtained is not unique and a number of equally valid parameter sets can be found. This means that the parameter set is only valid within the parameter range represented by the data set. These models are examples of general linear models and as such will fit best around the mean of the data sets with the results becoming less certain as we move towards the extremities of the data range.

Using these parameters to investigate a change in catchment condition associated with, say changed land-use is unlikely to give reliable results (Venables and Dichmont, 2004). Yet it is common to see such models of these types being used for just such purposes. Although the parameters in the model are attributed to certain physical processes by the models authors and users, the fitting process dictates that the actual parameters are likely to be a mixture of the processes identified and some that are not. Also as we move away from the mean of the data set processes that have not even been considered can now start to effect systems response. An example of this can be seen in Cook (2002) where experiments over 20 years have gradual extended the range of parameters included in the mathematical model of soil respiration.

Wooldridge et al. (2002) have suggested that a disaggregation method be used to determine which parameters are needed to describe the catchment behaviour by using different climatic and land-cover characteristics of the catchments. This adding of extra parameters to linear models is cautioned against by Venables and Dichmont (2004) as although the fit may appear better due to only a better fit around the medium range of the parameters

Modelling of systems usually results in scaling of processes in either the time domain or spatial domain and often both. It has been thought and argued in the past that if we capture landscape processes at a fine scale (bottom up scaling) then when we aggregate these up the resulting models will be better than lumped parameter models (top down models). There are a number of studies now from hydrology that would challenge this assumption (Beven and Freer, 2001). It has also been shown that at larger scales the effects of the fine scale processes cannot be distinguished. This was graphically shown by Chapman (2003). He considered two different descriptions of evapotranspiration (ET), one where the point at which the actual ET deviates from the potential ET is constant and another where the point of this deviation depends on the potential ET rate. He could find no improvement fitting of the model to the data by this added complication. This may have been related to the frequency of the measured data not being able to resolve this fine scale information. Kircher et al. (2000) using fractal approaches to analyse high frequency data of stream flow and stream chemistry, showed that this high frequency data was needed to resolve the solute transport processes within the catchment. They showed that although the effects of preferred pathways could not be discerned from the water flow data it could be from stream chemistry. This necessitated using a quite different model for solute transport within the catchment than would otherwise have been chosen.

This results in a conundrum with biophysical models where due to the paucity of data it is difficult to use parameterised processed based models and lumped models do not allow us to change particular processes in the model due to the empirical nature of the parameters in them. This means that it is difficult to use either type of models when we, for example, want to estimate the result of vegetation change on stream flow or some other parameter. This problem is one of indeterminacy which may be generally applicable to many similar up- down-scaling problems. As such we would like to term it the ‘Barnes Indeterminacy Principle’ for Dr Chris Barnes who certainly first drew this to the attention of the senior author.

In groundwater systems attempts have been made to use some of the volume averaging techniques developed in quantum mechanics such as renormalisation (Hristopulos, 2003) to get better average transmissivity values for acquifers. This approach can ‘preserve’ some of the variability in the original fine scale information. These techniques have worked well in quantum mechanics where the detail in fine scale information is large but this is not often the situation for groundwater models. Jose and Rahman (2004) found that in heterogeneous aquifers that stochastic mixing models where only qualitatively in agreement with experimental results. The results of McKenna et al. (2003) suggest that the non-uniqueness of parameter estimation by inverse modelling needs to be accounted for.

Another issue associated with ecological modelling is how to assess the stability and sustainability of the model. Cabezas and Fath (2002) have suggested using a combination of Fishers information index and phase diagrams. They only do this for a simple 2 component (dimensional) predator prey model, so extension to more components could be difficult. However, there are some developments in mathematics by John Norbury of Oxford University (pers. comm.) that may allow the response function for a highly dimensional system to be calculated. These calculations give insight into the emergent behaviour of higher dimensional systems.

2.3 **Social**

2.3.1 Complexity and uncertainty

Reichl (2005) has compared chemical systems where complex behaviour occurs with social systems and suggests that given “…the amazing structures that form in complex chemical systems, when they are changed slightly…” that this should make us “… pause when we contemplate even some small aspects of complex social systems”. Possible food for thought for politicians and policy makers. In his comparison of complex social structures with complex chemical reactions Reichl suggests that they are equally fragile. Although social structures can be resilient and stable over long periods, they require a continual flow of energy to maintain them and they often require a continual flow of information. They are often best sustained if they have a efficient communication network, which involves flow of information throughout the entire structure. (Reichl, 2005)

West (2005) suggested that models have not been successful in social and life sciences because these phenomena are much more complex than those in the physical sciences and therefore less amenable to traditional mathematical modelling. The notion of control of the system, the reductionist approach being one example, is common to all of science and through control we learn about the phenomena that we hope to understand. This approach can be difficult to achieve in studies of social systems.

Montroll (1987) suggested that the reason we have had little success so far in modelling complex social systems is due to the tyranny of many dimensionless constants. This idea of non-dimensional variables is further explored by West (2005) who uses physical systems of fluid flow defined by the Navier-Stokes equation, and controlled fusion power generation to illustrate his point. For fluid flow the Navier-Stokes equation can be written in terms of three non-dimensional constants; the Froude, Reynolds and Euler numbers. In ship building the Froude number is the dominant term. While in aircraft design the dominant term is the Euler number. In both cases this means that scale models can be used for design and experimental purposes. Unfortunately when there are more non-dimensional constants as in the magnetic fields associated with containment of fusion, the problem of finding an optimum solution is more difficult. West (2005) goes on to suggest that social systems are more like magnetic containment of fusion with many (often undefined) non-dimensional number and this leads to the complexity and dilemma in studying these systems.

2.3.2 Institutions, perceptions and uncertainty

Individual perceptions about uncertainty come to be reflected in cultural values within organisations and societies and within organisational policies and strategies, and public policies. In turn these social institutions affect the way individuals perceive uncertainty. At macrosystem dimensions the ways that societies manage uncertainty through cultural values and policies are a critical lever for change throughout the lower level sub-systems.

Professionals walk a fine line between arguing for the existence of uncertainty and providing service to reduce it, because their legitimacy depends on societal acceptance of a degree of uncertainty in a work domain, but not so much that specialist knowledge cannot help. Acceptance and manipulation of indeterminacy has played an important role in the development of the profession of medicine and other similar professions (Jamous and Pelloille, 1970)

2.4 Economics

One could say that the basic stuff of economics is uncertainty. This has not always been true. For a long time, economic analysis wallowed comfortably in a deterministic world-view. The pillar of the so-called neo-classical paradigm, perched on Leon Walras' *summum opus* of 1874, ignores uncertainty. John Maynard Keynes was perhaps the first, with Frank Knight in 1921 to highlight the importance of uncertainty for economic modelling – an initiative that went largely ignored until the 1970s. Meanwhile, business people have known all along that uncertainty underlies all economic decision-making. The upshot of this is that there has long been a gap between the theoretical world of economic analysis and the practical world of economic decision making. While the former ignored uncertainty, the latter was up to its neck in it, and sometimes drowning for lack of analytical tools.

Today, things are different, and the "uncertainty gap" between theory and practice has greatly narrowed. Accordingly, information has been seen as of primary importance for economic models. One needs to distinguish between the information held by decision making agents in the model and that held by the modeller. In addition, the distribution of information among agents is important: who knows what strongly influences outcomes both in the model and in the real world.

The first issue is how to describe, for one economic agent, decision making under uncertainty. Since von Neumann and Morgenstern (1947), expected utility theory (EUT) is the mainstream modelling approach. People are assumed to know the probabilities as well as the various possible outcomes; they then compute the expected outcome and use it for making decisions. This 'rule' assumes they are risk neutral; if they are risk averse, they will adopt a more cautious rule and require a risk premium to take risks. An important application has been portfolio analysis (Markowitz, 1952), whereby decision makers are modelled as spreading out their risks across various assets – a useful model for farmers and land managers as well as stockbrokers. This theory has been challenged and several non-expected utility theories have been proposed. However, as soon as one abandons EUT, one is faced with a multiplicity of available theories for behaviour under uncertainty, and it is not clear which one is to be chosen. More radically, when probabilities are themselves uncertain, EUT is deemed to fail. However, the theory of subjective expected utility (SEU) purports to short-circuit this problem by claiming that what really counts are the perceptions of decision makers. When a decision must be made, they will simply assume a certain probability distribution and act upon it. Belief replaces knowledge. Critics of this modelling approach point out that people are ‘ambiguity averse’ (Ellsberg, 1961) and do not behave the same way when they know and when they do not know the probabilities. Experimental studies seem to confirm this (Di Mauro and Maffioletti, 2001). In parallel, theories of learning have developed together with modelling of an agent’s uncertainty, to the extent they now overlap.

The next issue is what happens when information is unevenly distributed between two agents. This has led to principal-agent theory (PAT) and the theory of asymmetric information. Applications include contract theory, policy mechanism design, insurance theory, bargaining theory and so forth. Expanded to more than two agents, modelling uncertainty brings in the role of social norms and institutions, one function of which is to minimise uncertainty for decision makers. Indeed, the economics of uncertainty and the economics of information are now seen as fundamental to economic analysis and as underpinning both models of individual behaviour and of collective action and institution building. Social learning, whether through imitation, networking or otherwise, emphasizes the time dimension.

The uncertainties lying with the modeller, or in the model, have been dealt with much less rigorously. Econometrics relies on statistical data to support or disconfirm a given model, but very often the amount of noise in the data only produces ambiguous results. Recently, experimental economics has opened the way for more rigorous handling of model uncertainties, and in particular, for testing assumptions about the behaviour of agents in the model.

Economic modelling is closely related to decision making and policy making. With respect to the uncertainties involved, the practical concern is to reduce those in decision makers’ minds, while the analytical concern is to reduce those lurking in the model, and to some extent in the modeller’s mind. Unlike the biophysical sciences, modelling uncertainty in the social sciences is itself an interactive social process.

3. DISCUSSION

Non-linearity and uncertainty in processes that we want to control or manage can result in surprises and abrupt changes in system behaviour (Steffan et al., 2004). This means that in any scenario testing with models the effect of a scenario, for instance, where nuclear war is included have very large uncertainty as they are outside a normal extrapolation of the model.

Begun and Kaissi (2005) asked the question, “How would healthcare delivery be different if uncertainty were recognized and expected, rather than oversimplified and avoided?” In our case a similar question could be asked of resource management. They suggest that organisations that embrace uncertainty realise that they will be required to engage more in experimentation and learning, have loose connections in addition to tight ones, emphasis culture and participation as control mechanisms rather than formalised and centralised structure, and have top managers whose role is to make sense rather than make decisions. Weick (2005) has argued that sense-making is the important process and requires that we adopt more of a complex adaptive systems approach to the way in which we develop responses and policies for healthcare and human resources management. We would contend that the same applies with human/landscape modelling.

Eoyang (2004) proposes a practitioners landscape which consists of twelve partitions, which she suggests “provide a rubric to help a practitioner understand the wide variety of complexity-based approaches and to select the one that is appropriate for a given situation.” This approach appears to have promise for assisting researchers and in both defining the problem and what tools should be used when looking for a solution when working with complex problems. By their very nature complex problems mean that there will be a number of possible solutions.

In most systems where there are a number of inter-linked time scales that are operating at the same time, it is important to realise that these interlinking time scales can exacerbate or dissipate uncertainty in systems. This is often the case with natural resource management or social policy where the system response to change may be very slow and the effectiveness of the policy is difficult to determine in an appropriate time.

4. CONCLUSION

Uncertainty in the inputs and structure of human/landscape models will produce results with large uncertainty. This uncertainty needs to be conveyed to the users of the model outputs. It is therefore imperative to make users understand that such model systems (or decision aids) can only be used to understand how the real world might respond or react to various changes, but should not be used as predictive tools. Experience over the last few years has shown that discrete event based tools for sensitivity analysis of complex socioeconomic-bio-physical systems has considerable utility in aiding decision makers facing complex problems. It has also shown that it can be difficult to prevent an assumption of predictability from creeping in. Thus activities such as a monitoring and continual assessment process to promote and support sensemaking should be part of the use profile of any such model systems built to help “manage” the human and landscape resources successfully. Indeed, the dynamic between the uncertainties contained with the model and those in the minds of its clients is itself a social process that can be monitored and managed.

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