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Approaches to evaluating model quality across different regime types in environmental and public health governance

MacGillivray, B.H. and Richards, K., 2015.

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ABSTRACT

A reliance on mathematical modelling is a defining feature of modern global environmental and public health governance. Initially hailed as the vanguard of a new era of rational policy-making, models are now habitually subject to critical analyses. Their quality, in other words, is routinely queried, yet what exactly is quality in this context? The prevailing paradigm views model quality as a multi-dimensional concept, encompassing technical dimensions (*e.g.* precision and bias), value judgments, problem-framing, treatment of "deep" uncertainties, and pragmatic features of particular decision contexts. Whilst those technical dimensions are relatively simple to characterise, the broader dimensions of quality are less easily formalised and as a result are difficult to take account of during model construction and evaluation. Here, we present a typology of governance regimes (risk-based, precautionary, adaptive and participatory) that helps make explicit what these broader dimensions of model quality are, and sketches out how the emphasis placed on them differs by regime-type. We show that these regime types hold distinct positions on what constitutes sound evidence, on how that evidence should be used in policy-making, and to what social ends. As such, a model may be viewed within one regime as providing legitimate evidence for action, be down-weighted elsewhere for reflecting a flawed problem-framing, and outright rejected in another jurisdiction on the grounds that it doesn't cohere with the preferred ethical framework for decision-making. We illustrate these dynamics by applying our typology to a range of policy domains, emphasising both the disconnects that can occur, as well as the ways that modellers have adapted their practices to ensure that their evidence is brought to bear on policy problems across diverse regime types.

1. INTRODUCTION

What do the policy responses to swine flu, climate change, and the 2010 eruption of Eyjafjallajökull have in common? All were based in part on the use of mathematical models, which has been one of the defining features of public policy-making in recent decades. This widespread and prominent role for modelling has many drivers. It stems in large part from advances in computational power, mathematical methods, and in our theoretical understanding of a range of social, economic, and physical phenomena. Perhaps most importantly, such modelling techniques purported to usher in a new form of governance, wherein public policies would be developed based on neutral, rigorous evaluations of their likely consequences (Tribe, 1972; Sarewitz and Pielke, 1999). This rather technocratic rationale did not lack opposition, particularly from advocates of deliberative democracy (Dryzek, 1993). But what Porter (1995) called the "pursuit of objectivity" nevertheless held substantial influence on public policy. The idea was that decisions would no longer be driven by vested interests, mere speculation, ideology or horse-trading, but instead would find their basis in objective technical analysis. Of course today this seems a touch utopian, and models with the potential to inform public policy are now routinely subject to rigorous critical analyses by regulators and model developers alike. These analyses (*e.g.* NRC, 2007) focus on issues including the plausibility of modelling assumptions; precision and bias; the adequacy of the treatment of uncertainty; and the value judgments that models may implicitly or explicitly encode (*e.g.* in the choice of impact variables to be included). Model *quality*, in other words, is routinely queried. By quality, we mean the properties that are desirable in a model. We interpret quality broadly, as relating to the contents of the model (*e.g.* the entities included, the variables that characterise them, and the equations or algorithms that relate them), the model's formal properties (*e.g.* precision and bias), and

the processes through which the model is developed. When a model is evaluated as being of sufficient quality, it is often referred to as adequate or sound. As will become clear, we think that model quality is contingent and multi-dimensional. More on this later. To begin with, what does quality in the context of models-for-policy mean? What sort of properties are we dealing with?

These questions have crucial implications for the development, evaluation, and use of models in the policy context. Quality, after all, is perhaps the fundamental goal that researchers pursue in the model development stage; is the basic arbiter of whether a model is accredited by peers or regulators; is used to discriminate between competing plausible models; and shapes the level of confidence that policy-makers hold in model outputs. In what follows, we first sketch out a brief history of conceptions of model quality. We describe a shift from the originally dominant statistical paradigm, to a present approach that considers quality to be both a multi-dimensional concept and a function of how the model relates to the decision-making task it was designed to fulfil. We then argue that the question of what constitutes a good model is conditional upon the nature of the governance regime in which the model is to be applied. We identify a small set of governance types that resonate with different uses of scientific evidence: risk-based, precautionary, adaptive, and participatory. These governance regimes hold distinct norms about what constitutes valid evidence, how evidence should be used, and what constitutes the proper ethical framework for decision-making (*e.g.* means-ends *vs.* communicative rationality). As such, a model may be viewed within one regime as providing legitimate evidence for action, be down-weighted elsewhere for reflecting a flawed ontology (*e.g.* privileging universal over contextual knowledge), and be rejected outright in another jurisdiction on the grounds that it fails to

align with the preferred ethical framework for decision-making. This is a blindspot of the prevailing quality evaluation paradigm (*e.g.* NRC, 2007), and one which diminishes the capacity to understand and improve the use of science in policy-making

And so our argument is that model quality is not independent of, but rather is intertwined in complex ways with the types of governance regimes that models seek to inform. The corollary is that there can be no unitary set of criteria by which all models can or indeed should be evaluated. This has implications for how models are built, how they might be scrutinised, and how policy-makers use them. Our contribution is two-fold. The first is primarily theoretical: our typology of governance regimes has significant explanatory power when applied to the science policy interface across various jurisdictions and policy domains. That is, it helps us understand the ways that models have been used – and sometimes neglected – in particular cases. The second relates to the practical aspects of model building and evaluation. Although some policy domains have their own detailed rules covering the model-building process (and so there is less chance of mismatch between the models that are built and the models that are desired), there are many exceptions to this. This means that general, but tractable guidance on the sorts of model building practices that are favoured (or not) by different sorts of regulators might be of practical use to modellers. More concretely, as well as highlighting mismatches between distinct modelling practices and different regime types, we also discuss several examples where modellers have adapted their methodological approaches to ensure that their evidence was brought to bear on policy questions across a range of regime types, without sacrificing technical quality.

2. SCOPE, CONCEPTS, AND DEFINITIONS

Our argument about the relationship between different governance types and what is perceived as model quality is in part a logical one; however, we discuss a range of examples from several policy domains, necessarily in a somewhat schematic way. This ensures that our argument is empirically grounded, and helps to flesh out its implications and nuances. There are, of course, many different classes of model, and the definition we provide below is not the only way of thinking about models (c.f. Hastrup, 2013), but is introduced to clarify our scope and to make our argument tractable. Here, we therefore define a class of formal models as purposeful mathematical representations of some real world phenomenon of interest (see Grimm and Railsback, 2005). These are composed of equations, statistical relationships, algorithms, or some combination therein (NRC, 2007). Such models inevitably contain numerous simplifications, approximations, and exclusions, and hence they are never perfect representations of the systems that they aim to characterise (Winsberg, 2014). Moreover, their development is inevitably conditioned by methodological paradigms, computational capacities, and path dependency. Thus, we conceive of these models as unavoidably imperfect decision-making aids, rather than truth machines (Winsberg, 2014). In the policy context with which we are concerned, mathematical models have various functions. They are often concerned with the task of extrapolating beyond known observations, such as predicting or projecting a future (*e.g.* the potential impacts of climate change on species distribution), or answering “what-if” style questions about proposed policy interventions. Models are also applied for the purpose of classifying objects (*e.g.* is this chemical carcinogenic?), or for simply describing relationships amongst variables (*e.g.* statistical models in flood frequency analysis).

Two additional concepts require some definition for the purposes of our exposition: "evidence" and "knowledge." We understand evidence to be some property or material that speaks to the state, mechanics, or future conditions of a phenomenon (*e.g.* a model output). Put another way, evidence makes a difference to what it might be reasonable or justified to believe (Kelly, 2014). Knowledge, by contrast, is often thought of as justified true belief (Steup, 2013). We use the term only when distinguishing between abstract and contextual knowledge. Abstract or general forms of knowledge hold true across time and place (*e.g.* the Navier-Stokes equations). Contextual knowledge is contingent, local, and particular (*e.g.* knowledge of the particular form that general causal mechanisms take in a specific catchment; knowledge of local practices of disposing of radioactive waste, *etc.*).

3. A BRIEF HISTORY OF QUALITY EVALUATION PARADIGMS

Models-for-policy were initially viewed as tools that would allow decision-makers to determine the rational course of action in the face of environmental and public health hazards. Reflecting this mindset, early approaches to quality evaluation focussed upon the degree to which a model corresponded with reality. That is, the question of model quality was largely understood in terms of predictive accuracy (bias and precision) and, less significantly, fit to existing datasets. This approach was embodied in categorical tests for "validating" particular models (*e.g.* hypothesis testing), in measures of the difference between observed values and the values predicted by the model (*e.g.* mean square error), and in methods for discriminating between a range of plausible models (*e.g.* "goodness of fit"). These technical dimensions of quality are clearly still remarkably important (see Cox, 2013 for an overview), but a sole reliance on them has encountered criticism from various quarters. For example, Peterson (2006) has argued that quality is not just a question of

predictive accuracy, but also of the rigour of the methodological process by which models are built. Emphasising that models-for-policy were essentially social tools, Ravetz (1971) proposed that value and effectiveness should supplement "technical adequacy" as the core dimensions of quality. Elsewhere, philosophers argued that in open systems (*i.e.* natural systems), matches between model predictions and real world observations may be spurious and thus misleading. This negates the possibility of validating or verifying a model in the traditional sense (Oreskes *et al.*, 1994), or indeed, of falsifying it (Beck, 1987). More recently, Edwards (2010) has shown that what we think of as observational data can be heavily model-laden, suggesting that validation in practice sometimes entails comparing models against models (Pirtle *et al.*, 2010), rather than models with the real world. There are also often objections relating to logistical and ethical problems of collecting the data required to conduct conventional statistical tests (Kriebel *et al.*, 2001).

Building on these lines of thought, scholars argued that there are broader dimensions of model quality not always captured by historic verification and validation tests (that focussed on precision and bias). These include (Van der Sluijs *et. al.*, 2008; Oreskes et al., 1994; Beck, 2002; EPA, 2003; Rykiel, 1997; Clark and Majone, 1985; Refsgaard *et al.*, 2007; Maxim and van der Sluijs, 2011; Augusiak et al., 2014; Grimm *et al.*, 2014):

- the acceptability of the normative commitments embodied in certain models (*e.g.* the implications of discount rates for inter-generational equity);
- the value judgments reflected – or omitted – in model structures and practices (*e.g.* trade-offs between false positive and false negatives);
- the plausibility of underlying assumptions;
- whether boundary conditions have been appropriately specified;

- whether the computer code faithfully reflects the model's mathematical content;
- whether the dimensionality and resolution are adequate;
- the degree of transparency (*e.g.* whether algorithms and datasets are publicly available);
- the "pedigree" of the model building methodology; and
- whether parameter and model uncertainties have been acknowledged and accounted for *(e.g*. through sensitivity or scenario analysis).

Many of these dimensions are rather difficult to formalise, and as a result are difficult to take account of during model construction and evaluation. This can lead to the neglect and underutilisation of model-based evidence in policy contexts. In response to this concern, some authors have proposed explicit and uniform model evaluation criteria (*e.g.* Alexandrov *et al.*, 2011). However, there is a broad recognition that the nature of the problem being modelled, and the particular decision-making task that the model is designed to fulfil, also shape conceptions of quality (NRC, 2007). An influential statement of this is the Numerical Unit Spread Assessment Pedigree (NUSAP) approach (Van der Sluijs *et al.*, 2005, 2008; Risbey *et al.*, 2005), which draws on Funtowicz and Ravetz's (1993) concept of post-normal science. The basic idea is that particular types of problems – defined according to the "decision stakes" and the degree and nature of uncertainty – are best explored through particular types of science and models. Building on this, Renn and others have constructed various typologies of the "risk issues" faced by contemporary societies, setting out how each category of problems lends itself to particular analytical methods (*e.g.* Klinke and Renn, 2008; Pellizzoni, 2001). For example, routine, well characterised problems lend themselves to the methods of probabilistic risk analysis, whereas contested, ambiguous issues require

more participatory methods such as scenario planning to explore them. In this paper, we argue that this is only part of the story.

We suggest instead that factors such as the degree of uncertainty, complexity, and decision stakes are not simply characteristics of problems. Rather, problem characteristics and types of governance constitute one another; they are *co-produced* (Jasanoff, 2004). What we mean is that the risk-based type, for example, does not simply lend itself to problems that are well-structured, largely technical, and mathematically tractable. Instead, it also constructs problems as holding the aforementioned characteristics, through the particular ontologies, frames, methods, and types of evidence that it draws upon or applies (Shackley *et al.*, 1996; Clifford and Richards, 2005). Put another way, particular types of governance regime reveal, clarify, or suppress particular dimensions or characteristics of a problem, in part determining whether they are bracketed as well-characterised rather than ambiguous. And so to understand what constitutes quality in models-for-policy, we need to think about both the characteristics of the policy problem *and* the nature of the governance regime. Renn, Funtowicz, and others have emphasised the former; we focus on the latter.

Another development is the recognition that mathematical modelling is but one approach to analytical reasoning. For example, categorization tasks where multiple sources of evidence are relied upon, whose quality and strength cannot be specified in advance, are perhaps better suited to qualitative weight-of-evidence approaches than to mathematical modelling. Similarly, problems where there is limited analytical basis for defining or attaching probabilities to hazardous scenarios – such as threats to nuclear weapons complexes (Nuclear Studies and Radiation Board, 2011) – may be more suited to techniques

for structured deliberation (*e.g.* the Delphi method; Linstone and Turoff, 1975). Finally, various forms of reasoning by analogy – often misperceived as merely a lay method – have been used to inform public and environmental health policy (*e.g.* Flyvbjerg, 2008). Indeed, climate science has a long tradition of supplementing mathematical models with the use of temporal and spatial analogues in scenario development (Mearns and Hulme, 2001). This analogical approach is sometimes proposed as a check against the perceived indeterminacy – and potential for bias or strategic misrepresentation – encountered in those contexts where model outputs are particularly sensitive to arbitrary assumptions (*e.g.* Flyvbjerg, 2008*;* Pilkey and Pilkey-Jarvis, 2001). The general point is that in these situations, the question of model quality should consider the strengths and weaknesses not just of proposed models, *but also relative to alternatives to mathematical modelling*.

To summarise: model quality is now broadly accepted to be a multi-dimensional concept; quality evaluation is seen as an intrinsically comparative task; and quality is viewed as a function of how the model relates to the policy problem it was designed to address. However, many of the non-technical dimensions of model quality are difficult to formalise and so there is considerable ambiguity surrounding how they might be taken account of during model building and evaluation. In what follows, we introduce and apply a typology of governance regimes that helps clarify these broader dimensions of model quality and shows how the emphasis placed on them differs by regime-type. Throughout, we emphasise the implications of this for the uptake – or neglect – of scientific evidence in concrete policy settings.

4. JUDGING THE QUALITY OF MATHEMATICAL MODELS REQUIRES ATTENTION TO GOVERNANCE TYPES

Our basic claim is that the question of what constitutes a good model for use in policy cannot be separated from the question of the fundamental nature of the relevant governance regime. We illustrate this by introducing a typology of governance regimes, drawing on Jasanoff's (2005) work on civic epistemologies, which emphasises societal variations in forms of public reasoning on science and technological issues that are often highly institutionalised. The idea is that there exist multiple competing styles or types of governance, which embody different norms, values, preferences, and axioms relating to policy analysis and policy-making (see also Jasanoff, 2005; ESTO, 1999; Pellizzoni, 2003). These relate, for example, to questions about how natural phenomena should be modelled and what constitutes valid evidence, to debates about how evidence should be synthesised, to beliefs about how much evidence is required before acting, and to questions about what is the proper ethical framework for decision-making. In particular, we identify and characterise a set of regime types that determine the quality criteria for models and evidence from models: risk-based, precautionary, adaptive and participatory (Figure 1). Although these regime types vary along a number of dimensions, we suggest that three in particular are significant: a) knowledge as abstract *vs.* knowledge as contextual; b) process orientation *vs.* outcome orientation; and c) high *vs.* low deference to formal expertise (Figure 1). These conceptual distinctions are not exclusive when it comes to concrete empirical examples. A further clarification is that particular regimes are neither homogeneous nor static, but are composed of a multitude of evolving networks of actors, institutions, and political contexts. Some of the examples we discuss illustrate this. In short,

whilst our typology is necessarily an idealised one, it stands or falls based on the explanatory work that it does when confronted with empirical cases, as in this paper. Our analysis begins with a comparison of the risk and precautionary regime types, before turning to discuss adaptive and participatory regimes, once more highlighting contrasts and compatibilities with the risk-based approach.

4.1 Risk-based vs. Precautionary Regime types

4.1.1 Basic features of the risk based regime type

Risk based approaches (Figure 1) are rooted in theories of probability and utility maximisation (Kaplan and Garrick, 1981; Savage, 1972). They seek to characterise how the future might unfold if a policy maker was to undertake a particular course of action, using utility functions to determine which outcome is best or optimal (*i.e.* consistent with known preferences) (Kaplan and Garrick, 1981). The future is conceived of as amenable to empirical investigation – within limits – and uncertainty is represented using standard decision-theoretic concepts (*e.g.* probability distributions on uncertain variables). As such, probabilistic risk assessment combined with cost-benefit analysis is often held up to be the gold standard of policy analysis in risk-based regimes (*e.g.* Sunstein, 2002; Graham and Wiener, 1998; Löfstedt, 2011). This ties in with the fundamental goal of such regimes of making *coherent* decisions under uncertainty and within resource constraints (Pate-Cornell, 1996). Of course it is broadly accepted that risk analysis can never solve actual problems – as they are infinitely complex – but only idealisations of them (Jaynes, 2003; Savage, 1972). The core questions then become: is the idealisation a reasonable approximation of the system of interest (*e.g.* does it adequately represent the underlying causal structures, empirical laws, and current state of the world), and are the model inferences consistent

with basic axioms of probability and decision theory (Jaynes, 2003). Finally, risk based regimes maintain a clear separation between facts and values, and by extension seek to insulate expertise from politics (Sunstein, 2002).

4.1.2. Basic features of the precautionary regime type

The risk based approach is best suited for problems whose structure is sufficiently developed such that the full decision-theoretic apparatus can be applied (*ibid.*). However, this is not always the case in practice in environmental and public health applications, where problem structures may be ambiguous, there is often a lack of reliable data, and decisions may be urgent. In such situations, inexact, heuristic methods of problem-solving must be relied upon (Jaynes, 2003). These features characterise the precautionary approach to governance (*e.g.* UNESCO, 2005; Figure 1). Precautionary regimes tend to favour frugal modelling tools such as scenario analysis, and adopt heuristic approaches for considering costs, benefits and equity concerns, such as individual risk thresholds or feasibility-based regulation (*e.g.* best-available technology; Sinden *et al.*, 2009). Many observers distinguish between weak and strong forms of precaution (Wiener and Rogers, 2002; Wiener, 2003; Stewart 2002; Sunstein, 2005). The former involves broad statements of principles (*e.g.* "uncertainty does not justify inaction") that are consistent with a risk-based approach, albeit sometimes lacking clear operational meanings (more on this later). In contrast, the strong version is quite distinct from the risk-based type, and involves a minimax approach to decision making (*i.e.* concerned as much with equity as with efficiency, and with avoiding worst case scenarios rather than identifying optimal solutions), a shifting of the burden of proof from the regulator to the regulated, and a preference for false positives over false negatives.

4.1.2 Risk and precautionary conceptions of model quality: examples and issues

The contrast between the US EPA's approach to existing chemicals regulation (under the Toxic Substances Control Act) and that of the Stockholm Convention can be understood in terms of risk vs. precaution. The former's risk-based regime follows the classical, data-intensive four-step process of risk assessment to generate a probabilistic measure of harm (hazard identification, dose-response modelling, exposure assessment, and risk characterisation), and further relies on mathematical modelling to characterise the expected costs and benefits of policy options. This contrasts with the precautionary Stockholm Convention, which was developed in response to the perceived failings and gridlock associated with risk-based regimes. Here, simple threshold models of persistence and bioaccumulation are the primary basis for chemical risk assessment, and policy options are evaluated qualitatively with respect to various economic, health-related, feasibility, and ethical considerations.

In situations where there are multiple plausible models offering different predictions (*e.g.* of expected sea level rise), the strong precautionary regime type would treat the worst-case prediction as "true" and develop public communication strategies and policies on that basis. A recent official inquiry criticised the UK government's response to the 2009 swine flu outbreak for following precisely that pattern, and advocated instead the risk-based approach of conditioning communication on the model (ensemble) whose prediction is most likely to be accurate (*i.e.* the "most probable scenario") (House of Commons, 2011). This reflects the fundamental distinction between minimax approaches to decision-making (strong precaution), and those that aspire to rational choice (*i.e.* risk-benefit balancing).

Similarly, the rise of risk as perhaps *the* trans-national approach to governing climate change (Pidgeon and Butler, 2006) – in contrast to its more precautionary origins – led to the growing use of probabilistic modelling as a way of accommodating uncertainty. This included early attempts to attach probabilities to climate scenarios (Dessai and Hulme, 2004), the Stern Review and its analysis of climate futures within the cost-benefit framework (Stern, 2006), and more nascent programmes seeking to determine the odds with which severe weather events can be attributed to human influence (*e.g.* Pall *et al.*, 2011). What seems to be happening here is members of a modelling community adapting their methodological practices in attempts to align with the rationale of risk governance (and so maintain or enhance their policy relevance).

As we touched on earlier, there are weaker interpretations of precaution that do not necessarily conflict with the risk-based type (*e.g.* paying a healthy respect for the limits of our ability to assess uncertain risks, not using uncertainty as a reason or avoiding regulatory action, *etc.*) (Wiener and Rogers, 2002; Wiener, 2003; Stewart, 2002). Although these notions are sometimes rather vaguely stated, they can in principle be incorporated within a decision-theoretic framework if refined and formalised (Stewart, 2002). We see moves towards this in proposals to incorporate precaution within the framework of cost-benefit balancing, such as the European Commission's 2000 communication on the precautionary principle. The idea here is to qualify the broad principles of weak precaution with the ideas of proportionality and cost-benefit balancing, which is entirely coherent (Wiener and Rogers, 2002). To give a concrete example of how this might play out, one might express a healthy respect for "surprises" via relatively flat probability distributions (Stewart, 2002). The point here is that modelling practices can be adapted in ways that ensure that the

evidence they produce is coherent with more than one regime type, without sacrificing on technical quality or muddying the interpretation of analysis outputs. However, at other times the representation of precautionary ideals within risk-based approaches has been done rather informally. This can mean that analysis outputs are difficult to interpret, and potentially lead to skewed policy making (Majone, 2002). A perhaps extreme case in point is the modelling practices underpinning the design of the New Orleans' storm surge protection system, which had elements of both precautionary and risk-based approaches. Specifically, we refer to the adoption of "worst case" assumptions (strong precaution) in defining the standard project hurricane, which sat alongside the use of cost-benefit ratios in setting design standards. Although there were myriad other technical and institutional failures implicated in the subsequent breakdown of the levée system, one element of proposed reforms has been a call for greater modelling coherence. For example, the Interagency Performance Evaluation Task Force (IPET, 2006) advocated an explicitly risk-based methodology for planning and designing flood protection, whilst other scholars (*e.g.* Kysar and McGarity, 2006) have called for a singularly precautionary approach. The foregoing analysis suggests that care is needed in defining how precaution is understood in a particular modelling context, and in expressing that understanding in decision-theoretic terms, so as to ensure that analysis outputs retain a meaningful interpretation.

4.2 The Adaptive Regime Type

4.2.1 Basic features of the adaptive regime type

A third and distinctive regime type is that characterised as adaptive, which favours policy-making that is incremental, experimental, and open to adaptation based on feedback (Figure 1). These regimes are grounded in an admission of our lack of knowledge and

capacity to control complex natural systems, and conceive of policy-making as fundamentally about robustness, flexibility, and learning (Lee, 1999; Guston, 2008; Lempert *et al.*, 2003; Schindler and Hilborn, 2015; Holling, 1978; van der Pas *et al.*, 2013). That is, they do not seek optimal outcomes, but rather policies that will be *good enough* across a range of plausible futures, and that have explicit provisions for adaptation based on experience (Swanson et al., 2010). Moreover, they are typically concerned with governing particular *places* or systems (*e.g.* a particular catchment), rather than a particular technology or risk object. As they emerged as a critique of centralised, technocratic forms of governance, we might expect different emphases between adaptive and risk-based regimes on a number of dimensions of model quality. For example, adaptive regimes should have a comparatively greater preference for models that 1) have a fine level of resolution, rich contextual detail, and are spatially explicit; and 2) have sufficient flexibility to evaluate policy options with respect to a variety of assumptions about the state and mechanics of the world. The former reflects the fact that adaptive regimes are often focussed on how the features of *particular* places both condition, and are conditioned by, the causal processes that are at work (Lane, 2001). This contrasts with a search for general, abstract laws or regularities that can be readily extrapolated across space, time, and context, which is more characteristic of the risk-based regime type. The latter point does not imply that risk-based regimes neglect the question of model uncertainty; but there is a persuasive critique that they tend to focus on its more mathematically tractable forms (*e.g.* probability distributions, sampling error), to the neglect of indeterminacy and ignorance (*e.g.* Shackley and Wynne, 1996; Stirling, 2012). This again contrasts with adaptive regimes, whose emphasis on robustness implies that they will be particularly sceptical of model outputs that may be strongly conditioned by unexplored assumptions (Schindler and Hilborn, 2015).

4.2.2 Adaptive conceptions of model quality: examples and issues

The above contrasts are highlighted by a consideration of the degree to which modelling is "rule-bound." By rule-bound, we mean that the building and running of a model are shaped by rules for selecting model structure, extrapolation methods, and parameter values (MacGillivray, 2014). A classic example is the use of *default* parameter values, extrapolation approaches (*e.g.* "safety factors" to account for inter-species variability), and model structures (*e.g.* the non-threshold dose-response model for carcinogens), for example in conventional chemical risk assessment. Risk-based regimes typically favour models and modelling practices that are rule-bound. The logic is that rule-based reasoning aligns with their central values of truth-seeking, methodological consistency, and constraint of bias. These values stem from a commitment to objectivity, from a preference for stability in the regulatory system, and from the general principle that regulation involves a series of trade-offs (and hence consistency is required). By contrast, adaptive regimes are more sceptical of such practices, viewing dependence on rules as impeding learning about the phenomenon, excluding contextual knowledge, closing down uncertainty, and even increasing the danger that an inadequate model or modelling practice becomes locked-in to the regulatory process.

A prominent example of the above conflict is the long-running debate within and outside the US EPA on the use of defaults in chemical risk assessment. This has focused on the general merits of explicitly establishing explicit default rules of inference, on what kind and strength of evidence is required to overturn them, and on the extent to which they should be binding (NRC, 1983, 1994, 2009). Although the controversy surrounding defaults is often

interpreted as a conflict over conservatism in risk analysis, this element only relates to the question of which particular defaults to establish (*i.e.* how, if at all, "risk averse" the defaults should be). It fails to relate to the broader debate about whether to have default rules in the first place, and about the extent to which they should constrain modelling practices. In our view, this is better interpreted as a conflict between the risk-based logic of objectivity, consistency, predictability, and constraining discretion on the one hand, and the adaptive logic of learning, flexibility, and individualised judgement on the other. Highly rule-bound modelling practices are in a sense quasi-deterministic, in that they impose a set of constraints such that, for a given data set, a narrow range of outputs carry presumptive force. And of course determinism, and its close cousin formal optimisation, has traditionally been viewed somewhat sceptically by proponents of adaptive governance. This is on the grounds that the idea of optimality is problematic when dealing with complex open systems, and is at odds with the principles of experimentation, learning, scenario-generating, and robustness (Walters, 1978; Weaver *et al.*, 2013). Nevertheless, these tensions can be partially managed by ensuring that rules are treated as heuristics rather than mistaken for laws (*i.e.* that modellers do not neglect the typically approximate and contingent nature of methodological principles), and by ensuring that their application is consistent with a reasonable amount of flexibility and interpretive space (MacGillivray, 2014). In more concrete terms, this means that modellers and regulators should allow a healthy degree of flexibility in the definition of methodological and interpretive rules (allowing space for expert judgment), specify the scope conditions that govern their application, clarify the nature and extent of evidence required to justify a departure from them, and set up programs to periodically re-evaluate their empirical and theoretical support (to allow for learning and evolution). These principles are simple enough, but their not uncommon

neglect has led to questions about the credibility of modelling estimates in pollution management in the United States, in some cases leading to the over-turning of regulatory decisions at judicial review (*ibid*).

Similar tensions arise in many other domains and jurisdictions. For example, a high degree of rule-bound standardisation was part of the reason for the Indian Government's scepticism of model-based estimates of HIV-prevalence in the early 2000s (Mahajan, 2008). Here, the relatively rigid and generic model structures favoured by the World Bank and UNAIDS were perceived as neglecting place-based drivers of the spread of the disease, leading Government officials to reject their estimates as implausible. The logic was that the encoding of particular "at risk" categories from Western contexts, such as homosexuals and intravenous drug users, travelled rather uneasily to the Indian socio-cultural context, where a more valid set of categorisations might have emphasised the role of poverty, nutritional deficiencies, and gender relations (Karnik, 2001).

By contrast, the normative and factual commitments of risk-based regimes can lead them to be less concerned with accommodating contextual and place-based factors within models, as Britain's response to the 2001 foot and mouth outbreak illustrates. In this instance, the UK Government adopted a rigorous animal culling policy, based in large measure on the outputs of predictive modelling (Bickerstaff *et al.*, 2006). The significance lies in the Government's controversial reliance on a particular modelling approach – an epidemiological model, which emphasised abstract theory and objective knowledge – while neglecting other models that explicitly represented spatial and contextual detail (Bickerstaff and Simmons, 2004). The different modelling communities (principally epidemiologists *vs.*

veterinarians) had markedly opposed concepts of what constituted model quality. For example, the epidemiologists constructed their own "outsider status" as a virtue, as a marker of objectivity, whereas the veterinarians framed this as a deficiency, as it meant they lacked a grasp of local and spatial knowledge (*ibid*). Yet the epidemiologists' approach was more consistent with the dominant governance type of the time, which saw precision, predictability, and *centralised* control as virtues, an approach which was unsettled by the veterinarians' emphasis on place and context (*ibid*).

State-of-the-art climate modelling involves similar trade-offs, as well as lessons on how they can be managed. Climate models draw their authority from representing abstract, physical laws, the sort of knowledge emphasised by risk-based regimes (Rommetveit *et al.*, 2012). On the other hand, critiques of the "globalising instincts" of climate governance (Edwards, 2010; Hulme, 2010) have emphasised the coarse resolution of many climate models, together with their opaque and rule-based character. Some have argued that this makes them ill-suited to inform an *adaptive* approach to climate governance, with its emphasis on flexibility, incrementalism, learning, and place (*e.g.* Weaver *et al.*, 2013; Cash and Moser, 2000). Such tensions played out in NOAA's provision of probabilistic seasonal climate forecasts to water resource managers in the late 1990s (Rayner, 2012). These forecasts had their roots in the logic of the Harvard Water Program, where water system design, investment and operation problems are formulated as mathematically tractable trade-offs (Milly *et al.*, 2008). However, water resource managers largely neglected these predictions, mainly because they viewed NOAA's statistical estimates as largely irrelevant to *their* preferred approach to water system governance, which emphasised redundancy and flexibility, rather than notions of rational planning and efficiency (Rayner, 2012).

Yet recent years have seen climate models play an increasing role within adaptive regimes, with various methods of downscaling making their outputs more useful for local and regional decision making. An example is Mahony and Hulme's (2011) study of how the Hadley Centre's regional climate model – PRECIS – has been rolled out from its UK home to adaptation planners across the developing world. In an effort to be consistent with an adaptive regime type, PRECIS was designed with a fine resolution, and with what Mahony and Hulme call a degree of "plasticity" (2011). This is closely related to the idea of treating methodological principles as heuristics rather than laws, and in concrete terms meant that local modelling teams were able to adjust the model parameters and inputs to reflect their own particular places and knowledge. On this reading, PRECIS was a successful effort to balance methodological consistency and objectivity (the risk-based type) with flexibility, accommodation of local knowledge, and interpretive space (the adaptive type).

4.3 The Participatory Regime Type

4.3.1 Basic features of the participatory regime type

The fourth regime in our typology is participatory (Figure 1). These regimes evaluate the quality of decisions not according to means-ends rationality, but according to their adherence to (a conception of) democratic ideals. As such, they place a high degree of importance on engaging the public(s) in framing, evaluating, and deciding how to handle governance dilemmas, and are particularly sensitive to avoiding coercion within this process (Stirling, 2006; Dryzek, 1990; Habermas, 1975). Their organising principles are that "risk issues" are public issues with a technical dimension (not the reverse), and that public values and preferences *emerge* from a rich combination of discursive practices and practical

reasoning (rather than pre-exist them). Accordingly, they tend to place a premium on using models that are transparent and understandable to a range of audiences, and that provide space for lay or local knowledge, expertise and framings (*e.g.* in specifying relevant outcome variables, parameter estimates, or plausible scenarios; Stirling, 2006; Yearley, 2000; Ravetz, 2003). By contrast, they will look unfavourably on methodological approaches that are excessively complex, or that impose particular framings (*e.g.* through lacking explicit treatment of option definition, or having hardwired model structures; McIntosh *et al.*, 2005). They will be similarly sceptical of models that contain *proxies* for public values and preferences (*e.g.* measures of willingness-to-pay), or are constructed and evaluated by a technical elite (Stirling, 2006).

4.3.2 Participatory conceptions of model quality: examples and issues

The UK Government's current approach to health technology appraisal illuminates some of the issues sketched out above. This approach, beginning with the establishment of the National Institute for Clinical Excellence (NICE) in 1999, is a mixture of clinical (*e.g.* meta-analyses) and economic analysis, with resource allocation guided by a rough criterion of cost-effectiveness (Rawlins and Culver, 2004). The technical elements of the analysis sit alongside various participatory mechanisms, including a Citizen's Council (Rawlins, 2004), which is a deliberative forum designed to capture public views on the ethical dimensions of healthcare priority setting (*e.g.* should health be valued more highly in some age groups than others, *etc.*). In essence, the modelling process (*i.e.* the clinical and economic analysis) purposefully turns a blind eye to the "social value judgments," leaving them free for public deliberation in separate institutions (Rawlins, 2004). However, the UK Coalition Government (2010-) has expressed concerns about this division of labour, in particular with what they

perceive to be a lack of formality and clarity in how the deliberative panels actually inform decision making. Under their proposed reforms (Department of Health, 2010), the value judgments would be incorporated *within* the modelling process, being weighted and aggregated alongside the clinical and economic data. Crucially, this was to be done in a manner that is "evidence based, reflecting the views of experts," (Department of Health, 2010) suggesting a more limited commitment to participatory ideals. This serves as a reminder that social and ethical judgments can be included within modelling approaches in ways that in reality foreclose or crowd out public deliberation.

Moreover, some have criticised NICE's *current* appraisal process for failing to satisfy deliberative ideals, on the grounds that it maintains a relatively strict separation between analysis and deliberation (*i.e.* between fact and value), and offers limited scope for meaningful public participation in the modelling process itself (*e.g.* the economic models are designated as proprietary and so insulated from public scrutiny; Schlander, 2008). This ties in with a concern raised in other contexts, namely that even methodologies that seem well-suited to participatory modes of analysis – such as multi-criteria methods with their explicit treatment of option definition and characterisation of criteria – are often applied by a restricted group of technical specialists (Stirling, 2006). This suggests, again, that quality assessment requires a focus not just on the intrinsic features of particular types of model, but also on the *processes* through which they are constructed and scrutinised. Bearing on this, a small and largely experimental literature outlines how citizen juries, cognitive mapping, facilitated workshops, and extended peer review can be used to engage publics in model construction and evaluation (*e.g.* Renn et al., 1993; Yearley et al., 2003; Antunes *et*

al., 2006). Lane *et al.*'s (2011) pilot study of flood risk modelling in Pickering, Yorkshire, drew heavily on facilitated workshops and helps elaborate these concepts.

The context of this work was that repeated flooding had occurred in the area, which, coupled with an absence of meaningful progress in delivering risk reduction schemes, had led to a marked loss of local trust in the governing authority (the Environment Agency). This was exacerbated by the Agency's rather superficial public engagement practices, which took place *following* the modelling process (of risks and potential physical interventions) and were essentially attempts to manage or dampen controversy (Lane *et al.*, 2011). This provided a vacuum into which an academic modelling team could step. Lane *et al.* (2011) proposed a different set of simpler, *interactive* modelling procedures that re-built the trust of the local community as they were able to participate in exploring the possibilities of an innovative flood risk management strategy. The public's role extended beyond framing the modelling process (*e.g.* focussing on upstream storage rather than urban flood defence), to contributing to the model's conceptual development (*e.g.* drawing on local knowledge to question the data provided by a flow gauge), and participating in developing and testing policy options (*e.g.* related to the number and height of the proposed bunds). The model was ultimately based on a simple hydrological rather than hydraulic routing scheme, with perhaps less scientific and technical quality than state-of-the-art methods. Yet the way that it was co-constructed helped to constitute a shift towards participatory "governance," in a space where the credibility of the formal authority had been in question, and where local knowledge had previously been excluded from the policy process. Of course, this sort of heavily participatory modelling will not be practical in most situations. But the case does suggest that there may be some contexts – such as those characterised by a loss of public

trust and where local knowledge may play a crucial role in characterising risks and benefits – where it makes sense to compromise on technical dimensions of model quality, to ensure that scientific evidence can be brought to bear on policy problems.

5. CONCLUSIONS

The foregoing analysis suggests that we need to extend the maxim that model quality must be assessed in light of the task that the model is designed to fulfil (NRC, 2007; EPA, 2003; Beck *et al.*, 1997, 2009). Although this maxim is legitimate, it is also only *partial*, in that it is implicitly based on a "decisionist" (Habermas*, 1975,* Wynne, 2003) concept of governance, wherein the goal is to make sound, discrete inferences and choices. A richer view, we suggest, is to see governance not just as a series of loosely connected decision-making tasks, but as shaping a set of commitments to what counts as evidence, how evidence should be used, and to what social ends. The natural corollary of this is that processes of model development and evaluation need to take account of what Jasanoff (2005) calls the surrounding "civic epistemologies," the variable criteria by which societies and regimes hold knowledge production and utilisation to account. Many of these criteria are not purely technical and do not lend themselves to formal expression, and as a result they have proven difficult to take account of in model construction and evaluation. This has influenced the uptake – and neglect – of scientific evidence across a range of contexts. To try and clarify and explain this problem, we have identified four governance regime types, the distinctions between which map roughly onto long-standing philosophical disputes about epistemology and governance. We have shown that interpretations of what constitutes a good model are shaped not only by the characteristics of the policy-problem, but also by a broader set of norms relating to what constitutes good decision-making, sound data, and proper use of

evidence. A natural question is whether this state of affairs is simply just a fact of life, or whether our analysis offers some insights on how we might improve the construction and use of models for policy. To this end, throughout our analysis we have emphasised not just the tensions that can arise between different governance types and particular modelling practices. We have also emphasised the trade-offs and adaptations that modellers have made to increase the chances of their evidence being brought to bear on policy problems in diverse regime types, without unduly compromising on technical quality. Remaining in this normative spirit, our analysis also suggests that regulators should be explicit about the regime types that they subscribe to, reflect on the way these commitments shape their evaluation and use of models, and consider how alternative types might alter their regulatory practices (*e.g.* by bringing to light various dimensions of model quality that might otherwise be neglected). Together, this may help to counteract the not uncommon neglect, misunderstandings, and under-utilisation of models in policy contexts, as well as reduce the risks of poor choices and wasted resources in model development.

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Knowledge as abstract

High deference to formal expertise

Outcome oriented

Risk-based

- Philosophical / historical roots: utility maximisation
- Normative goal: select policies on basis of costs, benefits, and likelihoods of expected outcomes (maximise); prediction and control
- Ontology: facts and values are separate; nature accessible (within limits) to science; privileges universal over contextual knowledge; public preferences can be derived/extrapolated from market behaviour
- Standard problem frame: risk issues as (mathematically tractable) trade-offs
- Process norms: methodical analysis (stability, predictability, and constraint of bias); insulate expertise from politics

Precautionary (strong version)

- Philosophical / historical roots: minimax and Rio Declaration
- Normative goal: guard against plausible worst case-scenarios; balance equity and efficiency
- Ontology: conservatism of science constrains its ability to "know nature" within useful time-frames
- Standard problem frame: wicked problems that are understood at an exploratory level; urgent decisions required
- Process norms: relatively lower standards of proof; burden of proof on regulated community (premium on avoiding false negatives); and fast-and-frugal decision-making

Adaptive

- Philosophical / historical roots: adaptive control theory; policy as experiment; pragmatism
- Normative goal: reliable governance through iterative, incremental, robust decision-making that evolves based on feedback (trial and error)
- Ontology: natural systems as unique and beyond our capacities to predict and control; reductionist tendencies of conventional science limit usefulness for open systems; emphasis on contextual and place-based knowledge
- Standard problem frame: cycle of problem solving/learning
- Process norms: exploratory rather than strictly methodical; broad disciplinary participation to capture relevant expertise

Participatory

- Philosophical / historical roots: deliberative democracy and communicative rationality
- Normative goal: govern in a way that satisfies democratic ideals (rather than achieves means-ends rationality)
- Ontology: blurring of distinction between facts and values, and between description and evaluation; public preferences as *emerging* from deliberative processes
- Standard problem frame: "risk issues" as public issues with a technical dimension
- Process norms: upstream engagement; deliberative forum; non-coercive and non-hierarchical; consensus-seeking

Process oriented

Knowledge as contextual

Low deference to formal expertise

Figure 1: Governance types and their approaches to problems. For key references, see sections 4.1.1, 4.2.1, and 4.3.1