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

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

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18 <http://dx.doi.org/10.1016/j.gloenvcha.2015.04.002>

1 **ABSTRACT**

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

23

24

1 1. INTRODUCTION

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

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

6

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

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

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

23

24 **2. SCOPE, CONCEPTS, AND DEFINITIONS**

1 Our argument about the relationship between different governance types and what is
2 perceived as model quality is in part a logical one; however, we discuss a range of examples
3 from several policy domains, necessarily in a somewhat schematic way. This ensures that
4 our argument is empirically grounded, and helps to flesh out its implications and nuances.
5 There are, of course, many different classes of model, and the definition we provide below
6 is not the only way of thinking about models (c.f. Hastrup, 2013), but is introduced to clarify
7 our scope and to make our argument tractable. Here, we therefore define a class of formal
8 models as purposeful mathematical representations of some real world phenomenon of
9 interest (see Grimm and Railsback, 2005). These are composed of equations, statistical
10 relationships, algorithms, or some combination therein (NRC, 2007). Such models inevitably
11 contain numerous simplifications, approximations, and exclusions, and hence they are never
12 perfect representations of the systems that they aim to characterise (Winsberg, 2014).
13 Moreover, their development is inevitably conditioned by methodological paradigms,
14 computational capacities, and path dependency. Thus, we conceive of these models as
15 unavoidably imperfect decision-making aids, rather than truth machines (Winsberg, 2014).
16 In the policy context with which we are concerned, mathematical models have various
17 functions. They are often concerned with the task of extrapolating beyond known
18 observations, such as predicting or projecting a future (*e.g.* the potential impacts of climate
19 change on species distribution), or answering “what-if” style questions about proposed
20 policy interventions. Models are also applied for the purpose of classifying objects (*e.g.* is
21 this chemical carcinogenic?), or for simply describing relationships amongst variables (*e.g.*
22 statistical models in flood frequency analysis).
23

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

11

12 **3. A BRIEF HISTORY OF QUALITY EVALUATION PARADIGMS**

13 Models-for-policy were initially viewed as tools that would allow decision-makers to
14 determine the rational course of action in the face of environmental and public health
15 hazards. Reflecting this mindset, early approaches to quality evaluation focussed upon the
16 degree to which a model corresponded with reality. That is, the question of model quality
17 was largely understood in terms of predictive accuracy (bias and precision) and, less
18 significantly, fit to existing datasets. This approach was embodied in categorical tests for
19 “validating” particular models (*e.g.* hypothesis testing), in measures of the difference
20 between observed values and the values predicted by the model (*e.g.* mean square error),
21 and in methods for discriminating between a range of plausible models (*e.g.* “goodness of
22 fit”). These technical dimensions of quality are clearly still remarkably important (see Cox,
23 2013 for an overview), but a sole reliance on them has encountered criticism from various
24 quarters. For example, Peterson (2006) has argued that quality is not just a question of

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

13

14 Building on these lines of thought, scholars argued that there are broader dimensions of
15 model quality not always captured by historic verification and validation tests (that focussed
16 on precision and bias). These include (Van der Sluijs *et al.*, 2008; Oreskes *et al.*, 1994; Beck,
17 2002; EPA, 2003; Rykiel, 1997; Clark and Majone, 1985; Refsgaard *et al.*, 2007; Maxim and
18 van der Sluijs, 2011; Augusiak *et al.*, 2014; Grimm *et al.*, 2014):

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

- 1 • whether the computer code faithfully reflects the model’s mathematical content;
- 2 • whether the dimensionality and resolution are adequate;
- 3 • the degree of transparency (*e.g.* whether algorithms and datasets are publicly
- 4 available);
- 5 • the “pedigree” of the model building methodology; and
- 6 • whether parameter and model uncertainties have been acknowledged and
- 7 accounted for (*e.g.* through sensitivity or scenario analysis).

8

9 Many of these dimensions are rather difficult to formalise, and as a result are difficult to
10 take account of during model construction and evaluation. This can lead to the neglect and
11 underutilisation of model-based evidence in policy contexts. In response to this concern,
12 some authors have proposed explicit and uniform model evaluation criteria (*e.g.* Alexandrov
13 *et al.*, 2011). However, there is a broad recognition that the nature of the problem being
14 modelled, and the particular decision-making task that the model is designed to fulfil, also
15 shape conceptions of quality (NRC, 2007). An influential statement of this is the Numerical
16 Unit Spread Assessment Pedigree (NUSAP) approach (Van der Sluijs *et al.*, 2005, 2008;
17 Risbey *et al.*, 2005), which draws on Funtowicz and Ravetz’s (1993) concept of post-normal
18 science. The basic idea is that particular types of problems – defined according to the
19 “decision stakes” and the degree and nature of uncertainty – are best explored through
20 particular types of science and models. Building on this, Renn and others have constructed
21 various typologies of the “risk issues” faced by contemporary societies, setting out how each
22 category of problems lends itself to particular analytical methods (*e.g.* Klinke and Renn,
23 2008; Pellizzoni, 2001). For example, routine, well characterised problems lend themselves
24 to the methods of probabilistic risk analysis, whereas contested, ambiguous issues require

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

3

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

17

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

1 for structured deliberation (*e.g.* the Delphi method; Linstone and Turoff, 1975). Finally,
2 various forms of reasoning by analogy – often misperceived as merely a lay method – have
3 been used to inform public and environmental health policy (*e.g.* Flyvbjerg, 2008). Indeed,
4 climate science has a long tradition of supplementing mathematical models with the use of
5 temporal and spatial analogues in scenario development (Mearns and Hulme, 2001). This
6 analogical approach is sometimes proposed as a check against the perceived indeterminacy
7 – and potential for bias or strategic misrepresentation – encountered in those contexts
8 where model outputs are particularly sensitive to arbitrary assumptions (*e.g.* Flyvbjerg,
9 2008; Pilkey and Pilkey-Jarvis, 2001). The general point is that in these situations, the
10 question of model quality should consider the strengths and weaknesses not just of
11 proposed models, *but also relative to alternatives to mathematical modelling.*

12
13 To summarise: model quality is now broadly accepted to be a multi-dimensional concept;
14 quality evaluation is seen as an intrinsically comparative task; and quality is viewed as a
15 function of how the model relates to the policy problem it was designed to address.
16 However, many of the non-technical dimensions of model quality are difficult to formalise
17 and so there is considerable ambiguity surrounding how they might be taken account of
18 during model building and evaluation. In what follows, we introduce and apply a typology of
19 governance regimes that helps clarify these broader dimensions of model quality and shows
20 how the emphasis placed on them differs by regime-type. Throughout, we emphasise the
21 implications of this for the uptake – or neglect – of scientific evidence in concrete policy
22 settings.

23

1 **4. JUDGING THE QUALITY OF MATHEMATICAL MODELS REQUIRES**

2 **ATTENTION TO GOVERNANCE TYPES**

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

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

6

7 **4.1 Risk-based vs. Precautionary Regime types**

8 *4.1.1 Basic features of the risk based regime type*

9 Risk based approaches (Figure 1) are rooted in theories of probability and utility
10 maximisation (Kaplan and Garrick, 1981; Savage, 1972). They seek to characterise how the
11 future might unfold if a policy maker was to undertake a particular course of action, using
12 utility functions to determine which outcome is best or optimal (*i.e.* consistent with known
13 preferences) (Kaplan and Garrick, 1981). The future is conceived of as amenable to empirical
14 investigation – within limits – and uncertainty is represented using standard decision-
15 theoretic concepts (*e.g.* probability distributions on uncertain variables). As such,
16 probabilistic risk assessment combined with cost-benefit analysis is often held up to be the
17 gold standard of policy analysis in risk-based regimes (*e.g.* Sunstein, 2002; Graham and
18 Wiener, 1998; Löfstedt, 2011). This ties in with the fundamental goal of such regimes of
19 making *coherent* decisions under uncertainty and within resource constraints (Pate-Cornell,
20 1996). Of course it is broadly accepted that risk analysis can never solve actual problems –
21 as they are infinitely complex – but only idealisations of them (Jaynes, 2003; Savage, 1972).
22 The core questions then become: is the idealisation a reasonable approximation of the
23 system of interest (*e.g.* does it adequately represent the underlying causal structures,
24 empirical laws, and current state of the world), and are the model inferences consistent

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

4

5 4.1.2. Basic features of the precautionary regime type

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

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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).

1 Similarly, the rise of risk as perhaps *the* trans-national approach to governing climate change
2 (Pidgeon and Butler, 2006) – in contrast to its more precautionary origins – led to the
3 growing use of probabilistic modelling as a way of accommodating uncertainty. This
4 included early attempts to attach probabilities to climate scenarios (Dessai and Hulme,
5 2004), the Stern Review and its analysis of climate futures within the cost-benefit
6 framework (Stern, 2006), and more nascent programmes seeking to determine the odds
7 with which severe weather events can be attributed to human influence (*e.g.* Pall *et al.*,
8 2011). What seems to be happening here is members of a modelling community adapting
9 their methodological practices in attempts to align with the rationale of risk governance
10 (and so maintain or enhance their policy relevance).

11

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

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

19

20 **4.2 The Adaptive Regime Type**

21 *4.2.1 Basic features of the adaptive regime type*

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

1 capacity to control complex natural systems, and conceive of policy-making as
2 fundamentally about robustness, flexibility, and learning (Lee, 1999; Guston, 2008; Lempert
3 *et al.*, 2003; Schindler and Hilborn, 2015; Holling, 1978; van der Pas *et al.*, 2013). That is,
4 they do not seek optimal outcomes, but rather policies that will be *good enough* across a
5 range of plausible futures, and that have explicit provisions for adaptation based on
6 experience (Swanson *et al.*, 2010). Moreover, they are typically concerned with governing
7 particular *places* or systems (*e.g.* a particular catchment), rather than a particular
8 technology or risk object. As they emerged as a critique of centralised, technocratic forms of
9 governance, we might expect different emphases between adaptive and risk-based regimes
10 on a number of dimensions of model quality. For example, adaptive regimes should have a
11 comparatively greater preference for models that 1) have a fine level of resolution, rich
12 contextual detail, and are spatially explicit; and 2) have sufficient flexibility to evaluate
13 policy options with respect to a variety of assumptions about the state and mechanics of the
14 world. The former reflects the fact that adaptive regimes are often focussed on how the
15 features of *particular* places both condition, and are conditioned by, the causal processes
16 that are at work (Lane, 2001). This contrasts with a search for general, abstract laws or
17 regularities that can be readily extrapolated across space, time, and context, which is more
18 characteristic of the risk-based regime type. The latter point does not imply that risk-based
19 regimes neglect the question of model uncertainty; but there is a persuasive critique that
20 they tend to focus on its more mathematically tractable forms (*e.g.* probability distributions,
21 sampling error), to the neglect of indeterminacy and ignorance (*e.g.* Shackley and Wynne,
22 1996; Stirling, 2012). This again contrasts with adaptive regimes, whose emphasis on
23 robustness implies that they will be particularly sceptical of model outputs that may be
24 strongly conditioned by unexplored assumptions (Schindler and Hilborn, 2015).

1

2 4.2.2 Adaptive conceptions of model quality: examples and issues

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

19

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

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

1 neglect has led to questions about the credibility of modelling estimates in pollution
2 management in the United States, in some cases leading to the over-turning of regulatory
3 decisions at judicial review (*ibid*).
4
5 Similar tensions arise in many other domains and jurisdictions. For example, a high degree
6 of rule-bound standardisation was part of the reason for the Indian Government's
7 scepticism of model-based estimates of HIV-prevalence in the early 2000s (Mahajan, 2008).
8 Here, the relatively rigid and generic model structures favoured by the World Bank and
9 UNAIDS were perceived as neglecting place-based drivers of the spread of the disease,
10 leading Government officials to reject their estimates as implausible. The logic was that the
11 encoding of particular "at risk" categories from Western contexts, such as homosexuals and
12 intravenous drug users, travelled rather uneasily to the Indian socio-cultural context, where
13 a more valid set of categorisations might have emphasised the role of poverty, nutritional
14 deficiencies, and gender relations (Karnik, 2001).
15
16 By contrast, the normative and factual commitments of risk-based regimes can lead them to
17 be less concerned with accommodating contextual and place-based factors within models,
18 as Britain's response to the 2001 foot and mouth outbreak illustrates. In this instance, the
19 UK Government adopted a rigorous animal culling policy, based in large measure on the
20 outputs of predictive modelling (Bickerstaff *et al.*, 2006). The significance lies in the
21 Government's controversial reliance on a particular modelling approach – an
22 epidemiological model, which emphasised abstract theory and objective knowledge – while
23 neglecting other models that explicitly represented spatial and contextual detail (Bickerstaff
24 and Simmons, 2004). The different modelling communities (principally epidemiologists vs.

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

8

9 State-of-the-art climate modelling involves similar trade-offs, as well as lessons on how they
10 can be managed. Climate models draw their authority from representing abstract, physical
11 laws, the sort of knowledge emphasised by risk-based regimes (Rommetveit *et al.*, 2012). On
12 the other hand, critiques of the “globalising instincts” of climate governance (Edwards,
13 2010; Hulme, 2010) have emphasised the coarse resolution of many climate models,
14 together with their opaque and rule-based character. Some have argued that this makes
15 them ill-suited to inform an *adaptive* approach to climate governance, with its emphasis on
16 flexibility, incrementalism, learning, and place (*e.g.* Weaver *et al.*, 2013; Cash and Moser,
17 2000). Such tensions played out in NOAA’s provision of probabilistic seasonal climate
18 forecasts to water resource managers in the late 1990s (Rayner, 2012). These forecasts had
19 their roots in the logic of the Harvard Water Program, where water system design,
20 investment and operation problems are formulated as mathematically tractable trade-offs
21 (Milly *et al.*, 2008). However, water resource managers largely neglected these predictions,
22 mainly because they viewed NOAA’s statistical estimates as largely irrelevant to *their*
23 preferred approach to water system governance, which emphasised redundancy and
24 flexibility, rather than notions of rational planning and efficiency (Rayner, 2012).

1

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

14

15 **4.3 The Participatory Regime Type**

16 *4.3.1 Basic features of the participatory regime type*

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

1 reasoning (rather than pre-exist them). Accordingly, they tend to place a premium on using
2 models that are transparent and understandable to a range of audiences, and that provide
3 space for lay or local knowledge, expertise and framings (*e.g.* in specifying relevant outcome
4 variables, parameter estimates, or plausible scenarios; Stirling, 2006; Yearley, 2000; Ravetz,
5 2003). By contrast, they will look unfavourably on methodological approaches that are
6 excessively complex, or that impose particular framings (*e.g.* through lacking explicit
7 treatment of option definition, or having hardwired model structures; McIntosh *et al.*,
8 2005). They will be similarly sceptical of models that contain *proxies* for public values and
9 preferences (*e.g.* measures of willingness-to-pay), or are constructed and evaluated by a
10 technical elite (Stirling, 2006).

11

12 *4.3.2 Participatory conceptions of model quality: examples and issues*

13 The UK Government's current approach to health technology appraisal illuminates some of
14 the issues sketched out above. This approach, beginning with the establishment of the
15 National Institute for Clinical Excellence (NICE) in 1999, is a mixture of clinical (*e.g.* meta-
16 analyses) and economic analysis, with resource allocation guided by a rough criterion of
17 cost-effectiveness (Rawlins and Culver, 2004). The technical elements of the analysis sit
18 alongside various participatory mechanisms, including a Citizen's Council (Rawlins, 2004),
19 which is a deliberative forum designed to capture public views on the ethical dimensions of
20 healthcare priority setting (*e.g.* should health be valued more highly in some age groups
21 than others, *etc.*). In essence, the modelling process (*i.e.* the clinical and economic analysis)
22 purposefully turns a blind eye to the "social value judgments," leaving them free for public
23 deliberation in separate institutions (Rawlins, 2004). However, the UK Coalition Government
24 (2010-) has expressed concerns about this division of labour, in particular with what they

1 perceive to be a lack of formality and clarity in how the deliberative panels actually inform
2 decision making. Under their proposed reforms (Department of Health, 2010), the value
3 judgments would be incorporated *within* the modelling process, being weighted and
4 aggregated alongside the clinical and economic data. Crucially, this was to be done in a
5 manner that is “evidence based, reflecting the views of experts,” (Department of Health,
6 2010) suggesting a more limited commitment to participatory ideals. This serves as a
7 reminder that social and ethical judgments can be included within modelling approaches in
8 ways that in reality foreclose or crowd out public deliberation.

9

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

1 *al.*, 2006). Lane *et al.*'s (2011) pilot study of flood risk modelling in Pickering, Yorkshire,
2 drew heavily on facilitated workshops and helps elaborate these concepts.
3
4 The context of this work was that repeated flooding had occurred in the area, which,
5 coupled with an absence of meaningful progress in delivering risk reduction schemes, had
6 led to a marked loss of local trust in the governing authority (the Environment Agency). This
7 was exacerbated by the Agency's rather superficial public engagement practices, which took
8 place *following* the modelling process (of risks and potential physical interventions) and
9 were essentially attempts to manage or dampen controversy (Lane *et al.*, 2011). This
10 provided a vacuum into which an academic modelling team could step. Lane *et al.* (2011)
11 proposed a different set of simpler, *interactive* modelling procedures that re-built the trust
12 of the local community as they were able to participate in exploring the possibilities of an
13 innovative flood risk management strategy. The public's role extended beyond framing the
14 modelling process (*e.g.* focussing on upstream storage rather than urban flood defence), to
15 contributing to the model's conceptual development (*e.g.* drawing on local knowledge to
16 question the data provided by a flow gauge), and participating in developing and testing
17 policy options (*e.g.* related to the number and height of the proposed bunds). The model
18 was ultimately based on a simple hydrological rather than hydraulic routing scheme, with
19 perhaps less scientific and technical quality than state-of-the-art methods. Yet the way that
20 it was co-constructed helped to constitute a shift towards participatory "governance," in a
21 space where the credibility of the formal authority had been in question, and where local
22 knowledge had previously been excluded from the policy process. Of course, this sort of
23 heavily participatory modelling will not be practical in most situations. But the case does
24 suggest that there may be some contexts – such as those characterised by a loss of public

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

4

5 **5. CONCLUSIONS**

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

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

15

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19

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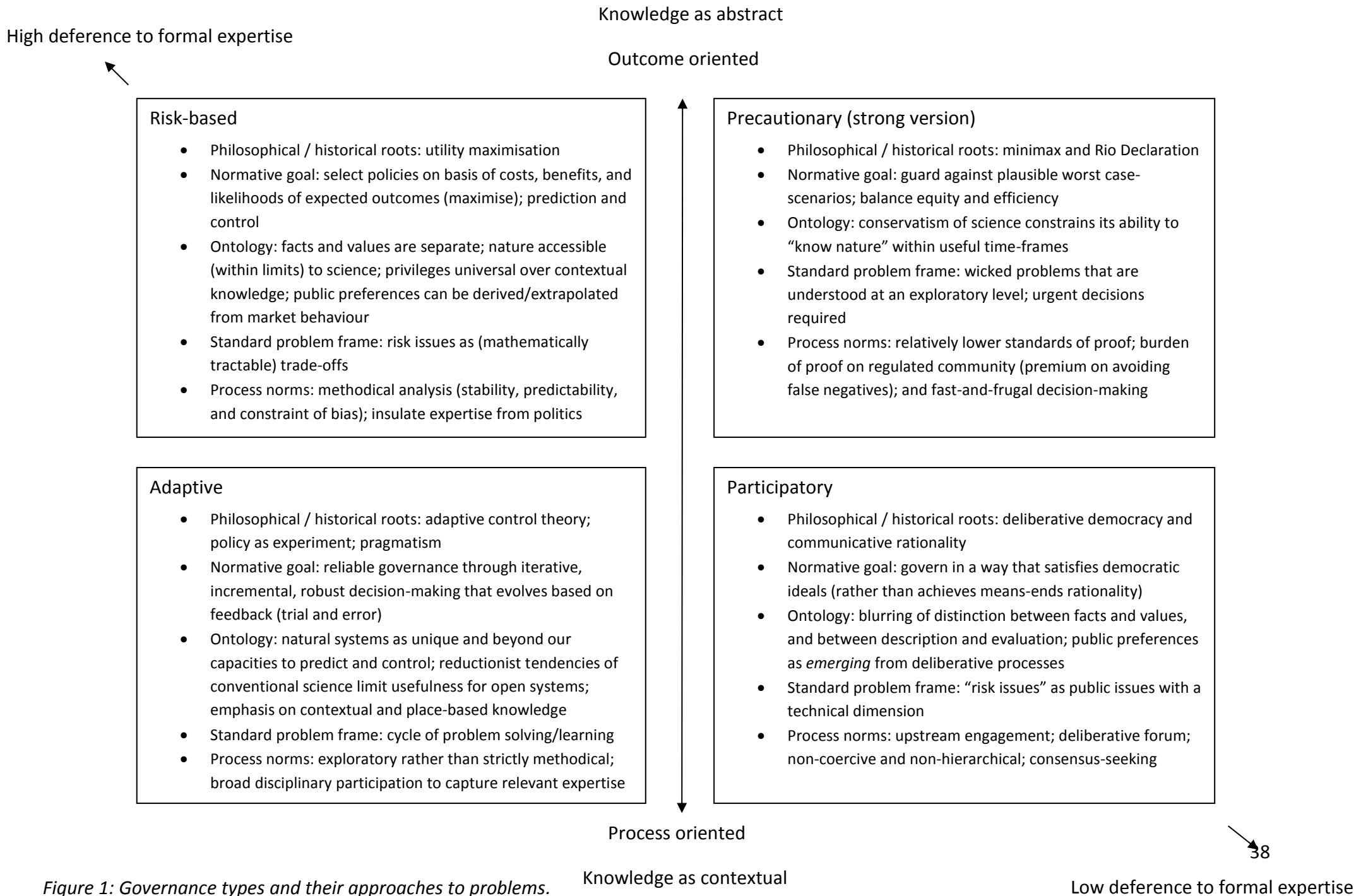


Figure 1: Governance types and their approaches to problems. For key references, see sections 4.1.1, 4.2.1, and 4.3.1